UNIVERSITY COLLEGE LONDON

THE RESILIENCE OF ASSET SYSTEMS TO THE OPERATIONAL RISK OF OBSOLESCENCE: USING FUZZY LOGIC TO QUANTIFY RISK PROFILES

A THESIS SUBMITTED TO UNIVERSITY COLLEGE LONDON FOR THE DEGREE OF DOCTOR OF ENGINEERING

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I, Kieran Mulholland confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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To all of the above and my friends and family, I would like to thank you all; without your help during the last four years, this would not have been possible.

ABSTRACT

This thesis sets out to explore possible methodologies to enable proactive obsolescence management for end users within the Built Environment. Obsolescence has shown to be a growing operational and financial risk as technology is further embedded into our buildings, seeking enhanced performance and connectivity. Obsolescence directly impacts the supportability of an asset system, manifesting into obsolescence-driven investments, which are typically managed reactively causing lifecycle costing complications. Gaps within academic literature and industry guidance have been identified herein and will be directly addressed by the research questions.

The challenge of researching into obsolescence surrounds the commercial value of the required datasets, requiring a novel methodology to address the research problem. Further to this, the multi-stakeholder nature of supply chains, along with the unknown nature of obsolescence, has created a level of ambiguity within the datasets. Fuzzy Logic was adopted, above other options, to create an Obsolescence Impact Tool (OIT) that would enable the user to quantify the risk profile of obsolescence within asset systems. This model, along with an enhanced Obsolescence Assessment Tool (OAT), were both developed and tested within a two-year case study environment. Additional research questions were answered by analysing the reverse engineered original equipment manufacturers (OEM) sales catalogues. Through the combination of both the results from OIT and OAT, along with the analysis of OEM catalogues, a visualisation of the resilience of asset systems in respect to obsolescence is presented.

The findings found herein provide evidence for the use of OIT and OAT for industrial application through the insights provided by data-driven models. The two models formulate a methodology that enables decision-making and proactive obsolescence management under uncertainty. The results of the OEM analysis provide explicit evidence that can immediately be used by the reader to enhance their obsolescence management plan (OMP). Evidence of the impact of sales strategies and how an end-user could utilise and reverse engineer the findings, hold potential for all Facilities Management teams. The findings culminate in a wide range of contributions that further the understanding of obsolescence within the Built Environment and importantly bridge some of the existing gaps. The Future Works chapter covers both observations made by the author and alternative methodologies that would provide further insight i.e. Type 2 Fuzzy Sets, Adaptive Learning Techniques, and Markov Chains.

IMPACT STATEMENT

This thesis contains three key elements that could be extracted and applied within an industrial application. These elements contain sub-elements that in themselves provide individual benefit to the user, however, for more detail please see Discussion chapter 5.0.

The Obsolescence Assessment Tool (OAT) is an indexing methodology that has been continually tested within this thesis, following a pilot study within a Master of Research (MRes) dissertation. This decision aiding tool enables an Asset Management or Facilities Management team to quickly use the data they already possess to provide insight information regarding their asset registers. OAT will empirically evaluate which components require attention due to a weakness to obsolescence, as a result of unavailable mitigation options. This tool holds the potential to strategically assign resources, whilst avoiding unforeseen lifecycle investments into systems that have reactively identified obsolescence.

The Obsolescence Impact Tool (OIT) is a risk assessment tool that was entirely developed and tested within this thesis, adopting a Fuzzy Logic architecture to account for ambiguous or imprecise input data. OIT gives an enhanced insight into an asset system's components with the added content of probability and impact. The most important and vulnerable components will be identified using a wider array of traditional onsite datasets. This tool has shown the potential to produce data-driven evidence, upon which, a Cost Benefit Analysis can be drawn for obsolescence mitigation strategies.

The reverse engineering of OEM sales catalogues has produced a range of evidence of the effect of obsolescence on component cost and availability. Probability density profiles can be extracted directly from the Results chapter of this thesis and applied into BMS systems across the industry. The results validate a new methodology and how it can be applied within an Obsolescence Management Plan (OMP) for an Asset Management or Facilities Management team. The results enable data-driven decision making and a more holistic approach to proactively managing obsolescence within the Built Environment.

The above three key elements in practice would combine within a single OMP document. The implementation of these three steps alone will enable proactive and ultimately evidential based decision making. In their respective components and collective whole, they contribute to several pieces of new knowledge. The challenge is reapplying such steps to new systems, or similar systems in a new context, the author strongly highlights that whilst the results are practical and insightful, they are not all necessarily directly transferable. However, there are profiles and conclusions deduced from the results of this thesis that will be useful on other sites, the methodology and models would need to be reiterated with the new localised datasets. This is just the beginning of incorporating more data-driven decision aiding tools into an industry that faces growing risk profiles from complex problems.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

AM	Asset Management
BAU	Business as Usual
BS	British Standard
BIM	Building Information Modelling
BMS	Building Management System
CLD	Causal Loop Diagram
CIBSE	Chartered Institute of Building Services Engineers
CM	Cognitive Map
COTS	Commercial of the Shelf Components
DMSMS	Diminishing Manufacturing Sources and Material Shortages
EOL	End of Life Notification
EngD	Engineering Doctorate
FM	Facilities Management
FCM	Fuzzy Cognitive Maps
I/O	Inputs and Outputs
IoT	Internet of Things
LO	Last Order
LTB	Life Time Buy
LCC	Lifecycle Costing
MRes	Master of Research
M&E	Mechanical and Electrical
MF	Membership Function
MOCA	Mitigation of Obsolescence Cost Analysis
OAT	Obsolescence Assessment Tool
OIT	Obsolescence Impact Tool
OM	Obsolescence Management
OMP	Obsolescence Management Plan
OEM	Original Equipment Manufacturer
PFIC	PFI Contractor
PPM	Planned Preventative Maintenance
PFI	Private Finance Initiative
PO	Purchase Order
RM	Risk Management
SS	Security System
SD	System Dynamics
UPM	Unplanned Maintenance

1 INTRODUCTION

The Built Environment is becoming heavily urbanised and complex because of rising populations, integration of systems, and technological advancements. As we take advantage of our progress and embed new methodologies such as Building Information Modelling (BIM) and the Internet of Things (IoT), Risk Management (RM) techniques must also be updated. RM in the context of this thesis refers to the risk of obsolete components within assets, which often form a system of assets providing a service within the Built Environment. Figure 1 and Figure 2 illustrate how within a decade the majority of the world will reside in dense and connected urbanised environments; the impact of such change is a key driver for this research. The major service systems within infrastructure and buildings require sustainment for the typical useful life of the structure (60 to 90 years) (UCL Engineering 2014). In order to do so, both Facilities Management and Asset Management play a key role in the efficacy of asset lifecycles.

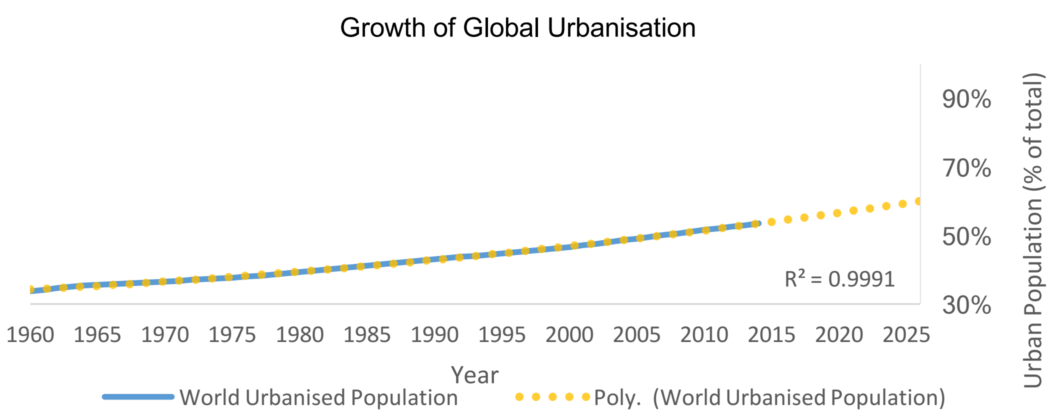


Figure 1 Growth of Global Urbanisation, adapted from The World Bank (2016)

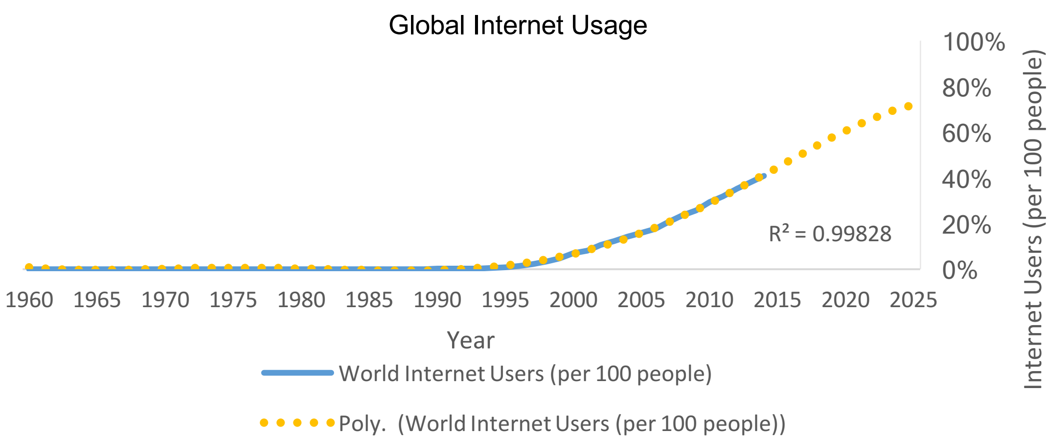


Figure 2 Global Internet Usage, adapted from The World Bank (2016)

Chapter 1.0 will introduce the research problem to the reader, citing news and research articles to contextualise the narrative and formulate the key elements. The main components of this thesis will then be briefly presented, aligning themselves with the subsections within the Literature Review (Chapter 2.0). Finally, the resultant key drivers behind this thesis will be concluded to help elucidate to the reader the 'what' and 'why' factors.

1.1 Problem

The problem occurs for building owners and facility managers, when components or assets are no longer supported or manufactured, which has a direct impact on one's ability to maintain and sustain an asset system. This includes both hardware and software. A recent example would be the UK National Health Service paying £5.5 million to Microsoft in 2014 for a year extension of support for Windows XP (The Guardian 2014). Within the context of this thesis, such an event is classified as an obsolescence-driven investment. Obsolescence has been widely defined as when an asset is no longer suitable for current demands or is no longer supported by the manufacturer (Sandborn 2004; BSI 2007; Bartels et al. 2012; CMCA UK 2013). Sandborn (2011) highlights the inability of engineers to quantitatively express the impact that obsolescence can have upon an organisation, leading to a predominantly reactive stance upon obsolescence management. Managing obsolescence reactively has widely been reported as not just an ineffective approach, but also the most commonly adopted at present (Stogdill 1999; Singh, P. Sandborn, et al. 2004; Merola 2006; Konoza 2012; Sandborn 2013).

The ability to proactively manage obsolescence within systems will become more complex, due to the greater adoption of connected devices (see IoT) and the increased revolutionising of the consumer electronics market (Bartels et al. 2012). Shortening lifecycles are the resultant effect of these changes, meaning that obsolescence management will have to operate within a shorter timeframe and on a more granular level than it currently does. Data directly sourced via online 'Google Trends' illustrates using a normalised y axis, how some of the broad aforementioned trends are growing in online search queries (see Figure 3). The observed growth appears to correlate with the uptake and saturation of global internet access as shown in previous figures. Whilst these illustrations are provisionally indicative, they paint a strong picture of how the Built Environment and its occupants communicate and cooperate is due to change dramatically. Please note, the data source is 'grey literature' and a live, publically available dataset that is therefore likely to have changed following the publication of this thesis. Please see the statement found in section 2.1 regarding the use of grey literature in this research project.

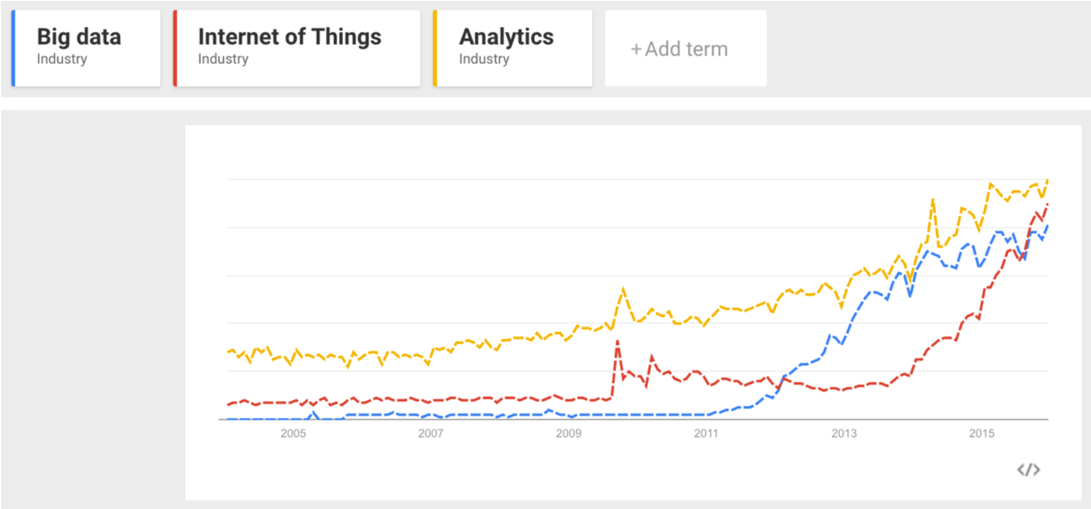


Figure 3 Google Tends for the terms 'Big Data', 'Internet of Things' and 'Analytics', from Data source: Google Trends (www.google.com/trends) (2016)

1.2 Obsolescence

Obsolescence has existed within academic research since the 1970's with Warmington's (1974) paper; both the research approach and the problem itself have evolved drastically since then with the emergence of the Information Age, with Lua Yali et al. (2012) declaring it 'inevitable within modern systems'. Traditionally, the term obsolescence was used when engineering organisations experienced high inventory costs, due to large spares holdings becoming obsolete after product lines ceased to be operated (Cobbaert & Oudheusden 1996; Masters 1991). This view has adapted as changes in management strategies of spares holdings matured. This multidisciplinary problem has expanded due to the continual evolution of consumer electronics and the further adoption of commercial off-the-shelf components (COTS), creating pressure upon manufacturers, resulting in component lifecycle shortening (Bradley & Guerrero 2008; Romero Rojo et al. 2010).

The defence industry illustrates a telling picture of the effect of adopting COTS components upon the supportable life of asset systems, first documented by Stogdill (1999), who used US weapon systems as an example (shown in Figure 4).

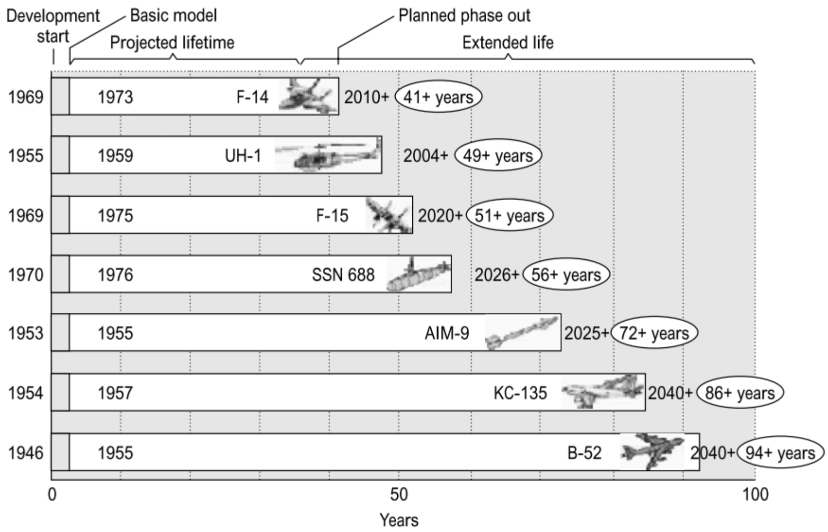


Figure 4 Supportable Life of Weapon Systems, from Stogdill (1999)

Long-life assets are particularly vulnerable to obsolescence within components from the wider consumer market, which typically innovates at a fast pace (Feng 2007; Sandborn 2008a). This has dramatically evolved from Elton and Gruber's (1976) view that technological innovation increases the efficiency of assets in a linear fashion, in reality, this relationship is far more volatile. Gravier and Swartz (2009) describe obsolescence as an 'economic phenomenon' that has been addressed by fast moving industries, such as avionics, semiconductor, aerospace, and the military. Findings within the preceding Master of Research dissertation suggest that long-life assets within the Built Environment are now also experiencing the same increase in obsolescence and unforeseen lifecycle investments. An example is lifecycle mismatches, which occur when the intended useful life of the parent asset significantly exceeds the lifecycle of the integral components, most noticeably the electronic components and/or software/firmware elements (Bradley & Guerrero 2008; Lua Yali et al. 2012). It is precisely the obsolescence-driven lifecycle investments, as described above, that are avoidable and will be addressed by this research project with the aim of enabling a more proactive management stance (Sandborn 2008a).

To further illustrate this point, historical purchase catalogues of SIEMENS BMS components were reverse engineered to map the occurrences of obsolescence, the timings, and also the effects upon unit prices. The data spans from 2007 to 2015 and contained 21,071 points. Figure 5 shows the behaviour of the data from a top-level view; it is clear to see the cyclical initiation of obsolescence within SIEMENS components occurring on a five-year rotation. This cycle is in line with the annual release of new products by SIEMENS; therefore, it may be possible to speculate that the increase in total products seen in 2013/14 will result in a reactive increase in obsolete components seen in 2017 (five years onwards).

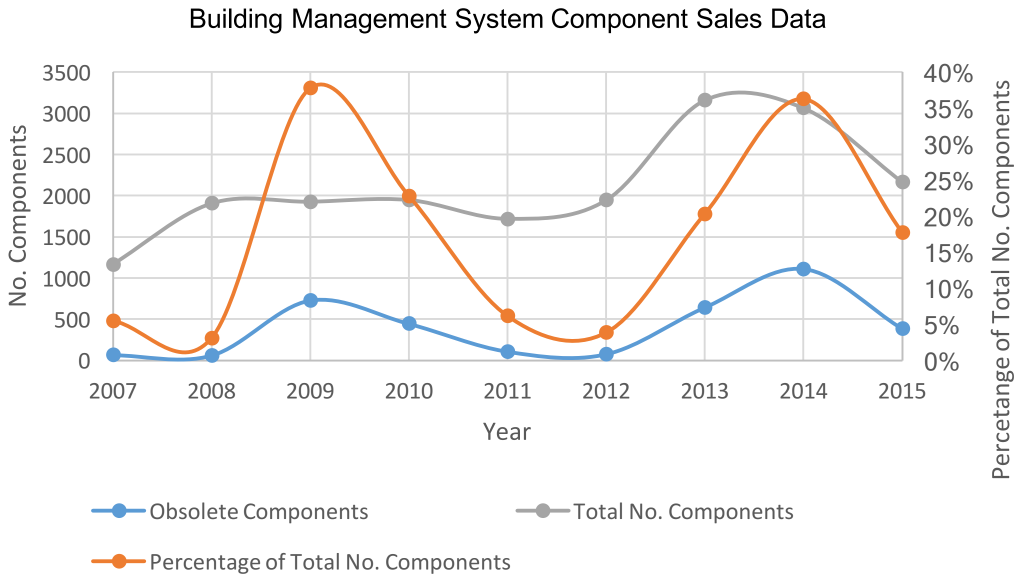


Figure 5 OEM Sales Strategy Analysis, created by author see Chapter 4.4

The data was further mined to investigate the length of time, in years, that SIEMENS were openly selling their components and then to compare this period with the life expectancy, via CIBSE guides, for these respective components.

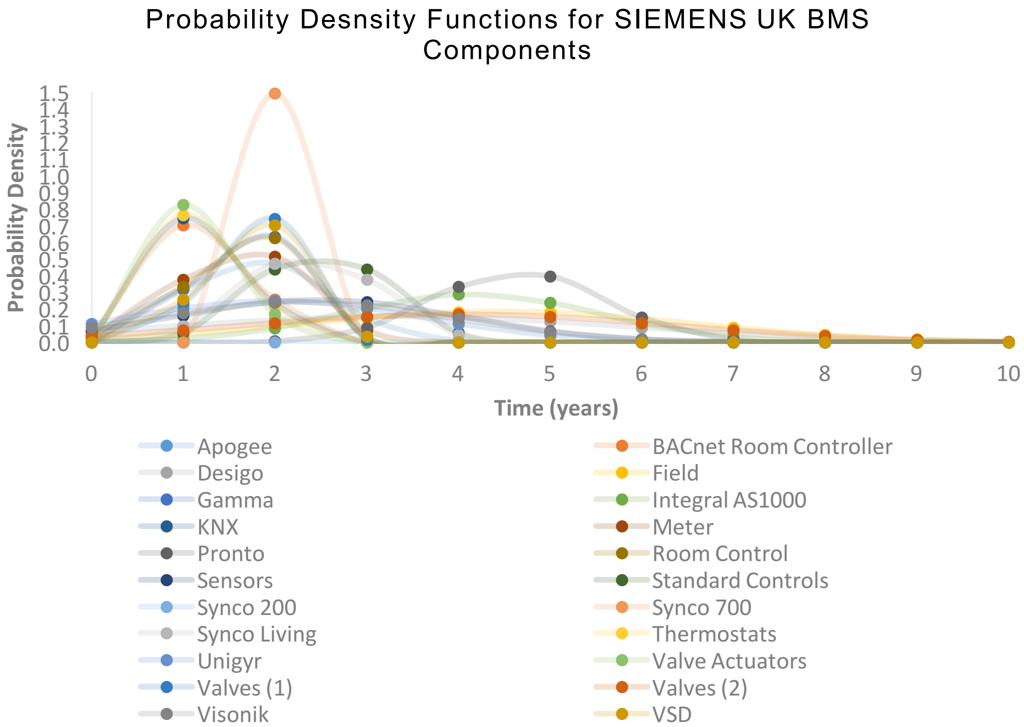


Figure 6 Component Probability Density Functions, created by author see Chapter 4.4

Although Figure 6 is congested, it does demonstrate the very short periods of time for which all SIEMENS products are being sold. Note, the components that exist within supply chains at distributors etc. are not considered within this dataset, albeit that this is a small hindrance. Two clear clusters appear within the data and they are shown in Figure 7 and Figure 8. Figure 7 contains the components on sale for the shortest period of time, which appear to centre around 1 – 2 years. Note, it is not possible with this dataset to distinguish the drivers behind such change i.e. is it due to drops in purchase demand? Is it related to technology road mapping? However, the insights found within this data are relevant to the typical consumer/facilities manager.

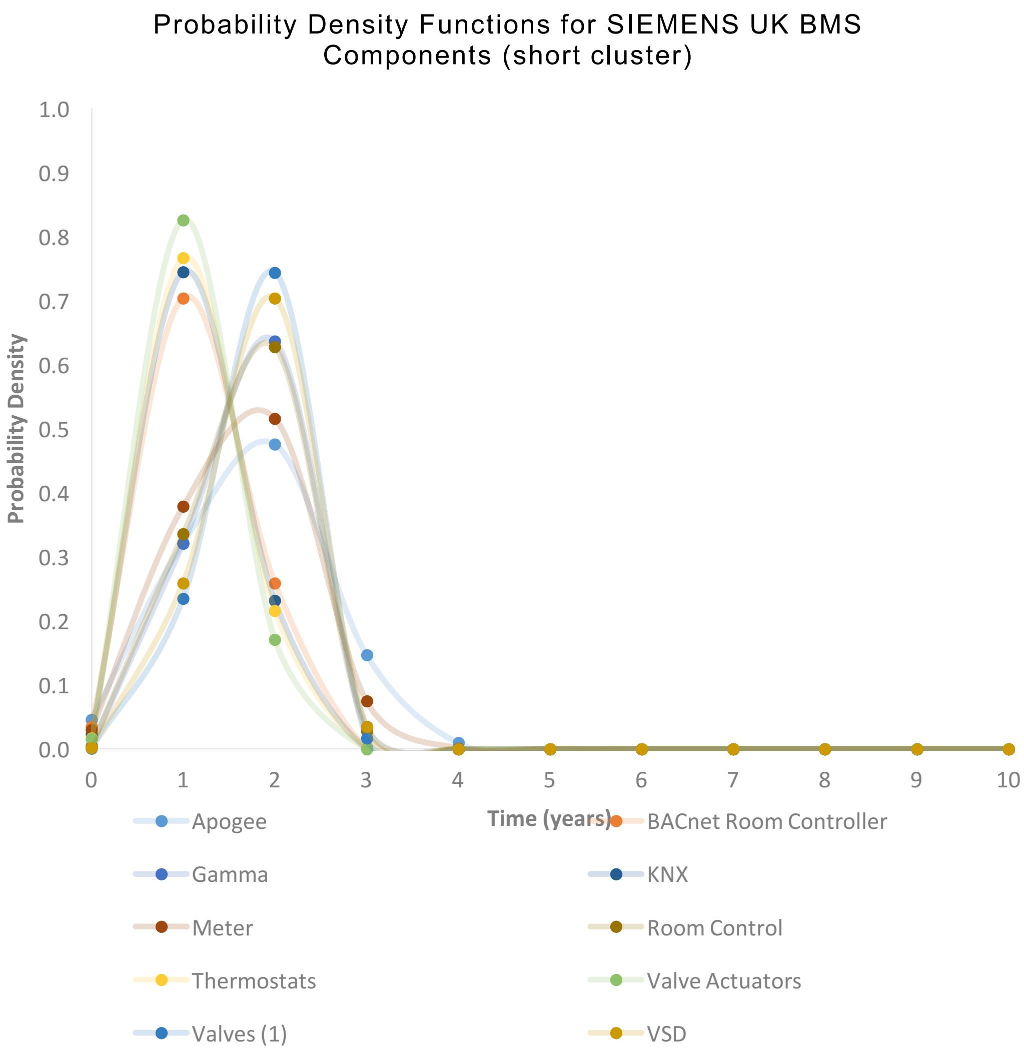


Figure 7 Probability Density Functions for Short Life Components, created by author see Chapter 4.4

Figure 8, in contrast, contains the data points that had a broader spectrum of years, showing the uncertainty within the dataset in regards to how long they were being sold by SIEMENS.

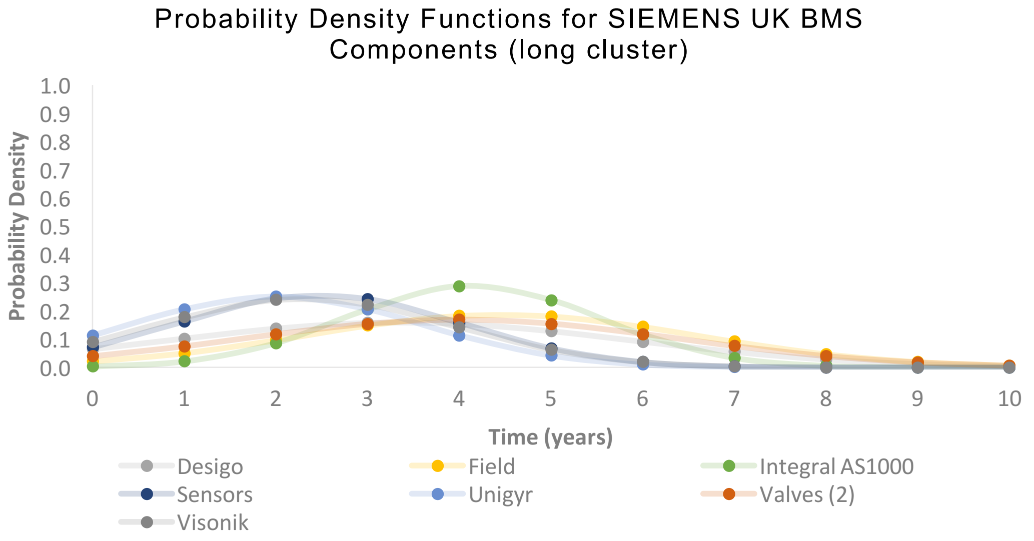


Figure 8 Probability Density Functions for Long-life Components, created by author see Chapter 4.4

The data used for the above figures could be used within routine business to undertake lifecycle requirements, but analysis of this type is not found within guidance or literature. The other element that came out of the data mining exercise was the effect of obsolescence upon the unit cost of components. This insight is linked to the suggestion of both component scarcity and the consequential costs of reactive management, illustrated in Figure 9.

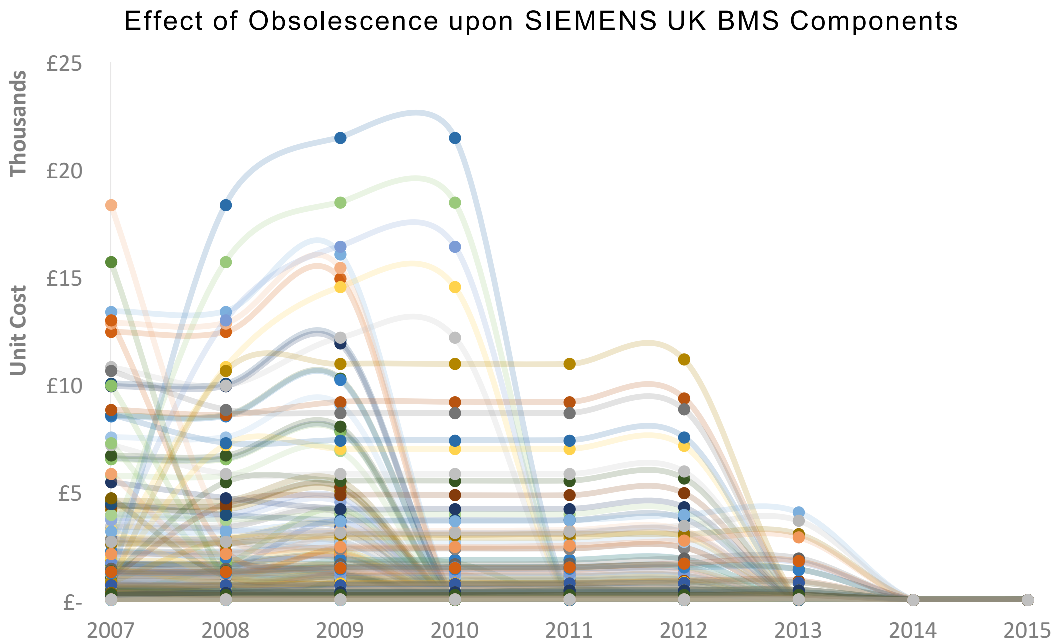


Figure 9 Effect of Obsolescence on the Unit Price, created by author see Chapter 4.4

Figure 9 contains data for components that were both new and existing in 2007, where it is clear to see the rise in component cost prior to becoming obsolete. The collection of Figure 7, Figure 8, and Figure 9 are all in themselves contributions both to new knowledge in the understanding of obsolescence and how it can behave. Also, it provides the evidence behind some of the key drivers to further understand this problem, its effects, and costs. To see more figures from this analysis, including normalised graphs to illustrate the ranges of unit cost increases, please see Chapter 4.4.

The work by Solomon et al. (2000), Singh and Sandborn (2002), Singh et al. (2004), and Feng et al. (2007) are among the most quantitatively advanced papers on obsolescence, explicitly testing methodologies for proactively managing its likely operational impact. The result of all the aforementioned pieces of research has led to the creation of MOCA (Mitigation of Obsolescence Cost Analysis), a software tool that generates and selects an optimum design refresh plan for a system. MOCA was developed by the University of Maryland, United States of America and led by Sandborn (2013). MOCA is a tool that is to be used by manufacturers and suppliers, which contain datasets of significant size, allowing for trend analysis upon demand. Whilst this tool has proven to show considerable success within some case-study testing, it is unsuitable for any end-user or equivalent with little to no historical data. This piece of research will locate itself within the Built Environment and assets that are commonplace within buildings and infrastructure across the world. The aim of the above two considerations is to produce a research project that directly tackles an existing problem, through producing a methodology that is truly applicable and useable to the end-user i.e. Facility Manager. These deliberate actions are not a criticism of the work that precedes this thesis, but rather a concerted effort to explore a field that has received little direct research attention. Directly speaking, this thesis aims to contradict the below extract from the current BS ISO 15686-2:2012 for Service Life Planning of Buildings and Constructed Assets:

> "[Lifecycle Planning] ... does not cover limitation of service life due to obsolescence or other non- measurable or unpredictable performance states."
>
> Service Life Planning - BSI, 2012

This section has introduced the concept of obsolescence to the reader by highlighting some of the key pieces of literature in order to provide context for the critique analysis that can be found in Chapter 2.2. Some preliminary data was also introduced and analysed to provide evidence behind some of the drivers for research into this field. The next section will tie obsolescence into the concept of long-life asset systems that are found within the Built Environment. This will bridge the research gap that currently exists and helps frame the research direction and key concepts to the reader.

1.3 Long-Life Asset Systems

The Built Environment has a wide network of systems, many of which have life expectancies that exceed 20 years (CIBSE 2008). Importantly, many of these systems contain components that have shorter lifecycles and therefore require lifecycle replacement during the intended useful life of the parent system as shown in Table 1.

Table 1 Life Expectancy of Components, extracted from Guide MCIBSE (2008)

Building management and controls	Years
head end (supervisor)	5
outstations	10
plant controller	10
operating system	5
remote display panels	10
communications network (hardwiring)	25
electric/electronic controls:	
electric controls	20
electronic controls	10
sensors	8
control valves	15
control dampers	15
hydraulic valve actuators	10
variable speed drives	15
pneumatic controls:	
air compressor	20
pneumatic controls	20
pneumatic valve actuators	15
dryer (pneumatic controls)	20
receiver	20
valves, connections	20
electronic/pneumatic interfaces	10
hydraulic valve actuators	10
leak detection:	
gas	0
refrigerant	10
water	15

Further to this point, the periods of time that these components are available from the original equipment manufacturers (OEM) is even shorter (please see Figure 6). This is the crux of obsolescence research within the Built Environment. The question arises as to how one sustains these systems without the comprehensive consideration of obsolescence.

Traditionally, this has been covered through the acquisition of spares and planned preventative maintenance (PPM) to observe condition deterioration. This creates a scenario where components have not failed and do not require replacement, however, are no longer supportable due to obsolescence – coined as lifecycle mismatch. Sandborn (2008b) also coined this phenomenon as the trailing edge of technology or the 'dark side of Moore's Law'.

As stated by CIBSE, the art of assessing life expectancy of assets is dependent upon many unknown or changing variables, importantly the nature of failure rates (CIBSE 2008). This creates issues for Facility Managers to accurately develop lifecycle replacement strategies. Figure 10 illustrates the insertion of the 'obsolescence phase' into a generic lifecycle profile; it is the unknown nature of when and how long this phase will manifest in reality that can cause supportability issues.

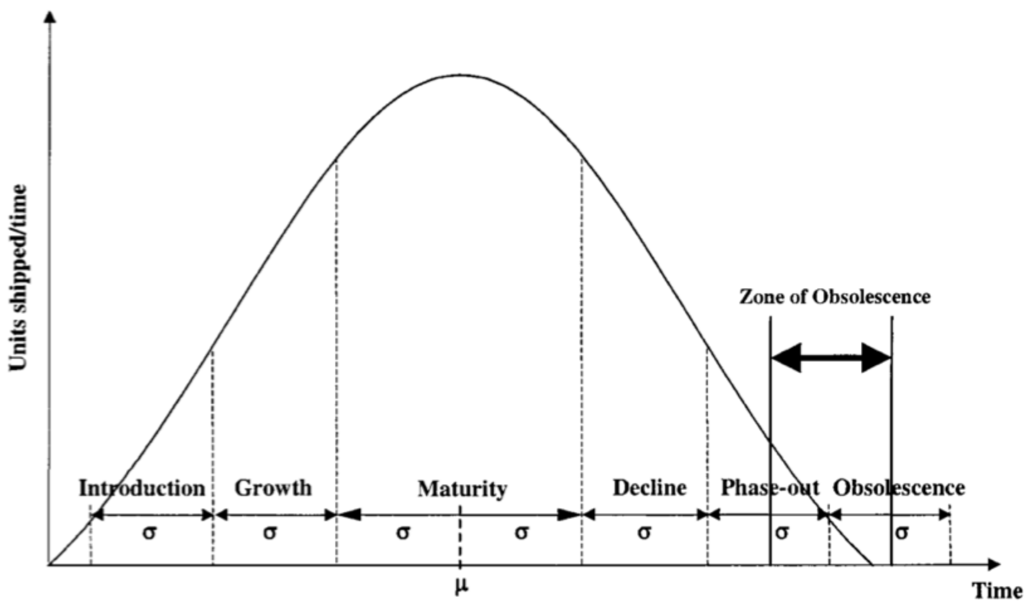


Figure 10 Lifecycle Stages, from Solomon et al. (2000)

To clarify, the research design of this thesis does not cover market conditions or supply chain management, leading to the explanation of the end of life notification release. As mentioned previously in this chapter, the approach will be from an end-user perspective; this has implications for the type and depth of data and therefore analysis possible.

Note that due to market conditions there is a component cost curve, which must also be considered as it compounds the financial impact of managing obsolescence reactively. **Error! Reference source not found.** shows the assumption within MOCA to linearly increase the cost of purchasing spare parts reactively (lifetime buy cost) once a component has already been announced as obsolete (t = 0) due to scarcity (Sandborn 2013). However, there is considerable literature sounding the principle of ‘scarcity’, and if there becomes a mismatch between demand for a component and its supply due to obsolescence (Lynn 1991), then costs may quickly become nonlinear.

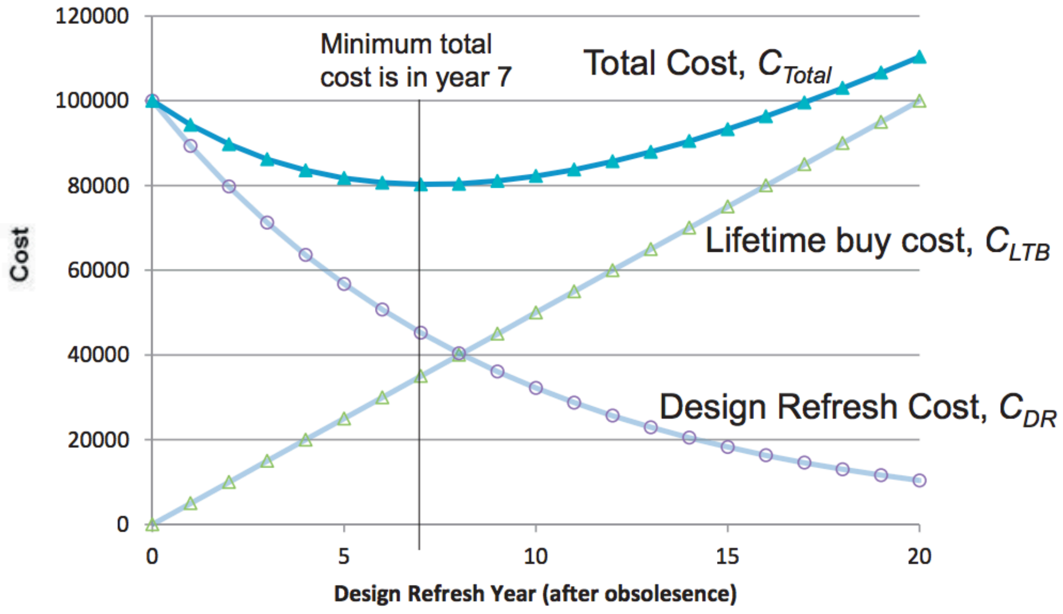


Figure 11 Key Output of MOCA Displaying Internal Assumptions, from Sandborn (2013)

To add wider context to the impacts of obsolescence within critical systems, the following examples have been highlighted. In 2005, Flaherty reported that the current fleet of UK Nuclear Submarines contains reactors controlled by Rolls Royce components. The current fleet is to be operational and supported until 2030-2040, the manufacturers of this component relocated to a country that was not acceptable to the UK MoD - deeming the component obsolete (Flaherty 2005).

Abili et al's (2013) paper covered a case-study of oil fields in the Tampen area of the Norwegian North Sea and the problems they were experiencing with obsolescence. The paper investigated a cost-benefit analysis, comparing obsolescence management techniques against the down time of the off-shore oil rig. The remote location of the oil rig, along with the lucrative nature of oil exploration, creates a dynamic set of pressures and drivers to effectively implement obsolescence management. Abili et al. state that the proactive obsolescence management strategy they employed saved $287 million in comparison to a reactive stance.

The scale of the financial impact that unforeseen obsolescence has driven investments was having on a UK Private Finance Initiative (PFI) was published by Mulholland (2014), highlighting the substantial financial drivers for this research. Across a ~3-year period £1.7m worth of capital expenditure was required due to obsolescence driven investments (see Figure 12), further analysis can be found in Mulholland et al. (2016c).

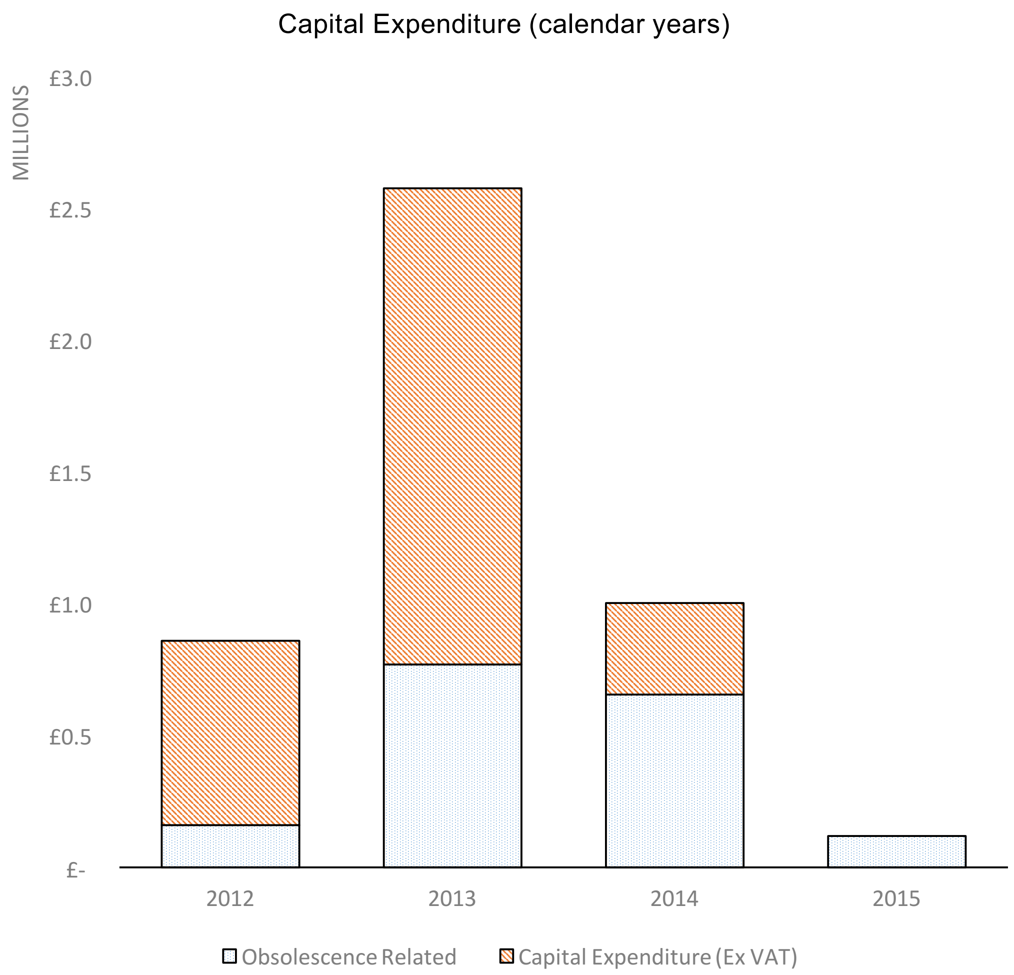


Figure 12 Obsolescence Related Lifecycle Expenditure, adapted from Mulholland et al. (2016c)

This section has begun to connect the two concepts of Asset Management within the Built Environment, and the financial impact of unforeseen obsolescence driven investments. First-hand data was shown to provide the initial evidence for this connection; however, the insight currently is limited by the lack of literature and research into the connections between these fields. Importantly, it is the long-life nature of assets within buildings and the short life nature of obsolescence that epitomises the research problem. The next section will begin to look at this problem with the wider picture in mind. Government-level policy and modelling techniques will be covered to investigate the potential avenues for this research thesis.

1.4 Systems Resilience

The UK government produced the industry strategy for construction in 2013, which stated the holistic targets for 2025 (HM Government 2013). Importantly, they included:

- 33% reduction in the initial cost of construction and the **whole life cost of built assets;**
- Invest in smart construction and digital design, anticipating **future integrated cities.**

By proactively considering obsolescence and the resultant impact it can have on an asset or group of assets, it is categorically possible to reduce whole life costs and prepare for an increased amount of technology within the Built Environment.

"Obsolescence is not just a component engineering problem; obsolescence is not just a program problem; obsolescence is an enterprise problem"

Pobiak et al. (2014)

This thesis adopts the definition provided by the System Dynamics Society (2016) for a system dynamics approach, which '…begins with defining problems dynamically, proceeds through mapping and modelling stages, to steps for building confidence in the model and its policy implications'. However, as highlighted by the 'father of Systems Dynamics' - Forrester (1969), SD allows for the holistic approach to understanding problems but is not the whole picture; it is only through simulation that inconsistencies within our models become present (Forrester 2007).

It is widely accepted that the human brain is bounded in its ability to effectively make decisions within complex situations (Sterman 2000). Errors are made when feedback loops and wider variables are not known or considered when decision-making, aligning with the 'what you see is all there is' heuristic (Kahneman 2012; Sterman 2000). This also occurs when the assumption is made that the cause and effect are tightly coupled in both space and time, which is often not the case – leading to unintentional effects (Sterman 2000). This is very applicable to the FM industry's approach/understanding upon obsolescence, very little is known and therefore it does not feature within Asset Management decision-making processes or guidelines.

However, what type of decision aiding model architecture would be appropriate within a field where such little data and knowledge currently exists?

Modern SD software packages contain the ability to adopt relationships between variables that are both Probability Theory and Possibility Theory, the latter being the cornerstone for the theory of Fuzzy Logic. In brief, Possibility Theory was first coined by Zadeh (1978) as an uncertainty theory for the consideration of incomplete information. Dubois and Prade (2011) summarise Possibility Theory as either ‘a coarse, non-numerical version of probability theory, or a simple approach to reasoning with imprecise probabilities’.

Our understanding of the real world is full of concepts which do not have crisp boundaries (i.e. tall, short) and to some degree are both true and false (Sivanandam et al. 2010). These concepts are called Fuzzy or grey concepts – they align well with how the human brain naturally operates, however, this conflicts with the binary (0s and 1s) nature of computers (Sivanandam et al. 2010). Broadly, Fuzzy Logic harbours an inference structure that enables ‘appropriate human reasoning capabilities’ – their utility comes in the ability to model uncertain or ambiguous data, see Figure 13 (Sivanandam et al. 2010; The MathWorks Inc. 2015; Ustundag et al. 2010; Cigolini & Rossi 2008).

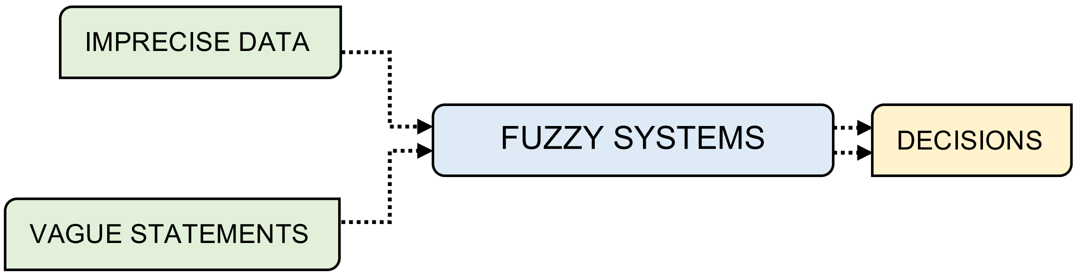


Figure 13 Fuzzy Systems Model, adapted from Ross (2010)

It is well documented that Fuzzy Systems are ‘universal approximators to algebraic functions’ (Ross 2010; Dubois & Prade 1998; Babuška & Verbruggen 1996), however, it is their applicability to systems where analytic functions do not exist that make them appropriate.

The notion of Fuzzy Sets is central to Fuzzy Logic and has been acknowledged as a key tool in connecting human knowledge and numerical data (Dubois & Prade 1998). Classic Logic implies that objects satisfy crisp criteria of a membership; Fuzzy Sets contain objects that satisfy memberships with fuzzy boundaries (Ross 2010; Sivanandam et al. 2010; Dubois & Prade 1998; Zadeh 1965) – which accounts for the ambiguity of an event. This is potentially an important trait for this thesis due to the fact that the relationship between the inputs and the output risk due to obsolescence is also fuzzy and ambiguous (Sandborn 2013).

The limitations of Fuzzy Systems include their orientation around deductive reasoning, in which they infer the specific from the general (Ross 2010). Therefore a Fuzzy System will seek to describe the behaviour observed within the data and not necessarily account for the underlying realities (Ross 2010). The accuracy of a Fuzzy System is dependent upon the design, specifically the rules in place or equally the ‘designer of the system’ – ‘naturally, smart rules lead to a smart system, equally dumb rules lead to a dumb system’ (Sivanandam et al. 2010; Dubois & Prade 1998). It is commonly agreed that Fuzzy Systems are not replacements of probability models, they have shown to be superior and inferior in a variety of applications – however, they exceed in modelling complex problems (Sivanandam et al. 2000; Ross 2010).

The Fuzzy System required within this thesis will be representing an asset system's resilience, using feedback loop and a systems level view to conceptualise the model (adopting an SD approach). To clarify, the below definition of resilience provided by Haimes and Horowitz (2005) has been adopted by the author:

> "Resilience is the ability of a system to absorb external stresses. Resilience is a system capability to create foresight, to recognise, to anticipate, and to defend against the changing shape of risk before adverse consequences occur."
>
> Haimes & Horowitz (2005)

In practice assets across the Built Environment provide a service i.e. cooling, heating etc. In their absence, it can be difficult to quantify the impact. It very quickly becomes an intangible and almost social science question to evaluate the impact. However, within the framework of a private finance initiative (PFI) contract, the services and therefore the absence of services have resultant contractual performance deductions and financial penalties. This thesis will not only view assets as systems but investigate the resilience 'trade-off'. In this context, the resilience trade-off represents the cost of investing into an asset system i.e. spares, warranty extension etc. against the resultant financial penalties of asset downtime. This contains assumptions, firstly PFI terms and conditions vary site to site, secondly in contrasting situations, certain asset systems are deemed more critical and thirdly the wider costs associated with spares holding are excluded. The objective of this thesis is to become a vehicle for 'information feedback' through the development of tools to aid the transition from reactive to proactive management. It is not a cost-benefit analysis or economic view upon obsolete stock and replacement strategies.

This section has introduced the ideas of Fuzzy Systems and Systems Resilience to the reader as key topic areas looking to holistically tackle the problem of appropriately modelling obsolescence. The aim is to create and test a model that is able to function upon ambiguous data from a range of sources, with useable outputs to benefit Facility Managers. The next section will cover the financial and operational risks posed by obsolescence and highlighting the need to address them within this thesis.

1.5 Operational and Financial Risk

Obsolescence manifests itself as an operational and financial risk to end-users via the medium of asset downtime and the inability to maintain or support an asset.

To clarify, it is the conceptual ordinal operational risk posed by obsolescence that will be explored by this thesis, specifically regarding the availability of assets. In order to cover this element, historical planned and unplanned maintenance (UPM) records will be analysed to assess component demands along with supplier sales data (see Chapter 3.3.4.4).

In contrast, there is a range of financial risks that will be covered within this thesis from spares procurement and component scarcity to the penalty deductions within PFIs, all of which will be covered in Chapter 3.3.4.5.

Finally, multiple modelling techniques will be reviewed for their applicability for assessing the risk profile created by obsolescence, both financially and operationally. This will culminate the research questions designed within this thesis into independent contributions to new knowledge.

This section brings together the resultant outputs for this thesis; what are the financial and operational risks posed to the business by obsolescence within asset systems? In order to begin answering that question, the literature review will take the reader through all of the key topic areas in detail to allow for the literature landscape to be identified. To conclude the introductory chapter, the next section will explicitly detail the drivers behind this research project and the structure of the upcoming chapters.

1.6 Drivers for research

This research rides upon the recent wave of trends suggesting that urbanisation will force us all to live within dense cities, wrapped in wireless internet, relying upon embedded technology and big data to provide efficiencies within our complex systems. These wider trends will create significant innovation across the Built Environment; however, it is the 'dark side' of this innovation that creates significant drivers for further research into the impacts and risks.

The title of this thesis was born from the 'Future Works' section of the MRes Dissertation, which was later reviewed and accepted via the Engineering Doctorate Upgrade assessment. The next chapter will review literature that will cover the following key elements; Obsolescence, Systems Resilience and Fuzzy Logic.

These sections will have sub-sections, allowing for the landscape of literature to be inspected and for a gap analysis to be extracted. The result being an informed research design chapter, focusing the direction of this thesis.

2 LITERATURE REVIEW

2.1 Introduction

The following multidisciplinary literature review will seek to pull together the current plethora of existing research and theories, allowing for a concise critique. Literature has been collated from a range of peer-reviewed journals, textbooks, online articles and conference proceedings, with the aim of illustrating the landscape and also identifying any gaps in current knowledge.

Please note, within the entirety of this thesis there is a handful of figures produced via unpublished data sources or grey literature. It is important to stress, that the types of grey literature sources can be classified into two groups; online, live datasets held by Google i.e. Google Trends and unpublished datasets generated by the author i.e. citation networks. The stance of the author during the generation of this thesis was to be clear with the use of grey literature and transparent with the data sources for all information found herein. All figures have been appropriately cited with given online URLs for publically available datasets. The purpose of using grey literature in this context is to further enhance the literature being reviewed and presented to the reader, either to capture internet based and therefore global trends or equally to give a reflection of the chosen material read in support of the creation of this thesis.

The review has been dissected into four key research topic areas; Obsolescence, Systems Resilience, and Fuzzy Logic. These four areas make the research boundaries both wide and diverse; covering the relevant fields to answer the research title. In support of the literature reviewed, the author has published several elements of this thesis in peer-reviewed journals and conference proceedings:

- Pitt, M., McLennan, P. & Mulholland, K., 2016. Understanding the role of obsolescence in PPP/PFI. In *RICS COBRA 2016*. Toronto, Canada: Royal Institute of Chartered Surveyors.
- Mulholland, K., Pitt, M. & McLennan, P., 2016. Changing Societal Expectations and the Need for Dynamic Asset Lifecycling and Obsolescence Management. In N. Achour, ed. Proceedings of the CIB World Building Congress 2016: Advancing products and services. Tampere, Finland: Tampere University of Technology, pp. 1048–1059.
- Mulholland, K., Pitt, M. & McLennan, P., 2016. Development and Testing of a Boolean Obsolescence Assessment Tool for Built Environment Asset Systems. *Journal of Facilities Management*, 14(3).
- Mulholland, K., McLennan, P. & Pitt, M., 2015. Identifying and Managing Asset Obsolescence within the Built Environment. In RICS COBRA AUBEA 2015. Sydney, Australia: Royal Institute of Chartered Surveyors.

- Mulholland, K., 2014. Planning for obsolescence within long-term contracts: A case-study of a UK redevelopment PFI. University College London.

This list demonstrates the applicability and validity of the literature reviewed to this research field. In addition, this research project was undertaken in partnership with HCP Social Infrastructure Limited who provided the case-study material that exists herein. Throughout the tenure of this research project, live confidential business documents and processes were reviewed, influencing the literature structure and ensuring the outputs are both practical and academically important. It is key to state that throughout the entire tenure of this research project all developments and results were kept a secret to the industry sponsor as to avoid the Hawthorne effect upon subjects. Information regarding this project was strictly on a 'need to know' basis, with participating contractors being completely partitioned from all project progress meetings. This enabled the author to gather opinions, views and insights into both how the business operated and equally how obsolescence affected the day to day operations of certain departments.

In order to embed this research project into the industry, a full-time position was held within the case-study, spanning a three to four-year period (see Research Design, Chapter 3.0). This quasi-academic/industrial led project gave insight into the real-world impacts of this research area and its direct effect on people's jobs and workload. Such rich material is a testament to the Engineering Doctorate (EngD) research vehicle. Please note that confidential documents and contents will not be found in this thesis, and all partaking members have been anonymised.

The next section will outline the problem statement and planned structure to be expected within the Literature Review chapter, detailing the research direction, and setting out to the reader the narrative behind the proceeding chapters.

2.1.1 Problem Statement

Ideally, Facility Managers and Asset Managers across the globe will have correct and live data regarding the assets they both own and maintain, and are ultimately responsible for. Pragmatic and simple algorithms, alongside human intuition, would be used to assess and inform pre-existing lifecycle projections of said assets which would allow for truly Strategic Asset Management.

The problem occurs in reality when, whilst Facility and Asset Managers own assets, they are not partial or do not record essential asset information and data. The problem manifests itself when maintenance is no longer possible, service delivery is lost, and the solution via reactive management is both financially expensive and operationally disruptive. This is all because a part, piece of software, skill set, type of chemical etc. is deemed obsolete by external factors out of one's sphere of control.

The financial cost of said disruptions has begun edging into the realm of hundreds of thousands annually for a single UK-based PFI contract, see Mulholland et al. (2016c). This ignores any potential additional operational impacts.

Evidence of the impacts of obsolescence have been intermittently captured in academic publications, however, they reside in a wide and diverse range of journals. This suggests that industry and academia are indecisive on where to place this research topic. Further empirical evidence was captured within Mulholland's (2014) dissertation consolidating a foundation to further research knowledge.

The solution, like in many industries, is to adopt proactive management techniques and to test any existing methodologies or create new ones. However, all proposed techniques are underwritten by data. The quality, consistency, and even existence of historical data in certain circumstances are very sparse. However, it is felt by the author that pragmatic, simple algorithms can be used to aid decision-making by Facility and Asset Managers. Such mechanisms do not exist under current industry guidance.

The benefits largely target lifecycle planning for long-term contracts, such as Private Finance Initiatives (PFI Contracts). This would be categorised as risk management in the eyes of lenders. The benefits also transfer over to the operational side of the Built Environment, through the enhancement of resilience within such asset systems.

Recent developments have begun to sprout evidence of this problem within the Built Environment, as systems become more complex and technology continues to embed itself further. This results in a broad opening question for this thesis:

‘Can we proactively manage obsolescence within the Built Environment? If so, how?’

This research project seeks to provide first-hand evidence in a way no other academic has done previously to both illustrate this problem and address the above question.

2.1.2 Literature Review Structure

We now return to the title of this thesis – ‘*The Resilience of Asset Systems to the Operational Risk of Obsolescence: Using Fuzzy Logic to Quantify Risk Profiles’.* This chapter will build upon the literature reviewed within Mulholland's (2014) dissertation, specifically focussing on new pieces of literature that are relevant to the thesis title.

The narrative behind the structure flows from continuing the knowledge on obsolescence within the Built Environment, capturing new publications and critiques. The opening three chapters will address the first part of the broad research question of ‘*can we proactively manage obsolescence within the Built Environment?*’ It is the final chapter on Fuzzy Logic which ties everything together to provide a particular solution for how one would undertake such a task and the limitations associated with doing so.

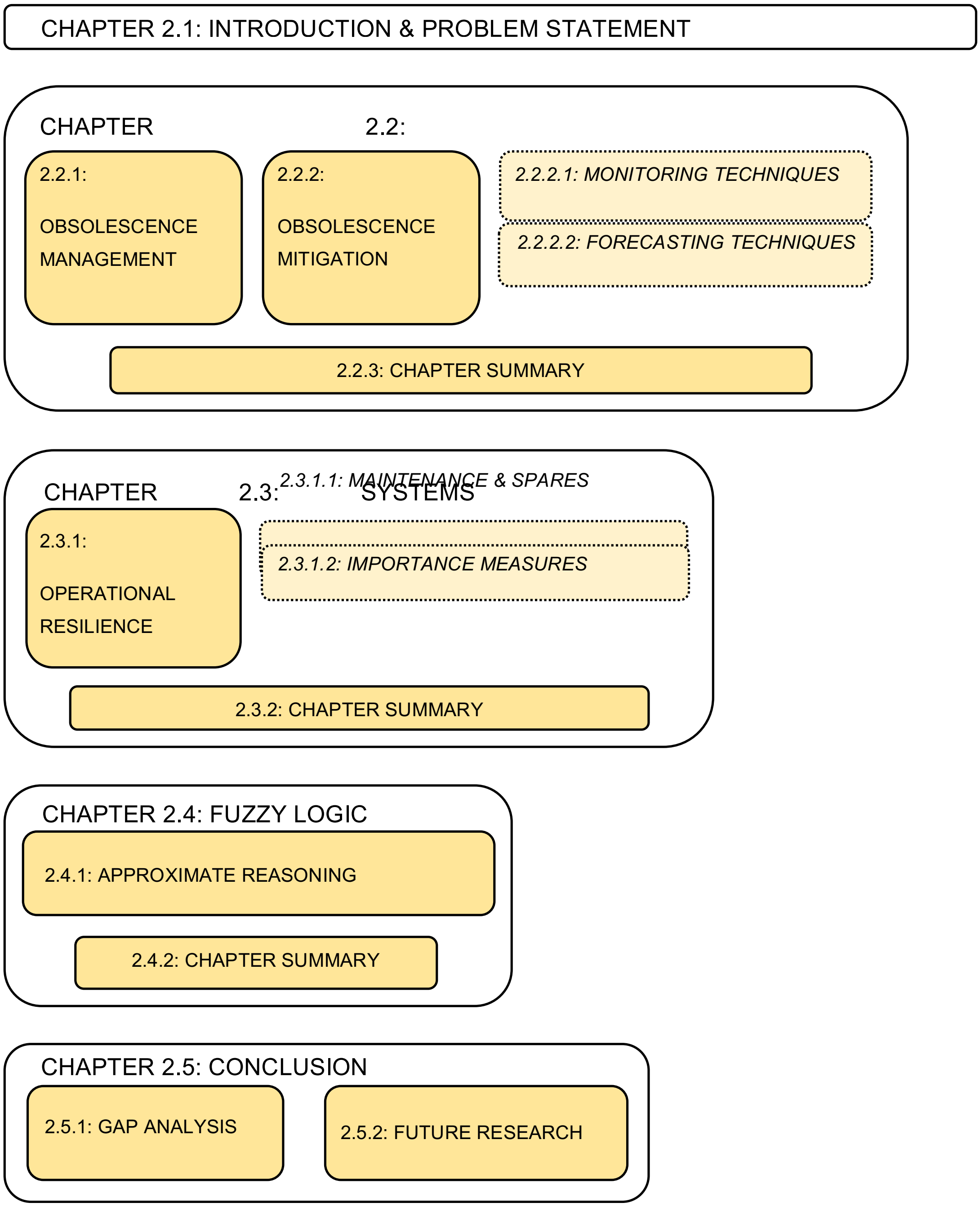


Figure 14 Literature Review Structure

Chapters and their respective subsections may be read in isolation; however, they follow a narrative in their sequencing and also signpost one another. In essence, they begin at the foundations of this thesis direction and narrow down to specific areas of technical contribution.

Figure 14 was created to visualise the content of the Literature Review to the reader, aiding the interpretation of the direction of this research project. In addition, to help the reader visualise the landscape of literature that was reviewed a network diagram using the Gephi software package was generated. The entire database of literature read during the tenure of this research project was converted into nodes and paths within an Excel file. This enabled Gephi to quantify two things:

1. The most prominent author(s) in terms of quantity of publications.
2. The most influential author(s) in terms of citation connections.

Please note, this database is not exhausted, but rather the resultant final bibliography that the author concluded this research project with. Analysis (1) was then reflected by a scale of size and colour. **Error! Reference source not found.** is the said bibliometric and it is clear that there is a clear industrial sway upon the literature, with the British Standards Institute (BSI) authoring a comparatively large section. This is not a surprise given the influence of an industry sponsor and industrial requirements of an EngD thesis. Additionally, this is followed by Sandborn from Maryland University, USA. Sandborn has been a pioneer of obsolescence related research since the turn of the millennium, with key publications such as Sandborn and Singh (2002), Singh and Sandborn (2005) and Sandborn (2008). Sandborn published frequently with his associate Pameet Singh, who has also produced several key pieces of literature. Other significant author nodes are Zadeh (1975), the 'father of Fuzzy Logic' and Ruud H. Teunter (1998), who specialises in inventory management. In total 483 individual literature sources were reviewed, filtering down to authors of count 3 or more, figure 15 was created.

To create analysis (2) further mining of the literature bibliometric data was required to uncover the citation network that existed behind each publication. It was felt a network diagram would be best suited to construct such a bibliometric, however, a previous example of such a visual had not been found. Figure 16**Error! Reference source not found.** is an infographic that illustrates the communities within the landscape; obsolescence, fuzzy logic, industry standards, inventory management, and peripheral groups. Please note, the bibliography was converted into notes and pathways to illustrate which papers had cited who and how therefore they were academically connected. Through optimising this visual using an algorithm within Gephi, Figure 16 was created, clearly demonstrating clusters within the literature. The length of the path and size of the nodes is a result of an optimisation algorithm, accounting for the number of citations and therefore the size of the communities. By visualising the data to the reader in this manner, a quick assessment of the landscape of the literature and how it is empirically connected to one another is possible. Also note, that the circles and colour coordination of figure was superimposed by the author to help illustrate the clusters found. Naturally, this diagram will aid the gap analysis (found in Chapter 2.6.1) as it allowed the author to strategically position this thesis amongst the existing landscape.

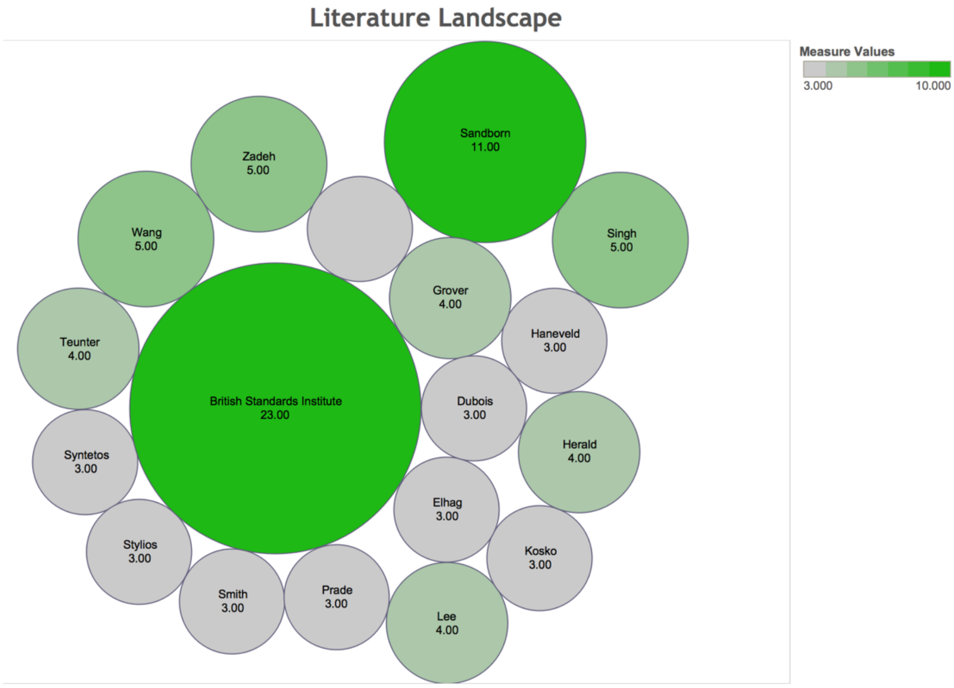
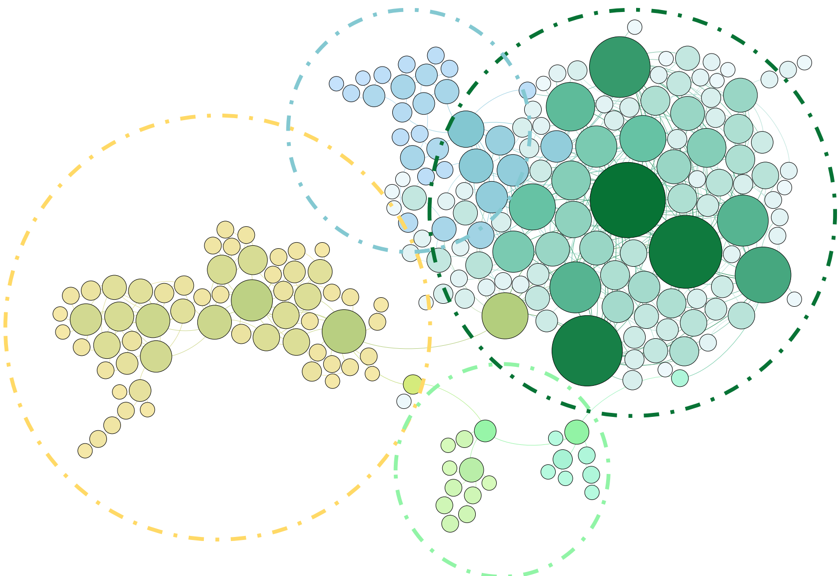


Figure 15 Bibliometric of the Literature Landscape, created by the author



Obsolescence		Industry Standards		Inventory Management		Fuzzy Logic	

Figure 16 Network Diagram of Literature Landscape, created by author

As detailed within the Literature Review structure (see Figure 14) the opening chapter will expand upon the previous literature review that can be found within Mulholland's (2014) preceding dissertation. The literature will be built upon the understanding in 2014, including new citations that give a broad but detailed understanding of obsolescence and related research. This sets the foundation for the direction of the literature review, with the ensuing chapters narrowing the focus. For example, addressing assets on a holistic scale requires some understanding of Systems Resilience, allowing for the reader to appreciate the importance of these respective fields when addressing obsolescence within a real-world context. Finally, Fuzzy Logic was selected as an appropriate modelling medium and this will be covered in finer detail, carefully outlining the positives and negatives of such a technique, especially its limitations or assumptions within this context.

2.2 Obsolescence

Obsolescence has existed within academic research since the 1970s with Warmington's paper in 1974; however both the research approach and the problem itself have evolved drastically since then with the emergence of the Information Age. Lua Yali et al. (2012) recently declared the phenomenon 'inevitable within modern systems'. Traditionally, the term obsolescence was used when engineering organisations experienced high inventory costs due to large spares holdings becoming 'obsolete' after product lines ceased to be operated (Cobbaert & Oudheusden 1996; Masters 1991). This view has adapted, possibly following changes in management strategies for spares holdings, resulting from advances in inventory management techniques.

Obsolescence within the 21st century now refers to an asset that is no longer suitable for current demands or is no longer supported by the manufacturer (CMCA UK 2013; BSI 2007; Bartels et al. 2012; Singh, Peter Sandborn, et al. 2004). This multidisciplinary problem has expanded due to the continual evolution of consumer electronics and the further adoption of commercial off-the-shelf components (COTS). This creates pressure upon manufacturers and distributors, resulting in component lifecycle shortening (Romero Rojo et al. 2010; Bradley & Guerrero 2008). A more detailed coverage of the drivers behind the shortening of lifecycles due to consumer electronics can be found in the adjacent MRes dissertation (Mulholland 2014).

Gravier and Swartz (2009) describe obsolescence as an 'economic phenomenon', one that has been addressed by fast moving industries, such as avionics, semiconductor, aerospace and military. The proactive behaviour of these industries has been led by the typically long lifecycles of asset systems that exist within them. For example, the lifecycle of a COTS product, typically five years or less, is different from the lifecycle of a defence system, typically more than 20 years (Bil & Mo 2013). Findings within Mulholland's (2014) Master of Research dissertation suggest that long-life assets within the Built Environment are now also experiencing the same increase in obsolescence and unforeseen lifecycle investments. A typical example would be 'lifecycle mismatches'; which occur when the intended useful life of the parent asset significantly exceeds the lifecycle of the integral components, most noticeably the electronic components and/or software/firmware elements (Bradley &

Guerrero 2008; Lua Yali et al. 2012). Several authors have attempted to categorise obsolescence, typically into physical, technological and environmental; with some further peripheral groups such as legislative obsolescence (Bowie 1985; Kessler & Brendel 2016). To clarify the position of this thesis amongst existing literature, the core focus will be upon physical obsolescence, which covers supportability of assets and their systems – not to be confused with depreciation, a common topic within property research.

The next subsection will cover existing literature on obsolescence management, with a critical analysis of industrial standards. This will begin to illustrate the reader the potential growth areas within this field and its current strengths and weaknesses.

2.2.1 Obsolescence Management

In 2007 the Obsolescence management - Application guide (BS EN 62402:2007) was published and remains ‘current’ as of 2016 (BSI 2007). This standard clearly outlines the drivers for a defined obsolescence management process:

> ‘Obsolescence management is essential to achieve optimum cost-effectiveness throughout the life cycle of a product. The purpose of this standard is to provide guidance on planning a cost-effective obsolescence management process that takes into account essential factors to ensure product life cycle costs are considered and applied.’
>
> Obsolescence management - Application guide (BS EN 62402:2007)

The need for a structured obsolescence management approach is further supported by the influential author P. Sandborn (2011), who champions the need to quantify the financial costs associated with obsolescence. This need is captured by Sandborn’s following example; ‘When determining where to put resources and what problems to focus on, management asks the following questions:

1. Has a serious event occurred in the field due to this problem (loss of life, equipment or mission)?
2. What future impact will this problem have on me if I don’t address it e.g. costs, availability?’

Both of these fall under the description of reactive management and are even possibly negligent. BS EN 62402:2007 contains Figure 17, a framework to illustrate the typical activities within obsolescence management (OM).

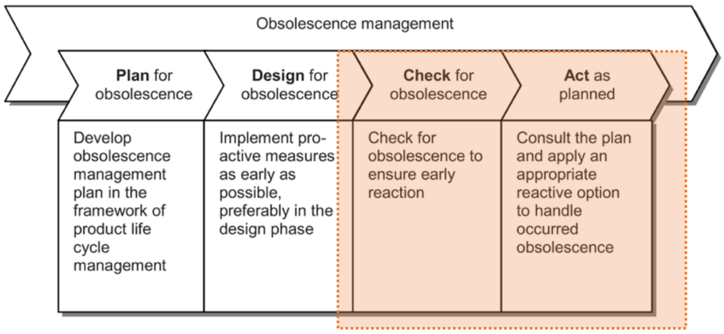


Figure 17 Process Steps for Managing Obsolescence, from BSI (2007)

This thesis is orientated towards Facilities Managers and Asset Managers, who have no access to the design or manufacturing stages of a lifecycle, and therefore only the 'Check' and 'Act' stages are to be addressed. To address the problem statement, this thesis will show how a management team could undertake these tasks; something not detailed within BS EN 62402:2007. Figure 18 has been extracted from BS EN 62402:2007 and illustrates a perfect scenario where OM aligns itself with the product lifecycle. In reality, due to the functions of the FM team, these cycles become misaligned as depicted in Figure 19.

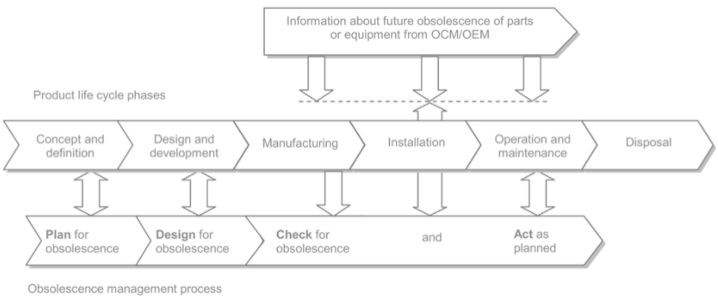


Figure 18 Obsolescence Management versus Product Life Cycle, from BSI (2007)

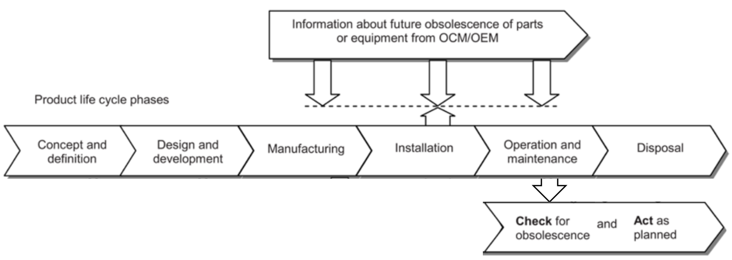


Figure 19 Amended Obsolescence Management versus Product Life Cycle, created by author

This has an impact both on what elements of the British Standards should be considered, but also the data type considered for this research. For the research output to be applicable to industry, it must rely upon resources that would be present during the 'Operation and maintenance' and 'Disposal' phases.

Lifecycle costing and operational risks within the Built Environment provide the majority of drivers behind OM, as detailed earlier in this chapter. This is present within traditional procurement channels i.e. design and build, however, the impact of obsolescence is exacerbated by long lead times, typical of the defence sector (Freeman & Paoli 2015). Long lead times are also witnessed between design and commission within the private finance initiatives (PFI) (now Public Private Partnerships, PPP). Figure 20**Error! Reference source not found.** illustrates how lead times commonly range between 2.5 and 3 years within the UK, resulting in the potential to inherit systems containing obsolescence before they are in service, as there is no statutory requirement to consider obsolescence (HM Treasury 2014).

Figure 20**Error! Reference source not found.** was created by using the most recent HM Treasury report – Private Finance Initiative Summary Report 2014, to empirically analyse how long on average it takes UK PFI contracts to transition from Financial Close to Construction Completion (HM Treasury 2014). The connection between this lead time and its potential effects on both the lifecycle of assets and obsolescence has not been found within the current literature landscape.

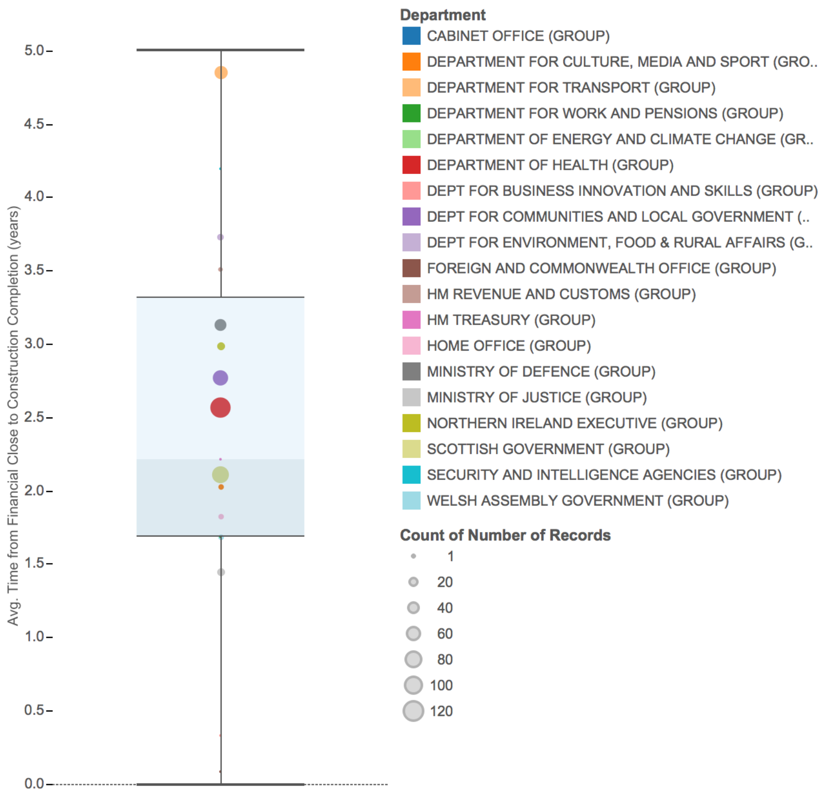


Figure 20 Average Time from Financial Close to Construction Completion for UK Private Finance Initiatives, created by author from HM Treasury (2014)

By coupling Figure 20**Error! Reference source not found.** and Figure 21, the crux of lifecycle mismatches and supportability issues becomes apparent. Figure 21 was generated from data extracted from the commercial databases CAPSXpert Semiconductors and PARTSXpert. These two databases provided the specifications data, part number, manufacturer, supply voltage, manufacturing process technology, and whether the component met the guidelines for military use for over 2.7 million semiconductors. Logistical Regression was used on this dataset to extract the presence of obsolescence amongst semiconductors and the importance of variables i.e. age. Note ‘Years of Design’ is from the perspective of a manufacturer, therefore represents time zero of a component’s existence. In reality, when designing new systems for a new PFI (2.5 to 3-year lead time) the components selected will not be at time zero, increasing the likelihood of having no viable manufacturers in the short term.

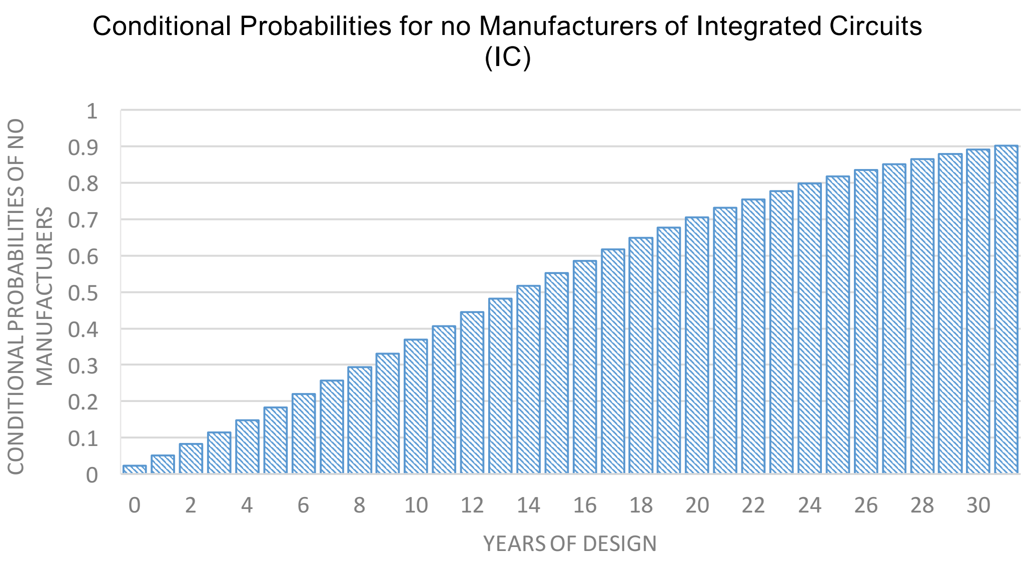


Figure 21 Conditional Probabilities for no Manufacturers of Integrated Circuits, adapted from Gravier & Swartz (2009)

Finally, although not a primary focus of this thesis, there are corporate responsibility and sustainability benefits available to organisations adopting proactive OM processes. Zhang et al. (2012) and Lilley et al. (2016) cover the topics of E-waste and cosmetic obsolescence that we now see within our ‘throwaway society’; highlighting obsolescence as a barrier toward a circle economy style of service delivery. It is felt that research of this nature is more applicable on a domestic or micro scale (consumer electronics), as opposed to a macro view of commercially delivered infrastructure within the Built Environment. Figure 22 along with the ‘Global E-Waste Monitor’ report by Baldé et al. (2015) outline the growing environmental impact of E-waste, a by-product of obsolescence, especially when managed reactively.

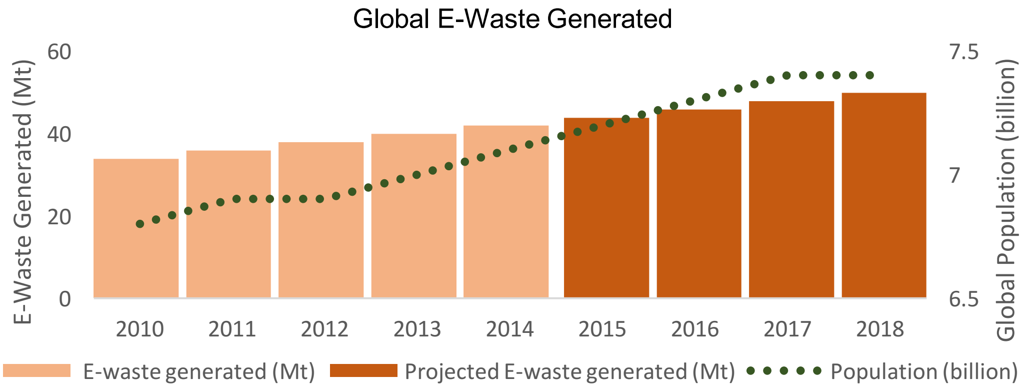


Figure 22 Global E-Waste Generated versus Population Growth, adapted from Baldé et al. (2015)

This section underlined the drivers behind OM practice, however, in order to clarify the research position of this thesis, the next sections will begin focusing on proactive mitigation techniques.

2.2.2 Obsolescence Mitigation

Erkoyuncu and Roy (2015) summarise that there are two approaches to OM; proactively through mitigation or reactively through resolution. This thesis will focus on proactive management strategies; specifically within the 'Planning' branch of mitigation techniques (see Figure 23**Error! Reference source not found.**), as illustrated by Romero Rojo et al. (2010) and later supported by Freeman and Paoli (2015). Note that this aligns with the 'Check' stage within the OM Framework (see Figure 17).

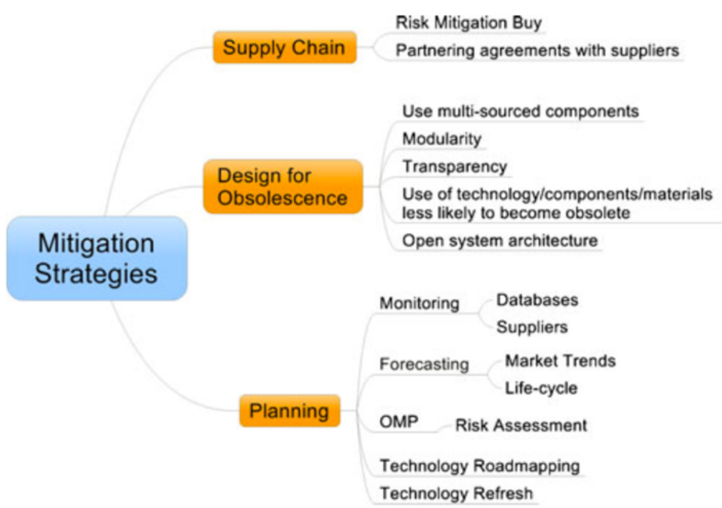


Figure 23 Obsolescence Mitigation Strategies, from Romero Rojo et al. (2010

Obsolescence mitigation refers to measures taken to minimise the impact or likelihood of having an obsolescence problem (Erkoyuncu & Roy 2015). Industry guidance suggests ‘obsolescence issues should be considered as early as possible in the lifecycle to reduce the risks’ (BSI 2007). Whilst this seems trivial, in practice, this is not always possible; leading to inevitable ‘obsolescence issues’. Figure 24 illustrates how within the ‘Planning’ branch, the guidance recommends management teams to incorporate Risk Management with OM. This thesis will focus on the three stages within the OM framework that have been highlighted in Figure 24. These elements tackle the identification of obsolescence in order to enable proactive management, a key driver of this thesis.

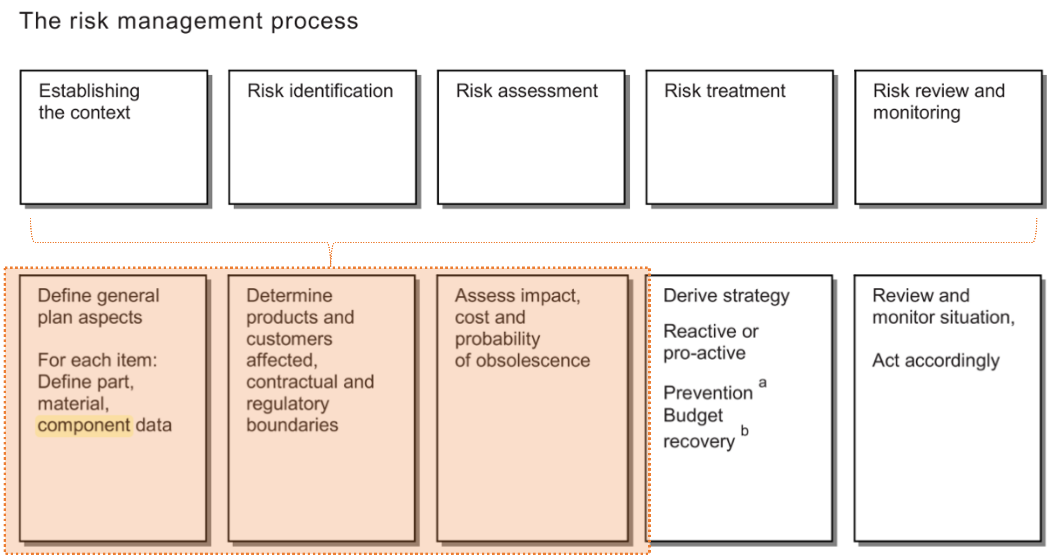


Figure 24 Project Risk Management versus Obsolescence Management, adapted from BSI (2007)

Whilst BS EN 62402:2007 contains the above frameworks that give top level descriptions on the aims and objectives of Obsolescence Management, there is not one single piece of explicit or technical advice as to how to achieve said objectives. To generically begin a Risk Assessment without knowing what to measure or how is a rather moot point. In many ways, the document almost sets out the niceties of achieving proactive management methods but will no current vehicle of how.

In summary, the problem statement has highlighted a severe lack of explicit guidance as to how to manage obsolescence within the Built Environment and this chapter has explored some of the existing frameworks. The FM industry is constrained to acting reactively to obsolescence due to the nature of being an end-user, framing the research angle of this thesis. Specifically, there is a need to better understand how one would implement a Risk Assessment or begin informing decision-making with regards to obsolescence. However, besides this point, the following chapter will explore the research surrounding forecasting obsolescence and its applicability to this research.

2.2.2.1 Monitoring Techniques

In order to monitor behaviour, it must first be defined. Bowie's (1985) paper epitomises the first uses of the term obsolescence within buildings; heavily connecting obsolescence with asset depreciation/physical deterioration. This is a view that was adopted by the Royal Institute of Chartered Surveyors (RICS) and published in their *Appraisal and Valuation Standards* (The Red Book) in 2014. The Red Book was rightly criticised by Grover and Grover (2015) for its 'subjective' approach to valuing obsolescence depreciation of assets; due to the association of physical obsolescence with physical deterioration. Recent publications by Grover and Grover (2015) and Stacchetti and Stolyarov (2015) clarify the distinction between physical obsolescence and deterioration. This disconnect between the two definitions was again clarified by Muñoz et al. (2015) who explained the difference between software obsolescence and that of mechanical or electrical items. Software does not physically depreciate or deteriorate at all, but solely is exposed to supportability issues (Muñoz et al. 2015). Therefore, the following obsolescence monitoring examples from literature adopt the modern interpretation of physical obsolescence.

Monitoring techniques, as illustrated in Figure 23, cover the methodologies of databases and suppliers, an area very closely associated with obsolescence indexing. The British Standards Institute define it as the tracking of 'processes, materials and components used in the product design' (BSI 2007). Obsolescence indexing refers to the use of material risk indexing of components; using methods similar to that found in Bartels et al. (2012) and Mulholland et al. (2016). The objective of these models is to give a reflection of the ordinal risk posed by obsolescence within individual components and to provide alternatives (Bartels et al. 2012; BSI 2007). This area still possesses an element of experimentation, in seeking best practice.

Mulholland et al. (2016) remains the only paper within academic circles empirically testing monitoring methodologies within case-study environments. There are challenges, however, regarding technology diffusion which are inherent of obsolescence. Stoneman (2002) comprehensively covers technology diffusion and how it has evolved from Griliches (1957) publication on hybrid corn to Vickery and Northcott (1995) later covering the diffusion of microelectronics. Both authors gathered evidence supporting the theory of technology diffusion following a sigmoidal curve (S curve), as shown in Figure 25, showing initial growth, maturity and then saturation as the curve plateaus.

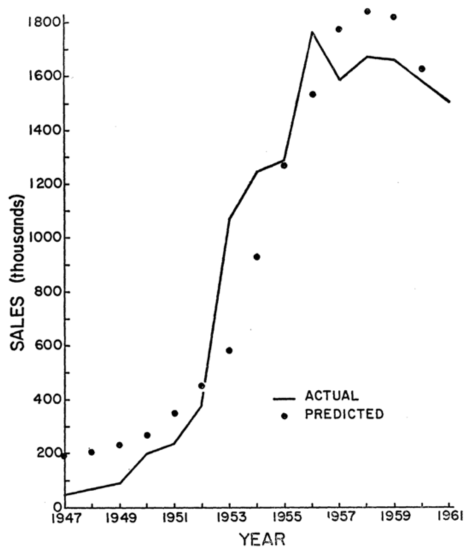


FIG. 4. Actual sales and sales predicted by regression equation

Figure 25 Sigmoidal Curve or S-Curve of Technology Diffusion, from Bass (1969)

Product growth or diffusion models were comprehensively established by Bass (1969), who initiated the labelling of innovators and imitators within society and their respective purchasing behaviour. Innovators were influenced by external sources of information (mass media), and imitators, influenced by the internal sources of communication or 'word of mouth' (Bass 1969; Gravier & Swartz 2009). Impressively, Bass (1969) compared his growth theory (sigmoidal curve) against sales data for eleven different consumer products, resulting in very accurate imitation and also forecasting (see Figure 26**Error! Reference source not found.**).

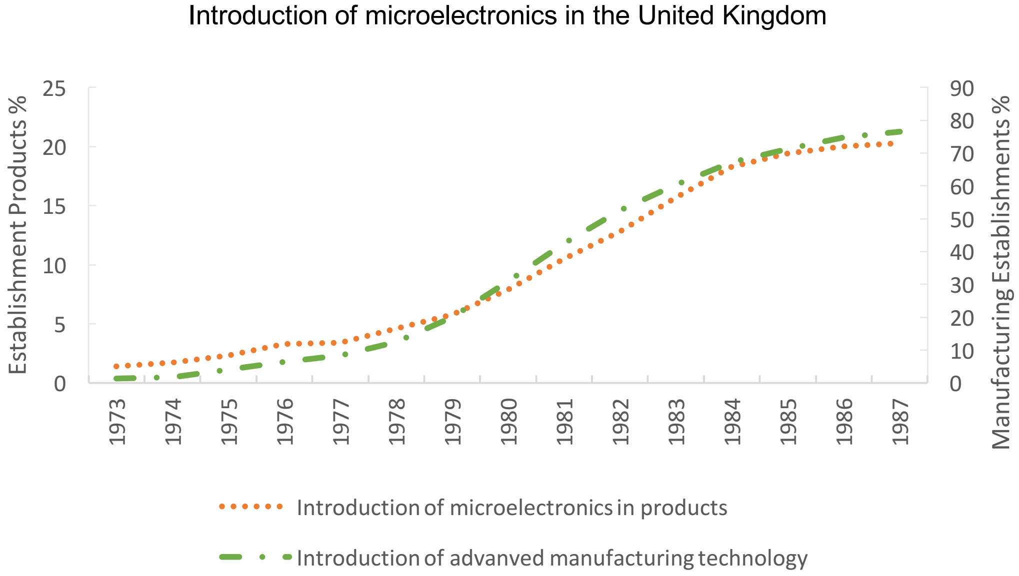


Figure 26 Introduction of Microelectronics in the UK, adapted from Bass (1969)

This theorem and view upon technology diffusion has stood the test of time; however, in the information age due to the enabling of the internet, modern technology diffusion is more aggressive. This point is illustrated in Figure 27, showing the increasing pace of which technology diffuses within a market. This observation is statistically backed up by Van den Bulte's (2000) 74-year case-study into electronic consumables (1923 to 1996). Lawlor (2014) also highlights the accelerating rate of diffusion of new technology.

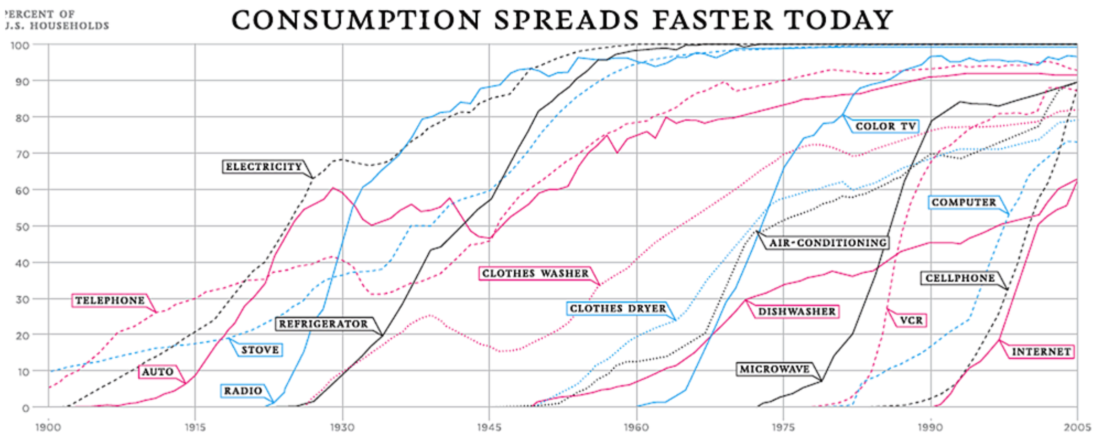


Figure 27 Modern Technology Diffusion Examples, from Lawlor (2014)

The result of such change creates greater emphasis upon management teams on adopting and enhancing approaches to obsolescence as the time frame for reactive management is shortening.

Similar to the obsolescence assessment tool (OAT) detailed within Mulholland et al's (2016b) paper, Clay et al. (2016) propose a similar material risk index (MRI) model to be used within the design stage of new electronic products. The further consideration of obsolescence within the design stage to manage the effects of obsolescence is also championed by Lawlor (2014). Clay et al's (2016) MRI model hold similarities in the form of outputting ordinal values of risk, allowing for designers to monitor the components they are selecting for obsolescence, alongside cost and performance. In contrast, Clay et al. (2016) approach obsolescence from the viewpoint of a manufacturer, therefore, MRI is used to rank components and then apply quadratic discriminate analysis (QDA) to categorise these components, allowing for a more informed selection. Whilst this paper does not contain any empirical evidence of its use, allowing for it to be critiqued, it does show support for the use of monitoring tools to mitigate obsolescence.

Of the wide-reaching amount of literature that surrounds the modern view of obsolescence, only a select few adopt empirical methodologies, such as Solomon et al. (2000), Singh and Sandborn (2002), Singh, P. Sandborn, et al. (2004), Feng et al. (2007) and Bradley and Guerrero (2008). What enables all of the aforementioned pieces of literature to exist, along with the monitoring techniques highlighted in this chapter, is the use of commercial databases. Commercial databases such as ‘Silicon Expert’, ‘Total Parts Plus’, ‘HIS Parts Universe’, ‘Q-Star’, ‘Part Miner’ and ‘IHS DMS Alert Service’ all exist to compile the explicit pieces of information that induce obsolescence. Through the monitoring of obsolescence and supportability changes within the market, one can begin building their own database, which can be used to help monitor the behaviour of obsolescence (Jenab & Noori 2013). Databases as a ‘monitoring mitigation strategy’ feature highly within literature because of its suitability for recording external constraints or changes within the market. Notably, it is the changes in industry standards, legislation, availability of hardware and software along with alternatives that are provided by the aforementioned commercial databases. Recognise, however, that the above databases are geared towards the semiconductor and microelectronics industries and therefore cater for a specific set of products. Figure 28 is an example of the complexity sometimes involved with seeking to monitor obsolescence in aid of mitigating it. Whether the Facilities Management sector contains the appropriate personnel to undertake such tasks in-house or the available on-site resource remains to be seen, but it is unlikely.

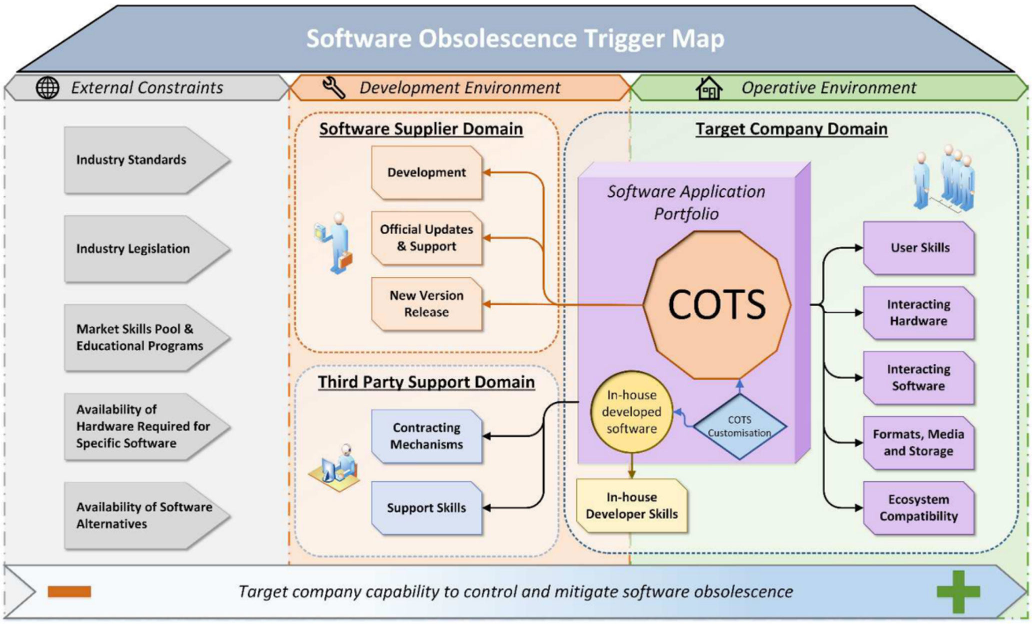


Figure 28 Software Obsolescence Trigger Map, from Muñoz et al. (2015)

Monitoring techniques have shown to be applicable, however, appear to be limited when data pools are small or immature in their development. However, once databases mature for relevant products and components then more advanced methodologies are possible in the form of forecasting. Industry guidance on the use of monitoring techniques suggest it is appropriate for asset systems found within the Built Environment, specifically for property portfolio management (BSI 2007). The following section will examine where and how some researchers have pushed the boundaries of obsolescence management and the limitations they carry.

2.2.2.2 Forecasting Techniques

The forefront of proactive mitigation techniques surrounds the ability to forecast obsolescence. In order to gauge the difficulty of this task, Bowie (1985) provided a table of asset life expectancy, which forms a good example of how life expectancy of asset systems within the Built Environment have changed. A comparison of Bowie's table and The Chartered Institute of Building Services Engineers (CIBSE) guidelines can be seen in Table 2 (CIBSE 2008). It is interesting to see how the resultant lifecycle shortening of components has influenced policy used to advise industry.

Table 2 Indicative Life Comparison Between Bowie (1985) and modern CIBSE Guidance (2008)

Equipment Item.	Bowie Indicative Life / Years	CIBSE Indicative Life / Years

Electric traction lifts	20 – 40	20
Electric traction lifts (packaged)	20 – 40	15
Lift installation	20 – 40	15
Hydraulic cylinder		15
Hydraulic oil		5
Oil cooling system		10
Chilled ceiling panels		25
Chilled beams	20 – 40	20
Computer room air conditioning	20 – 40	15
Double duct terminal units	20 – 40	15
Fan coil units	20 – 40	15
Induction units	20 – 40	20
Split systems	20 – 40	10
Terminal reheat units	20 – 40	20
VAV terminal units	20 – 40	15
Ventilated ceilings		25
VRV units	20 – 40	10
VVT fan powered terminal units	20 – 40	15

Alternatively, this also shows that methodologies need to continue advancing with how to monitor and forecast the useful life of assets found within the Built Environment.

Solomon et al's (2000) paper on '*Electronic part life cycle concepts and obsolescence forecasting*' remains as the cornerstone of obsolescence forecasting techniques within obsolescence research. The authors used historical sales data for 'dynamic random access memory' (DRAM) units to extrapolate the projected lifecycle curve of current models. Such a methodology has the potential to inform the users of when the obsolescence phase (see Figure 10) will likely be initiated. Such information holds operational benefits of supportability and financial incentives in the form of procuring components before prices rise due to scarcity (Haneveld & Teunter 1997). However, these types of methodologies carry two significant caveats; they assume a product follows a typical lifecycle curve and also that the user has access to the required datasets. Two significant assumptions for the applicability of such methodologies for the audience of this thesis.

An underlying constraint with obsolescence forecasting is related to the small amount of literature that exists regarding obsolescence. Simple questions such as; how does it behave? How often will it appear? Which methodologies work within which industries? remain not only unanswered but have been declared a rather debatable point following industry guidance classing obsolescence as a 'non-measurable or unpredictable performance state' (BSI 2012).

The pinnacle of forecasting research can be found in the form of the MOCA (Mitigation of Obsolescence Cost Analysis) software tool, that has been designed to generate and select an optimum design refresh plan for a system (Myers 2007). This tool was first developed by

Sandborn and Singh (2002) at the University of Maryland and has been cited in several publications - see Myers (2007), Feng et al. (2007) and Pobiak et al. (2014). MOCA takes the bill of materials (BOM) as an input for a given asset, along with procurement cost and project obsolescence date of the components. Note that the method used here for forecasting is similar to those cited above; demand levels are mapped and then used to project forwards the declining phase of the bell curve. MOCA outputs a timeline of possible design refresh dates, coupled with obsolescence events (see Figure *29*). The costs of both the refreshers and short-term investments are then combined within the outputted lifecycle cost by MOCA as illustrated in Figure 30**Error! Reference source not found.**. The optimum plan would be the lowest data point, which represents the optimum combination of refreshes and short-term investments.

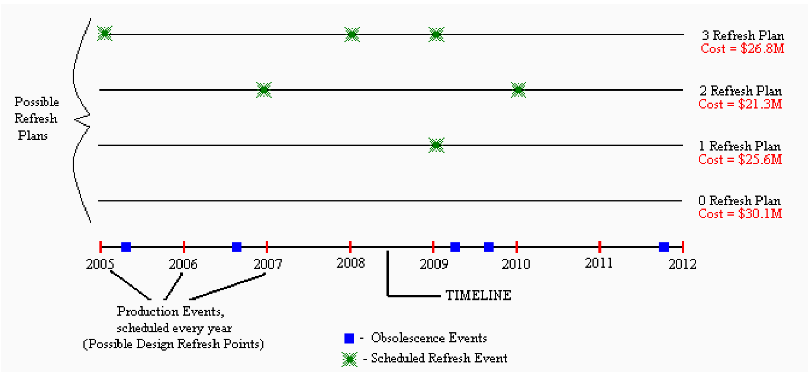


Figure 29 *Simplified Timeline used by MOCA to Generate Possible Refresh Events, from Myers (2007)*

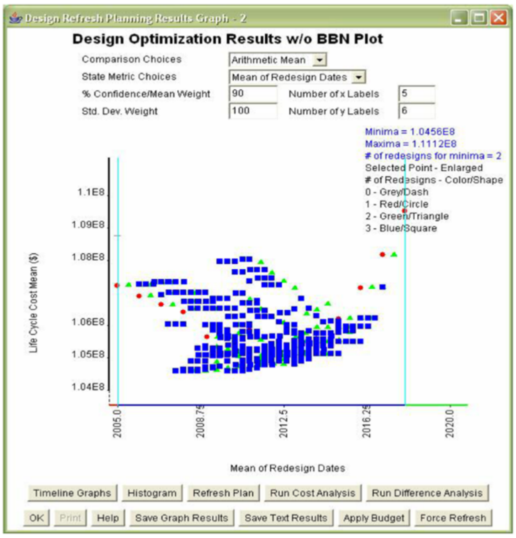


Figure 30 MOCA Design Optimisation Output, from Myers (2007)

Feng et al. (2007) used MOCA for a case-study with Motorola; the problem surrounding a commercial off-the-shelf (COTS) base station communication system that provided radio frequency platforms for a variety of systems. As Figure 31 illustrates, Motorola had a forecasted demand model for these units, which was used as the foundation for forecasting.

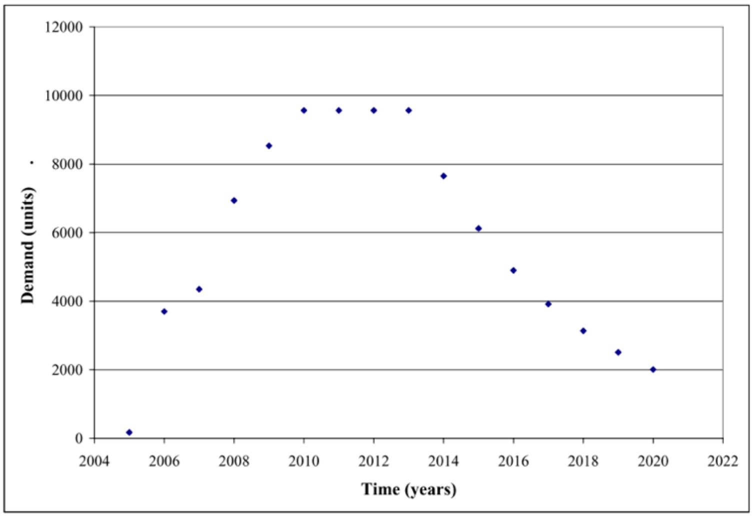


Figure 31 Production Profile for Motorola Infrastructure Base Station, from Feng et al. (2007)

Combine Figure 31 with Figure 32**Error! Reference source not found.**, to illustrate the lifecycle mismatches that were to occur during the same period and then you have an optimisation problem for MOCA. Note, that the aforementioned research was sponsored by the Original Equipment Manufacturer (OEM) and that in fact, MOCA would be useless for an end-user due to the data requirements.

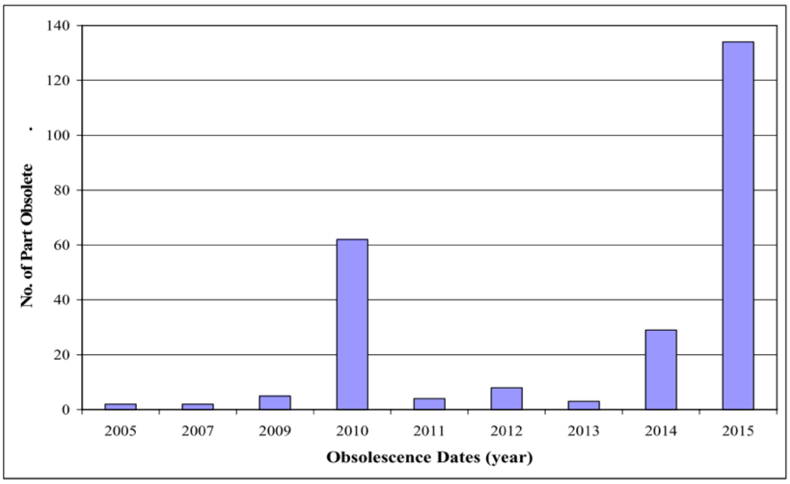


Figure 32 Number of Obsolete Parts versus Obsolescence Dates, from Feng et al. (2007)

A further critique of researching into forecasting methodologies was raised by Gravier and Swartz (2009), who state that the above methods are only possible when the product begins the ‘decline’ phase of the lifecycle. Prior to this point, it would be inaccurate to speculate when the plateau and decline may occur along the time axis. This is the crux of current research in the opinion of the author, and is categorically how this thesis will distinguish itself against current literature.

Regarding the behaviour of obsolescence, whilst there are no direct pieces of literature, heed can be taken from Grover and Grover's (2015) comments on the clustering of ‘innovations’ and that ‘if innovations occur in clusters, then it is likely that there will be groups of buildings, which become obsolete’. This would suggest cyclical-type behaviour in obsolescence, also suggesting rather predictable behaviour. Whilst there is no empirical evidence to support such a claim, Mulholland et al's (2016a) paper begins to illustrate the type of data required to support or disprove Grover and Grover's (2015) comments.

To clarify, this thesis does not seek to investigate the use of planned obsolescence; however, it has been useful to review Kessler and Brendel's (2016) take upon the use of using obsolescence to drive sales. Planned obsolescence refers to the policy of planning or designing a product with a limited lifespan to stimulate replacement buying (Bulow 1980; Tukker 2004; Kessler & Brendel 2016). Kessler and Brendel (2016) produced Figure 33, which illustrates an example of how obsolescence can be used as a tool to drive sales. The definitions used within the figure were:

- (P) Psychological obsolescence occurs when products seem ‘worn out’ because the design of new products or new generations of the same product changed.
- (T) Technological obsolescence includes the functional enhancement through adding or upgrading product features and making new products seem more desirable.
- (R) Regulatory obsolescence occurs when whole products or certain components have to be replaced after a given time or usage because of legal regulations.
- (Q) Qualitative obsolescence (also called physical obsolescence) refers to products with a limited functional life, a limited possibility to repair, and fast wear and tear.

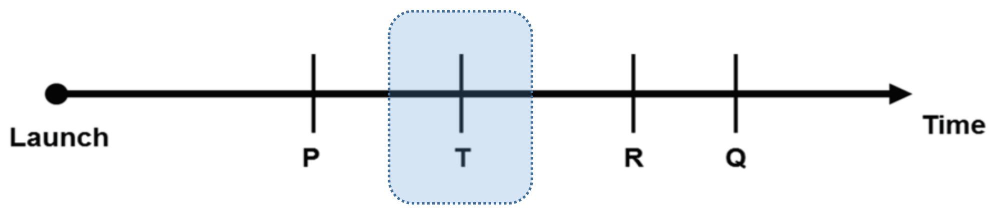


Figure 33 Example of 'Planned Obsolescence' within a Product, from Kessler & Brendel (2016)

In the example given in Figure 33, the company first tries to make the product psychologically obsolete, then the technological obsolescence sets in and if the customer is still not willing to replace her product, the regulatory obsolescence forces her to do so. In this example the qualitative obsolescence comes last, not to harm the company’s reputation if the product brakes before the customer is forced to replace it due to legal regulations (Kessler & Brendel 2016). This thesis, in relation to Figure 33, would be positioned under T or Technological Obsolescence to conform to this framework. It is primarily focussed upon the supportability of a system in disregard of psychological obsolescence.

Finally, whilst outside the remit of this thesis, planned obsolescence is a key tool for creating ‘dynamism’ within the marketplace; essentially allowing manufacturers to capture both innovators and imitators by overlapping and superseding their products (Mahajan & Muller 1996; Gravier & Swartz 2009).

2.2.3 Chapter Summary

The focus of this chapter has been upon obsolescence; what guidance and frameworks exist for its management and methodologies. This chapter consists of literature from both academic and industrial citations, in order to outline the current boundaries that exist. Note, the most prominent authors within this research field have not been publishing of late, the cornerstone pieces of research were published in the mid to late 2000s, such as Singh and Sandborn (2006), Feng et al. (2007), Sandborn and Myers (2008), Rojo et al. (2009), Bartels et al. (2012) and Sandborn (2013).

The literature within this chapter has highlighted that there is support for monitoring techniques, but further work is required within the context of the Built Environment. Whilst forecasting techniques have seen little development in recent publications, it still remains the most important area to unlocking proactive mitigation in the long term for the Built Environment. Gaps found in this chapter along with the research drivers can be found within Chapter 2.6.1; however, below is a summary extract:

- Lack of research within Built Environment.
- Lack of research from an end-user perspective (Facilities Management).
- No ground level guidance on how to implement Frameworks.
- No case-study evidence that Frameworks work.
- Technology diffusion rates (driving obsolescence) are increasing, creating pressure to adopt proactive methodologies to mitigate obsolescence.
- A slight reduction of recent publications within this field.

Many of these drivers are not new, and most were highlighted within Mulholland's (2014) dissertation. Importantly, this chapter allowed for the strategic positioning of this thesis amongst the current research literature. The title of this thesis - *The Resilience of Asset Systems to the Operational Risk of Obsolescence: Using Fuzzy Logic to Quantify Risk Profiles*; entails an element of obsolescence monitoring and also forecasting in order to enable proactive management methodologies. Underneath the title a broad set of questions were created within the problem statement, which are:

‘Can we proactively manage obsolescence within the Built Environment? If so, how?’

This chapter has confirmed that proactive management is possible, but currently not practised and has little industrial guidance. Further to this, the data likely to be made available will also differentiate this thesis from forecasting papers reviewed within this chapter. This develops the question further to, ‘*if so, how?*’, which is something that is to be directly addressed within this thesis.

In order to appropriately continue this research into how one could quantify the risk of obsolescence or begin understanding how it impacts the resilience technically, a review of Systems Resilience is required. The understanding of how obsolescence and resilience are connected is a key academic connection to make to the reader. The next chapter will introduce Systems Resilience to the reader, its key terms, and topics, and then how within the Built Environment these concepts can be linked to obsolescence and maintenance practices.

2.3 Systems Resilience

The term systems resilience is a growth area of research. Figure 34**Error! Reference source not found.**, produced by Google Books Ngram Viewer, illustrates this trend as a bibliometric via the Google Books corpus. The Google Books Ngram viewer, is a publically available and live dataset, which is also grey literature. Due to this, the below figure is likely to no longer reflect the updated dataset now found online. Please see the statement in section 2.1 regarding the use of grey literature within this thesis. The below figure is a result of data mining all English texts held by Google Books for the bigram (case insensitive) ‘system resilience’ and ‘systems resilience’ to produce this exponentially smoothed growth curve.

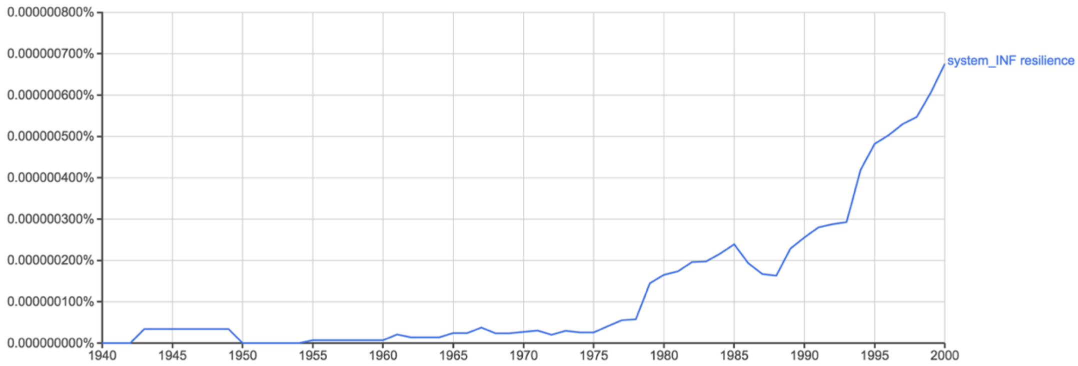


Figure 34 Bibliometric via Google Books for 'System(s) Resilience', from Data source: Google Books Ngram Viewer (http://books.google.com/ngrams)

Bhamra et al. (2011) undertook a sample review of resilience literature to understand the landscape; they found that resilience has proven to be a multidisciplinary and multifaceted topic, spanning several industries. In summary, the term resilience stemmed from Holling's (1973) paper on ecosystem stability, which aligns approximately with the step increase in Figure 34 (Manyena 2006; Bhamra et al. 2011). Manyena (2006) highlighted that even earlier references of the term resilience can be found in works by Norman Garmezy, Emmy Werner, and Ruth Smith in the field of psychiatry in the 1940s (also seen in Figure 34).

Broadly, the term resilience refers to the capability and ability of an element to return to a stable state after a disruption (Bhamra et al. 2011). Whilst the exact definition is disputed due to its applicability in contrasting fields, Manyena (2006) highlights the broadly agreed definition by the United Nations Office for Disaster Risk Reduction (United Nations 2005):

‘The capacity of a system, community or society potentially exposed to hazards to adapt, by resisting or changing in order to reach and maintain an acceptable level of functioning and structure. This is determined by the degree to which the social system is capable of organising itself to increase this capacity for learning from past disasters for better future protection and to improve risk reduction measures.’

United Nations (2005)

How can the resilience of a system, in this context a system of assets delivering a physical service, be associated with obsolescence?

In the Disaster Management Cycle, as highlighted by Malalgoda et al. (2015), construction practitioners play a crucial role in creating a resilient Built Environment. Resilience within the Built Environment has been identified as a key contributor to reducing the economic and financial impacts of disasters (Malalgoda et al. 2015; Haigh & Amaratunga 2010). However, as the extensive research undertaken by Richard Haigh at the Global Disaster Resilience Centre highlights, there are considerable knowledge gaps in the developing world with regards to resilience and its implementation. Now, it is important to reiterate that Disaster Management research from a Built Environment context, is primarily aimed at the more physical and structural elements of buildings. However, regardless of whether a technical fault (i.e. component failure) is caused due to age, wear and tear or lack of maintenance, or the effects of a natural event, the speed of recovery and its hindrance due to obsolescence is transferrable to both scenarios. This research project seeks to create both awareness and a tested methodology for improving the resilience of systems within the Built Environment in anticipation of unforeseen maintenance requirements. This holds benefits for both the speed of recovery (time) and the available mitigation options to restore performance (cost). The recovery of damaged infrastructure requires considerable investment to repair and replace, especially public infrastructure, emphasising the need to enhance resilience (Auzzir et al. 2014). However, as rightly highlighted by Ginige et al. (2013) there are considerable pressures upon finances, lack of governance structure and guidance that all act as barriers to proactive management such as an Obsolescence Management Plan. Auzzir et al. (2014) explore the possibility of implementing PPP or PFI contracts in the face of Disaster Management, as a tried and tested method for raising private sector investment with a clear transfer of risk. In their research paper, they cite Mandell's (2001) comment, describing Disaster Management as a ‘complex societal problem’ and comparing the success of PPP to ‘complex societal problems'. Auzzir et al. (2014) detail several drivers and barriers to such a suggestion, however, the author is of the opinion that a formulated PPP/PFI structure could very simply incorporate modern lifecycle and obsolescence management processes, enhancing the resilience of the infrastructure. Assuming the definition of Disaster Risk Reduction (DRR) given by Ginige et al. (2013) and Haigh & Amaratunga (2010), to ‘actively' and ‘systematically' reduce the exposure of an asset system to extended downtime, following an event, albeit caused by a disaster or not, would connect DRR to Obsolescence Management. Ginige et al. (2013) explicitly summarise the ‘developing/improving of infrastructure to increase resilience’ as a key task of improving DRR within the Built Environment. This narrative aligns itself very closely to this research project, whilst the primary case study features the commercial market within the developed world, the issues and therefore benefits, can transcend across the Built Environment.

The need to undertake unplanned (UPM) and preventative maintenance (PPM) regimes within modern buildings upkeep a level of service. Such activity, along with lifecycle requirements, are all dependent upon parts (software and hardware) being available and therefore not obsolete. By that very logic, obsolescence can directly prevent a maintenance team from ensuring the resilience of a system through an inability to support it. It is the aim of this thesis to explore how one could analyse and improve the resilience of a system from the Built Environment. However, in order to undertake such a task, this chapter must first review the key elements.

In 2013 the UK Government set out its targets for the construction industry in 2025, importantly the following are appropriate to mention (HM Government 2013):

- 33% reduction in the initial cost of construction and the ***whole life cost of built assets*** (based upon 2009/10 benchmark).
- The UK government expects to have ***integrated city systems*** by 2030.
- The UK government anticipates an increased focus on ***whole life costs of assets***.

Since the Construction 2025 document, the UK Government have published the 'Digital Economy Strategy 2015 – 2018', reconfirming the imminent arrival of the Internet of Things (IoT) with a reported 30 billion connected devices to the Built Environment (HM Government 2013; Innovate UK 2015). Interestingly, the Digital Economy Strategy also highlights that this emerging trend will 'drive demand for components, devices, wireless connectivity, middleware and decision support tools' (Innovate UK 2015). In summary, with rising pressure from the government to reduce whole life costs within integrated systems, one can only speculate the increasing importance of systems resilience. This chapter will now continue into what is meant by operational resilience, addressing the title of this thesis, and how this can be associated with obsolescence.

2.3.1 Operational Resilience

McDaniels et al. (2008) wrote an important paper on resilience within physical infrastructure, in the context of disaster management and noted that 'resilience of complex systems has emerged as a fundamental concern for system managers, users, and researchers'. McDaniels et al. (2008) quote one widely cited methodology for attempting to measure resilience in the form of the MCEER framework. MCEER identified 'robustness' and 'rapidity' as two key characteristics of resilience:

- Robustness - the ability to withstand a given level of stress without suffering degradation or loss of function.
- Rapidity - the capacity to meet priorities and achieve goals in a timely manner in order to contain losses and avoid future disruption.

The two above characteristics are illustrated in Figure 35. In the context of this thesis, robustness and rapidity will be translated in the coming sub-chapters to further define the direction and definitions of the adopted terms.

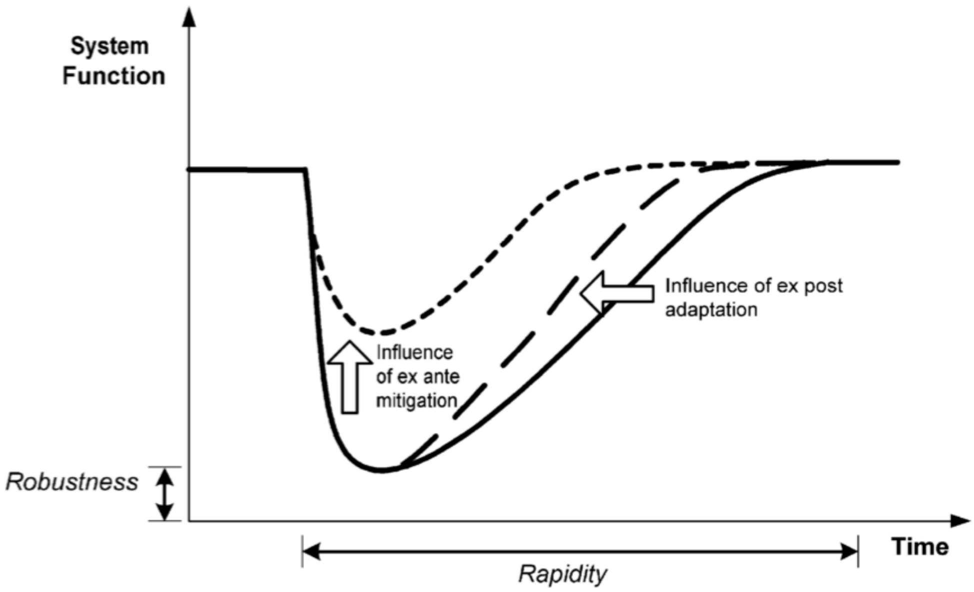


Figure 35 Visualisation of Resilience, from McDaniels et al. (2008)

Importantly, McDaniels et al. (2008) conclude that resilience can be enhanced by both risk mitigation before an event (proactive management) and response activities following an event (reactive management). However, due to the non-binary nature of obsolescence, it is not always possible to undertake reactive measures whilst avoiding considerable investment.

Little (2002) is the only author found within this literature review that highlights the importance of not just the hardware but the service provided by the system, when discussing infrastructure resilience. Little's (2002) paper also goes onto to identify that 'first order effects' of a failure can have ramifications upon other systems or other elements within the same system, creating 'second order effects'. This is an important consideration when seeking to address the impact of obsolescence holistically. Another way to illustrate how systems resilience can be bridged with obsolescence is to recreate Figure 36, first produced by Little (2002).

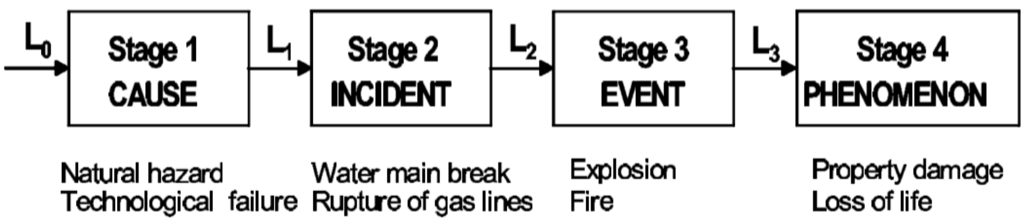


Figure 36 Event Stages and How They Affect Resilience, from Little (2002)

The cause of a maintenance requirement can simplistically be due to component failure or prescribed requirement (PPM). If managed, this can create an incident in the form of resource being required to undertake UPM and/or PPM. The event is likely to involve the un-operational status of an asset, either in isolation or the entire asset system. The phenomenon is either an immediate return to full operational status, through successful maintenance, or a prolonged un-operational status or partial return to performance levels due to unavailability of correct components. The length of state 4 dictates the operational and financial impact of obsolescence. In contrast, the resilience to obsolescence surrounds stage 3 and one's ability to support and sustain the systems held within a site.

The following sections will cover how UPM and PPM related explicitly to systems resilience as defined above and also inventory management and centrality as two key elements to managing obsolescence within a real-world context.

2.3.1.1 Maintenance and Spares

Referring back to Figure 35, robustness is the availability of the correct components and skillset on-site to perform the required activity and the rapidity refers to the time taken to undertake said activity. Logically, the on-site relationship between maintenance requirements and spares is an important one when seeking to improve system resilience.

But how do you assess the future maintenance and spares requirements?

Huiskonen (2001) declared 'spare parts inventory management is often considered as a special case of general inventory management with some special characteristics, such as very low demand volumes'. Assets within the Built Environment are typically defined as low demand items, meaning they often experience periods of zero demand (Emmett & Granville 2007). This is a key point of this chapter as it dictates the types of statistical methods that could be applied to enable proactive management. However, there is a human element within the process, Syntetos et al. (2010) highlight the importance of 'judgmental adjustments by managers' upon forecasts for fast and slow moving demand volumes. Otherwise statistically, this has proven difficult to analyse and forecast (Emmett & Granville 2007; Syntetos & Boylan 2005). Thomopooulos (2015) gives a brief history of the 'forecasting pioneers' of demand analysis; citing the work by Brown, Holt, and Winters. Amongst the three of them, the majority of forecasting models still in use today were developed; their work was only limited by the storage and computational power available in the 1950s. Single exponential smoothing, often used for horizontal forecasts and double exponential smoothing, used for trend forecasts formed the foundations of modern forecasting (Thomopoulos 2015). It was in the 1960s that the third and final fundamental method of incorporating seasonal components for exponential smoothing was developed

(Thomopoulos 2015). As mentioned, components from the Built Environment do not adhere to the above forecasting methods due to their low volume or 'lumpy' statistical nature. A common methodology adopted for slow demand profiles is the Poisson Distribution, derived by the French mathematician Poisson in 1837, first applied to describe the number of deaths caused by horse kicking in the Prussian army (Emmett & Granville 2007). This method is also described as 'stationary Poisson Distribution', in that the mean value used remains static at the point of calculation. An example would be:

Average demand per period (λ) = 0.4

Supply lead-time periods = 4.0

Target service level = 95%

Average demand over the lead time = 0.4*4.0 = 1.6

Using the standardised Poisson Distribution table, the probability of the range of demands for a demand over the lead time of 1.6 provides the following:

Demand Over the Lead	Probability
0	0.2019
1	0.3230
2	0.2585
3	0.1378
4	0.0551
5	0.0177
6	0.0047
7	0.0010

The set order point influences the statistical chance of demand causing a stockout. A stockout is a demand for a component that exceeds stock held on-site, leading to a prolonged un-operational status. This type of methodology has also been called the Service Level approach (Thomopoulos 2015). Below an arbitrary value of two is used as an example, however, in practice, it is likely to be zero and ordered last minute, reactively.

Set Order Point of 2:

(3-2) * 0.1378 = 0.1378 + …

(4-2) * 0.0551 = 0.1102 + …

(5-2) * 0.0177 = 0.0531 + …

(6-2) * 0.0047 = 0.0188 + …

(7-2) * 0.0010 = 0.0050

Average Stockout = 0.3249

Assuming that a new item is ordered as one is used, the statistical Service Level can be calculated to reflect the probability of a stockout not occurring using set order points.

$$Service\ Level = 1 - \frac{Average\ Stockout}{Average\ Lead - Time\ Demand} \times 100$$

$$Service\ Level\ with\ a\ set\ order\ point\ of\ 2 = 1 - \frac{0.3249}{1.6} \times 100 = 79.69\ \%$$

Repeating the process for a range of set order points will produce the following Service Levels:

Reorder Point	% Service Level
2	79.69
3	93.21
4	98.12
5	99.58
6	99.94

As part of a proactive obsolescence management plan, such a process as this example would be an important step to ensuring that you hold an appropriate number of spares if that is the adopted mitigation strategy. However, as with many real-world problems, this is an economic decision where the costs of holding spares need to be considered.

As with any statistical method, it is important to be aware of the assumptions and weaknesses of the methodology. Poisson has two significant assumptions; events are discrete and also homogenous in their behaviour or fail at the same rates. When considering a data set that covers an asset system, sometimes spanning the breadth and width of a site, it may be insignificant to consider the effect of one failure upon an adjacent component, albeit still a consideration for the results. Additionally, reliability engineers adopt the bathtub curve when describing the probability of component failure within a data population. However, the bathtub curve is only a guide, Yan and English (1997) wrote a comprehensive paper modelling the occurrences of 'latent defects', occurring within the electronics industry (see Figure 37). The bathtub curve translates to a component being more likely to fail when it is new and when it is old, but to hold a reduced risk during its mature period. Again, such granularity is unlikely to exist within a dataset held within the intended case-study. The significance is that the mean would not be homogenous or stationary but rather rising and falling depending on the age.

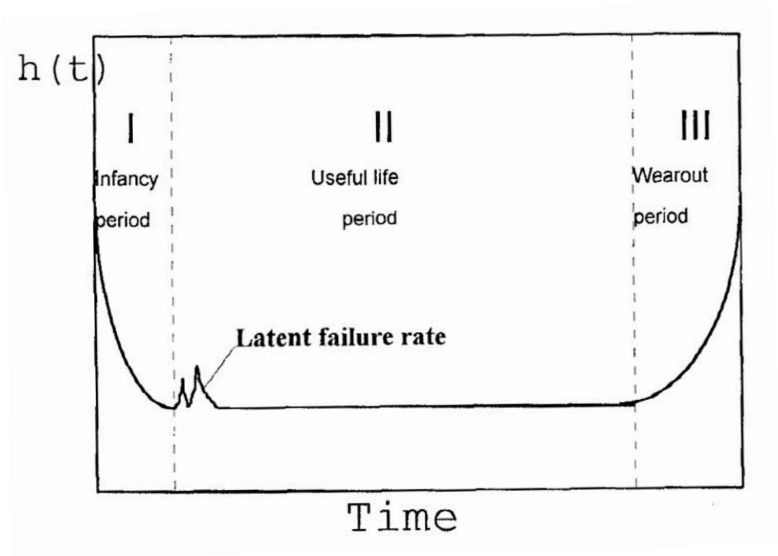


Figure 37 Example of the Bath-Tub Curve use in Reliability Engineering, from Yan & English (1997)

Nonstationary Poisson Distribution (sometimes referred to as non-homogenous) is a methodology derived to better model scenarios where demand fluctuates i.e. queuing within a restaurant, the difference between peak and off-peak hours (Hall 1991; Pourakbar et al. 2012). In fact, the expected number of occurrences (λ) is now a function of time ($\lambda(t)$) and described as a rate, often a count within a time period. Therefore, the expected occurrence (Λ) within a time period is reflected as:

$$\Lambda(t) = \int_a^b \lambda(t)\, dt$$

Please note, this formula can be used for stationary Poisson applications when $\lambda = \lambda(t)$. The actual number of occurrences can be larger or smaller than Λ, it is merely the expected. $\Lambda(t)$ can be expressed graphically, with the derivative (slope) of the function being the rate $\lambda(t)$, please see Figure 38 for an example.

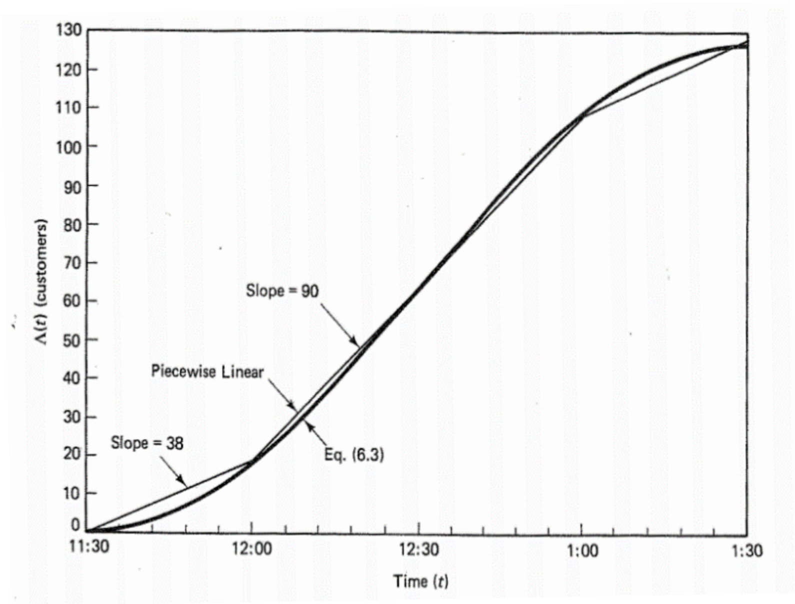


Figure 38 Expected Cumulative Arrivals at Restaurant versus Time Example, from Hall (1991)

Hall (1991) gave the following example to illustrate the use of non-stationary Poisson Distribution to calculate the probability of customer arrival:

A restaurant owner would like to determine the probability that three or fewer customers will arrive between 11:30 and 11:45, using Figure 38, $\lambda(t) = 38$. The expected number of arrivals is:

$$\Lambda(t) = \int_0^{0.25} 100 \sin\left(\frac{\pi\tau}{2}\right) d\tau \; = \left(\frac{200}{\pi}\right)\left[1 - \cos\left(\frac{\pi t}{2}\right)\right]$$

$$\Lambda(0.25) = \left(\frac{200}{\pi}\right)\left[1 - \cos\left(\frac{\pi t}{2}\right)\right] = 4.85$$

$$\Lambda(0) = \left(\frac{200}{\pi}\right)\left[1 - \cos\left(\frac{\pi t}{2}\right)\right] = 0$$

$\Lambda(0.25) - \Lambda(0) = 4.85$ customers

The probability of *n* customers arriving is…

$P(n\ arrivals\ between\ 11{:}30\ and\ 11{:}45) = \frac{4.85^n}{n!} \times e^{-4.85}$ n = 0, 1, …

The probability of three or fewer arrivals is found by evaluating the above equation for n = 0, n = 1, …, n = 3, which equals 0.008 + 0.038 + 0.092 + 0.149 = 0.287.

It can only at this point be speculated that the non-stationary Poisson Distribution method could be utilised for incorporating the bathtub failure curve for slow demand items. Whether or not the dataset being built within current business processes allow for that particular level of granularity is currently unknown.

The final statistical method used for intermittent demand profiles that will be covered is the Croston method. Croston (1972) produced an approach based on exponential smoothing for intermittent demand forecasting. Simplistically, the method separates simple exponential smoothing and the frequency or timing of periods between demands (Xu et al. 2012; J D Croston 1972). The method only updates following a positive demand, therefore dormant periods of zero demand have a lesser impact on the forecast (Xu et al. 2012). The formula is as follows:

x_t = Demand in period t.

y_t = 1 if the transaction occurs in period t, 0 otherwise.

z_t = Size of the transaction in time t.

n_t = Number of periods sine last transaction.

α = Smoothing coefficient.

IF: (no transaction occurs)

$x_t = 0\ (no\ demand)$

$z_t = z_{t-1}\ (the\ size\ of\ transaction\ equals\ previous)$

$n_t = n_{t-1} + 1\ (the\ number\ of\ periods\ since\ last\ transaction\ increases)$

This part of the formulae is key to indicating how Croston's manages periods of zero demand and how it separates it from the resultant ratio.

IF: (transaction occurs)

$x_t > 0\ (positive\ demand)$

$z_t = \alpha \times x_t + (1 - \alpha) \times z_{t-1}$

$n_t = \alpha \times n_t + (1 - \alpha) \times n_{t-1}$

FORECAST:

$x_{t,t+1} = \frac{z_t}{n_t}$

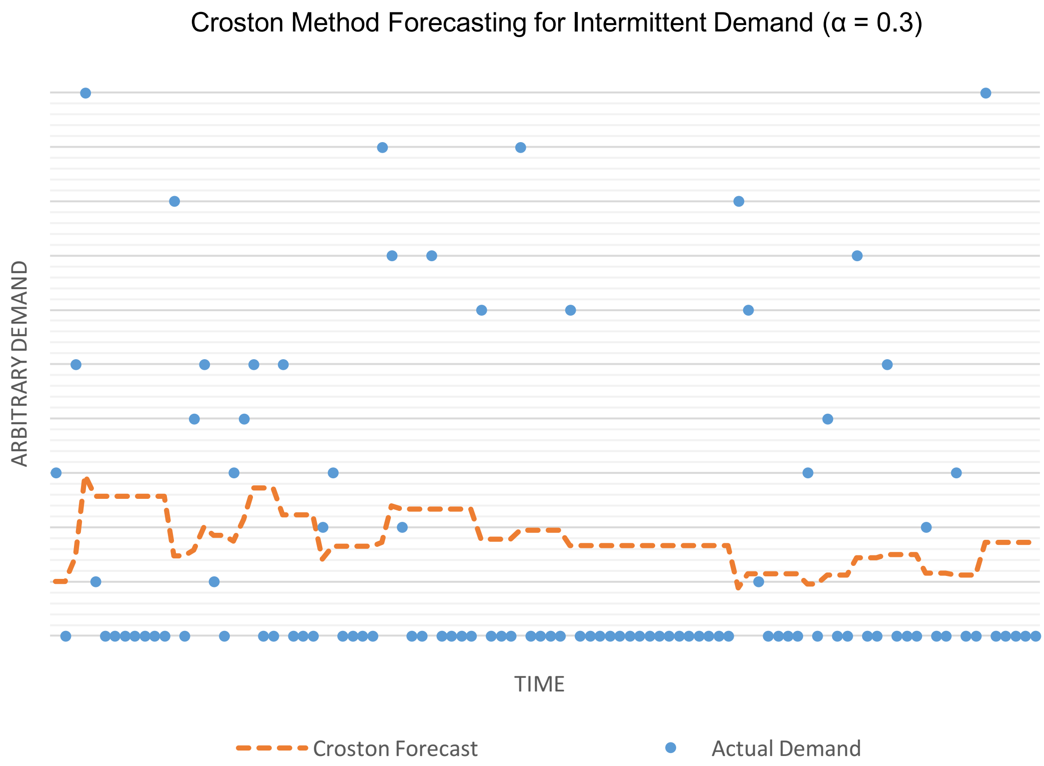


Figure 39 Example of Croston's Method for Intermittent Demand Forecasting, created by author

Croston's method has shown prowess when applied to intermittent demand profiles, however, Syntetos and Boylan (2005), Syntetos et al. (2010) and Xu et al. (2012) all give comprehensive reviews of the weaknesses and biases that exist within the algorithm. Xu et al. (2012) clarify that Croston's method is still considered the benchmark method, however it is an area that requires improvement and holds great potential for optimisation. It important to note the statistical difference to the outputs of the Poisson and Croston's method; Poisson provides a probability distribution, whilst Croston's provides a single forecast. The probability distribution is key for calculating the probability of a Stockout.

However, when seeking to generate probabilities to reflect future demand for physical components, should all components be considered equal?

The remainder of this chapter will seek to answer the above question by reviewing literature that covers centrality and how one could identify critical components within a system. Such a methodology would allow decision-makers to prioritise resource and add an element of strategy.

2.3.1.2 Importance Measures

Reliability Engineers have used several methodologies for identifying the most important or critical components within a system to optimise resources, whilst still improving the reliability of the greater system. Huiskonen (2001) stated that 'the criticality of a part is related to the consequences caused by the failure of a part of the process in case a replacement is not readily available'. How does one identify or quantify criticality?

Barlow and Proschan (1975) cover one of the most basic approaches, the fault tree, which is often used to visually highlight 'bottlenecks' or events that collectively can cause failures greater than their sum of parts. Figure 40 was used to demonstrate how event 'G3' does not occur until incident '6' and '7' arise, similarly event 'G2' and incidents '4' and '5'.

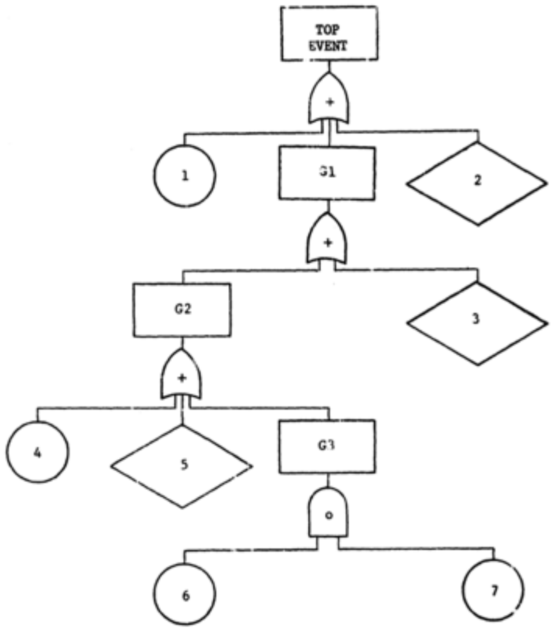


Figure 40 Fault Tree Example, from Barlow & Proschan (1975)

Whilst such methodology is primal, where a Reliability Engineering management process does not exist, it is a viable framework that could be retrospectively adopted. Another typical methodology used by many organisations is the ABC analysis, sometimes referred to as Pareto's principle or analysis (Braglia et al. 2004). ABC analysis requires management to classify components or stock, into the following three classes; very important (A class), important (B class), less important (C class)

Only the components belonging to class A are given management attention. Braglia et al. (2004) were directly very critical of this methodology, due to its ignorance for 'intangible' influences such as obsolescence. However, the nature of this field requires an element of expert subjectivity, which carries bias and other scientific issues.

Importance Measures (IM) are a more empirical attempt to index or indicate more critical or important components within a system (Espiritu et al. 2007; Ramirez-Marquez & Coit 2007; Ramirez-Marquez et al. 2006). Birnbaum (1969) introduced one of the first widely used methods defined as:

$$I_i^B(t) = \frac{\partial R_s(t)}{\partial R_i(t)} = R_s(t;\ R_i(t) = 1) - R_s(t;\ R_i(t) = 0)$$

Where $I_i^B(t)$ is the Birnhaum importance of component i; $R_s(t)$ is the system reliability at time t; $R_i(t)$ the reliability of component i at time t; $R_s(t;\ R_i(t) = 0)$ the system reliability at time t given component i is failed and $R_s(t;\ R_i(t) = 1)$ is the system reliability at time t given component i is perfectly working (Espiritu et al. 2007). The Birnhaum importance of component however, does not account for component reliability, which in practice is an important characteristic, which was later added to create the 'Criticality Importance (CI) measure' (Espiritu et al. 2007; Sallak et al. 2013).

$$I_i^{CR}(t) = I_i^B(t)\frac{F_i(t)}{F_s(t)} = [R_s(t; R_i(t) = 1) - R_s(t;\ R_i(t) = 0)]\frac{F_i(t)}{F_s(t)}$$

Where $F_s(t)$ is the system unreliability at time t and $F_i(t)$ is the unreliability of component i at time t. In addition to the Birnhaum Importance of component and Criticality Importance methods, there are two other well-established methods; Reliability Reduction Worth (RRW) and Reliability Achievement Worth (RAW) (Espiritu et al. 2007; Ramirez-Marquez & Coit 2007; Ramirez-Marquez et al. 2006). RRW and RAW work in contrasting fashions; RRW considers the increase of reliability, whilst RAW considers the loss of reliability.

$$RRW_i = \frac{R_s(t)}{R_s(t;\ R_i(t) = 0)}$$

$$RAW_i = \frac{R_s(t;\ R_i(t) = 1)}{R_s(t)}$$

RAW is the ratio of the actual system unreliability obtained when element i is removed or is always failed, to the actual value of the system unreliability (Espiritu et al. 2007; Rausand 2003). RAW represents a measure of the worth of component i in achieving the present level of system reliability (Rausand 2003). In other words, RAW identifies the most important component, if failed, would lead to the greatest increase in risk (Dimitrijevic & Chapman 1996). In contrast, RRW is a ratio of the actual system unreliability with the conditional system unreliability when element i is replaced with a perfect component (Rausand 2003). Highlighting the component, if made completely reliable would make the biggest reduction in risk (Espiritu et al. 2007; Dimitrijevic & Chapman 1996). The Birnhaum, Criticality Importance, RRW and RAW empirical methods are all functionally slightly different and therefore are considered as equal within literature (Espiritu et al. 2007; Ramirez-Marquez & Coit 2007; Ramirez-Marquez et al. 2006). It should be noted that the above methods are applicable to binary systems only, however, Ramirez-Marquez et al. (2006) given an insight into how these measures can be adapted for multistate analysis. However, to implement any of them, a significant amount of appropriate data is required within the field.

The papers by Sabidussi (1966), Nieminen (1974) and Freeman (1978) combined to produce what is known as the 'centrality measures', which were introduced as IM for complex interactions and networks (Zio & Sansavini 2011). Due to this characteristic, you will find centrality discussed amongst literature from social science – human communication, communication within groups and the relationship between structural centrality and influence in group processes (Latora & Marchiori 2007; Freeman 1978). The four classical topological centrality measures are (Zio & Sansavini 2011; Freeman 1978; Latora & Marchiori 2007):

- Degree Centrality, C^D

$$C_i^D = \frac{k_i}{N-1} = \frac{\sum_{j \in G} a_{ij}}{N-1}, \; 0 \leq C_i^D \leq 1$$

C^D Identifies the node (N) with the largest number of neighbours (k_i), this is normalised over the total number of nodes.

- Closeness Centrality, C^C

$$C_i^C = \frac{N-1}{\sum_{j \in G} d_{ij}}, \; 0 \leq C_i^C \leq 1$$

C^C identifies the node that is closest to all other nodes, valuing the speed of communication within a network. d_{ij} is the topologically shorted path from node i to j, again normalised by all remaining nodes within the network.

- Betweenness Centrality, C^B

$$C_i^B = \frac{1}{(N-1)(N-2)} \sum_{j,k \in G, j \neq k \neq i} \frac{n_{jk}(i)}{n_{jk}}, \; 0 \leq C_i^B \leq 1$$

Similar to C^C, C^B calculates the number of shortest paths within a network, evaluating whether a node is central to the network in regard to the number of shortest paths pass through a single node. n_{jk} is the number of topological shortest paths between nodes j and k and $n_{jk}(i)$ is the number of topological shortest paths between nodes j and k via node i.

- Information Centrality, C^I

C^I uses the network's ability to respond to a deactivated node and therefore network topological efficiency E[G] is used.

$$E[G] = \frac{1}{N(N-1)} \sum_{i,j \in G, i \neq j} \varepsilon_{ij}$$

$$C_i^I = \frac{\Delta \mathrm{E(i)}}{E} = \frac{E[G] - E[G'(i)]}{E[G]}, \; 0 \leq C_i^I \leq 1$$

Where G'(i) is the graph with N nodes and $(K - k_i)$ edges obtained by removing from the original graph G the edges incident in node i. The topological information centrality of node i is defined as the relative drop in the network topological efficiency caused by the removal of the edges incident in i.

Logically, all four classical methods are applicable depending on the network and the agenda of the network, this will influence whether one node is more critical than another (Freeman 1978). Within Zio and Sansavini's (2011) review of the centrality methods within cascade failure scenarios, C^D was found to be the most useful for highlighting the most critical nodes within the system. However, as with many of these techniques there are still criticisms or weaknesses that must be considered; Freeman and White (1991) highlight that they can be too 'simple' in comparison to real world application.

Due to the structural nature of physical assets within the Built Environment and likelihood of cascading component failures, Degree Centrality methodology will be adopted herein for this research project.

2.3.2 Chapter Summary

This chapter covered Systems Resilience and its connection to obsolescence the review outlined and critiqued current literature and highlighted several gaps that are to be addressed by this thesis. In summary, the following key topics were covered:

- Systems Resilience terminology.
- Connection to obsolescence.
- Intermittent forecasting techniques.
- Importance Measures.

Resilience in a broad sense has received growing research attention. This has led to a plethora of definitions and terms as its application ranges several industries. The following definition has been adopted by the author, along with Figure 41, clarifying the two key terms to be used herein.

> 'The capacity of a system, community or society potentially exposed to hazards to adapt, by resisting or changing in order to reach and maintain an acceptable level of functioning and structure. This is determined by the degree to which the social system is capable of organising itself to increase this capacity for learning from past disasters for better future protection and to improve risk reduction measures.'
>
> United Nations (2005)

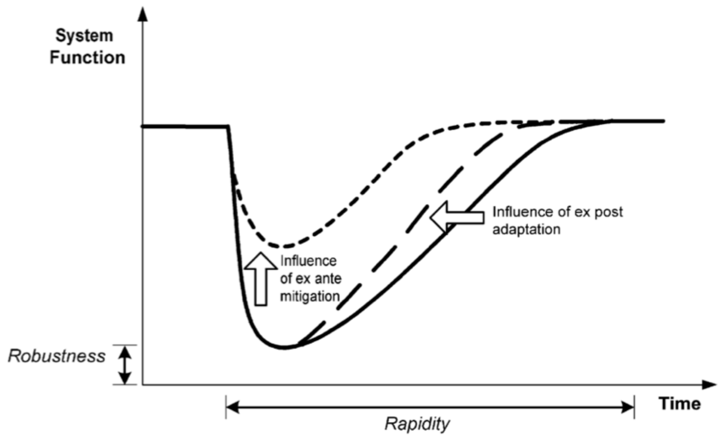


Figure 41 Visualisation of Resilience, from McDaniels et al. (2008)

Using the terms 'robustness' and 'rapidity' a connection has been made within the literature review between the physical resilience of an asset against the ever-changing obsolescence landscape. Recent research from the Global Disaster Resilience Centre was also included to illustrate the wider applications of Obsolescence Management research, specifically in respect to disaster management recovery. This culminated in the explicit use of maintenance and spare components as a primary mitigation technique. This mitigation method carries a challenge in the form of intermittent demand profiles, common amongst service delivery assets within buildings.

Poisson Distribution and Croston's method were covered in this chapter as methods for forecasting the demand profiles of components. The accuracy of said methods are reliant upon the granularity of the dataset, which is still unknown and may present an area for future research. The two methods produce different outputs statistically, therefore both will be utilised for two different reasons (see section 3.3.4.2). Finally, in order to ascertain the most critical or important components within a system, Important Measures (IM) were reviewed. Each measure varies slightly and has a contrasting statistical meaning. The Degree of Centrality was highlighted as a likely method to be used within this thesis, due to its applicability to physical systems and its topological data requirements. The degree of centrality will highlight the asset within the system that contains the most connections, identifying the most critical asset in the context of impact upon the system connections.

This chapter introduced how this research project views assets within the Built Environment and also the importance of considering the wider system when holistically problem-solving. What is not covered is any method other than IM, for how to model a system as a whole.

The next chapter will cover Fuzzy Logic and Fuzzy Inference Systems; which has been identified previously as important vehicles to mitigate data limitations barriers and provide a robust modelling methodology.

2.4 Fuzzy Logic

Chapter 1.0 gave the reader a broad introduction to Fuzzy Logic and its applications within Fuzzy Inference Systems (FIS) for handling both ambiguous data and linguistic inputs. Fuzzy Logic was selected amongst other probabilistic orientated methods such as Monte Carlo simulation, Boolean tree analysis and Markov Chains. The key drivers were its apparent suitability for mapping input to output space, when the interlinking relationships were unknown, along with the added ability to compute linguistic variables (qualitative) with quantitative inputs (Ross 2010; Babuška & Verbruggen 1996). Lee (1990) and Mamdani (1976) describe expert Fuzzy Logic Systems as ‘a means of emulating a skilled human operator’, in their ability to consider several ambiguous inputs to arrive at a single crisp output or decision. The lack of research and data that surrounds obsolescence, along with the vast amounts of intangible data that exists within experienced employees, adds further support (Masmoudi & Haït 2012; Cigolini & Rossi 2008). Klawonn and Kruse (1993) highlight how there is growing evidence that expert Fuzzy Systems have shown surprising levels of robustness and can even compete with advance supervised adaptive methods. Before moving into key subsections within this chapter, Table 3 is an important reference point, illustrating the birthplace of Fuzzy Logic and its key contributors.

Table 3 Prominent Fuzzy Logic Publications, adapted from C. C. Lee (1990)

Year	Author(s)	Title
1972	Zadeh	A rationale for fuzzy control
1973	Zadeh	Linguistic approach
1974	Mamdani and Assilian	Steam engine control
1977	Willaeys et al.	Optimal fuzzy control
1979	Komolov et al.	Finite automation
1980	Fukami, Mizumoto and Tanaka	Fuzzy conditional inference
1983	Hirota and Pedrycz	Probabilistic fuzzy sets (control)
1983	Takagi and Sugeno	Derivation of fuzzy control rules
1983	Yasunobu, Miyamoto et al.	Predictive fuzzy control
1986	Yamakawa	Fuzzy controller hardware system
1988	Dubois and Prade	Approximate reasoning

The following chapter will expand upon key topics within Fuzzy Logic; Possibility Theory, Membership Functions, Fuzzy Rules, and Defuzzification. Examples will be provided to the reader in order add context to the concepts being outlined, along with their applicability to the research direction.

2.4.1 Approximate Reasoning

‘Fuzzy sets seem to be relevant in three classes of applications: classification and data analysis, reasoning under uncertainty and decision-making problems.’

Dubois & Prade (1998)

Approximate reasoning plays an essential role in the remarkable human ability to make rational decisions in an environment of uncertainty and impression (Lee 1991). Obsolescence is a real world problem experienced within a range of industries, evidence now shows that it could be defined as a complex one (Mulholland 2014). It is a complex problem; not fully knowable, but reasonably predictable (NOOP.NL 2008). It is for this reason that obsolescence is both difficult to manage and applicable to Fuzzy Logic.

The entire world is complex; it is found that the complexity arises from the uncertainty in the form of ambiguity. According to Dr. Lofti Zadeh in *Principle of Compatibility*, the complexity and the imprecision are correlated, and adds that the closer one looks at a real-world problem, the fuzzier becomes its solution.

Zadeh (1973)

Obsolescence along with many other industrial processes are complex, which cannot be precisely controlled by traditional methods, due to unavailable data regarding input-output relationships (Lee 1991). Whilst skilled (expert) human operators use heuristics and intuition to successfully monitor and manage such processes. It is such cases where rule-based control logic becomes an attractive alternative (Lee 1991). As initially stated by Dr Zadeh, ‘Fuzziness’ describes the ambiguity of an event and ‘randomness’ describes the uncertainty in the occurrence of an event (Sivanandam et al. 2010; Markowski & Mannan 2008). It can be generally seen in classical set theory that there is no uncertainty, hence they have crisp boundaries, but in the case of a Fuzzy Set, since uncertainty occurs, the boundaries may be ambiguously specified (Sivanandam et al. 2010). It is because of the adoption of Fuzzy Sets that Fuzzy Systems have been labelled as universal approximators and also linguistic rule based non-linear systems (Fuzzy Systems for short) (Ross 2010; Sivanandam et al. 2010). The first recorded industrial implementation of a Fuzzy System was by Danish cement plant manufacturer F. L. Smidth in 1979, which was based on the Sugeno architecture (C. Lee 1990). Whilst Lee's (1990) paper is dated, it holds examples of the earliest applications for Fuzzy Systems, further examples can be found within Ross (2010) and Sivanandam et al's (2010) respective textbooks. Works by Markowski and Mannan (2008) and Markowski and

Mannan (2009) begin to combine the use of Fuzzy Logic Systems and Risk Assessment models, producing notable work. Their work focusses upon Traditional Risk Assessment Matrix (TRM) methodologies and their reliance upon crisp categories, however, often the real situation is not crisp and deterministic due to uncertainties (Markowski & Mannan 2008). Creating further drivers for the use of Fuzzy Logic to provide more precise risk profiles (Markowski & Mannan 2008).

'The first step toward predicting the future is admitting you can't', is an important perspective (and caveat) to adopt when modelling, by its very definition you are modelling history propelled forwards, not the future (Siegel 2013). Further to this, the underlying aim of models is to map the input space to the output space via a black box of some kind (see Figure 42). The black box for a Fuzzy Logic System, is called a Fuzzy Inference System (FIS), it adopts a modus ponens architecture using IF-THEN Rules, along with Membership Functions (MFs) to create the algorithm to map input to output (Ross 2010; Sivanandam et al. 2010; The MathWorks Inc. 2015; C. Lee 1990; Babuška & Verbruggen 1996). Figure 43 by Babuška and Verbruggen (1996) furthers Figure 42 in illustrating how the input Fuzzy Sets are mapped to output Fuzzy Sets via a Fuzzy Inference System (FIS) or 'Fuzzy Relation' in this case. It is the creation of the FIS that allows an engineer to turn Fuzzy Logic and Possibility Theory into a decision-making tool, framed on top of an algorithm.

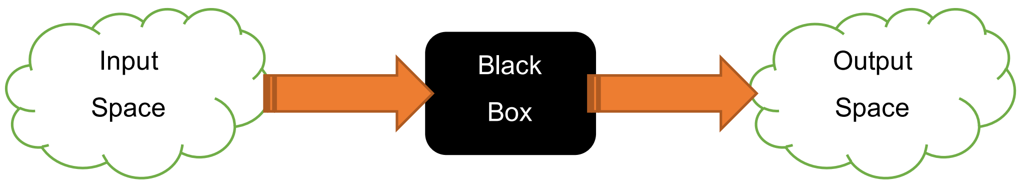


Figure 42 An Input-Output Map, adapted from The MathWorks Inc. (2015)

Whilst the complexity of algorithms varies hugely, Daniel Kahneman (2012) cites the work by Meehl (1955), who made clinical predictions on first-year undergraduate final's grade. A simple algorithm was used, inputting few data points and outperformed 11 of the 14 counsellors who were given the same data set and more, along with a 45 minute one on one interview with each subject. 'Why are expert's inferior to algorithms? One reason, which Meehl suspected, is that experts try to be clever, think outside of the box, and consider complex combinations of features in making their predictions' (Kahneman 2012; Dawes 1979). This is just one example, but a poignant one, as this research thesis aims to aid decision-making under uncertainty around an area that contains little literature. Fuzzy Logic is one of many methods for approaching the 'black box' element of a model, but history shows that even simple algorithms can hold value to real world complex problems (Kahneman 2012; Lee 1991).

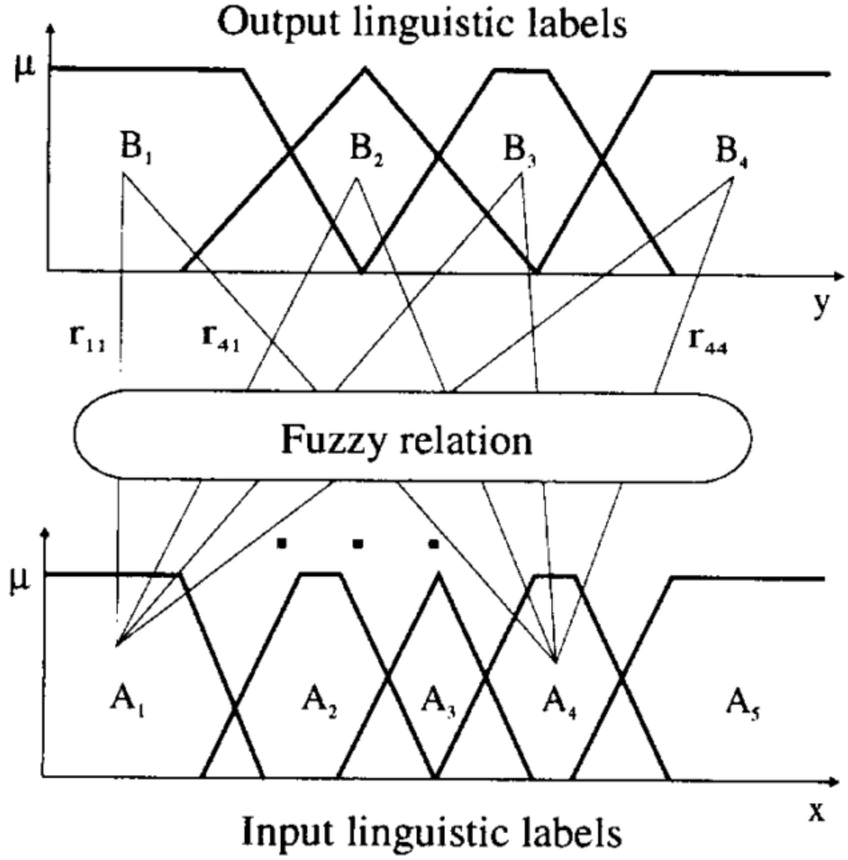


Figure 43 An Example of a Fuzzy System Mapping Input to Output Space, from Babuška & Verbruggen (1996)

Possibility Theory was first detailed by Dr Zadeh (1978) in the paper titled 'Fuzzy Sets as a basis for a theory of possibility'. The above paper set out the need for a new theory in addition to Probability Theory, stating the requirement to understand the meaning of data as opposed to simply its measure (Zadeh 1978; Dubois & Prade 1998). Decision-making under uncertainty was quoted in 1978 as one of the major issues not addressed by Probability Theory, driving research into the use of Fuzzy Logic and classic control theory (Zadeh 1978).

'Fuzzy sets are acknowledged as a major tool in information engineering for the purpose of bridging the gap between human-orientated formalised knowledge, and numerical data.'

Dubois & Prade (1998)

Possibility Theory was framed upon the use of Fuzzy Sets, which in turn was also a new concept (Zadeh 1978). The notion of Fuzzy Sets is central to Fuzzy Logic and has been acknowledged as a key tool in connecting human knowledge and numerical data (Dubois & Prade 1998). Classic Logic theory implies that objects satisfy crisp criteria of a membership; Fuzzy Sets contain objects that satisfy a degree of membership with fuzzy boundaries (Ross 2010; Sivanandam et al. 2010; Dubois & Prade 1998; Zadeh 1965) – which accounts for the ambiguity of an event (C. C. Lee 1990). Fuzzy Sets and Possibility Theory combine to create a framework which is sufficient in accounting for the gradual or flexible nature of many requirements and the representation of missing data (Dubois & Prade 1998). In addition to Fuzzy Sets, there are also Membership Functions (MFs), which interpret crisp input data points and assign a degree of membership to Fuzzy Sets, it is the combination the two that create what is known as the 'Fuzzification Interface' (Sivanandam et al. 2010). Figure 44, shows conceptually, how Possibility theory is the architecture, allowing for the Fuzzy Sets and Membership Functions to combine, creating the interface with the inputs and the 'Decision-making Unit' (C. C. Lee 1990; Babuška & Verbruggen 1996; Markowski & Mannan 2008; Markowski & Mannan 2009; Lin et al. 2009; Sivanandam et al. 2010).

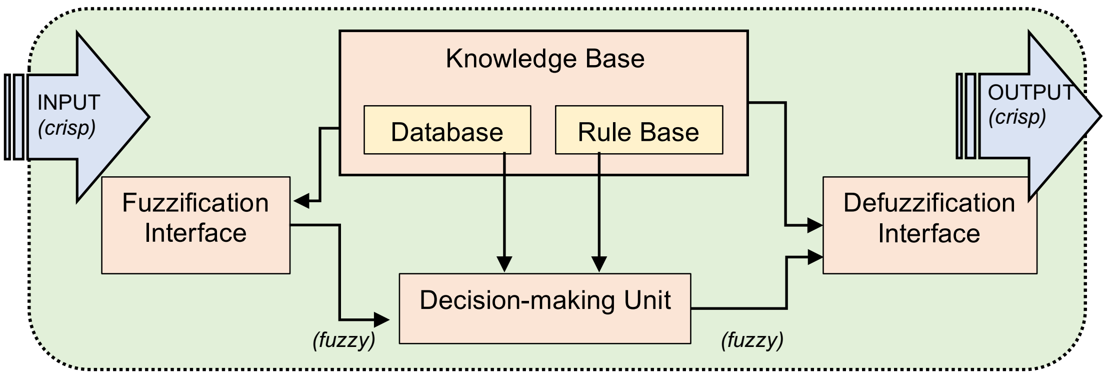


Figure 44 Key Elements of a Fuzzy Inference System or 'Black Box', adapted from Sivanandam et al. (2010)

To give an example of a Fuzzification Interface (Fuzzy Sets and Membership Functions), the following example was provided by Ross (2010). The data consists of a set of heights from five to seven feet (crisp); the set of heights in the region around six feet is imprecise, or fuzzy. There is a collection of data points (x), which make up the universe of discourse, χ. Within this universe of data points, certain elements are assigned to the set A or not (crisp set). Mathematically this would be represented as:

$$\chi_A (x) = \begin{cases} 1, & x \in A, \\ 2, & x \notin A \end{cases}$$

Where χA (x) indicates the unambiguous membership of element x in set A – whilst $\in$ and $\notin$ represent containment or non-containment respectively. For this example, suppose set A is a crisp set of all heights of people within 5.0 ≤ x ≤ 7.0 feet – shown in part (a) Figure 45. Membership of all elements is binary to set A, either with membership value of 1 or 0. Fuzzy

Logic extends this line of thought to 'varying degrees of membership' within the interval [0,1] – where 0 and 1 represent non-membership and full membership respectively. It must be noted that these membership functions do not represent probability density functions but rather membership to fuzzy sets (Zadeh 1965). Consider now a set H of heights near 6 feet, the designer of the Fuzzy System must decide what membership function (denoted μ_H) should look like – in this case, a symmetrical function was applied, shown in part (b) of Figure 45.

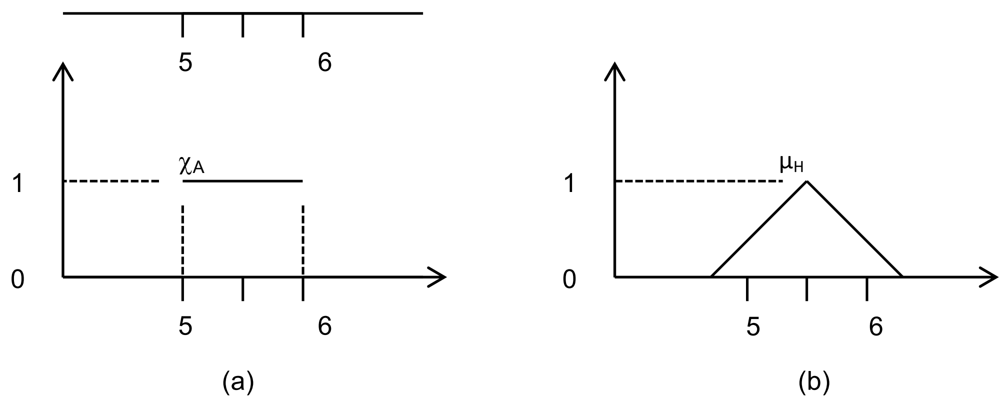


Figure 45 Membership Function Example for (a) Crisp Set A and (b) a Fuzzy Set H, adapted from Ross (2010)

The universe of discourse (X) can be characterised by the *cardinal number*, which is the number of data points within the universe, that are to be mapped into Fuzzy Sets (Ross 2010; Sivanandam et al. 2010). Additionally, the *power set* represents all possible combinations of Fuzzy Sets within the universe of discourse (X), denoted as P(X) (Sivanandam et al. 2010).

The Fuzziness within a Fuzzy Set is depicted by the Membership Functions (MFs). It defines the characteristics of the Fuzzy Set, whether it is discrete or continuous. MFs can take many shape profiles and there are a number of methodologies for selecting the most appropriate (Sivanandam et al. 2010):

- **Intuition:** Intuition is based on the human's own intelligence and understanding to develop the membership functions.
- **Inference:** This method involves the knowledge to perform deductive reasoning. The membership function is formed from the facts known and knowledge.
- **Rank Ordering:** The polling concept is used to assign membership values by rank ordering process.
- **Angular Fuzzy Sets:** The angular Fuzzy Sets are different from the standard Fuzzy Sets in their coordinate description. These sets are defined on the universe of

angles, hence are repeating shapes every 2Π cycles. Angular Fuzzy Sets are applied in quantitative description of linguistic variables known trust-values. When membership of value 1 is true and that of 0 is false, then in between 0 and 1 is partially true or partially false. This method could be used for motor rotations for example.

- **Neural Networks:** Neural networks are used to simulate the working network of the neurons in the human brain. The concept of the human brain is used to perform computation on computers. In this case, the fuzzy membership function may be created for fuzzy classes of an input data set. The data set is split into training and testing sets. The training set is passed through a neural network to identify clustering within the data, assigning best-fit membership function profiles. The neural network is then tested for its performance, with the remainder of the data set.
- **Genetic Algorithms:** Genetic Algorithms (GA) use the concept of Darwin's theory of evolution, based upon the concept of 'survival of the fittest'. GA can be used upon assumed MF profiles and then the internal 'fitness function' of GA's is used to amend profiles to fit the Fuzzy Sets.
- **Inductive Reasoning:** The membership can also be generated by the characteristics of inductive reasoning. The induction is performed by the entropy minimization principle, which clusters the parameters corresponding to the output classes. For inductive reasoning method, there should be a well-defined database for the input-output relationships. This method is suited for complex systems where the data are abundant and static.

The existing knowledge surrounding obsolescence, along with the evidence highlighted by the case-study within the MRes Dissertation, suggests that the intuition and inference methods will be best suited to build an 'expert system' (Mulholland 2014). Linstone and Turoff (1975) and Dubos (2011) both highlight the use of the Delphi method as holding promise for the generation of rules for an FIS (intuition method). Alternatively adaptive methods are seen as the forefront of this research field, however, currently the data sets simply do not exist to exercise adaptive neuro-fuzzy inference methods or genetic algorithms (Mamdani & Assilian 1975; Sivanandam et al. 2010; Ross 2010; The MathWorks Inc. 2015).

Referring back to Figure 44, following the Fuzzification Interface the Decision-Making Unit must be created, or alternatively the intelligence of the system. The fuzzy inference system (algorithm) combines IF-THEN Rules (found within the *look-up* table) to map fuzzy sets in the input space to fuzzy sets in the output space (Sivanandam et al. 2010; Bai & Wang 2006). The following four checks should be applied to the *look-up* table to ensure that the logic remains valid; an important note when designing the rules by intuition or inference (Sivanandam et al. 2010; Bai & Wang 2006).

- **Completeness:** A set of IF-THEN rules are complete if any combination of input values results in an appropriate output value.

- **Consistency:** A set of IF-THEN rules is consistent if there are two rules with the same rules-antecedent but different rule-consequents.
- **Continuity:** A set of IF-THEN rules is continuous if it does not have neighbouring rules with output fuzzy sets that have empty intersection.
- **Interaction:** In the interaction property, suppose that is a rule, 'IF x is A THEN y is B', this meaning is represented by a fuzzy relation R^2, then the composition A and R does not deliver B.

Figure 46 is an illustration created by Sivanandam et al. (2010) to demonstrate how the Fuzzy Sets, MFs and IF-THEN Rules combine to generate an output (fuzzy). The crisp inputs (x_0 and y_0) are given degrees of membership to Fuzzy Sets and form the antecedents to the rules (now fuzzy). The inference system then interprets the degree of membership and therefore the rule strength, to combine and create the consequent (Output Distribution). Validation of such models typically undergoes a trial and error process with expert panels, such as used by Babuška and Verbruggen (1996) and Mamdani (1976) or use hindsight to compare outputs with real world context to calibrate either MFs, IF-THEN Rules or both.

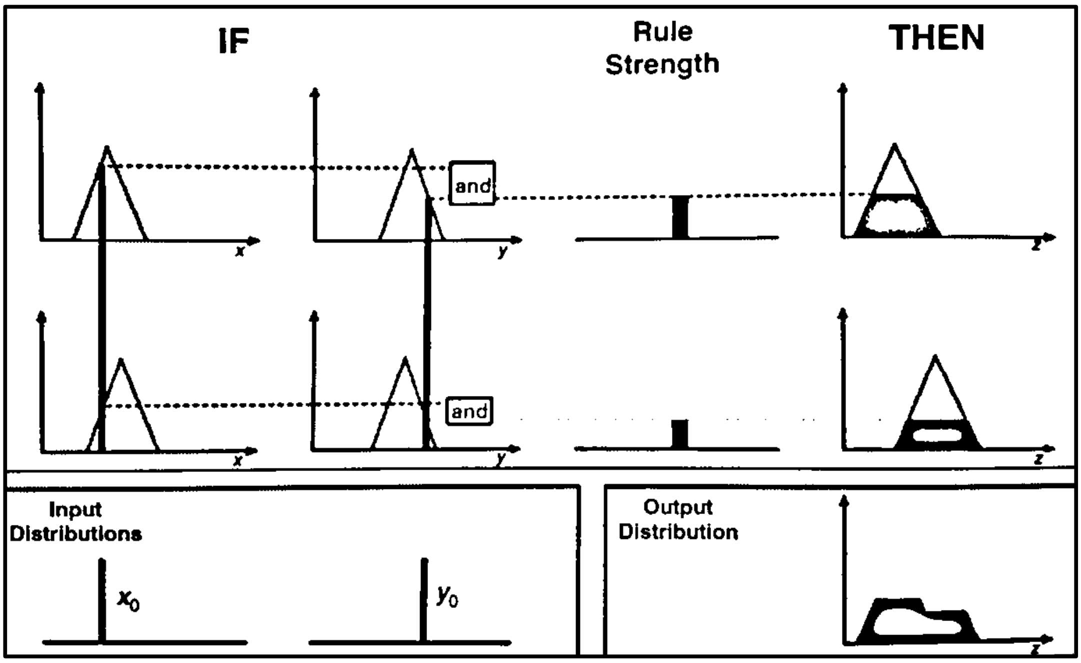


Figure 46 Fuzzification Process Using IF-THEN Rules, from Sivanandam et al. (2010)

This leaves the Defuzzification step to be explained. Defuzzification refers to the conversion of fuzzy back to crisp, to allow for further processing i.e. heuristic decision-making (C. C. Lee 1990; Ross 2010; Sivanandam et al. 2010; The MathWorks Inc. 2015). Defuzzification has also been called the 'rounding off' process, as it reduces the collection of MF values (Output Distribution) into a single crisp quantity (Sivanandam et al. 2010). There are several methods that have been used, along with two distinct types of FIS; Mamdani and Sugeno, all will be compared here.

The main seven methods reported by Sivanandam et al. (2010) for defuzzifying the fuzzy output functions were:

- **Max-Membership Principle:** also, referred to as the height method. The highest point (max membership) is then traced symmetrically to the z-axis to locate the z* variable (crisp output).

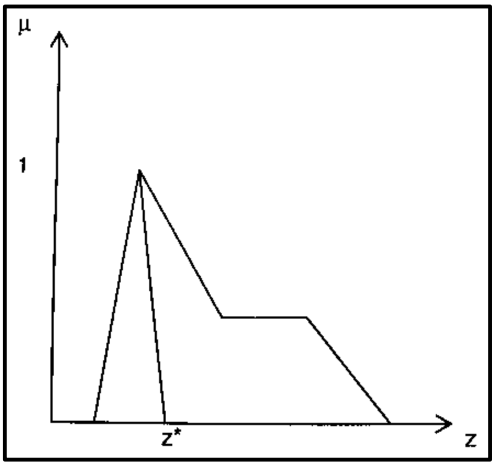


Figure 47 Max-Membership Principle, from Sivanandam et al. (2010)

- **Centroid Method:** the most widely used method. This is also known as the centre of area method, by its nature the centre point of the output distribution is found and then a parallel apex is found to locate the z* variable (crisp output).

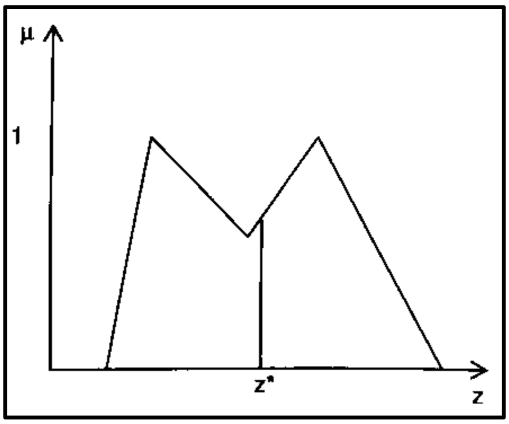


Figure 48 Centroid Method, from Sivanandam et al. (2010)

- **Weighted Average Method:** this method cannot be used for asymmetrical output membership functions and applies a weighted consideration for output MFs with the largest membership.

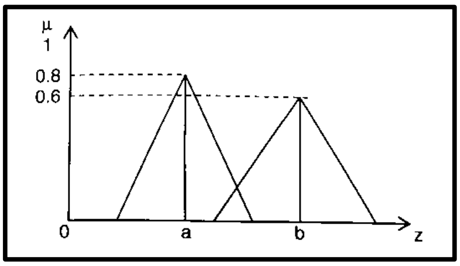


Figure 49 Weighted Average Method, from Sivanandam et al. (2010)

- **Mean-Max Membership:** similar to the max-membership method, although the maximum membership point need not be a single point but a range.

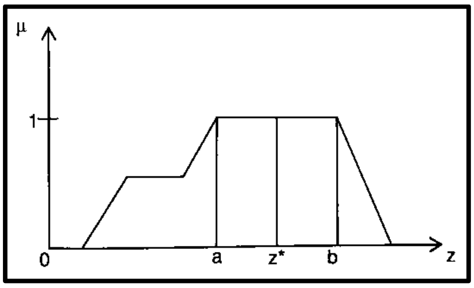


Figure 50 Mean-Max Membership, from Sivanandam et al. (2010)

- **Centre of Sums:** involves the individual calculation of the output fuzzy sets, instead of a union in a similar fashion to the weighted average method. Note, the overlapping sections of the fuzzy sets are weighted twice.

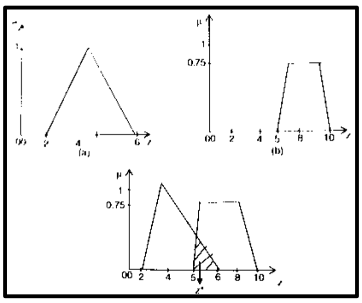


Figure 51 Centre of Sums, from Sivanandam et al. (2010)

- **Centre of Largest Area:** if the fuzzy set has two convex sub-regions, then the centre of gravity can be calculated using the largest region.

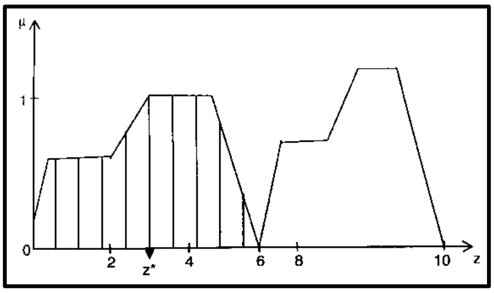


Figure 52 Centre of Largest Area, from Sivanandam et al. (2010)

- **First of Maxima or Last of Maxima:** this method computes all of the individual output fuzzy sets with full membership to find the first of the last maximum membership values.

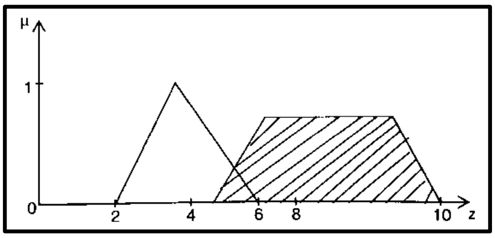


Figure 53 First of Maxima of Last of Maxima, from Sivanandam et al. (2010)

The centroid method is reported as the most commonly used for a whole range of applications, a number of recent authors within the field has chosen to adopt the centroid method (Bellon et al. 1992; Babuška & Verbruggen 1996; Combs & Andrews 1998; Chang 1999; Hayward & Davidson 2003; Mendel et al. 2006; Chang et al. 2006; Markowski & Mannan 2008; Nepal et al. 2008; Paul & Azeem 2010; Ustundag et al. 2010). The centroid method gives greater consideration of the membership strengths, as opposed to the Mean Max method, which leads towards the position of greatest membership. A weakness of the Mean Max method is evident when there are two or more max membership values, this creates indecision within the model (Hayward & Davidson 2003). Lee (1990) reported that the centroid method produced a smaller mean square error than that based on mean of maximum method, however, as stated the appropriateness of Defuzzification methodology as well as the level of *granularity* (no. Fuzzy Sets within an input or output) is dependent on application (Babuška & Verbruggen 1996; Bellon et al. 1992; Bai & Wang 2006). The added benefit of Defuzzifying the output of an FIS, is the 'understandability' of the model and its mechanisms increases, widening the audience to both technical and non-technical (C. C. Lee 1990). This unique characteristic also enables the designer to iteratively calibrate them model in a transparent manner by adjusting the linguistic IF-THEN Rules (Eloff & de Ru 1996).

As mentioned, there are two schools of thought with regards to the structure of an FIS; Mamdani and Sugeno styled models. The main difference between the two methods lies in the consequent of the IF-THEN Rules (Ross 2010; Sivanandam et al. 2010). Mamdani fuzzy systems use fuzzy sets as rule consequents whereas Sugeno fuzzy systems employ linear functions of input variables as rule consequents and are therefore data-driven by nature (Ross 2010; Sivanandam et al. 2010; Ustundag et al. 2010). Figure 54 illustrates how linear functions are built into the Defuzzification step of a Sugeno FIS.

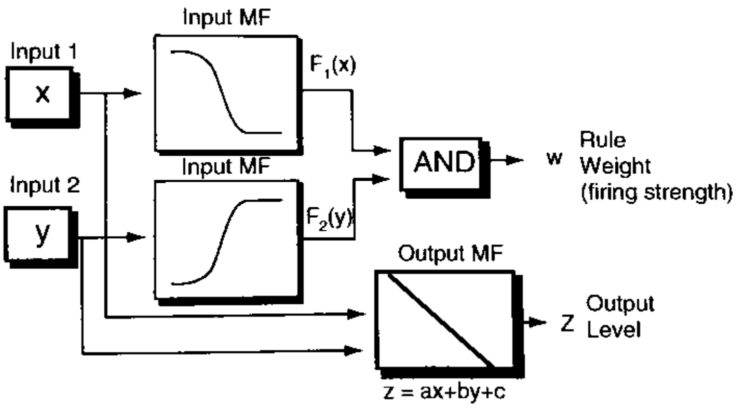


Figure 54 Linear Defuzzification of a Sugeno Architecture, from Sivanandam et al. (2010)

Whilst the Mamdani method has widely been accepted, the advantages of using a Sugeno style model are (Ross 2010; Sivanandam et al. 2010):

- It is computationally efficient.
- It works well with linear techniques (i.e. PID Control).
- It works well with optimisation and adaptive techniques.
- It has guaranteed continuity of the output surface.
- It is well suited to mathematical analysis.

However, Mamdani models are more intuitive and better suited for human input (linguistic variables). Additionally, computational efficiency is unlikely to impact heavily and also the variables involved with physical assets (real world context) are non-linear.

Sivanandam et al. (2010) set out a real-world decision-making example of a Fuzzy System for Product Life Cycle Management. The aim of the model was to highlight when a product was within the 'maturity phase' of the lifecycle (see Figure 55). This instigates the appropriate time to launch new products prior to the 'satisfaction phase', where sales are declining. An expert model was created, which would produce three fuzzy sets within the output; 'preservation of current product status', 'introduce a new product', and 'withdraw the product from the market'.

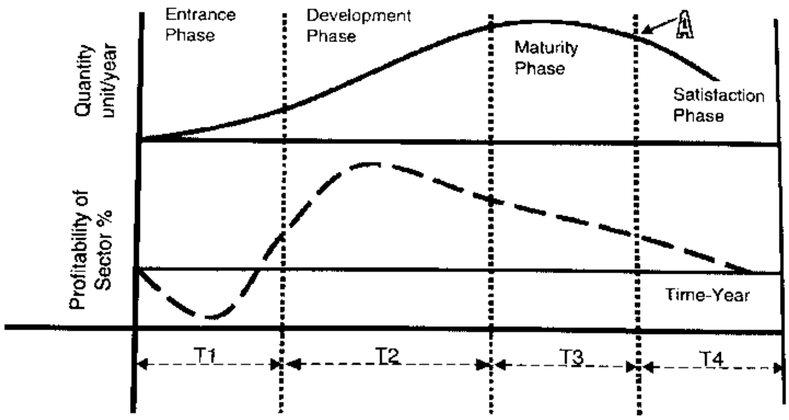


Figure 55 Fuzzy System Being Deployed for Product Life Cycle Management, from Sivanandam et al. (2010)

Figure 56**Error! Reference source not found.** shows the number of inputs into the FIS and also the decision-making units, resulting in a single performance (crisp) output. This particular model was framed upon a liquid detergent manufacturer, with the aim of maximising profits through sales optimisation.

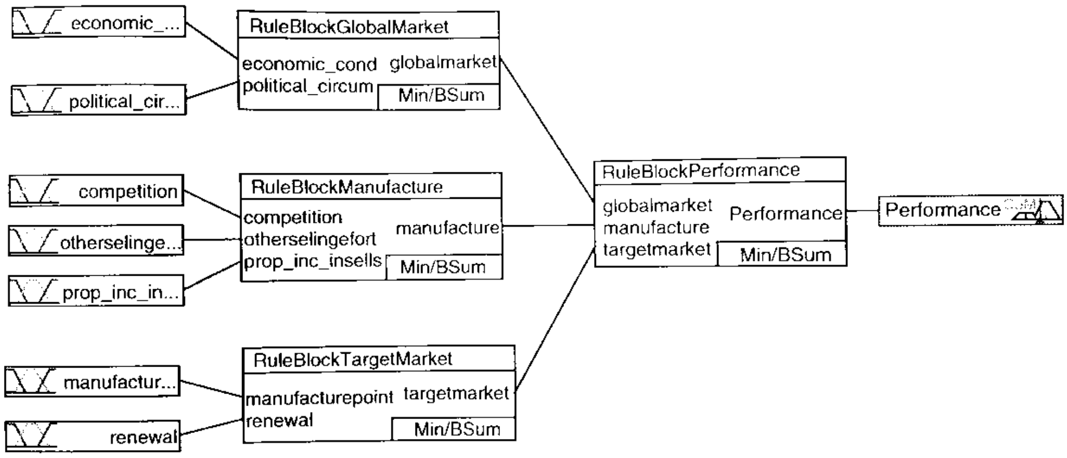


Figure 56 Range of Inputs and Fuzzy Inference Systems within Product Life Cycle Management Example, from Sivanandam et al. (2010)

Table 4 is an example of the *look-up* table within the decision-making unit, illustrating the antecedent and consequents that the algorithm is processing. The centroid method was used here for the Defuzzification step. Whilst this example did not show the results of this model against actual, to gauge performance, it is evidence for the support of using FIS in decision-aiding tools. By adopting an expert system approach, the model has been influenced by the knowledge held by the employees of the case-study organisation.

Table 4 Look-Up Table of IF-THEN Rules for Product Life Cycle Management Example, adapted from Sivanandam et al. (2010)

	IF		THEN
Economic cond.	AND	Political circumstances	Global market
Negative		Negative	Pessimistic
Negative		Ineffective	Pessimistic
Negative		Positive	Pessimistic
Ineffective		Negative	Pessimistic
Ineffective		Ineffective	Pessimistic
Ineffective		Positive	Optimistic
Positive		Negative	Pessimistic
Positive		Ineffective	Optimistic
Positive		Positive	Optimistic

2.4.2 Chapter Summary

This chapter has delved into Fuzzy Logic by covering Possibility Theory, Fuzzy Sets, Membership Functions, Fuzzy Inference Systems (FIS), and Defuzzification in more detail that can be found within the introduction. Importantly, Fuzzy Logic was selected in Mulholland's (2014) Dissertation as a possible vehicle to be used for modelling. This initial view was confirmed and consolidated within this chapter. Other methodologies such as Markov Chains, Monte Carlo Simulation, and Boolean Tree Analysis were considered but discarded due to the probabilistic nature and precise data requirements. Simply, not enough quality historical data exists surrounding the assets within the case-study. This creates ambiguity within the data set, which does not compute with the crisp modelling methods. The key drivers for Fuzzy Logic were its suitability for mapping input to output space, when the interlinking relationships are unknown.

This chapter also gave examples where relevant to illustrate to the reader a form of context for this type of modelling; culminating in Sivanandam et al's (2010) example of a detergent company using a Fuzzy System to model product replacement to optimise sales. This is an area closely linked to obsolescence. Explicitly, it is the opposite side of the coin; the view from a manufacturer upon product lifecycles as opposed to this research direction. The examples found within add further evidence to the robustness of Fuzzy Logic as a professional modelling tool for when ambiguity exists within the data set. However, it is important to note that although it was proven to be a good approximator, an approximator it still is. Fuzzy Logic has shown strength in combining several ambiguous inputs to aid decision-making, results should still be taken as an aid to human decision-makers.

Following the literature review and still to be compiled within the Research Design chapter, several decisions were made in regards to the Fuzzy Logic System design, as follows:

- Several published authors used the MathWorks MATLAB software for its ‘Fuzzy Logic Toolbox’, validating its use and preference on a professional level.
- The Mamdani method was selected for this research project because it is more intuitive and better suited for linguistic inputs. Additionally, some of the benefits of the Sugeno method are not constrained by this particular model.
- Whilst the Membership Functions have not been fully designed, the majority of profiles used within the reviewed literature adorned a simple Triangular profile. This profile was further supported verbally by UCL Teaching Fellow Andrew Whiter, who holds a PhD in the field of Fuzzy Logic. Dr Whiter advised that for approximator models, variances within the profiles will make negligible differences.
- The Centroid Method (CM) for Defuzzification was selected. CM’s strength comes from its ability to consider a range of degrees of membership amongst inputs, importantly when degrees of membership contrast each other. In such a scenario, the Max Membership method would be inaccurate for example.

Please note, there are significant elements of the model that require development and decisions, such as; Model Inputs, Fuzzy Sets and IF-THEN Rules. Some these will be conducted within a Delphi style methodology with a panel of industry experts in order to develop an ‘expert model’.

This chapter has provided a robust methodology that could be used to answer the problem statement set out by this thesis. Fuzzy Logic or more specifically, a Fuzzy Inference System (FIS) is a viable method for addressing the ‘how?’ element of the problem statement, a key missing element within literature.

The next chapter will conclude the literature review, cross-referencing the four key research fields to both summarise the literature landscape and begin forming the potential research questions. Concluding the literature reviewed to undertake this research project, the next step will be to begin developing the research design and methodology to be implemented by this thesis.

2.5 Conclusion

This literature review has continued to highlight that the majority of research within this field is sponsored by large original equipment manufacturers (OEMs), meaning that commercially sensitive data sets are utilised to illustrate the behaviour of obsolescence. Such research approaches are not applicable to Facilities Management (FM) from the viewpoint of an end-user. This thesis will, therefore, deal with considerably smaller data sets and seek to use simple algorithms to aid decision-making under uncertainty.

Under the problem statement, a broad set of questions were devised, they were:

'*Can we proactively manage obsolescence within the Built Environment? If so, how?*'

The literature has highlighted that proactive management is possible, however, most of the current frameworks are not applicable to FM. This creates a gap in the literature for new methodologies to implement Risk Assessments and ultimately define how one would proactively management obsolescence within the Built Environment. This narrative is to be further developed within the research design into a set of research questions.

In order to achieve this aim and ultimately answer the research title, an appropriate modelling medium is required. It was observed by the author that a significant amount of intellectual property is held within the minds of the employees. This subjective and qualitative form of data storage can be translated into a model input via the use of Fuzzy Logic. Fuzzy Inference Systems are very good approximators and can aid in decision-making, especially with ambiguous data sets.

However, as outlined by Dr Kahneman, it is important to remember that it is 'ordinal risk' being quantified, as 'real risk' is merely a point of view. Therefore, like many modelling tools, the methodology seen here should be iterated to further calibrate the output.

> 'Risk' does not exist 'out there,' independent of our minds and culture, waiting to be measured. Human beings have invented the concept of 'risk' to help them understand and cope with the dangers and uncertainties of life. Although these dangers are real, there is no such thing as 'real risk' or objective risk.
>
> Kahneman (2012)

The key points to be taken from the literature review and carried forward into the research design are:

- Lack of obsolescence research within Built Environment.
- Lack of obsolescence research from an end-user perspective.
- No bottom level guidance on how to implement Frameworks.

- No case-study evidence that Frameworks work.
- Technology diffusion rates (driving obsolescence) are increasing. Creating pressure to adopt proactive obsolescence mitigation methodologies.
- A slight reduction of recent publications within this field.
- Stationary Poisson Distribution and Croston's method to be used for intermittent demand forecasting.
- The Degree of Centrality to be used to identify most critical components.
- Fuzzy Cognitive Mapping to be used to illustrate the model key elements.
- Fuzzy Logic to be adopted as modelling medium to create an 'expert system'.
- MATLAB to be utilised for Fuzzy Logic Controller design.
- Mamdani Fuzzy Logic architecture to be adopted.
- Triangular Membership Function profiles to be used.
- The Centroid Defuzzification method to be applied.
- Internal algorithm IF-THEN structure to be created using the Delphi method.

Whilst the above items are key extracts from the literature review, the preceding chapters contain the critical analysis that foretells how the above decisions were made.

As with any research, there are limitations that become apparent; Section 2.2 highlighted that the most cited and prominent pieces of research were completed in the mid-2000s. This poses both an opportunity and challenge for the author. Thanks to the nature of an Engineering Doctorate, a vast amount of industrial expertise is available as a valid information pool to fill gaps that exist within academic literature.

2.5.1 Gap Analysis

This thesis will attempt to undertake a gap analysis in a unique manner, firstly; noteworthy gaps that were identified during the literature review will be detailed here. Then, using Figure 16**Error! Reference source not found.**, which was introduced in section 1.0, the author will illustrate where this thesis positions itself and how it will combine contrasting research fields. The aim of this exercise to is to aid the reader in visualising both the gaps identified and the narrative adopted.

The gaps identified were:

- Further empirical obsolescence indexing testing.
- Obsolescence Risk Assessment methodology.
- The combination of Inventory Management and Obsolescence Management.
- Fuzzy Logic applied to obsolescence related Risk Assessment.

The most notable publication using an obsolescence indexing technique is Clay et al. (2016), who wished to implement this tool in the design stage. Whilst this model holds promise, it was not empirically tested and therefore was conceptual. It was suggested that continued development and testing within a real-world context was required.

This literature review highlighted that there is no current published work, containing a model or methodology for assessing the risk posed by obsolescence. It is speculated that this may be due to the difficulty of quantifying a sometimes subjective risk. In order to implement proactive management in any field, first you must create a quantifiable benchmark in regards to obsolescence risk; this is not possible until a datum is created. This is a key objective of the research project.

There are several reactive mitigation methods possible for obsolescence. The most common are the use of spare parts and last time buys. However, in order to cover the required demand of components for the planned lifecycle of an asset and/or system and element of strategy is required. However, there exists no literature that combines the fields of Strategic Inventory Management and Obsolescence. The literature review explored these currently separate fields and applied them to a clear logic, connecting the two. This thesis will, therefore, contribute to new knowledge by directly creating literature bridging this gap.

A key challenge for this research are the data sets collected via the case-study. This poses the challenge of limiting the types of analysis possible and therefore the insights. When adopting a heavily quantitative modelling approach, one that may rely upon probability profiles and Boolean clarity, this is a significant research challenge. Fuzzy Logic has been applied to Risk Assessments previously, however, none have included obsolescence as the risk. This is seen as an important gap to again be addressed by this research project. The gap analysis has detailed four areas that will be considered for the research design. With this in mind, it is possible to now place this thesis amongst existing literature. Figure 57 illustrates four clusters within the literature landscape.

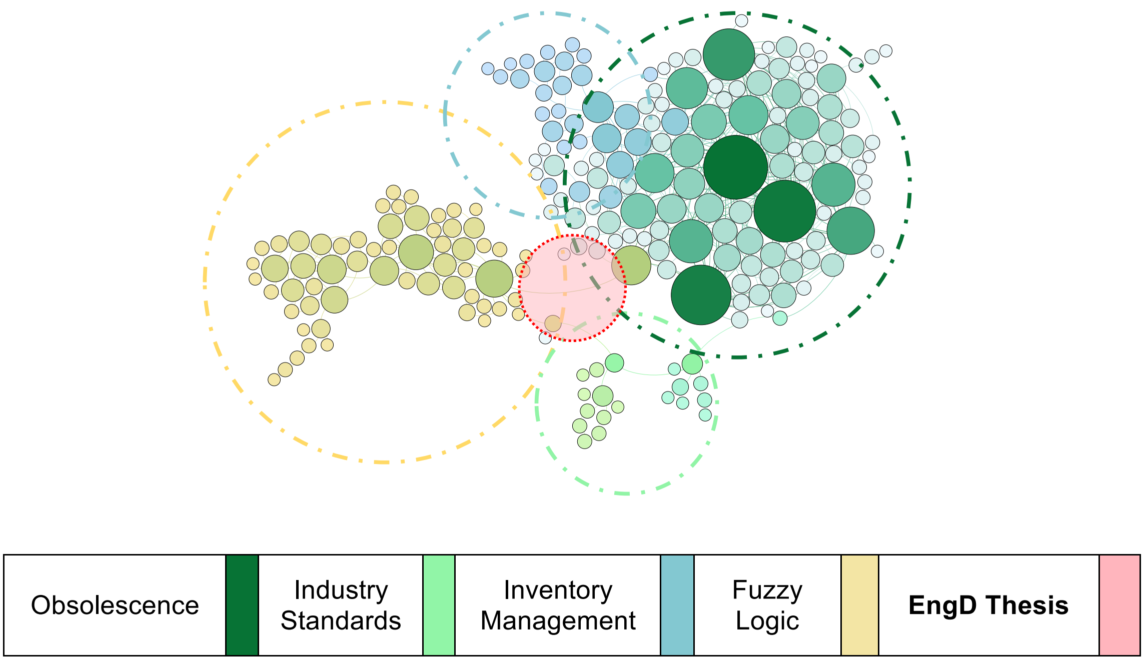


Figure 57 EngD Thesis Placement within Literature Landscape, created by author

Referring back to the title of this thesis; *The Resilience of Asset Systems to the Operational Risk of Obsolescence: Using Fuzzy Logic to Quantify Risk Profiles*, a bridge will be created between all four of the research clusters. In a space that currently is uninhabited, this is crucial for contributing to new knowledge. Now that the research narrative, title and direction are quasi-set out, it would be prudent to notify the reader of areas that do not fall within the scope of this work.

2.5.2 Future Research

The literature review has now set the research boundaries of this thesis; however, the following areas hold potential for future pieces of research in conjunction.

Section 2.3 covered the uses of non-stationary Poisson Distribution for intermittent demand forecasting. If the appropriate data was available, it may be possible to adopt the assumed bathtub failure curve, often used within Reliability Engineering, as a non-stationary expected number of occurrences ($\Lambda(t)$). This would statistically allow for the consideration of premature and latent failures as the probability decreases and then increases.

As well as there being a lack of research associated with obsolescence and the Built Environment, there is also a small amount of diversification of case-study material. The Built Environment is not a homogenous field; there are very specialised buildings that naturally contain equally specialised asset systems. This EngD is constrained by typical time frames and sponsor bias, however, future research reapplying this methodology in contrasting environments would be an interesting prospect. Understanding if and how this research could be applied to specific buildings would provide additional useful insight.

The last element raised for future research concerns the use of System Dynamics modelling to mirror complex real world situations and also apply policy change. An intrusive case-study experiment, looking to implement policy change on an SD model would be very interesting. It is felt by the author that this would particularly aid with engaging stakeholders and create buy-in with regards to obsolescence management. It was too often observed that management take a far too simplistic view on certain business processes and therefore disregard the law of unintended consequences. An SD model, illustrating exactly that whilst also pinpointing bottlenecks within current processes would be a very powerful exercise for any organisation.

This subsection is supported by Further Works (see section 6.4), which follows the results and conclusion chapters of this thesis. The two combine to allow the reader to see several avenues that the author feels contain merit for any future works in related fields. This concludes the Literature Review and flows into the Methodology section containing the Research Design subsection where the research questions of this thesis will be detailed.

3 RESEARCH DESIGN

3.1 Introduction

Structurally this chapter will refine the reviewed literature and identified gaps into a set of research questions, each containing a set of explicit aims and objectives. Figure 58 colour coordinates the research design process found herein, dissecting the Literature Review, Research Design, and concluding chapters.

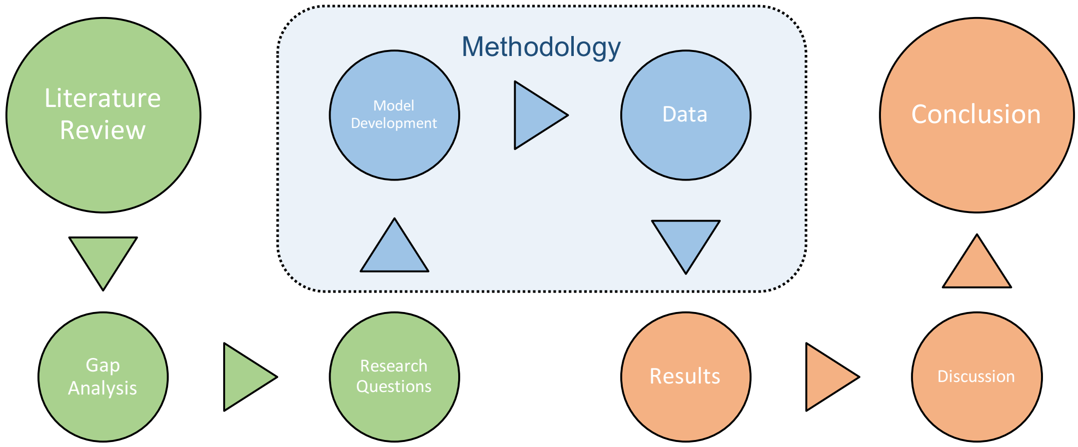


Figure 58 Research Design Structure, created by author

Before outlining the intended research design, a summary of the outputs and contributions to new knowledge found within Mulholland's (2014) dissertation will be appraised. In periodic order the highlights of the aforementioned dissertation were:

- The uncovering of the extent of obsolescence driven investments.
- Wide-reaching literature review.
- Identification of literature gaps.
- Adaptation and extension of obsolescence indexing technique.
- Empirical testing of the new Obsolescence Assessment Tool (OAT).

The OAT tool, containing the 'adapted and enhanced' obsolescence indexing methodology was a contribution to new knowledge. In addition, the following gaps within the literature were identified:

1. Consideration for long-life, low volume components.
2. Consideration for assets typical of the Built Environment.

3. Consideration for end-users who are unlikely to have access to vast sales databases.
4. Empirical testing of indexing methodologies.
5. Quantifying the risk posed by obsolescence.

Items 1, 2, 3, and 4 were covered within the Master of Research project, whilst item 5 is to be explored in greater detail as an Engineering Doctorate objective. In order to repeat point 4 and undertake point 5, an industry-led placement was required in order to both better understand current Asset Management practice and also gain access to new datasets. Mulholland's (2014) dissertation covered a year full-time placement (2013 – 2014) in the Commercial Team within the sponsor organisation, which was followed by a three-year full-time placement (2014 – 2017) as a Project Manager in the Asset Management team.

Crucially, this provided case-study material that spanned several years, allowing for a comprehensive insight into how obsolescence affects people's daily jobs and responsibilities, along with typical business processes. This type of insight can be difficult to document and truly reflect within a thesis; however, where possible the following chapters will contain extracts to add further qualitative evidence. This quasi-industry academia led project is not the only testament to the EngD programme but also a champion of Gravier and Swartz's (2009) recommendation that this type of approach will help uncover the 'economic phenomenon of obsolescence'. The proceeding subsections will cover the research questions and the chosen methodology to generate new knowledge and address the research title. However, before these sections can be populated, it is important to recap where conceptually this piece of research is positioned. Figure 59 was created by Sandborn (2013), a prominent author, and sets out a simple framework.

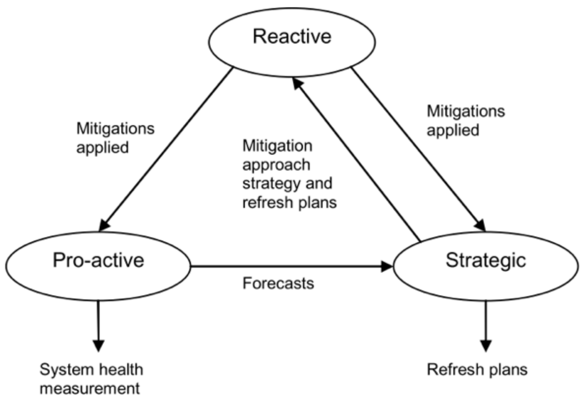


Figure 59 Three Obsolescence Management Levels, from Sandborn (2013)

Current practices are typically reactive; OAT is an indexing method or 'System Health Measurement' and therefore defined as proactive. Whilst OAT does not produce forecasts, if used correctly, it can allow for proactive management decision-making. This thesis will seek to further develop OAT and create a new tool to support proactive management. It is felt by the author that case-study testing of said tools is a requirement for truly Strategic Asset Management. This narrative follows the guidance provided within BS EN 62402:2007 for Obsolescence Management, if you reverse engineer Figure 60 (BSI 2007). OAT and OIT would produce technology transparency and support lifetime buys and obsolescence monitoring, therefore falling into the category required to 'apply a proactive strategy'.

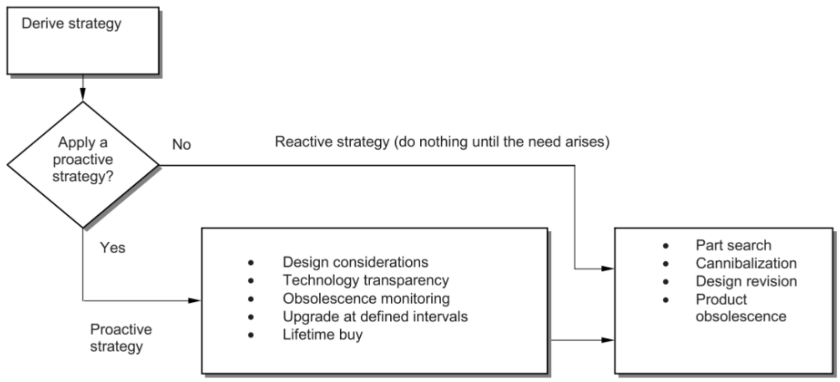


Figure 60 Reactive versus Proactive Strategy, from BSI (2007)

However, in order to manage something, you must first be able to measure it, which is a gap to be addressed by this thesis in order to justify reactive or proactive management techniques. Figure 61 was created to demonstrate the natural progression of obsolescence management, in accordance with BS EN 62402:2007. Whilst the 'Strategic' ring is well defined in the form of possible reactive mitigation strategies; the remaining two categories are both ill-defined and not well documented. It is difficult to therefore to explain how one would undertake or implement a strategy without solely relying on human intuition, which is something that has been recorded to contain fallacies when faced with non-linear and complex decision-making.

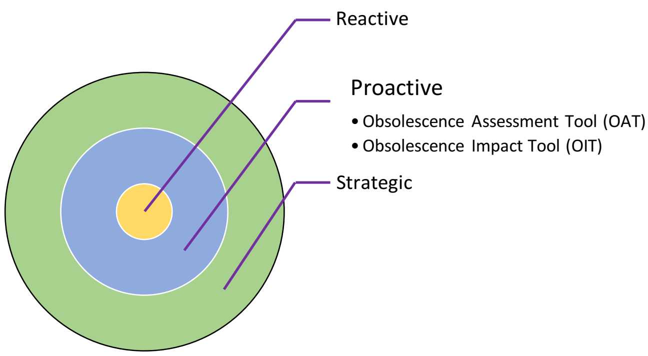


Figure 61 Three Obsolescence Management Levels, adapted from Sandborn (2013)

The next chapter will generate the research questions to be answered by this thesis. It by these very questions that the success of this research project can be both benchmarked and assessed for its contribution to new knowledge. The research questions will be clearly and explicitly defined to that the choice of the methodology can be critiqued appropriately.

3.2 Research Questions

The research questions have been designed to achieve the requirements of an Engineering Doctorate in regards to contributing to new knowledge. The Gap Analysis found in section 2.6.1 identified the following:

- Further empirical obsolescence indexing (OAT) testing needed.
- A need for an Obsolescence Risk Assessment methodology.
- The combination of Inventory Management and Obsolescence Management.
- Fuzzy Logic to be utilised for an obsolescence-related Risk Assessment.

The empirical testing of OAT from Mulholland's (2014) dissertation was published in the Journal of Facilities Management (Mulholland et al. 2016b). Mulholland et al's (2016a) publication of the original OAT algorithm and methodology, illustrates the validity of the chosen methodology for designing a simple decision-aiding tool. This is a significantly difficult task when establishing a novel tool within a relatively immature research field. However, the adoption of an expert model approach improved the robustness of the structure and validity through the expertise of industry. Following a review of the initial results, it was felt that an extended case-study and further enhancement of the algorithm would improve the accuracy of the indexing output. This is a direct key contributor to Research Question 1. There is currently no published methodology for quantifying the risk posed by obsolescence. There is also no published model combining inventory management and obsolescence management. This, combined with a form of importance measure (IM), is seen potentially as a significant contribution to new knowledge, and therefore culminates in Research Question 2. Fuzzy Logic has been used for Risk Assessments (RA) previously and therefore holds pedigree; however, its application in Obsolescence Management would be another contribution to new knowledge. The development of a Fuzzy Inference System (FIS) and its results address the third and final Research Question of this thesis.

The explicit research questions of this thesis are:

1. Can OAT be further enhanced to consider compatibility?
2. What is the operational risk posed by obsolescence?
3. Can Fuzzy Logic be used to robustly quantify obsolescence risk?

In order to answer the above questions and fulfil the research title, this thesis will output two very independent models that cover two different aspects of obsolescence. The Obsolescence Assessment Tool (OAT) is defined as an indexing tool, which will be enhanced in the following chapter and also coded into a MATLAB script. The second will be an Obsolescence Impact Tool (OIT), defined as a Risk Assessment tool. OIT will adopt a Fuzzy Logic architecture. OAT and OIT will be supported by a wider analysis on component sales catalogues, enabling analysis on how obsolescence affects component cost and lifespan on the market. Additionally, a resilience trade-off exercise will be undertaken to conceptually visualise the financial decision-making of proactively mitigating obsolescence via a lifetime buy. The research questions set out within this thesis hold the potential for several contributions to new knowledge, which are:

- Further development and empirical testing of obsolescence indexing technique.
- Development and empirical testing of a new obsolescence RA technique.
- Visual evidence of product obsolescence and the effect on component cost.
- Visualisation of the resilience trade-off for Asset Managers/Facility Managers.

Each contribution of new knowledge will be assessed within the Results section of this thesis. The above contributions will explore areas that are not well-documented and contain no publicly available datasets. It can therefore be difficult to simply validate the outputs of such research, when compared to more established fields. In order to justify the methodology used and the architectures of said models, expert industrial panels were consoled to dictate how the 'expert models' would behave. Where OAT is the second generation, it will be compared with the original algorithm to illustrate the added granularity of the tool. However, the output of OIT is a RA for ordinal risk and therefore is to aid decision-making under uncertainty. It is not the objective of the model to make decisions, but rather reflect the validated logical heuristics of the respective decision makers. It therefore, will be presented as an 'untested' model. The model by design and development is original and has no pre-existing benchmark or historical dataset to test performance. However, the logic of OIT's output can be assessed for accuracy, but not strictly validated or benchmarked. To further illustrate the research approach the author has adopted the same philosophy regarding validation as that held by both Forrester and Sterman; that one should not be seeking to validate models but instead disprove them – illustrated in the following quote (Forrester 1969; Sterman 2000).

> Many modellers speak of a model 'validation' or claim to have 'verified' a model. In fact, validation and verification of models is impossible. The word 'verify' derives from the Latin versus – truth; Webster's defines 'verify' as to 'establish the trust, accuracy, or reality of'. 'Valid is defined as 'having a conclusion correctly derived from premises … Valid implies being supported by objective truth'.
>
> By these definitions, no model can ever be verified or validated. Why? Because all models are wrong. All models, mental or formal, are limited, simplified representations of the real world. They differ from reality in ways large and small, infinite in number. The only statements that can be validated – shown to be true – are pure analytic statements,

propositions derived from the axioms of a closed logical system, because, as stated by the philosopher A J Ayer 'They do not make any assertion about the empirical world, but simply record our determination to use symbols in a certain fashion'.

Sterman, p846 (2000)

The impact of presenting an 'untested' model effects the potential direct use of OAT in reaction to this thesis. An untested model requires historical datasets to assess the performance, allowing for confidence to be applied to its usability. The models found herein, cannot be simplistically copied and applied into a new environment without technical oversight. Blindly doing so, would contradict both the intention of an 'expert model' and the aim of utilising a Delphi Method. It is therefore recommended by the author, that the methodology should be adopted and iterated on a new case study, in order to ensure a calibrated model is produced.

It is true to say however, that in future works the results can be assessed for their performance once the identified risks by OIT have manifested themselves in reality. The comparison then of the predictive nature of OIT and the eventual manifestation of the risk of obsolescence will give the researcher a benchmark. However, note this is not possible within the time constraints of an EngD. It is therefore recommended by the author to repeat the methodology found herein, if the reader wishes to replicate the uses of OIT as opposed to copying its existing architecture to ensure relevant model outputs.

The research questions have been set out above, and next to the methodology framework will be detailed. The chosen approach will aim to deliver upon objectives and contribute to new knowledge, whilst transparently outlining limitations and considerations of the author.

3.3 Methodology

This thesis will adopt a pragmatist research approach as it is felt from the literature and industry observations that obsolescence can appear in many forms and affect systems in contrasting ways (Wahyuni 2012). To tackle such a problem whilst filling research gaps, a pragmatic approach is required when designing and testing tools for the workplace. Obsolescence in broad terms has been approached by a range of methodologies and certain scenarios can be rather subjective, a pragmatic approach was required to best address this area from the viewpoint of the end-user positioned within the Built Environment. The output of this thesis will be intended to solve a specific problem found within the industry, but will require contributions to new academic knowledge. Pragmatism in this context brings with it a mixed method approach to research in order to holistically approach obsolescence and utilise the range of datasets available (Patton 2002; Wahyuni 2012). A mixed method also aids this research project to fill knowledge gaps either in academia or industry, or both. Through focussing on a specific problem within a certain environment, a research design could be developed to both test a solution and document how obsolescence behaves explicitly. This research will naturally be predominantly quantitative, however, due to the use of a case-study methodology there is an abundance of qualitative evidence that will be displayed to support findings (Wahyuni 2012). The structure of the Engineering Doctorate, allowing for the author to embed themselves in the case-study, has provided a holistic understanding of this research field beyond the scope of this thesis.

As mentioned, the Literature Review chapter contains many publications from the field of obsolescence by authors approaching it from contrasting angles. However, in the interest of the reader, there are other ways one could ideally approach this problem. An original equipment manufacturer (OEM), for example, will contain datasets that will equally be useable for developing contributions to new knowledge and furthering the understanding of obsolescence within the Built Environment. Typical examples would be sales data, demand data, and legacy component data, all of which would allow a researcher to analyse how changes in the marketplace affect the supportability of asset systems embedded within buildings. Not having access to the above data sets is a result of their commercial value. However, as highlighted in the introduction of this thesis, there are significant drivers for the development of methodologies to better understand obsolescence from the viewpoint of an end-user. In summary, whilst other methodologies were identified by the author, the pragmatic situation of the problem scenario has dictated the research design angle. This is both a constraint and an opportunity for the author to create a new methodology that is applicable to industry for Facilities Management/Asset Management teams across the sector.

A deductive approach from the general understanding of obsolescence behaviour has been taken to then narrow the focus of the scope into proactive Obsolescence Management. This top-down approach has been guided by both academic research and industry guidance in the form of a wide literature review, British Standards, and industry placement. However, it is the narrowing down to a set of research aims and then critical analysis of results that will enable this thesis to further this research field. Currently, there is no relatable research from the Built Environment to enable an inductive or bottom-up approach to this research project. However, in future this would be helpful to ascertain whether obsolescence is homogenous across contrasting case studies.

Similar to the methodology used within Mulholland's (2014) dissertation and the peer-reviewed publication Mulholland et al. (2016a), this thesis will utilise a case study spanning a two-year period within the sponsor organisation. The unit of analysis of this case-study will be a UK-based private finance initiative (PFI) contract, *Building A* (please see the Research Strategy 3.3.2 for more information). This case-study will be supported by a full-time occupation held within *Building A* to make observations and fully immerse the author. This multi-method approach will, therefore, rely upon both quantitative and qualitative methods to gather evidence. Naturally, the time horizon will be a longitudinal one as the outputs of the developed models are mapped in a y versus time plot. This type of analysis will allow the author to cross-check permutations within the outputs with events within the real world (case-study).

The remainder of this chapter will set out the objectives of the thesis, which will be sourced from the research questions. The objectives will be followed by the research strategy, methodology, model development, datasets, and analysis. The chapter will conclude with a limitations section that will contain a Risk Assessment (RA).

3.3.1 Objectives

The three research questions set out in this thesis contain four contributions to new knowledge or aims. These have been broken down into deliverables or objective tasks to ensure the appropriateness and completeness of this Engineering Doctorate thesis and allow for an explicit review.

Table 5 Contributions to New Knowledge: Aims and Objectives, created by author

Aim (1)	Further develop and empirically test the obsolescence indexing technique (OAT), then to benchmark the new iteration against the previous to illustrate the added precision to the model and validate its use.
Objective (1)	Enhance OAT's internal algorithm to now consider additional parts and confirmed compatibility. This will enable OAT to provide a more accurate characterisation of obsolescence.
Objective (2)	To enhance validity and increase industrial application of OAT, internal validity checks for the input dataset will be developed. This increases the transparency and validity of the model.
Aim (2)	To develop and empirical test a new obsolescence risk assessment technique herein called OIT. OIT is an 'expert model' and will be developed via an expert panel to ensure robustness within the methodology and model behaviour.
Objective (3)	An Importance Measure (IM) to be used for categorisation of case-study asset systems. This will identify the most critical components and add context to the model output. The output will then be used as input (1) for the Obsolescence Impact Tool (OIT).
Objective (4)	Stockout probability calculations are to be undertaken using data from onsite UPM records and stock inventory data. This will be used as input (2) into OIT. Stockout probabilities use the statistical forecast demands, essential for risk

	calculation.
Objective (5)	Data collected for Aim (1) will be used to act as input (3), concerning the obsolescence status of each asset system.
Objective (6)	A Delphi methodology will be used amongst industry experts to create the internal IF-THEN rules to govern the FIS rules. This will now enable the testing of OIT on real world data. It also adds robustness to the validity of the model and its behaviour.
Aim (3)	Critical analysis on sales catalogues from an original equipment manufacturer (OEM). The outputted visuals will provide evidence of the influence of obsolescence upon both unit costs over time and also generate density probability functions for the life of components on the market.
Objective (7)	Annual catalogues from a key OEM will be reverse engineered to extract the price change both when a product is new and becoming obsolete. This dataset spans over a decade and will provide a robust foundation for analysis.
Aim (4)	Visualising the conceptual resilience trade-off for Asset Managers/Facility Managers. This novel visual will attempt to demonstrate the informal decisions made when seeking to mitigate obsolescence and improve resilience.
Objective (8)	The case-study PFI penalty mechanism will be extracted and simplified to illustrate how costs rise over time with asset downtime. This is cross referenced with a quotation from the OEM for identified spare parts.

The case-study used within this thesis will be detailed in the following chapter, however, the case-study timeline governs aims (1) and (2). The respective objectives must be achieved in chronological order during this time period. Aims (3) and (4) can occur at any time during this same period. In order to project manage this research project, Microsoft PROJECT was utilised and a full project programme can be found in appendix 8.1. The programme also contains key milestones and other UCL requirements i.e. lectured modules and training.

The next sections will cover the strategy used in detail, the model development, and the resultant datasets and analysis. Table 5 will be cross-referenced within the Conclusion in order to gauge the success of contributing to new knowledge and therefore the impact of this research project.

3.3.2 Research Strategy

A case-study strategy has been chosen to best illustrate the industrial application of this research project, whilst also collecting first-hand data to generate novel analysis and insights. Case studies are appropriate when there is a need to investigate phenomena where it is not possible to introduce an intervention and do not wish to remove any external variables (de Vaus 2001). These traits are all relevant for a live business that is experiencing obsolescence instigated by factors outside of their sphere of influence. The case-study unit of analysis is a UK private finance initiative (PFI) redevelopment contract of a fifteen story, neoclassical, Grade I Listed Government Building in London. This operational building has a total footprint of 100,000 m^2, which from here onwards, will be referred to as *Building A*.

The insights provided are limited due to a single case study approach to this research project. A single case study strategy can be vulnerable to generalisation and validity questions, with regards to how they were selected and whether they illustrate a representative case. A discussion of the advantages and weaknesses of using a single case study approach has been widely covered by Kennedy (1979) and Gomm et al. (2000) who predominantly cite the social science area of research. Multiple case study environments, enable the author to investigate explicitly whether the observations are confined or homogenous. In argument, this single case study contained multiple asset systems, however, again this would be enhanced through the adoption of more subjects.

A single case study was chosen due to the time constraint of an EngD, the time required by the author at a single site to oversee data collection and validation made it unfeasible. Further to the constraints of an EngD, obsolescence is not a generalised problem; whilst it exists in systems across the Built Environment, how it occurs, behaves and impacts a business will differ. This important point aligns with an argument placed by Kennedy (1979), suggesting that the weakness of generalisation within single case study methodologies is likely to be more detrimental to studies seeking to generalise findings. This research project is looking to test new methodologies, seeking to generalise their use, as opposed to the strict results found from this case study. In further support, the case study found herein is representative of a building containing modern systems. Allowing for some generalisation from results, however, that would not be advised due to the complex nature of obsolescence likely manifesting in a contrasting environment.

Despite this, the author did explore the possibility of adding an additional case study of a hospital environment. In reflection, the political circumstances of the contrasting set of stakeholders added further barriers for implementation. As a strength of using a single case study, the author was able to devote a significant amount of time embedded within the organisation, observing intangible behaviours and methods used by employees to undertake Asset Management responsibilities. An example being, the art of negotiation when seeking to undertake lifecycle investments and optimise the effective life of assets within buildings.

A ‘descriptive’, ‘theory building case-study’ design was adopted to reflect the need to further understand develop existing theories as to the behaviour of obsolescence within the Built Environment (de Vaus 2001). This is opposed to an ‘explanatory’ ‘theory testing case-study’, which would require better-defined theories in order to *explain* how obsolescence should behave within the Built Environment and therefore *test* said theory within the case-study. Specifically, two asset systems were strategically chosen based on the assumption held within literature that obsolescence targets the more technologically advanced systems more aggressively than contrasting systems within a building. Mulholland (2014) and Mulholland et al. (2016b) both add evidence to the above assumption, highlighting the concentration of obsolescence related lifecycle expenditures within *Building A*. The above criteria allow for a case-study to build theory, adding more evidence to how it changes within ‘multiple cases’ in an ‘embedded’ environment (de Vaus 2001). Due to the lack of tested theory, multiple cases embedded within a case-study mitigates the risk of designing a case-study that is not reflective of reality. This particular PFI contract was a redevelopment project and involved the installation of new asset systems, creating a new asset age datum. The assets are now over a decade old, allowing for a historical review of the real expenditure. This dictated the case-study be undertaken in ‘parallel’ and by its nature be ‘prospective’ as opposed to sequential and/or ‘retrospective’ (de Vaus 2001). A case-study of this design is as a significant strain on time, therefore decreasing the number of cases that can be undertaken during this research project and limit the dataset. It was quickly observed that the Facilities Management sector was not prepared for a retrospective case study as the data storage and business processes were not sufficiently robust within *Building A*. In many ways, it was the ground level situation of the case-study site and the existing literature review that influenced the resultant case-study design by the process of elimination. Please see de Vaus (2001) for a clear matrix for case study selection, as it aided the research design of this thesis.

However, from the results of this case-study it would be possible to either repeat this design or adopt a ‘holistic unit’ or ‘theory testing’ approach, to build upon this thesis.

As with most methodologies, there are inherent issues that if not identified have adversely bias results. de Vaus (2001) highlights internal validity, external validity and reactive effects as three important areas to consider. In order to ensure internal validity within the case-study, all input datasheets from contractors were checked both by the author and the case-study Asset Management Team. However, the risk is posed by miss communication and incompetence of personnel who may not be trained in respect to obsolescence and/or Asset Management. External validity is commonly a criticism of case studies due to the real world not being strictly homogenous (de Vaus 2001). However, a key characteristic of this case-study is the asset systems used, which are broadly transferable to other sites, not by design but by specification. This reduces the external validity and allows for this work to be transferable and applicable to other systems within the Built Environment. Finally, in the same way Mulholland (2014) kept results and progress secret, this case-study will not share preliminary results with the case-study organisation. The aim is to mitigate the Hawthorne Effect upon employees who manage assets and liaise with contractors. However, naturally by the very presence of a Research Engineer on-site requesting asset-related information, attention will be applied and behaviour may change. The above and more can be found in the Risk Assessment in section 3.4, which covers the identified risk to this thesis and its outputs.

The author has been a full-time occupant of the case-study site since August 2013; however, the case-study as referred to herein covers the time period 2015 to 2017. During this two-year period, quarterly obsolescence data collections were made, very similar to those made during the Mulholland's (2014) dissertation period of 2013 to 2014. Exactly what was collected and why, can be found within the Data Collection chapter (see chapter 3.3.4). Figure 62 illustrates how this case-study fits within the wider project. It is important to note that qualitative evidence and observations were made throughout the entire EngD project and may cover a time period outside of this case-study strictly.

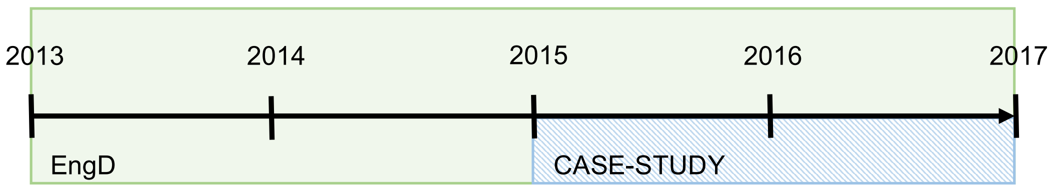


Figure 62 Timeline for EngD Project, created by author

The asset systems that feature herein are the Building Management System (BMS) and Security System (SS). As mentioned, these two systems respectively rely heavily upon technology and deliver crucial services to the Built Environment, making them relevant case-study units of analysis over other systems.

The BMS contains 191 individual components as it manages *Building A*, meanwhile, the SS contains 45. According to CIBSE Maintenance engineering and management: Guide M, BMSs hold the following indicative life expectancies:

(*n*) Controls

Building management systems (BMS):

— head end (supervisor)	5
— outstations	10
— plant controller	10
— operating system	5
— remote display panels	10
— communications network (hardwiring)	25

Figure 63 Extract from CIBSE Guide M, from CIBSE (2008)

If you were to design a lifecycle model or lifecycle cost (LCC) the useful life of a BMS you would use the above indicative time periods to plan financial requirements. The guidance for SSs are not too dissimilar, as shown below:

Intruder detection	15
Intruder system control panel	20
Closed circuit television (CCTV) and video	10
Communication systems	20
Intruder alarms and intercommunications	10

Figure 64 Extract from CIBSE Guide M, from CIBSE (2008)

These systems are both large and complex, reducing the likelihood of the Asset Manager/Facilities Manager being able to identify all of the operational risks. Equally, due to their size and independently planned lifecycle requirements, the asset registers are continually changing. However, it has been witnessed that these are not updated and therefore in themselves obsolete. This leads to an all too common scenario where an Asset Manager will not know, explicitly, what is installed on an entire system in specific detail, let alone comment on whether said components are obsolete or not.

Across the Built Environment asset systems vary slightly by design, however, a core structure is homogenous, such as is shown in Figure 66 and Figure 65**Error! Reference source not found.**. Due to the anonymity of the case-study, this structure will be adopted to represent how one would apply an importance measure (IM). The degree of centrality for the two systems is shown in Table 6 and Table 7 and is to be adopted for this case-study. Note, Building Management Systems can contain a number of head ends, each with an even greater number of outstations and in turn sensors/actuators. In the context of the below exercise for calculating the degree of centrality, the case-study BMS contains several thousand outstations per headend and is therefore denoted with an $\propto$ as the greatest degree of centrality. This is not reflected within the example graphic used in Figure *66*.

Table 6 Building Management System Degree of Centrality, created by author

Component	Degree of Centrality (C_D)
HEADEND	$\propto$
OUTSTATION	2
ACTUATORS	1
SENSORS	1

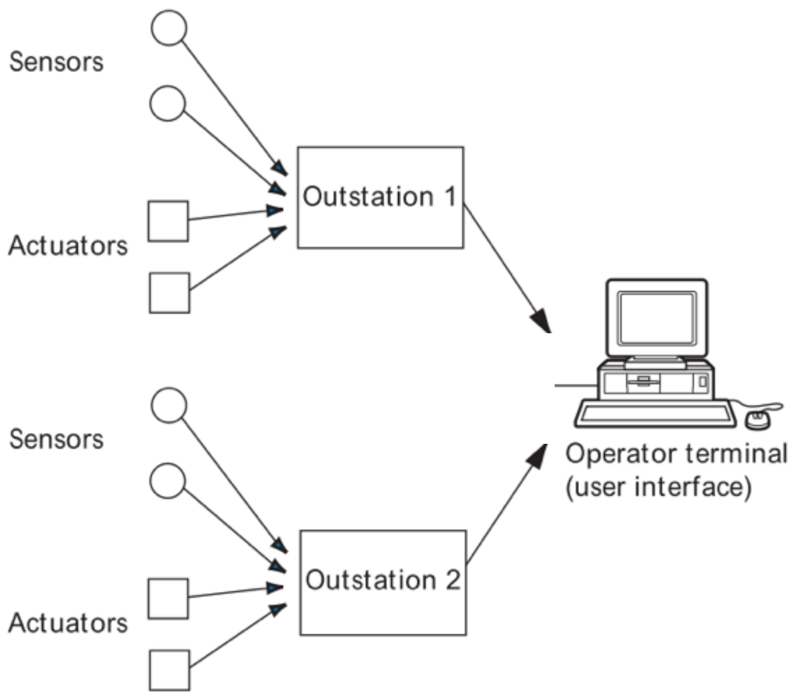


Figure 66 Case-study Building Management System Topology Structure, from CIBSE (2008)

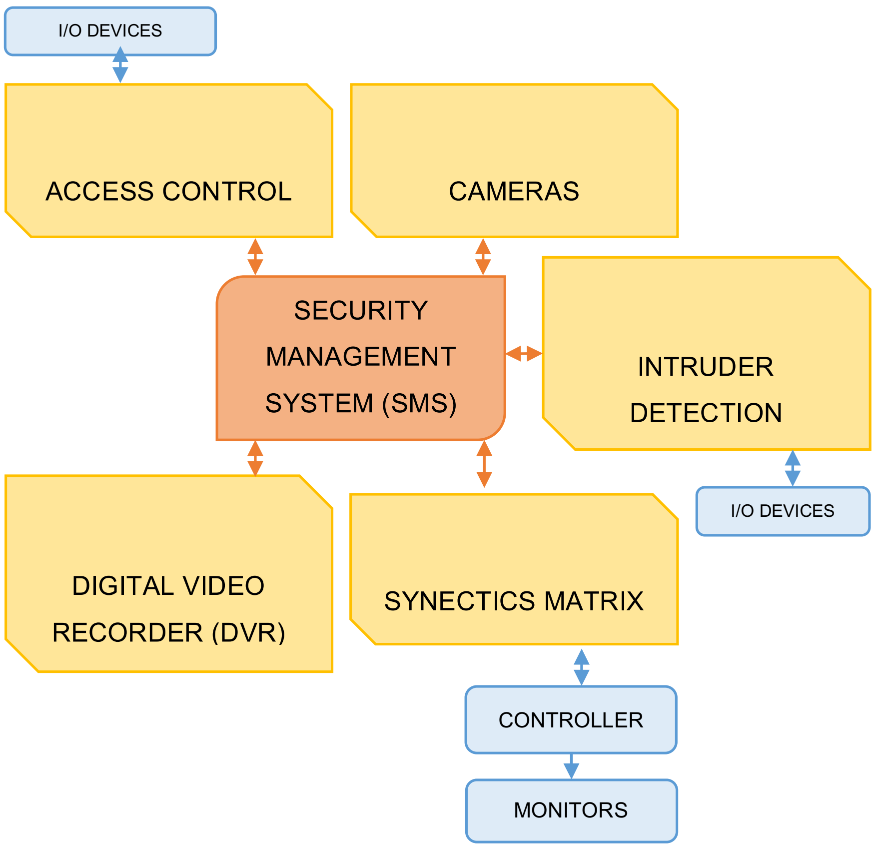


Figure 65 Case-study Security System Topology Structure, created by author

Table 7 Security System Degree of Centrality, created by author

Component	Degree of Centrality (C_D)
SECURITY MANAGEMENT SYSTEM (SMS)	5
ACCESS CONTROL	2
CAMERAS	1
INTRUDER DETECTION SYSTEM (IDS)	2
SYNECTICS MATRIX	2
DIGITAL VIDEO RECORDING SYSTEM	1
I/O DEVICES	1
CONTROLLER	2
MONITORS	1

To clarify, both the BMS and SS contain and rely upon a local area network (LAN) to communicate between assets. In the context of SSs, it is common for certain assets within the wider system to host their own internal LANs. This adds resilience to the system in the eventuality of a fault. For the purpose of this exercise, both systems have not had their LANs considered within the context of assets. However, such a level of granularity would require the detail of the systems to be published, against the wishes of the sponsor.

This chapter has covered *Building A* and the case-study assets to feature herein, and the system structures and expected life statistics have also been extracted for the reader. Importantly, objective (3) has been accomplished with the results shown in Table 6 and Table 7. Now that the case-study has been illustrated, this chapter will continue into the Model Development phase where OAT and OIT will be enhanced for testing on the datasets found in the proceeding chapter.

3.3.3 Model Development

This chapter will cover the two respective models, OAT and OIT, explicitly detailing the changes enacted following a review of Mulholland's (2014) dissertation and Literature Review respectively. In order to undertake the envisaged changes and formalise the models, professional MATLAB training was required. The MATHWORKS Fundamentals five-day classroom course was completed in order to ascertain the required skills to develop and test both OAT and OIT. This was supported by additional MATLAB Digital Skills Development training courses at University College London.

3.3.3.1 *Obsolescence Assessment Tool (OAT)*

Mulholland's (2014) review highlighted that whilst OAT showed promise for indexing obsolescence within asset systems; there was no way of capturing whether promised alternative parts would be compatible. It is commonly seen within the industry that whilst alternatives or upgrades are available, compatibility drives further sales into components to combine legacy systems. This added functionality is reflected in the below algorithm in red.

$$AH = 100\frac{(\sum S + \sum Y_1 + \sum A_1 + \sum B_1)}{(\sum S + \sum Y_1 + \sum Y_2 + \sum O + \sum U + \sum A_1 + \sum A_2 + \sum B_1 + \sum B_2)}$$

AH = Asset Health

S = Two or more suppliers and no EOL

Y_1 = One supplier and no EOL notice

Y_2 = One supplier and EOL notice

A_1 = Alternative part, no EOL notice and confirmed compatibility

A_2 = Alternative part with EOL notice

B_1 = Alternative part, confirmed compatibility and EOL notice or Unknown EOL

B_2 = Alternative supplier and EOL notice

O = Obsolete part with no solution

U = Unknown status

Figure 67 New Obsolescence Assessment Tool Algorithm, created by author

OAT's internal structure is shown in Figure 67. In addition to the above changes, it was decided to incorporate a data validity step into the algorithm. This chapter will cover in detail the data validity and OAT algorithm steps. To find the entire length of the code, please see appendix 8.2. The amended algorithm, added validity checks, and MATLAB coding complete objectives (1) and (2) of Aim (1), leaving only the testing to be undertaken.

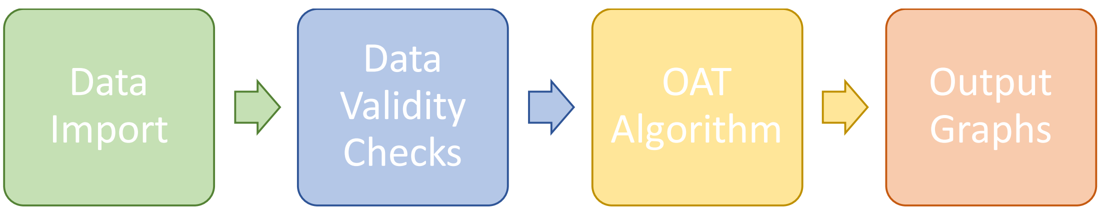


Figure 68 Obsolescence Assessment Tool Structure, created by author

The data validity checks consist of five separate checks covering some logical steps that should be present in the dataset. Whilst the failure of any single set of tests may not necessarily mean that the data is invalid, it is a routine that can highlight both human error in the form of data entry and also systematic mistakes in the form of misinformation.

1. EOL released but no recorded date.
    - If this check is failed then there is a possible mistake within the datasheet or in fact, the date is unknown, meaning that no proactive action can realistically be taken. Misinformation is common within industry.

Note in the below table there are variables that were created from the import of the Excel input sheet. These can be found within the MATLAB report in appendix 8.2. However, the author has attempted to label the founding variables with self-explanatory names (please see the explanation column for guidance).

Table 8 Logic Test 1 MATLAB Script, created by author

MATLAB Code	Explanation
`san_EOL_Released = ~isnan(EOL_Released);`	%This line highlights all entries within the 'EOL_Released' data field. Blank entries are denoted 0 and entries 1.
`Ssan_EOL_Released = san_EOL_Released == 1;`	%Now all the entries (1's) have been extracted and entered into a new blank variable.
`newdata = data(Ssan_EOL_Released,:);`	%the index created by the new variable is then used to extract all of the rows from the original data table. This will include the other fields i.e. part name etc.
`newtable = newdata(:,[1,3,5,7,9]);`	%to simplify the output to the user, only the relevant columns are chosen to be presented by the new variable 'newtable'.
`Date_Released = isnan(newtable.EOL_Date);`	%within the 'newtable' this line will search for blanks within the 'EOL_Date' field. Note, this new table only contains components that have an EOL released against them.
`disp('Logic Test 1: ')` `disp('The below components have a recorded EOL notification against them, but no recorded date.')`	&now the appropriate variables have been created to cut up the original data table. The following lines will explicitly apply the logic test.

`Logic1Testa = newtable.EOL_Released== 1;`	`%store into this variable the components that are marked by 1 (do contain an EOL notification).`
`Logic1Testb = Date_Released == 1;`	`%store into this variable the components that are marked by 1 (do not contain a date released field).`
`Logic1Test = Logic1Testa & Logic1Testb;`	`%now combine these two elements into a single logic test.`

`newtable.Properties.VariableNames = {'Part_Name','Part_Ref','No_Parts','EOL_Released','EOL_Date'};`
 `Logic1Result = newtable(Logic1Test,:);`
 `disp(Logic1Result)`
	`%display the new formatted table to the user, this will be blank if all components pass this logic test.`

The above code will produce a table to the user, showing any lines within the datasheet (components) that have failed this first logic test.

2. EOL date is stated but not EOL notification recorded.
    - If this check is failed, then there is a possible error within the datasheet. It is illogical that a date can be recorded with no notification released; the said date would be contained within a notification.

Table 9 Logic Test 2 MATLAB Script, created by author

MATLAB Code	Explanation

`disp('Logic Test 2: ')`
 `display('The below components should be check for errors.')`
 `display('They are reporting no EOL but state a date.')`
	`%display some pre-test blurb to the user.`

`Nonblank_EOL_Date = ~isnan(EOL_Date);`	`%This code scans the ‘EOL_Date’ column for entries, highlighting entries with 1.`
`NoEOL = EOL_Released == 0;`	`%The ‘EOL_Released’ column is scanned for blank entries (0’s).`
`BlankEOL = isnan(EOL_Released);`	`%The ‘EOL_Released’ column is scanned for blank entries (NaNs). NaNs are ‘not a number’ entries, used for blank entries.`
`BlankEOL_or_NoEOL = BlankEOL | NoEOL;`	`%Combine the two filters to find entries that are either blank or`

	false within the 'EOL_Released' column.
`LogicTest2 = Nonblank_EOL_Date & BlankEOL_or_NoEOL;`	%Combine the filtered list with the fields that contain an 'EOL_Date'. LogicTest2 will now contain all elements that failed this test.
`LogicIndex2 = find(LogicTest2);`	%Find the index of all components that failed this logic test. This will be needed to extract from the original data table the results.

`Logic2Result = data(LogicIndex2,[1,3,5,7,9]);`
 	
`disp(Logic2Result)`
	%The index is used to extract the results and then appropriate columns are chosen to be displayed also.

The above code will produce a table to the user, showing any lines within the datasheet (components) that have failed the second logic test.

3. Number of parts entered into the datasheet
    - If this check is failed, then there is a possible error within the datasheet. This code will check that the number of parts is both filled with a number and not zero, this check would be invalid with an entered character for example.

Table 10 Logic Test 3 MATLAB Script, created by author

MATLAB Code	Explanation
`Logic3Testa = isnan(No_Parts);`	%This line of code will highlight any components that a NaN against the 'No_Parts' column. This could be created by text being present i.e. a typo.
`Logic3Testb = No_Parts == 0;`	%This will highlight any components that have had zero entered against them for 'No_Parts'. A component should not exist within an Asset Register if it has no parts.
`Logic3Test = Logic3Testa | Logic3Testb;`	%Combine the first two variables into a single logic test.

`LogicIndex3 = find(Logic3Test);`
 	
`Logic3Result = data(LogicIndex3,[1,3,5,7,9]);`
	%Find the index of the components that exist within the above variable. Then use the indexes to extract the answer from the original data table. Also filter out the columns that are not needed for the results

`disp('The below component quantities should be checked.')`
 	
`disp(Logic3Result)`
	`table.`
	
	`%Display the table back to the user.`

The above code will produce a table to the user, showing any lines within the datasheet (components) that have failed the third logic test.

4. No recorded EOL notification but a date of release
    - If this check is failed, then there is a possible error within the datasheet. This code will check for components that have no EOL notification but have a date of release. It is possible that the date of release is so recent that the full details are not all present.

Table 11 Logic Test 4 MATLAB Script, created by author

MATLAB Code	Explanation
`Logic4Testa = EOL_Released == 0;`	`%Components with no 'EOL_Released' noted against them.`
`Logic4Testb = ~isnan(Date_Of_Release);`	`%Components that contain a 'Date_Of_Release' filed against them will be stored within this variable.`
`Logic4Test = Logic4Testa & Logic4Testb;`	`%Combine the above two variables into a single logic test.`

`LogicIndex4 = find(Logic4Test);`
 	
`Logic4Result = data(LogicIndex4,[1,3,5,7,8]);`
	`%Find the index of components that fail this logic test. Use the indexes to extract the answer from the original data table.`

`disp('The below components should be checked for their EOL release dates.')`
 	
`disp(Logic4Result)`
	`%Display the components that failed this logic test to the user.`

The above code will produce a table to the user, showing any lines within the datasheet (components) that have failed the fourth logic test.

5. Six or more blank data fields per component
    - If this check is failed, then there is a strong possibility that there is an insufficient amount of data for a particular component. This logic test will highlight components that hold six or more blank fields.

Table 12 Logic Test 5 MATLAB Script, created by author

MATLAB Code	Explanation
`Logic5Test = ismissing(data);`	`%This code returns a 1 for every blank data field and a 0 for entries.`
`rowsum = sum(Logic5Test,2);`	`%Each row is then summed to equate the number of missing fields.`
`Logic5TestIndex = find(rowsum>=6);`	`%Components with six or more blank fields are entered into this variable.`
`Logic5Result = data(Logic5TestIndex,:);`	`%The index of the above variable is used to then extract the answers from the original data table.`
`disp('The below components have 6 or more missing data points. Continue?')` `disp(Logic5Result)`	`%Display the answer to the user.`

The above code will produce a table to the user, showing any lines within the datasheet (components) that have failed the fifth and final logic test.

In order to enact the changes stated in Figure 67 and incorporate both alternate parts and compatibility, the following lines of code were generated to create the internal algorithm for OAT.

Table 13 Obsolescence Assessment Tool Algorithm: Status Assigning, created by author

MATLAB Code	Explanation
`oattable = data(:,[7,11:13]);` `[m, n] = size(oattable);` `result = cell(m,1);`	`%A for loop was required to pass through all of the components, review their data fields and then assign a status to each respectively. 'oattable' was required to store the said statuses.`
`for i = 1:m` `testtable = oattable(i,:);`	`%The data fields being reviewed by the loop are:` 6. EOL Released (level 1) 7. Alternative Supplier (level 2) 8. Alternative Parts (level 3) 9. Confirmed Compatibility

	(level 4) All four of the above checks can be seen within the for loop code. The checking process follows the decision tree logic shown in Figure 69.

`if testtable.EOL_Released == 0`
`level1 = 0;`
`elseif testtable.EOL_Released == 1`
`level1 = 1;`
`else level1 = 'U';`
`end`
 	
`if testtable.Alternative_Supplier == 0`
`level2 = 0;`
`elseif testtable.Alternative_Supplier == 1`
`level2 = 1;`
`end`
 	
`if testtable.Alternative_Parts == 0`
`level3 = 0;`
`elseif testtable.Alternative_Parts == 1`
`level3 = 1;`
`end`
 	
`if testtable.Confirmed_Compatability == 0`
`level4 = 0;`
`elseif testtable.Confirmed_Compatability == 1`
	%This part of the for loop passes through all of the above four fields. Assigning a 1 or 0, categorising where within the tree this particular component (i) sits.
	The decision tree is broken into four levels. Each level is assigned a 1 or 0.

level4 = 1; end	
if level1 && level2 && level3 && level4 == 1 status = 'B1'; elseif level1 && level2 && level3 == 1 && level4 == 0 status = 'A2'; elseif level1 && level2 == 1 && level3 == 0 status = 'B2'; elseif level1 == 1 && level2 == 0 && level3 && level4 == 1 status = 'B1'; elseif level1 == 1 && level2 == 0 && level3 == 1 && level4 == 0 status = 'Y2'; elseif level1 == 1 && level2 == 0 && level3 == 0 status = 'O'; elseif level1 == 0 && level2 && level3 && level4 == 1 status = 'A1'; elseif level1 == 0 && level2 && level3 == 1 && level4 == 0 status = 'S'; elseif level1 == 0 && level2 == 1 && level3 == 0 status = 'S'; elseif level1 == 0 && level2 == 0 && level3 && level4 == 1 status = 'A1'; elseif level1 == 0 && level2 == 0 && level3 == 1 && level4 == 0 status = 'Y1'; elseif level1 == 0 && level2 == 0 && level3 == 0 status = 'S'; elseif level1 == 'U' && level2	%Now a predefined status needs to be assigned to the 1s and 0s.

`&& level3 && level4 == 1`
`status = 'B1';`
`elseif level1 == 'U' && level2 && level3 == 1 && level4 == 0`
`status = 'U';`
`elseif level1 == 'U' && level2 == 1 && level3 == 0`
`status = 'U';`
`elseif level1 == 'U' && level2 == 0 && level3 && level4 == 1`
`status = 'B1';`
`elseif level1 == 'U' && level2 == 0 && level3 == 1 && level4 == 0`
`status = 'U';`
`elseif level1 == 'U' && level2 == 0 && level3 == 0`
`status = 'O';`
`end`	

`result{i} = status;` `end`	%To close the for loop, the status chosen in the present loop is assigned to component i before the next loop begins.

The algorithm has now created a new variable containing statuses for all the components. The statuses need to be counted to then be computed through the formula (see Figure 67).

Table 14 Obsolescence Assessment Tool Algorithm: Status Counting and Formula Execution, created by author

MATLAB Code	Explanation

`statuscolumn = cell2table(result);`
`oattable2 = data(:,[1:3,5]);`
`finalstatustable = [oattable2,statuscolumn];`
	%This code firstly converts the data type of the statuses and then conjoins it to the original data table.

`finalstatustable.Properties.VariableNames = {'Part_Name','Part_Function','Part_Ref','No_Parts','OAT_Status'}`	Then certain columns are filtered and given titles. The table is finally sorted to group the statuses together by type.

; sortedfinalstatustable = sortrows(finalstatustable,'OAT_Status','descend'); disp(sortedfinalstatustable)	

u = strfind(result,'U');
 	
 u = cell2mat(u);
 	
 [u,~] = size(u);
 	
 o = strfind(result,'O');
 	
 o = cell2mat(o);
 	
 [o,~] = size(o);
 	
 s = strfind(result,'S');
 	
 s = cell2mat(s);
 	
 [s,~] = size(s);
 	
 b1 = strfind(result,'B1');
 	
 b1 = cell2mat(b1);
 	
 [b1,~] = size(b1);
 	
 b2 = strfind(result,'B2');
 	
 b2 = cell2mat(b2);
 	
 [b2,~] = size(b2);
 	
 y1 = strfind(result,'Y1');
 	
 y1 = cell2mat(y1);
 	
 [y1,~] = size(y1);
 	
 y2 = strfind(result,'Y2');
 	
 y2 = cell2mat(y2);
 	
 [y2,~] = size(y2);
 	
 a1 = strfind(result,'A1');
 	
 a1 = cell2mat(a1);
 	
 [a1,~] = size(a1);
 	
 a2 = strfind(result,'A2');
 	
 a2 = cell2mat(a2);
 	
 [a2,~] = size(a2)
	%The table is then searched by status and assigned into variables. In order to count the number of statuses ‘size()’ has been used.

positive = (s+y1+a1+b1);
 	
 negative = (s+y1+y2+o+u+a1+a2+b1+b2);
	%The next lines of code contain the OAT formula and also provide the user with the choice of weighting upon the computation.

`OAT = 100*(positive/negative);`	
`criticalityweighting = menu('Asset Criticality Weighting:','1.0','1.23','1.46','1.7');`	Menus created to interact with the user.

`if criticalityweighting == 1`
`    criticalityweighting = 1;`
`elseif criticalityweighting == 2`
`    criticalityweighting = 1.23;`
`elseif criticalityweighting == 3`
`    criticalityweighting = 1.46;`
`else`
`    criticalityweighting = 1.7;`
`end`
`OATcriticality = 100*(positive/(negative*criticalityweighting));`
`valueweighting = menu('Asset Value Weighting:','1.0','1.23','1.46','1.7');`
`if valueweighting == 1`
`    valueweighting = 1;`
`elseif valueweighting == 2`
`    valueweighting = 1.23;`
`elseif valueweighting == 3`
`    valueweighting = 1.46;`
`else`
`    valueweighting = 1.7;`
`end`
`OATvalue = 100*(positive/(negative*valueweighting));`
`OATaverage = (OAT+OATcriticality+OATvalue)/3;`
	Separate variables are created so they can individually be inputted into a graphic visual.

OAT has now computed the algorithm, and the results now need to visualised by the user in a formalised way. To find the full length of the code, please see appendix 8.2. The internal decision tree structure for the above algorithm can be seen below and is governed by the following arrow convention.

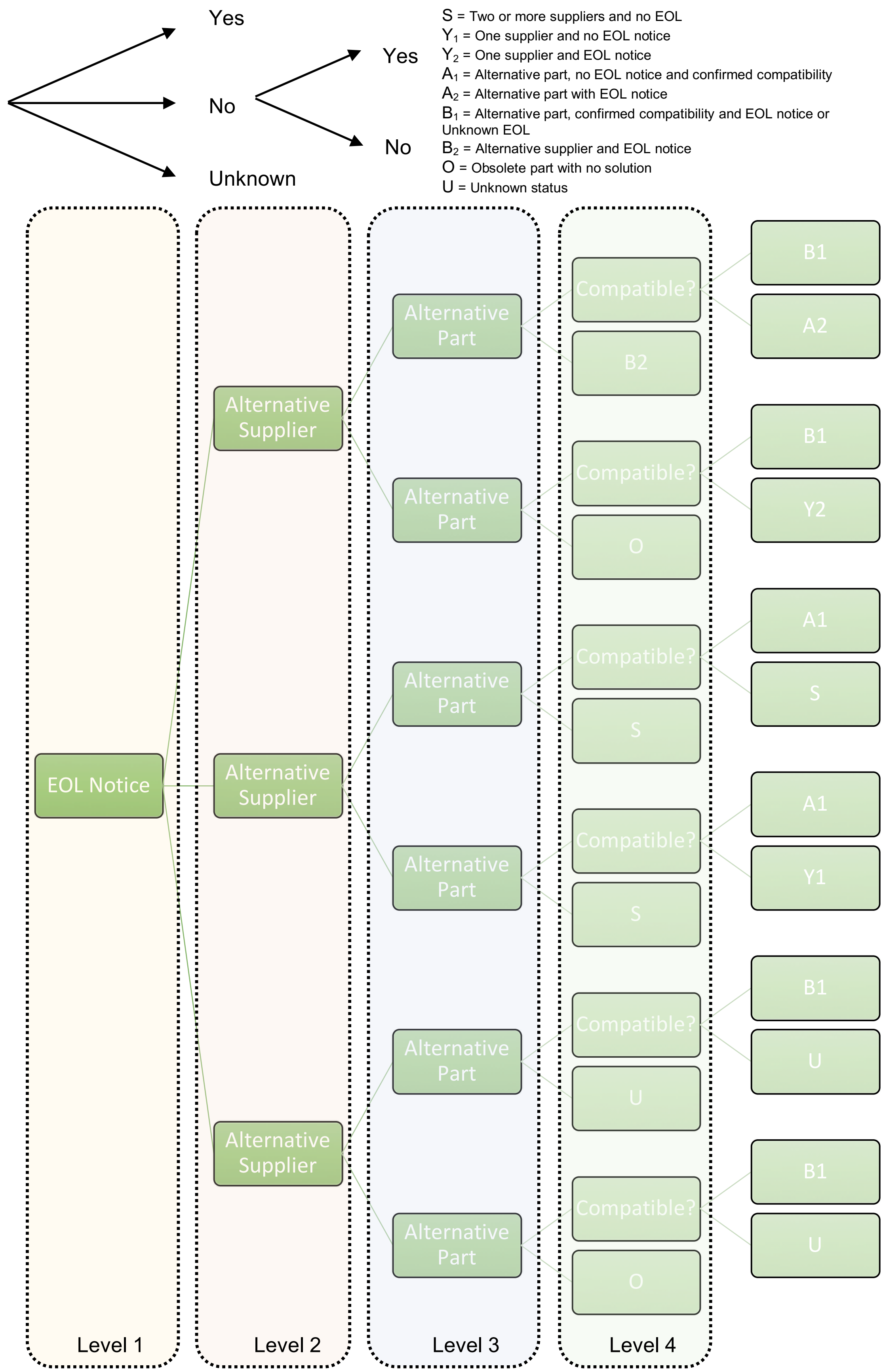


Figure 69 Obsolescence Assessment Tool Algorithm: Status Assignment Decision Tree, created by author

It is important to highlight any known limitations of the above algorithm and to remember this is only the second iteration of the development stage. The input sheet (see appendix 8.3) for OAT is populated by the commissioning contractor and then checked in-house. However, it is important to note the differing of drivers/incentives to get accurate data onto the sheet. Whilst the above checks help stock check some potential fallacies in the data, this type of methodology is dependent upon the competence of the data entry point of contact. This thesis intends to mitigate some of these risks by implementing a formal Risk Assessment, which can be found in section 3.4. Additionally, if any of the above five checks are falsified and presented to the user, no solutions are provided. OAT is an aid for decision-making; it will highlight where to draw your attention, but it will not generate an all-encompassing obsolescence management strategy. This could be viewed as a limitation if the intentions of this tool are misunderstood. Finally, OAT contains a simple algorithm that expects certain inputs and will generate a formalised output that is then usable. However, due to this simplicity the age-old adage of ‘put rubbish in, get rubbish out’ applies here.

The next section will cover the development of the Obsolescence Impact Tool (OIT) and how its design has come to be. This will also contain an element of MATLAB code and also the limitations of Fuzzy Inference Systems (FIS).

3.3.3.2 Obsolescence Impact Tool (OIT)

In order to quantify the ordinal risk posed by obsolescence, a new model was required to consider two challenges; (a) incorporating inputs of varying degrees of accuracy and ambiguity (b) robustly converting quantitative and qualitative inputs into a risk profile. The difficulty posed by both (a) and (b) is overcome via a Fuzzy Inference System (FIS) because an expert based system allows the designer to incorporate the knowledge held within employees. This trait allows for the quantification of a risk that currently has little related research to undertake this in an alternative manner. Additionally, Fuzzy Logic allows for the combination of several data types as they become Fuzzified via Membership Functions, which allows the author to build a pragmatic approximator to tackle a specific problem. In order to devise the key inputs to consider the risk posed by obsolescence, a Fuzzy Cognitive Map (FCM) was generated using the experience gathered via the on-site case-study. FCMs are an elementary way of scoping the boundaries of a model and its inputs, making it a useful step in this Research Design (Ross 2010). Figure 70 illustrates the key elements involved and how they linguistically affect one another:

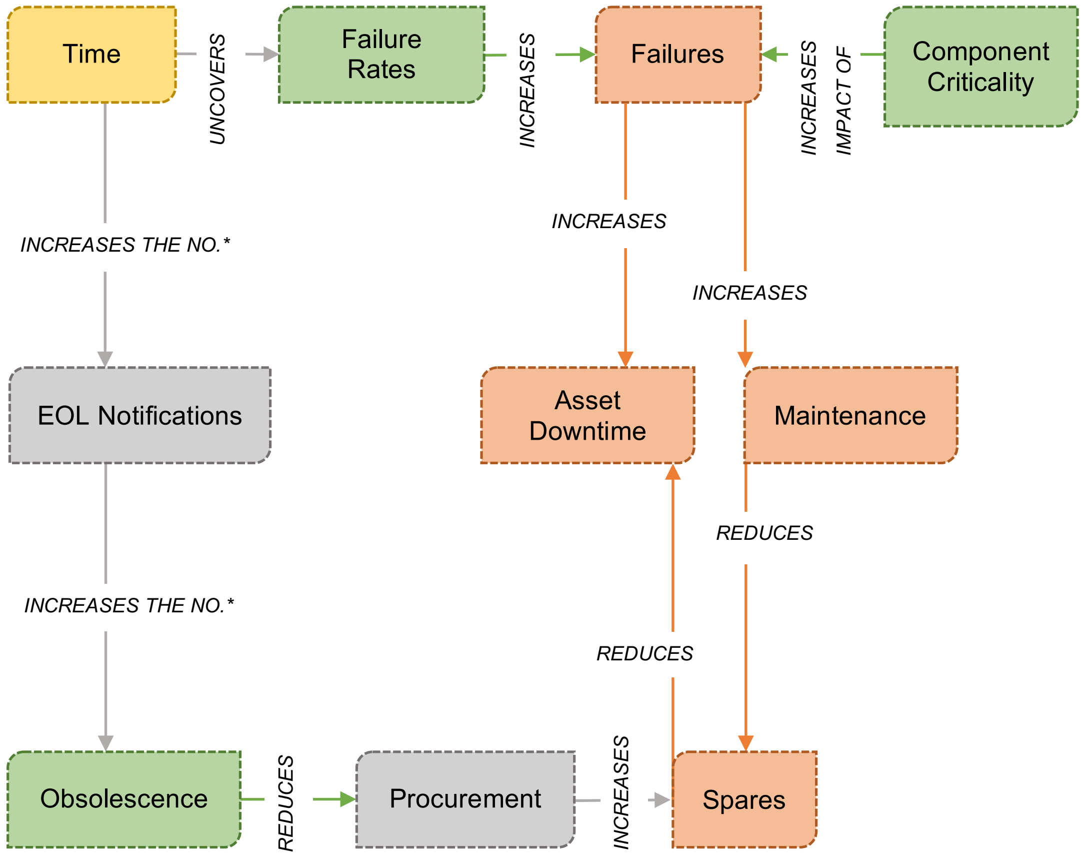


Figure 70 Fuzzy Cognitive Map of Obsolescence Management, created by author

It was identified that obsolescence manifests itself as a risk once it impacts maintenance and in turn asset downtime. This 'inner cycle' is highlighted in orange and covers the key operational obligations of an FM team. This inner cycle is effected by three 'influencers', highlighted in green, these were isolated as key terms to use for quantifying the impact of obsolescence risk. The two grey elements of the FCM were identified as areas outside of this scope but suitable for future research. EOL Notifications fall under obsolescence research from the perspective of an OEM as opposed to end-user, whilst the act of procurement would be associated with Strategic Asset Management or inventory management. These areas are appropriate to highlight here as important, but not to continue further into this specific research project.

Figure 71 is an illustration showing the main components highlighted by the FCM that now are used within the Obsolescence Impact Tool (OIT), and this section will now explicitly detail how each component came to be and the considerations made.

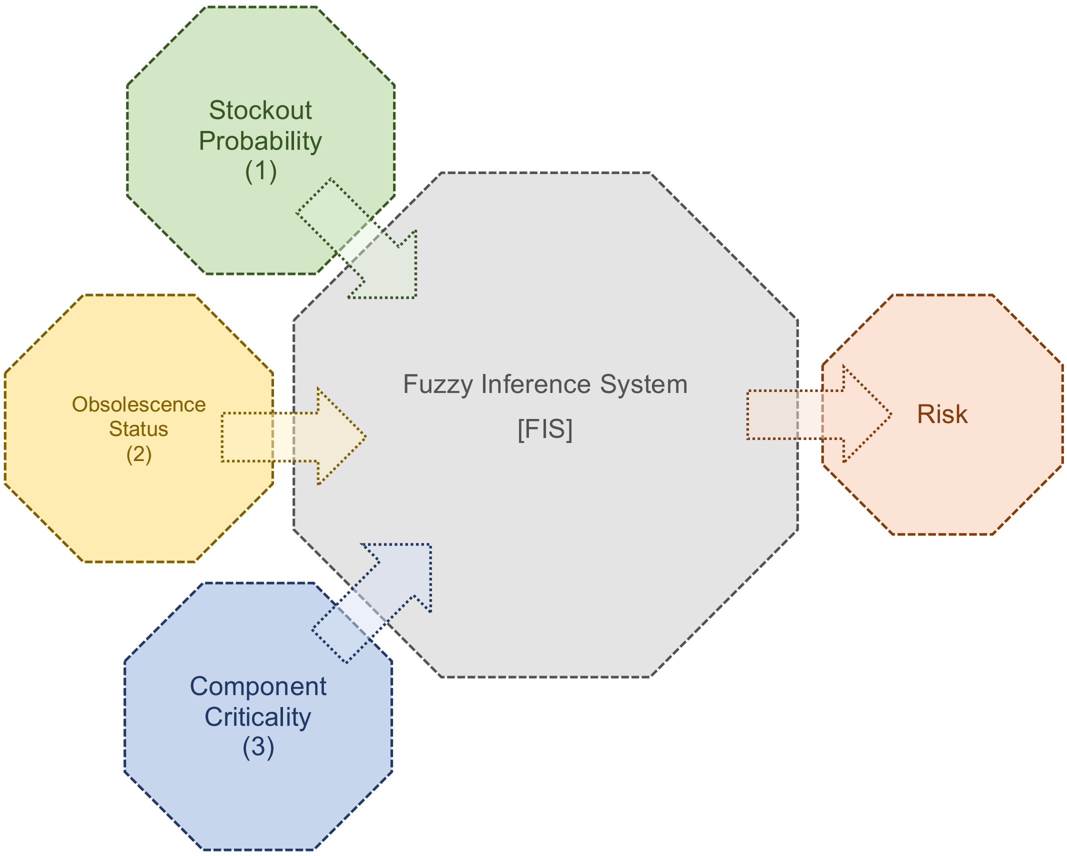


Figure 71 Obsolescence Impact Tool Model Structure, created by author

The three inputs for OIT were chosen following Mulholland's (2014) dissertation, which contained the development of OAT. OAT as a tool is designed to enhance an asset register, combining obsolescence relevant data attached to a simple algorithm highlighting components. What it categorically does not do is consider context or probability. It is universally accepted that a generic and basic framework for risk is:

Risk = Impact (or severity) x Probability

Within academic literature, there are a few throwaway comments such as - 'Relying on obsolete, unsupported equipment greatly increases the risk of system downtime' (Hoppin 2002). Behind such statements there are no formal or informal frameworks or models; currently these are mere observations. Using these observations and following the opinion of industry, there was a need for a model to begin bridging this research gap and incorporate risk. In order to enter the realm of risk, the model had to consider one's ability to support said system, as well as adopt a method for highlighting the most critical components.

MATLAB has been widely used in journals and articles regarding Fuzzy Logic, due to its 'Fuzzy Logic Tool Box' module (The MathWorks Inc. 2015). MATLAB has been used by Schouten et al. (2002), Wang and Elhag (2008), Ustundag et al. (2010) and Sivanandam et al. (2010) for Fuzzy Inference System development and testing. It has therefore been adopted as the chosen software to host OIT. Screenshots will be used within this chapter to illustrate profiles; however, full MATLAB code can be found in appendix 8.4.

In section 2.5, a Mamdani-styled Fuzzy Logic architecture was chosen for being more intuitive and better suited for linguistic inputs, and additionally the computational benefits of a Sugeno architecture would not be realised in a model of this size. Now that the architecture has been chosen, the inputs and their Membership profiles can be designed and justified.

The Stockout probability input (1) will range from 0 to 1 (shown on the x-axis). This range will statistically reflect the probability of the demand for the next time period (see section 2.3.1.1) to exceed the current stores kept on site, 0 being impossible and 1 being certain. This statistical definition is converted into five Fuzzy Sets to reflect their linguistic translation. The input value will be generated using stationary Poisson Distribution profiles for Stockout probability calculations of intermittent demand profiles. Following discussions with Dr. Whiter regarding membership profiles and consulting the works by Hayward and Davidson (2003), Bai and Wang (2006) and Ustundag et al. (2010), triangular profiles were selected. Triangular profiles are the most basic profile presented, however, when developing an expert model based on intellectual knowledge rather than data, there is no evidence to support a profile of a different type.

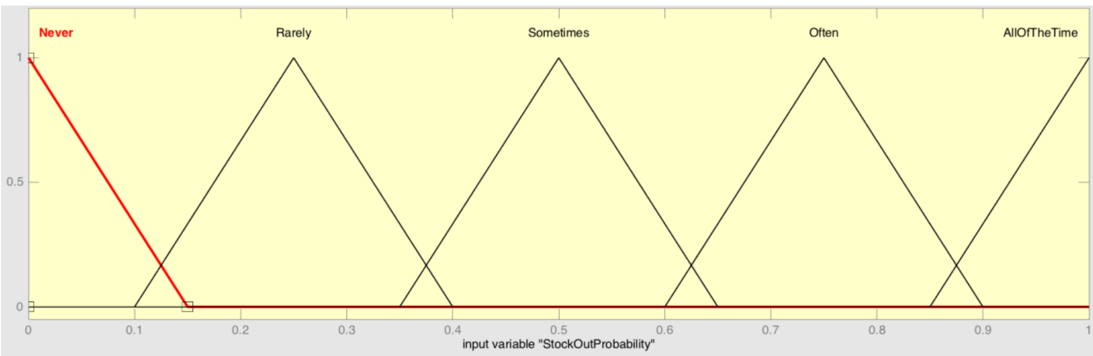


Figure 72 Screenshot of Membership Functions for Input (1), created by author

The Obsolescence Status input (2) will cover three pivotal 'statuses' a component can hold, which dictate one's ability to purchase parts both currently and in the future in order to support a system. The input will range from 0 to 1 (x-axis). The Fuzzification process is detailed in Table 15:

Table 15 Fuzzification Rules for Obsolescence Status Input (2) for OIT, created by author

Fuzzy Set	Fuzzification Process
No EOL	An arbitrary value for 'useful life' i.e. 5 years is to be used and then the ratio of current age against useful life, normalised to 0.5. The arbitrary value will be cited from either industry guidance or supported by the useful life analysis of SIEMENS BMS products. For example: Useful Life = 5 years Current Age = 3 (from commission) Input Value = 3/5 = 0.6, normalised = 0.3
EOL Released (but not exceeded)	If more than 1 year away = 0.3. Less than 1 year away from EOL exceedance, normalised to 0.2 and added to 0.3. For example: Time to EOL exceedance = 0.76 years EOL Age* = 1 – 0.76 = 0.24 years Input Value = 0.24/1 = 0.24, normalised = 0.048 (+0.3) = 0.348 *EOL Age is the time spent following an EOL notification.
EOL Exceeded	If less than a year has passed, then the time is normalised to 0.2 and added to 0.5. This accounts for any miscommunication regarding the EOL date and the assumed availability of parts around this point in time. Between 0.5 and 0.7 membership will be granted to both EOL Released and EOL Exceeded. For example: Time since EOL exceedance = 0.94 years Input Value = 0.94/1 = 0.94, normalised = 0.19 (+0.5) = 0.69 If more than a year has passed, then an arbitrary value is used for the period of time following an EOL that parts may be available i.e. 3 years. Then then above is repeated but normalised to 0.3 and added to 0.7. For example: Time since EOL exceedance = 3 years Input Value = 3/5 = 0.6, normalised = 0.18(+0.7) = 0.88

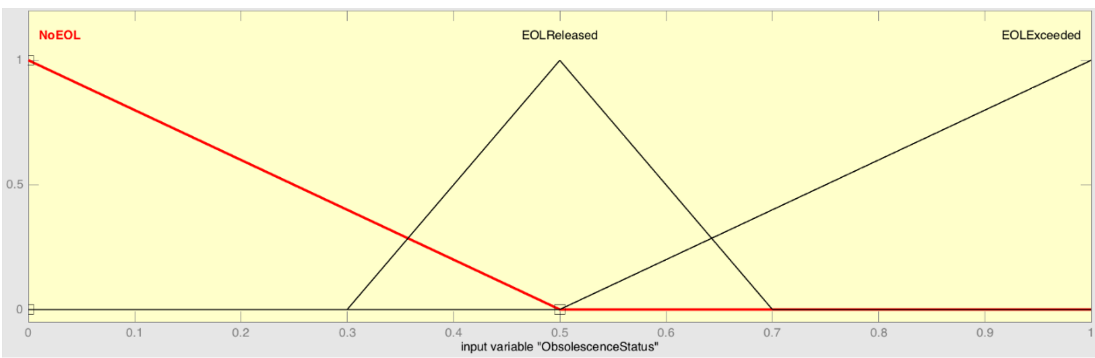


Figure 73 Screenshot of Membership Functions for Input (2), created by author

The above three sets of calculations are all undertaken using the Excel input data sheet so that each component will contain an individual input value that will then directly be used within the FIS.

The final input is the Component Criticality (3); the x-axis will be amended system by system to reflect the maximum Degree of Centrality. Please see section 2.3.1.2 for the input values of the two case-study asset systems. Note that the aforementioned importance measure calculations complete objective (3) under Aim (2) of this thesis. The range of criticality within a system can then be categorised into three Fuzzy Sets as part of the Fuzzification process to then be used within the IF-THEN Rules.

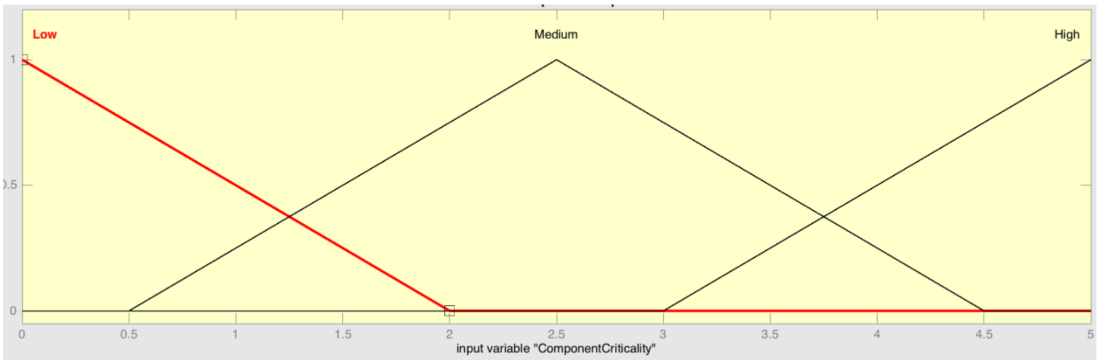


Figure 74 Screenshot of Membership Functions for Input (3), created by author

The internal IF-THEN Rules were generated using a Delphi Method to anonymously combine the thoughts of five individual experts from industry and combine them into an agreed logic. When looking to implement a Delphi method, as highlighted by Okoli & Pawlowski (2004) it is important to consider 'Bricolage'. Bricolage is a French term that means to 'use whatever resources one has to perform whatever task one faces'. The objective of the Delphi method is to obtain a reliable consensus from a group of experts, mitigating individual bias through the average of the group (Okoli & Pawlowski 2004; Pan et al. 1996). Whilst one is limited to the resources present within a case study, expert selection and the structuring of the Delphi process is key to adopting both 'Bricolage' whilst obtaining an appropriate group consensus.

It was the intention of the author to design a workshop panel that consisted of subjects from both academia and industry, with participants from contrasting contractual view-points. To avoid any conflict of interest during the Delphi method, all output from the panel was withheld and not regurgitated for feedback, a common feature of Delphi (Okoli & Pawlowski 2004; Pan et al. 1996). In addition, participants were to adopt a 'ranking-type' Delphi method approach, to subjectively rank scenarios by perceived risk (in this context) (Okoli &

Pawlowski 2004). Please see Skulmoski & Hartman (2007) for an extensive history of the Delphi method and its wide applications within research.

The five individuals, whilst remaining anonymous, held the following positions:

1. General Manager of Central Maintenance Contractor.
2. UCL Professor from the Bartlett.
3. PhD Graduate, now Innovation Manager of Central Maintenance Contractor.
4. Head of Asset Management in Sponsor Organisation.
5. Asset Management Project Manager in Sponsor Organisation.

The above panel was chosen due to their experience in the fields of Asset Management and Facilities Management, along with Management in general and the art of decision making. As a group, they are responsible for the maintenance and lifecycle support of a considerable large portfolio of assets as well as containing academic rigour. Please note the seniority of the figures that featured on the Delphi panel, which led to the possibility of only running a single round. This is a constraint, however both unavoidable due to business requirements and mitigated through the short range of options. Meaning, the range of potential options each subject could possibly have entered into the survey was narrow, mitigating the possibility of outliers in addition to the average of the group.

Please note that the above ordering of the panel is not reflected in the ordering of the 'users' in Figure 75. The above five were chosen to encourage diversity within the panel, and both academia and industry are represented with a range of experience. The analysis showed that although all five recorded similar answers, the extremities were balanced by the group. This can be viewed in Figure 75, which presents the spread of answers and the final IF-THEN Rules chosen. As expected, the risk profile increased in a step-like fashion. However, interestingly User 2 was risk sensitive in the earlier questions, but then levelled. Additionally, User 1 was risk sensitive at the other end of the spectrum. The final profile appears to have appropriately taken a middle ground, showing how this method balances some of the more extreme responses. The key to Figure 75 is shown in Table 16.

Table 16 Key to Figure 75

Fuzzy Set	NotI	Min	Low	Mod	Imp	VeryI
Fuzzy Set Identifier	1	2	3	4	5	6

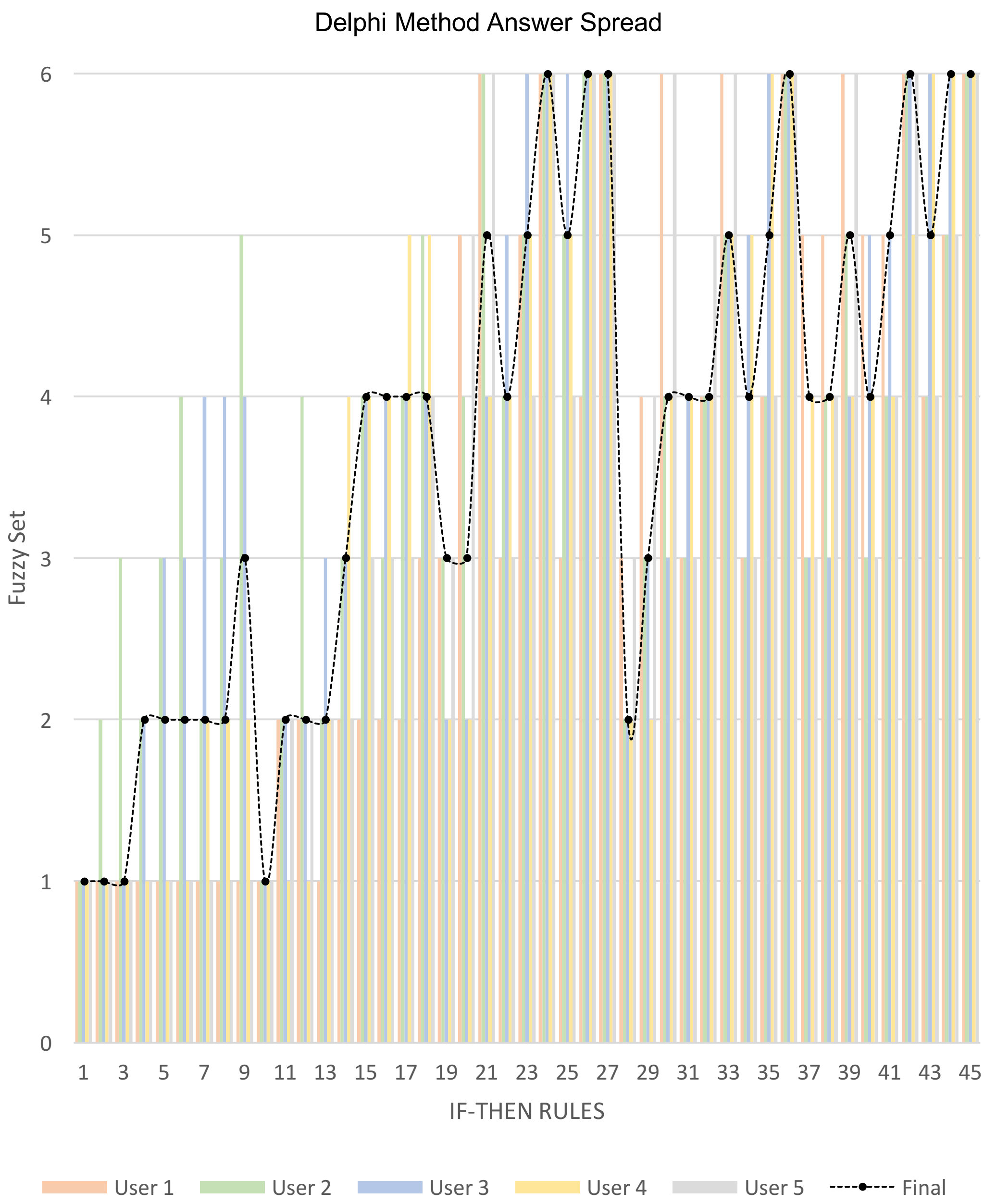


Figure 75 Delphi Method Results, created by author

The task at hand was to read all of the IF-THEN Rule combinations, shown in Table 17, and then use Figure 76 to assign a Fuzzy Set to each variation. There are 45 unique possible combinations of inputs, referring back to section 2.5, there are a set of checks to validate the integrity of the IF-THEN Logic. These checks were used to ensure that the FIS could interpret all possible input ranges and provide an output based upon the IF-THEN Rules.

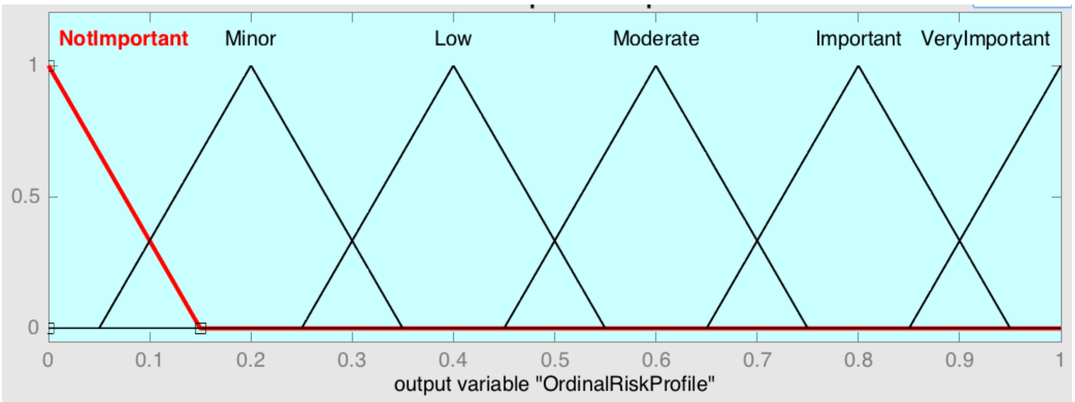


Figure 76 Screenshot of the Membership Functions for Output (1), created by author

Originally this exercise was undertaken with three Fuzzy Sets instead of six for Ordinal Risk Profile. The six Fuzzy Sets within the output variable were generated using a foundation of Bowles and Pelaez's (1995) work and the consultation of the panel. This was implemented following feedback from the panel that three did not have enough granularity.

Table 17 Look-up Table for Obsolescence Impact Tool, created by author

Serial	**IF** [Stockout Probability]	**AND** [Obsolescence Status]	**AND** [Component Criticality]	**THEN**
1	Never	NoEOL	Low	Not Important
2	Never	NoEOL	Medium	Not Important
3	Never	NoEOL	High	Not Important
4	Never	EOLReleased	Low	Minor
5	Never	EOLReleased	Medium	Minor
6	Never	EOLReleased	High	Minor
7	Never	EOLExceeded	Low	Minor
8	Never	EOLExceeded	Medium	Minor
9	Never	EOLExceeded	High	Low
10	Rarely	NoEOL	Low	Not Important
11	Rarely	NoEOL	Medium	Minor
12	Rarely	NoEOL	High	Minor
13	Rarely	EOLReleased	Low	Minor
14	Rarely	EOLReleased	Medium	Low
15	Rarely	EOLReleased	High	Moderate
16	Rarely	EOLExceeded	Low	Moderate
17	Rarely	EOLExceeded	Medium	Moderate
18	Rarely	EOLExceeded	High	Moderate
19	AllOfTheTime	NoEOL	Low	Low
20	AllOfTheTime	NoEOL	Medium	Low
21	AllOfTheTime	NoEOL	High	Important
22	AllOfTheTime	EOLReleased	Low	Moderate

23	AllOfTheTime	EOLReleased	Medium	Important
24	AllOfTheTime	EOLReleased	High	Very Important
25	AllOfTheTime	EOLExceeded	Low	Important
26	AllOfTheTime	EOLExceeded	Medium	Very Important
27	AllOfTheTime	EOLExceeded	High	Very Important
28	Sometimes	NoEOL	Low	Minor
29	Sometimes	NoEOL	Medium	Low
30	Sometimes	NoEOL	High	Moderate
31	Sometimes	EOLReleased	Low	Moderate
32	Sometimes	EOLReleased	Medium	Moderate
33	Sometimes	EOLReleased	High	Important
34	Sometimes	EOLExceeded	Low	Moderate
35	Sometimes	EOLExceeded	Medium	Important
36	Sometimes	EOLExceeded	High	Very Important
37	Often	NoEOL	Low	Moderate
38	Often	NoEOL	Medium	Moderate
39	Often	NoEOL	High	Important
40	Often	EOLReleased	Low	Moderate
41	Often	EOLReleased	Medium	Important
42	Often	EOLReleased	High	Very Important
43	Often	EOLExceeded	Low	Important
44	Often	EOLExceeded	Medium	Very Important
45	Often	EOLExceeded	High	Very Important

The result of creating the intelligence of the FIS, is called the 'surface' illustration, this visualisation is the combination of the Membership Functions and IF-THEN Rules. However, the 3D surface is limited to showing just two of the three inputs in one graphic; the surface therefore actually consists of Figure 77, Figure 78 and Figure 79. Note that the changing of colour is a reflection of the y-axis, Ordinal Risk Profile.

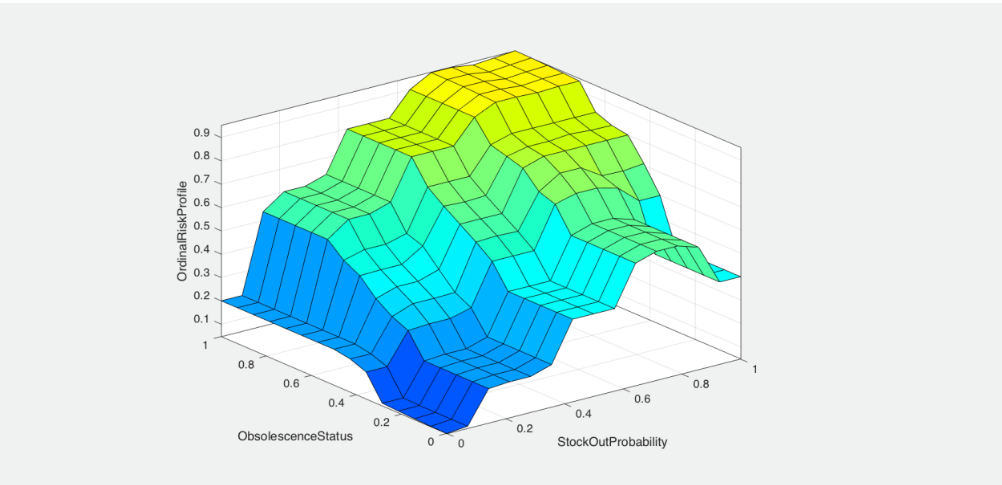


Figure 77 Input (1) and Input (2) Surface Map of IF-THEN Rules, created by author

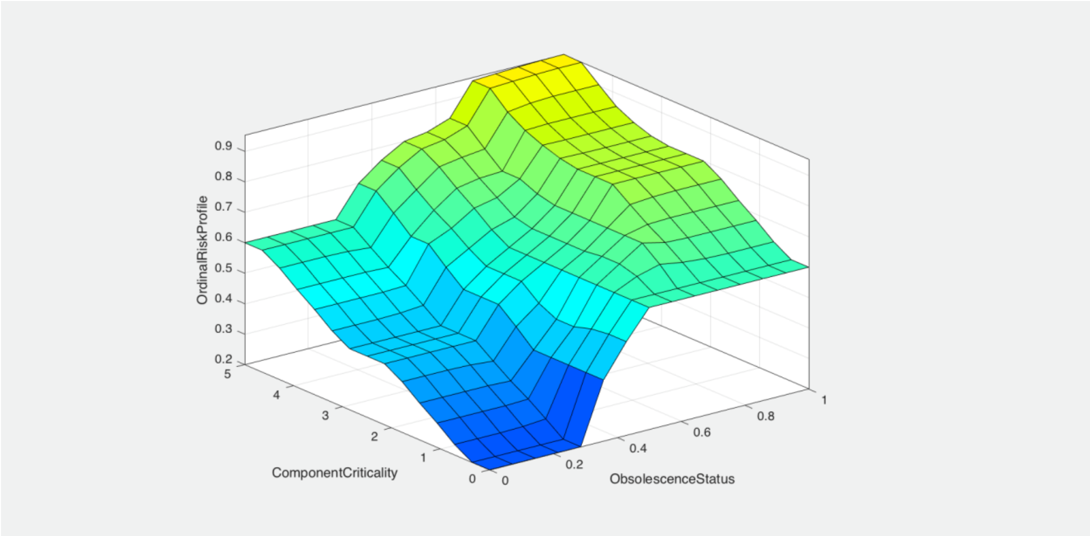


Figure 78 Input (2) and Input (3) Surface Map of IF-THEN Rules, created by author

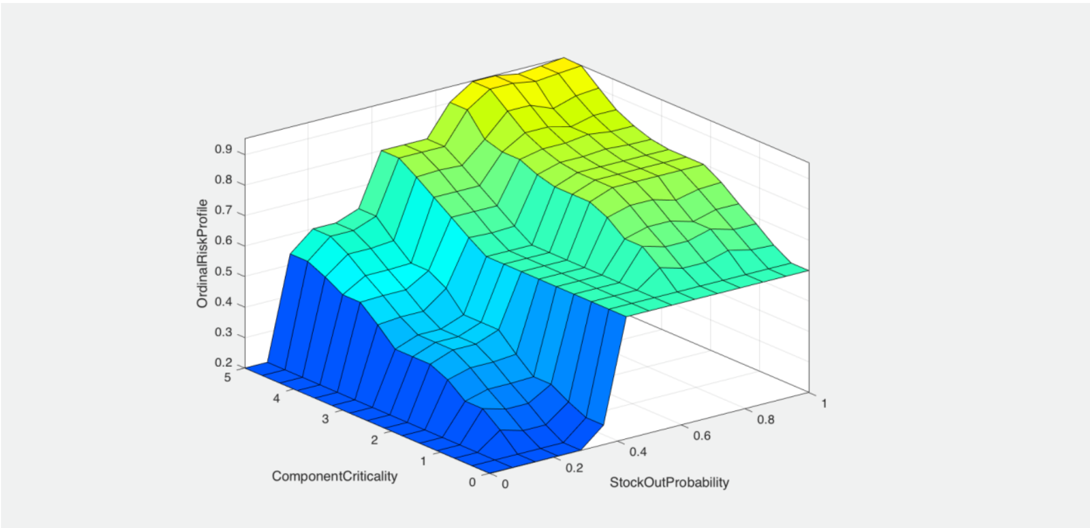


Figure 79 Input (1) and Input (3) Surface Map of IF-THEN Rules, created by author

The above three figures show the complex relationships between the input variables, governed by the IF-THEN Rules. This illustrates the use of Fuzzy Logic over human intuition, which, as already stated is insufficient with modelling non-linear or complex relationships. The output of OIT will have both a linguistic variable due to the output Fuzzy Sets (i.e. 'Very Important') and also a crisp numerical value between 0 and 1. Figure 77, Figure 78 and Figure 79 can be compared to Markowski and Mannan's (2008) work on a Fuzzy Risk Matrix, who used just two inputs (frequency and severity of impact). Markowski and Mannan (2008) produced Figure 80, as well as two other variations where they amended the FIS to produce a more and less sensitive model. Generally, the profiles are similar to that used above.

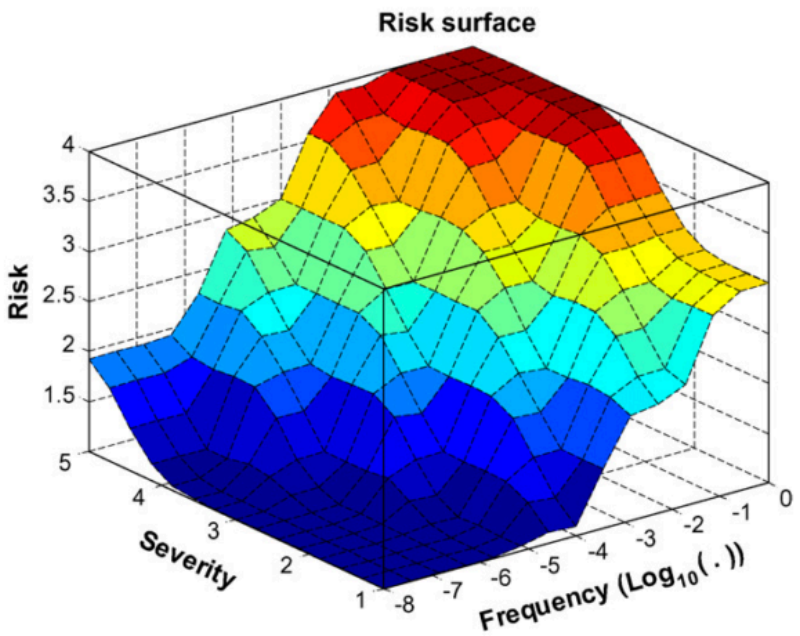


Figure 80 Risk Assessment Surface Map, from Markowski & Mannan (2008)

A model of this type has not been previously attempted, however, Wang and Elhag (2008) used an FIS for a Risk Assessment of a Bridge Maintenance Project and illustrated the results in a single graphic, shown in Figure 81. This provides an insight into which components of the system require the most attention at any given point in time.

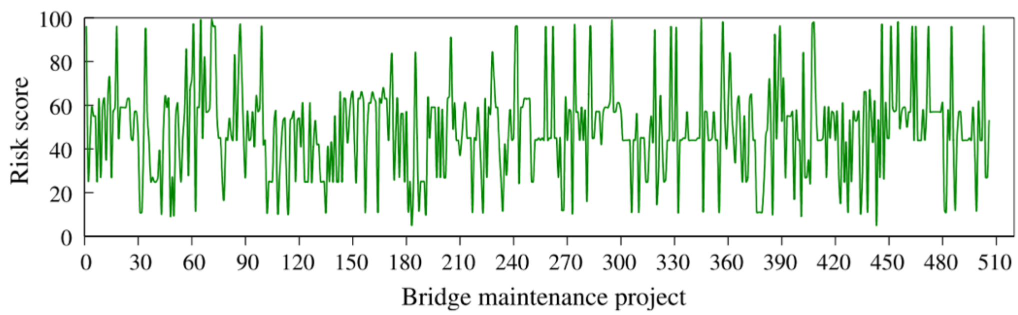


Figure 81 Output Risk Score Example, from Wang & Elhag (2008)

This thesis received data throughout the case-study period, on a quarterly basis. Therefore, such a plot as Figure 81 could be shown across a time x-axis. This adds an extra element of detail to the plot and also the potential to observe how obsolescence within a given system behaved over time. Table 18 contains the FIS MATLAB code. The table contains a written narrative along with the code to illustrate how MATLAB interprets the above-discussed features of the FIS.

Table 18 Obsolescence Impact Tool: Fuzzy Inference System MATLAB Script, created by author

MATLAB Code	*Explanation*
[System] Name='OIT' Type='mamdani' Version=2.0 NumInputs=3 NumOutputs=1 NumRules=45 AndMethod='min' OrMethod='max' ImpMethod='min' AggMethod='max' DefuzzMethod='centroid' [Input1] Name='StockOutProbability' Range=[0 1] NumMFs=5	%The FIS system is called OIT of Mamdani type, with three inputs and one output. There are 45 internal IF-THEN Rules. Default MIN MAX method has been used for Fuzzification method and the centroid method for Defuzzification. %Input 1 or StockOutProbability has a range of 0 to 1. It contains five membership functions, all of the triangular type.
MF1='Never':'trimf',[0 0 0.15] MF2='Rarely':'trimf',[0.1 0.25 0.4] MF3='AllOfTheTime':'trimf',[0.85 1 1] MF4='Sometimes':'trimf',[0.35 0.5 0.65] MF5='Often':'trimf',[0.6 0.75 0.9]	%The coordinates of each of the corners are then defined. The Linguistic labelling of each function is also detailed here i.e. 'Often'.
[Input2] Name='ObsolescenceStatus' Range=[0 1] NumMFs=3 MF1='NoEOL':'trapmf',[0 0 0 0.5] MF2='EOLReleased':'trimf',[0.3 0.5 0.7] MF3='EOLExceeded':'trapmf',[0.5 1 1 1]	%Input 2 or ObsolescenceStatus has a range of 0 to 1. It contains three membership functions, all of the triangular type.
[Input3] Name='ComponentCriticality' Range=[0 5] NumMFs=3 MF1='Low':'trimf',[-2 0 2] MF2='Medium':'trimf',[0.5 2.5 4.5] MF3='High':'trimf',[3 5 7]	%Input 3 or ComponentCriticality has a range of 0 to 5. It contains three membership functions, all of the triangular type 'trimf'.
[Output1] Name='OrdinalRiskProfile' Range=[0 1] NumMFs=6 MF1='NotImportant':'trimf',[0 0 0.15] MF2='Low':'trimf',[0.25 0.4 0.55] MF3='VeryImportant':'trimf',[0.85 1 1]	%The single output is the Ordinal Risk Profile, with a range of 0 to 1. It contains six membership functions of the triangular type.

MF4='Minor':'trimf',[0.05 0.2 0.35] MF5='Moderate':'trimf',[0.45 0.6 0.75] MF6='Important':'trimf',[0.65 0.8 0.95]	
[Rules] 1 1 1, 1 (1) : 1 1 1 2, 1 (1) : 1 1 1 3, 1 (1) : 1 1 2 1, 4 (1) : 1 1 2 2, 4 (1) : 1 1 2 3, 4 (1) : 1 1 3 1, 4 (1) : 1 1 3 2, 4 (1) : 1 1 3 3, 2 (1) : 1 2 1 1, 1 (1) : 1 2 1 2, 4 (1) : 1 2 1 3, 4 (1) : 1 2 2 1, 4 (1) : 1 2 2 2, 2 (1) : 1 2 2 3, 5 (1) : 1 2 3 1, 5 (1) : 1 2 3 2, 5 (1) : 1 2 3 3, 5 (1) : 1 3 1 1, 2 (1) : 1 3 1 2, 2 (1) : 1 3 1 3, 6 (1) : 1 3 2 1, 5 (1) : 1 3 2 2, 6 (1) : 1 3 2 3, 3 (1) : 1 3 3 1, 6 (1) : 1 3 3 2, 3 (1) : 1 3 3 3, 3 (1) : 1 4 1 1, 4 (1) : 1 4 1 2, 2 (1) : 1 4 1 3, 5 (1) : 1 4 2 1, 5 (1) : 1 4 2 2, 5 (1) : 1 4 2 3, 6 (1) : 1 4 3 1, 5 (1) : 1 4 3 2, 6 (1) : 1 4 3 3, 3 (1) : 1 5 1 1, 5 (1) : 1 5 1 2, 5 (1) : 1 5 1 3, 6 (1) : 1 5 2 1, 5 (1) : 1 5 2 2, 6 (1) : 1 5 2 3, 3 (1) : 1 5 3 1, 6 (1) : 1 5 3 2, 3 (1) : 1 5 3 3, 3 (1) : 1	%The internal IF-THEN Rules are detailed here in matrix form. The first the numbers indicate the three inputs and which Fuzzy Set they activate. The fourth number represents the activated output Fuzzy Set. The final numbers represent any internal weighting applied to the rules, which has not been applied in this FIS model.

Every model has limitations, assumptions, and considerations that may not be clear to the reader, and it is therefore important to highlight these before moving onto analysis to promote transparency. Ross (2010) labelled Fuzzy Systems as good algebraic approximators. This type of compliment is based upon the FIS's ability to deal with data that falls ambiguously in-between crisp sets. Fuzzification and Defuzzification as two processes compute data points that fall into these 'grey' areas, approximating the wider meaning or bigger picture found within the data. In other words, Fuzzy Logic has strengths that no other methodology can match, however, in this particular case the fact it is an approximator is one of those. An approximator should be treated as such; as a decision-aiding tool under uncertainty but not as fact. Combined with this, obsolescence mitigation is not a single pathed skill. There are many methods that are applicable in certain scenarios, all of which could not be accounted for within a single model. The terms algorithm and forecasting are commonly misunderstood and assumed to be far more than what statistically they are. Please see section 2.2.2.2 for the author's stance of forecasting. OIT does not forecast obsolescence, but rather forecasts the risk it may pose to your supportability of an asset system. This may not clearly be defined as a limitation of the model, but it is a common misunderstanding that should not be taken into the analysis chapters.

Finally, OIT is a basic FIS model in terms of its membership profiles and IF-THEN Rule development. It is a standard expert model, however, the forefront of modelling, 'machine learning' and 'artificial intelligence' revolve around adaptive learning techniques. See Wang et al. (2006) for work on a 'multi-criteria decision-making tool' (MCDM) using adapting FIS techniques. This means that, whilst an expert system is appropriate for this application, the complexity of the model and its potential insights are limited. In order to advance the model, adaptive neuro-fuzzy system techniques would need to be adopted using more detailed and larger datasets.

The models developed within this thesis have now been detailed, and the required datasets and analysis is to follow. Please see the next chapter for the explicit calculations and sanitisation that occurred within this methodology.

3.3.4 Data Collection

3.3.4.1 Obsolescence Datasheet

January 2015 marked the start of the case-study data collection, which involved the updating of an 'obsolescence datasheet' every quarter of the year. The updating of the sheet was undertaken by an SSE Plc technical engineer. SSE is a British energy company that provide the on-site maintenance and commissioning work for the Building Management System (BMS). Each update would be vetted by the contract manager and then by the author of this thesis and on-site Asset Management team to validate the contents. In contrast, Quadrant Security Group Ltd would fill out the same sheet for the on-site Security System, which they maintain and commission. The same checks and validations are also applied.

Table 19 Case-study Timeline, created by author

2015				2016			
Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
January to March	April to June	July to September	October to December	January to March	April to June	July to September	October to December

The case-study would therefore contain eight data collection points, with the aim of capturing the amendments to the asset system through this two-year period. The datasheets would capture the physical on-site changes i.e. lifecycle replacements or upgrades, and the market changes in the form of obsolescence. The datasheet templates were a development from those used within Mulholland's (2014) initial work; the column headings are:

Table 20 Obsolescence Dataset Column Headings, created by author

Part Name	Part Function	Part REF#	Part Description	No. Parts	Introduction Date	EOL Released?	Date of Release	EOL Date (Real or Estimated)	Current Supplier	Alternative Supplier (Y/N)	Alternative Parts (Y/N)	Confirmed Compatibility (Y/N)

The premise of the datasheet is to capture when the obsolescence phase of the life cycle is initiated and when it will end. This is supported by the alternative supplier, components, and confirmation of compatibility to aid decision-makers. The primary action applied to this dataset is the validation of data entry and also the validation of data types within each field, ensuring that the data is stored in the correct format. This is important for the MATLAB code to execute either the OAT or OIT models and reduce the occurrence of bugs. Please see appendix 8.6 for a datasheet template.

3.3.4.2 Component Demand Data

In this case-study the maintenance (both planned and unplanned) was outsourced via a single Facilities Management organisation, who held the majority of their historical records in paper form. Figure 82 illustrates the contractual relationship between the aforementioned parties. Whilst the Research Sponsor did not undertake or manage the contractor's (SSE and Quadrant Security Group), they pay both for this service and also the Lifecycle requirements. The Research Sponsor also holds the performance penalty risk that is held within the PFI contract, therefore, both a financial and operational interest into how the BMS and SS are being managed.

Figure 82 Case-study Structure of Organisations, created by author

The task of extracting component demand data consisted of the following steps before analysis could be undertaken:

1. Paper copy request.
2. Template creation.
3. Data entry.
4. Data validation.
5. Data categorisation.
6. Croston's Method.
7. Stockout Probability.
8. Transpose data onto obsolescence datasheet.

First, a paper copy of the planned or unplanned maintenance records will be requested for the two contractors within the case-study. Naturally, records do get lost and not all of the records requested will be made available, which is inherent in research within the field. Paper copies are to be converted into electronic forms and stored within a new template, the column headings used were:

Table 21 Unplanned and Planned Preventative Maintenance Extract Template, created by author

Concept Reference	PFIC VO Ref	Contractor	Part Number	Quantity	Part Description	Location	Unit Price	Work Type	Date of Invoice

Note that PFIC VO is an internal acronym used, essentially it is a unique identifier allocated to each job. The newly created extract database now needs to be populated with all records dating back to 2010. Records further back were not viable due to their storage condition. In order to undertake a data validation check, a random selection of entries was located and checked against the hard copies as well as the Asset Management team. The part description column is required to categorise the data into component types i.e. actuators. As mentioned previously both the non-stationary Poisson method and Croston's method are to be utilised. The stationary Poisson method will be used to calculate Stockout probabilities for each component. The use of stationary Poisson distributions has received wide support by White (1993), van Jaarsveld and Dekker (2010) and Pourakbar et al. (2012), who also recognised the potential of non-stationary methods. To calculate Stockout probabilities, on-site stock levels are required, which is an additional step. This sets the reorder point that in turn affects the output probabilities. It is these probabilities that will formulate the input (1) to OIT. Simultaneously, Croston's method is a useful tool for single forecasts that has shown robustness. Categories of components will be grouped and used to ascertain a forecast using Croston's method (please see section 2.3.1.1). The same categorisation method is also required within the obsolescence datasheets, once this is complete, the above database can be transposed across. This entire process of converting historical records into a form that can be used by the models featured within this thesis complete objective (4) under Aim (2) of this thesis.

3.3.4.3 IF-THEN Rules

In order to develop the internal IF-THEN Rules for the FIS, the Delphi method was adopted. Firstly, a panel needed to be formed (please see 3.3.3) and then the range of rules was presented (please see 4.3). All five participants undertook the exercise in isolation with the same information, the results were anonymously gathered and then compiled to create a single set of IF-THEN Rules. There was a range of 45 independent IF-THEN Rules and six Fuzzy Sets to choose from (see Table 17). In order to undertake this exercise, all participants were introduced to Fuzzy Logic and given a brief background to the model. This task is a rather logical one and relies upon their individual opinion as to what constitutes a risk. This exercise explicitly affects the sensitivity of the model to evaluating a risk. This exercise in practice would be an iterative one, using the results of such a case-study as this to influence future changes to the IF-THEN Rules. Completion of the Delphi method exercise and the resultant Table 17 of IF-THEN Rules completes objective (6) of Aim (2) of this thesis.

3.3.4.4 Sales Data

As previously mentioned, this thesis is not privy to sales data commonly used within research to forecast when the obsolescence phase may be initiated. However, the author was able to collate eight years' worth of sales catalogues from an OEM for a BMS to illustrate just how sales and component costs change in association with obsolescence (see section 4.4).

Simultaneous Excel tabs were used to monitor the changes in prices and also when both a new component was added to the catalogue and when a component was removed and no longer procurable. It was then assumed obsolete. The components contain official categories, provided by the OEM, and these were used to investigate whether certain categories held contrasting patterns to others. The entire dataset holds 21,061 no. data points and allowed the author to investigate whether there was a deliberate sales strategy, how obsolescence affected pricing, and also some 'useful life' distribution profiles. All of this information would be beneficial for the obsolescence mitigation strategy for this particular system. The generic 'useful life' profiles could also be transferred across to contrasting sites that use the same system. The full analysis can be found in section 4.4. This analysis completes objectives (7) of Aim (3), therefore fulfilling that aim of this thesis.

3.3.4.5 Resilience Trade-off Data

Mulholland (2014) identified that within the context of a Private Finance Initiative (PFI), it may be possible to visualise the resilience trade-off made by Facility Managers/Asset Managers when managing obsolescence. PFI contracts contain performance deductions and penalties associated with service delivery. Service delivery is affected by un-operational assets. Assets become un-operational when they no longer can be maintained, especially in an unplanned scenario. This problem is extended when required components are also obsolete or long lead items. In summary, there are two significant costs at play when viewing this scenario simplistically.

1. Penalty deductions within a PFI contract.
2. The cost of mitigating obsolescence or long lead items (via spares procurement).

The above decision is normally undertaken via informal and often mental models held within the Facilities Management/Asset Management, not via any explicit trade-off or business case. An example of the above narrative or resultant graphic was not found within any reviewed literature. As an additional aim of this thesis, it was identified as an exercise that could be achieved with the datasets available within the case-study. The data required is based upon the results of OIT; the results will identify high-risk components, which in turn will be quoted for by the primary contractor. These costs, along with an arbitrary value for holding stock will be used to simplistically evaluate the cost of proactively procuring spare parts. This line on a graph will be plotted against the cost of the said system becoming un-operational within this particular case-study. Typically, this cost contains a ratchet mechanism that increases the cost exponentially over time. In summary, there may be a point in time where it is financially beneficial to not invest and improve the resilience of a system, but rather allow components to both become obsolete and/or fail. In contrast, the result may illustrate that in fact the risk can be reduced and it financially makes sense when you evaluate the financial risk at large. This data collection is simple, but cannot be undertaken until OIT has been completely evaluated. Figure 83 has been retrospectively copied from section 4.5 to illustrate this trade-off. The above will complete objective (8) under Aim (4).

Figure 83 Resilience Trade-Off Graphic from OEM Analysis, created by author

3.3.5 *Analysis*

The following section will demonstrate the analysis intended upon the datasets collected from the case-study. By detailing examples of the analysis, the reader will be more informed to critique this methodology and appreciate the limitations stated within section 3.4.

As stated, every quarter an obsolescence datasheet (see appendix 8.6) is submitted for each of the systems, below is a step by step example of the intended analysis and outputs of this particular dataset. When you execute OAT, and submit an input Excel file, you firstly indicate which type of system you are analysing before the internal five validity checks are processed. Below is an example of the final dialogue screen with the user, as you can see the system consists of 191 components, three of which fail the first test.

- Obsolescence Assessment Tool [OAT]
- Please locate the Excel data file.
- Warning: Variable names were modified to make them valid MATLAB identifiers.
- 191 individual components within the Building Management System were found.
- Logic Test 1:
- The below components have a recorded EOL notification against them, but no recorded date.

Part_Name	Part_Ref	No_Parts	EOL_Released	EOL_Date
'Valve Body 3 Port 80mm Flanged'	'VXF41.80'	9	1	NaN
'700VA UPS'	'SU700I'	9	1	NaN
'LD -64'	'LD-64'	10	1	NaN

- Logic Test 2:
- The below components should be checked for errors.
- They are reporting no EOL but state a date.
- empty 0-by-5 table

- The below component quantities should be checked.
- empty 0-by-5 table

- The below components should be checked for their EOL release dates.
- empty 0-by-5 table

- The below components have 6 or more missing data points. Continue?
- empty 0-by-13 table

The user is next prompted to enter the criticality and value weightings into OAT; these influence the output graphs and allow the user to consider the more important systems. OAT then assigns every component with a status for the algorithm, which is returned in a table format. In consideration of page space, this table has been summarised into a pie chart (see Figure 84) with Figure 85 being the formal output of OAT.

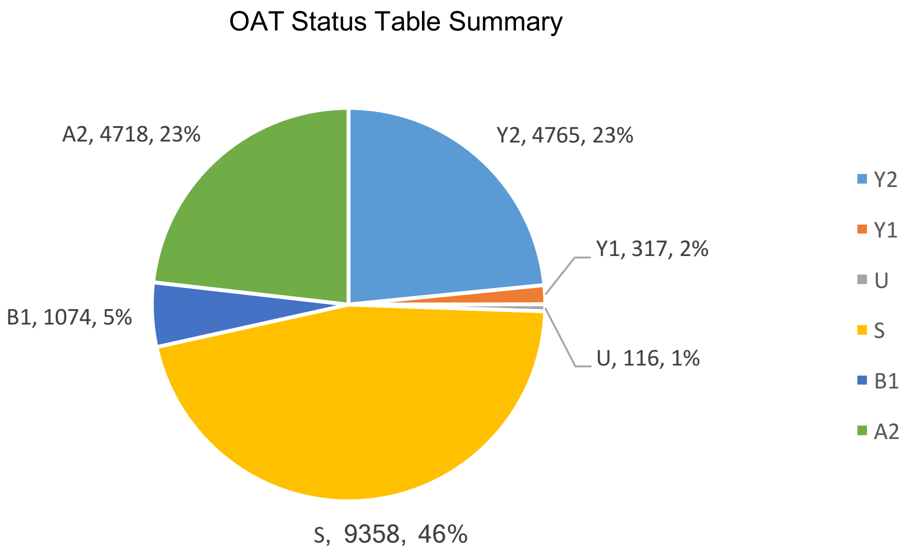


Figure 84 Pie Chart Example of Obsolescence Assessment Tool Output, created by author

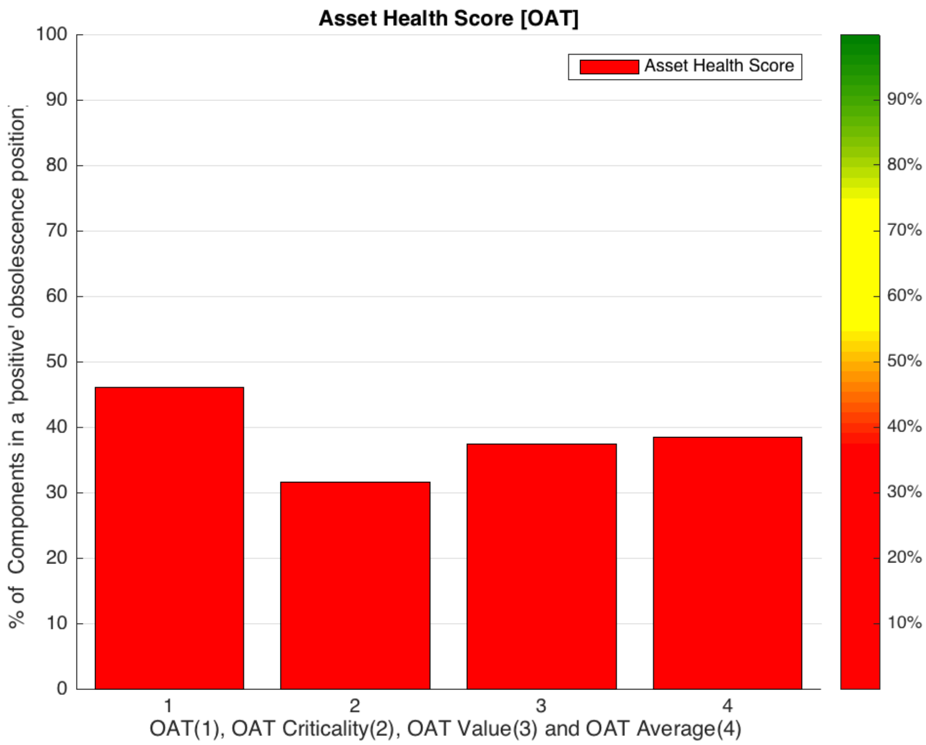


Figure 85 Asset Health Example of Obsolescence Assessment Tool Output, created by author

There are four bar charts; OAT in isolation, then two with independent weighting and a final bar to represent the average. These are measured against a benchmark range, which colour coordinates the graphic for the user. These have not been changed following Mulholland's (2014) dissertation feedback.

The unplanned and planned maintenance records will undergo two different types of analysis; one will produce a probability distribution, the other a crisp forecast. Firstly, each category of the component will need to be sorted by date to then calculate an average demand across the entire length of the dataset. Microsoft Excel contains a POISSON.DIST() function, which is to be used to calculate probability distributions. Figure 86 is an example of the generated profiles when the average demand is below 1, i.e. not every time period contains demand.

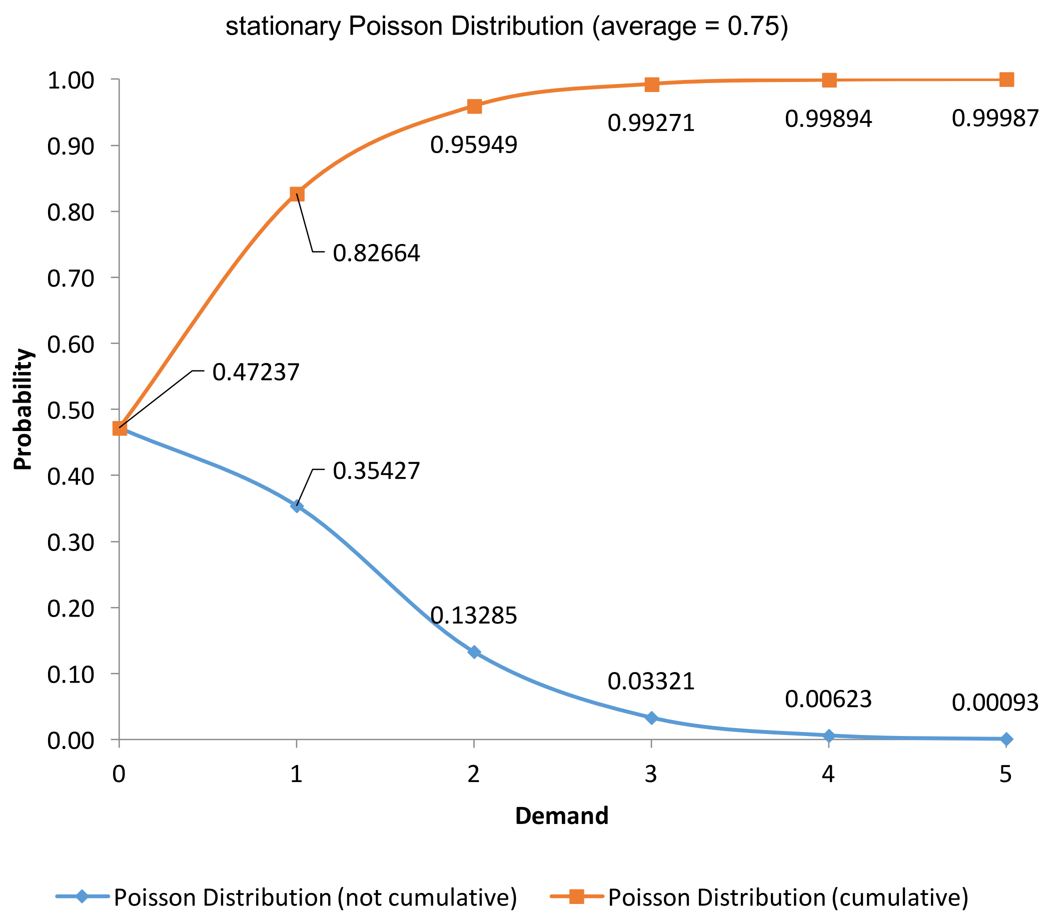


Figure 86 Stationary Poisson Distribution Example, created by author

Using the above profile and an on-site stock level of 1 in this example, a probability distribution for a Stockout can be generated (see Figure 87). The sum of the distribution equals the total Stockout probability, 0.222366553 and therefore would activate the Fuzzy Set 'Rarely'.

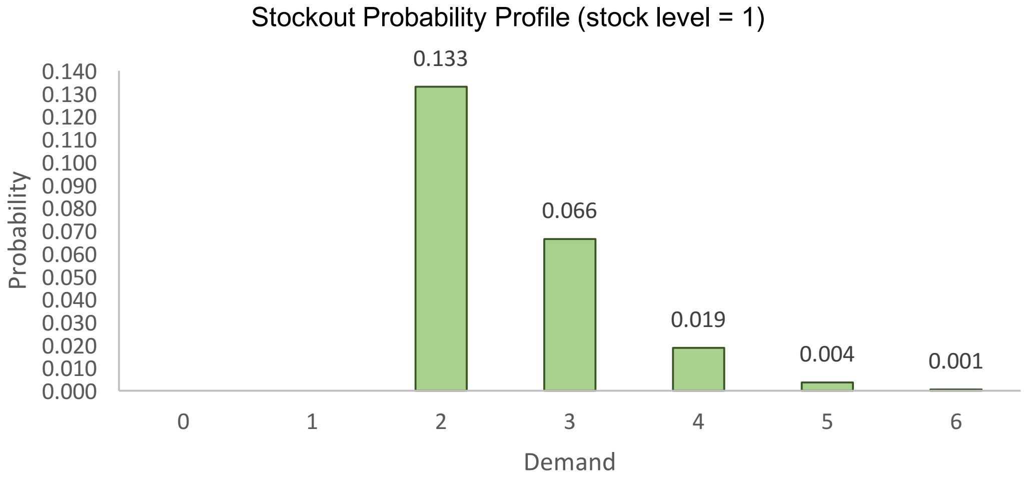


Figure 87 Stockout Probability Example, created by author

The Stockout probability is then to be used as input (1) for OIT. To support the probability distributions, Croston's method will be used to produce a set of forecasts of the future demand for comparison. Microsoft Excel again will be utilised to generate the forecast ($x^{(t, t+1)}$) using the below set of functions, to produce Table 22 and finally Figure 88.

- Alpha (α)= 0.3;
- Beta (β) = 0.3;
- C2 = E2/F2;
- D3 =IF(B2>0,1, D2+1);
- E3 =IF(B3>0, α*B3+(1-α)*E2, E2);
- F3 =IF(B3>0, β*D3+(1-β)*F2, F2);

Table 22 Croston's Method Example Dataset, created by author

	A	B	C	D	E	F
1	t	Actual Demand	$x^{(t, t+1)}$	n(t)	$z^{(t)}$	$n^{(t)}$
2	1	3	1	1	2	2
3	2	0	1	1	2	2
4	3	5	1.45	2	2.9	2
5	4	10	2.958823529	1	5.03	1.7
6	5	1	2.56442953	1	3.821	1.49
7	6	0	2.56442953	1	3.821	1.49

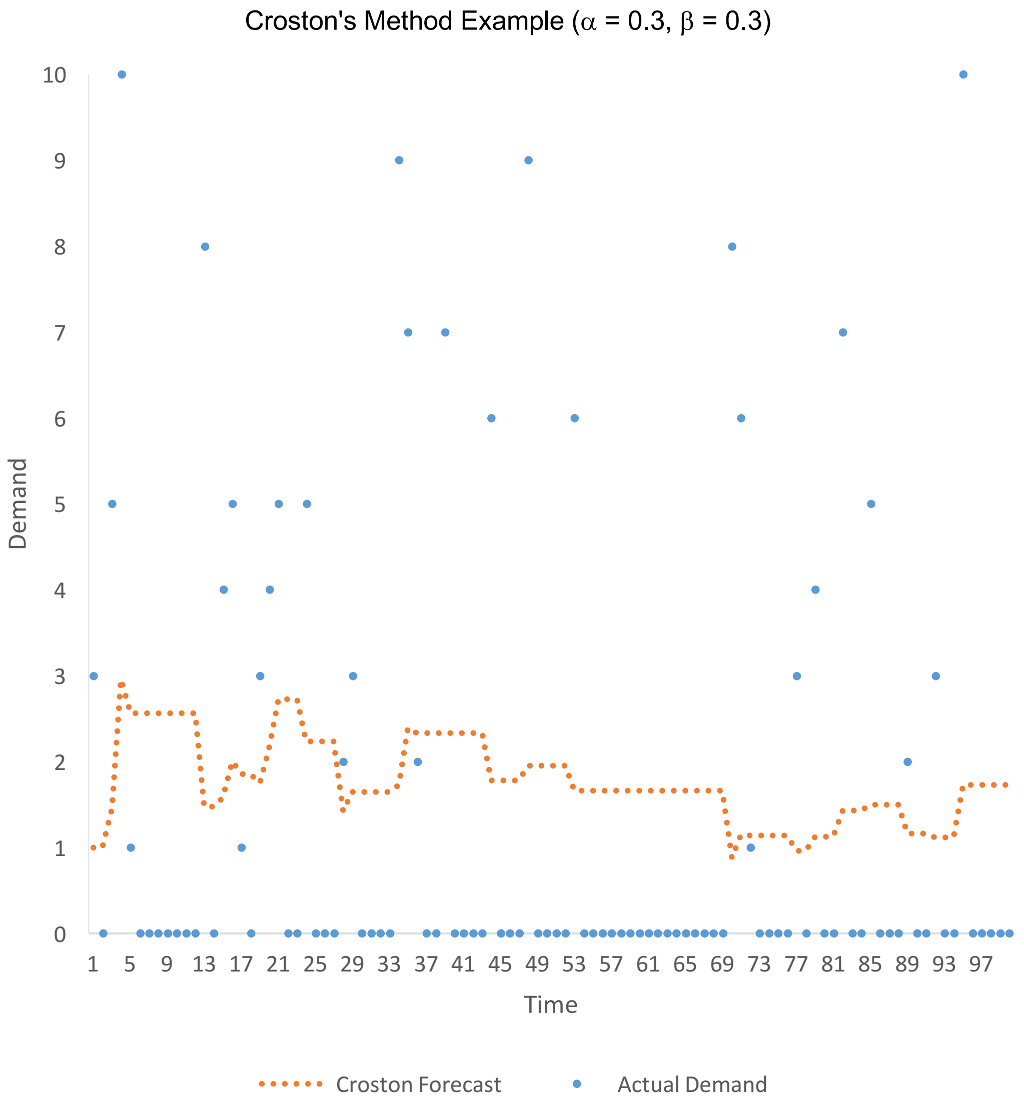


Figure 88 Croston's Method Example, created by author

Input (3) consists of identifying the most critical components within a system and the Important Measure (IM) degree of centrality (C^D) has been selected. The formula for complex systems is:

$$C_i^D = \frac{k_i}{N-1} = \frac{\sum_{j \in G} a_{ij}}{N-1}, \quad 0 \le C_i^D \le 1$$

In order to compute C^D, the number of nodes (N) and a number of neighbours k_i are required. The case-study asset systems are not too complex and have also been anonymised, producing simplistic system structures. Therefore, C^D can be calculated visually using Figure 89 and Figure 90, producing Table 23 and Table 24.

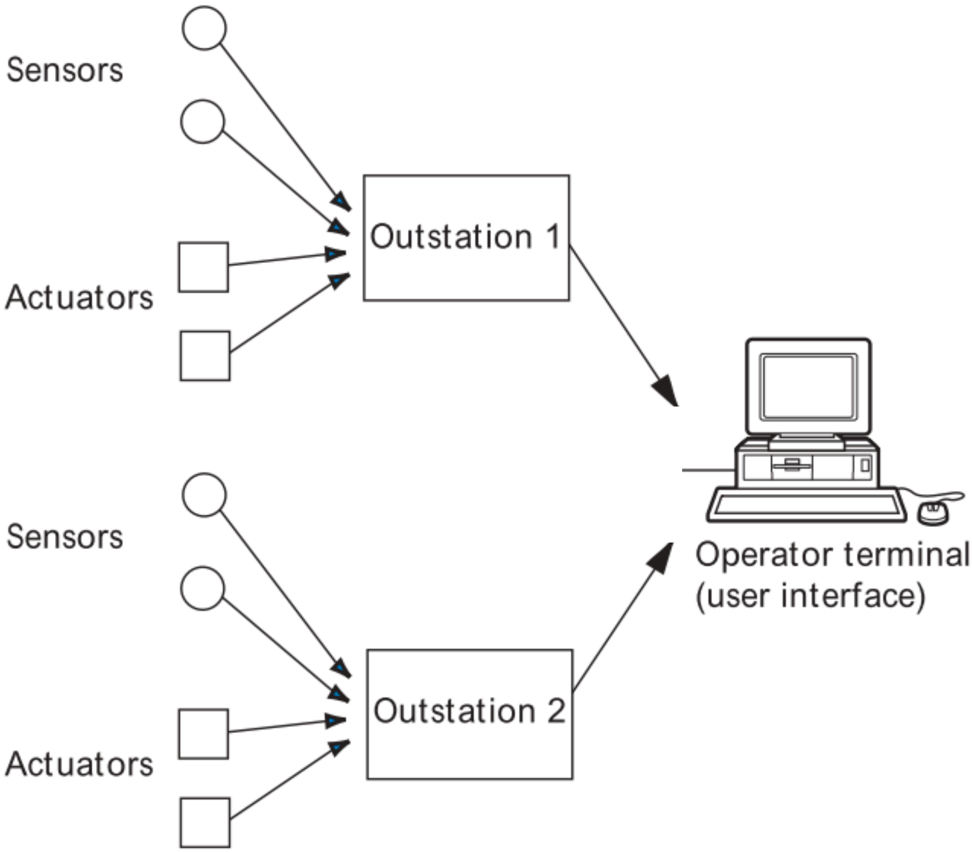


Figure 89 Case-study Building Management System Topology Structure, from CIBSE (2008)

Table 23 Building Management System Degree of Centrality, created by author

Component	Degree of Centrality (C_D)
HEADEND	$\propto$
OUTSTATION	2
ACTUATORS	1
SENSORS	1

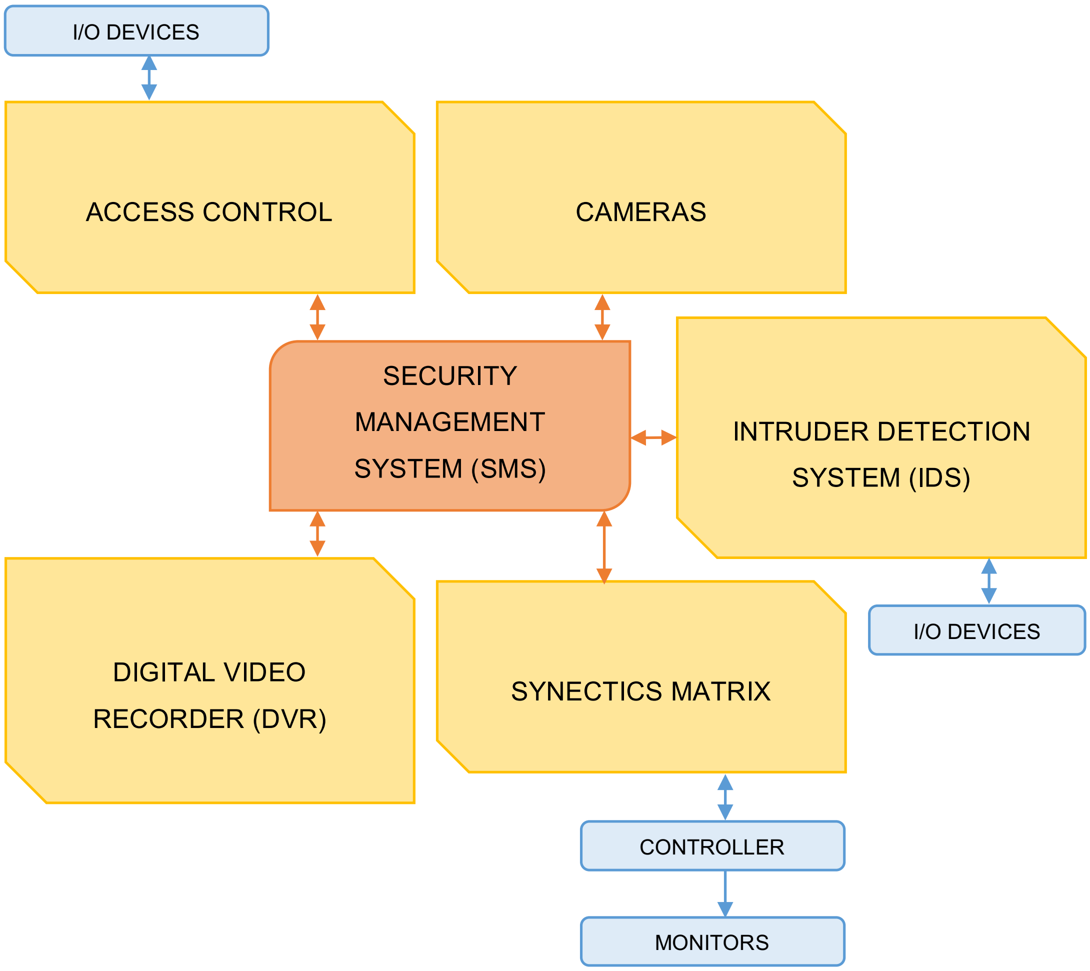


Figure 90 Case-study Security System Topology Structure, created by author

Table 24 Security System Degree of Centrality, created by author

Component	Degree of Centrality (C_D)
SECURITY MANAGEMENT SYSTEM (SMS)	5
ACCESS CONTROL	2
CAMERAS	1
INTRUDER DETECTION SYSTEM (IDS)	2
SYNECTICS MATRIX	2
DIGITAL VIDEO RECORDING SYSTEM	1
I/O DEVICES	1
CONTROLLER	2
MONITORS	1

The processing of OIT is on a quarterly basis cannot start until all other steps within this section have been complete. Figure 91 is the Rules viewer within the ‘FuzzyLogicDesigner’ toolbox of MATLAB. This screen allows the user to precisely enter the input values and record the activated Fuzzy Sets and output crisp values.

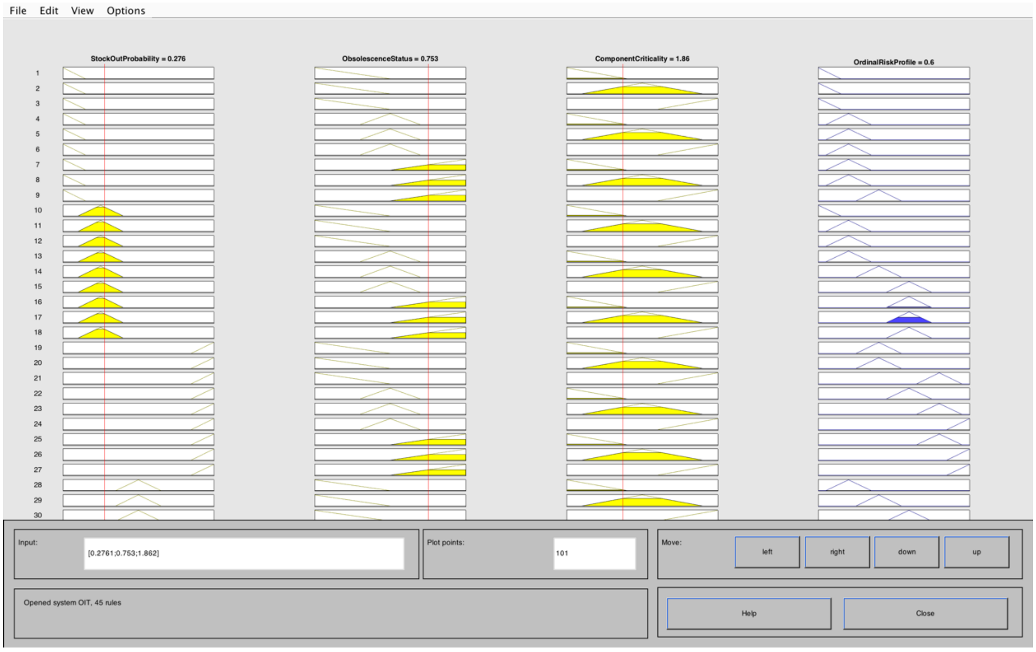


Figure 91 MATLAB IF-THEN Rule Viewer, created author

This final step of OIT is done manually, for two reasons:

- It removes the need to use Simulinks to create a system, requiring more code.
- By manually observing how the internals of the model actually move and react it allows the author to deduce how the current system architecture works and make any observations of future changes.

The crisp outputs of OIT will be visualised in two ways. The first is a static visual of each quarter showing the output of every component. The second is an overtime visual showing how the respective components risk profile changed.

The final piece of analysis covers the sales catalogues from an OEM for BMS components they provide. Predominantly this involves data gathering and sanitisation; the analysis is solely visual. Each fiscal year is provided in an individual Excel spreadsheet, each containing new components and also missing ones from the previous year. These sheets are collated into a single file and then Excel code to extract ages, price changes and when components have been added and removed. The OEM officially categorise their components, allowing for analysis into how obsolescence affects price across several product groups.

3.4 Limitations

The analysis steps have been developed following a conscious decision to approach this research area from a new angle. Figure 92 was first produced by Gravier and Swartz (2009) and is a good illustration of the aforementioned limitations. The datasets available from the end-user do not include the 'Market Factors' and some of the 'Technical Factors', leaving the on-site data and some from peripheral suppliers i.e. number and type.

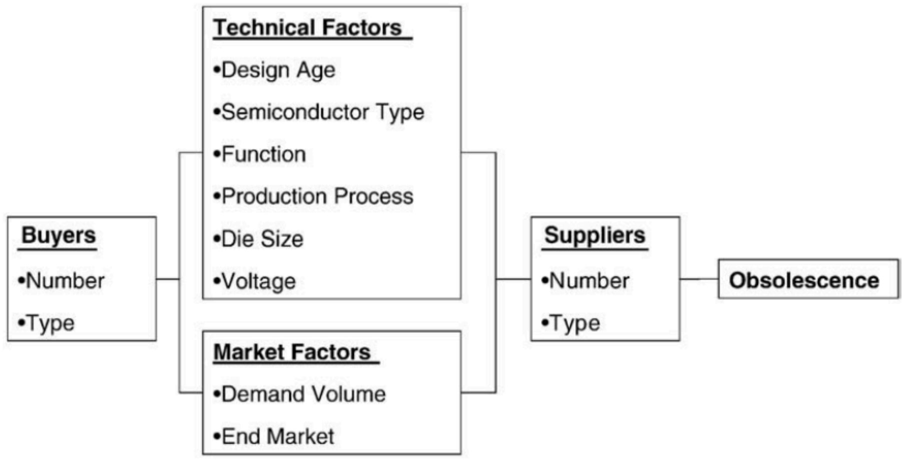


Figure 92 Research Approaches to Obsolescence, from Gravier & Swartz (2009)

This naturally limits the datasets and therefore some of the possible analysis; however, it caters for a completely new set of stakeholders.

The methodology that has been set out to the reader is one course of action amongst many when seeking to research into obsolescence. Inherently when researching in the field there are compromises and assumptions required to continue and progress research, as well as risks to the project. Table 25 is a Risk Assessment undertaken by the author to illustrate the wider risks to the results and conclusion sections of this thesis. It is important to encourage transparency and illustrate the risks and how one has attempted to mitigate their impact.

The research design has been set out to the reader, what this thesis aims to produce, how it intends to do so, and what the known risks are to it achieve its goal. This thesis will contribute to four pieces of new knowledge through the action of 8 objectives, which collectively enable the reader to quantify the risk posed by obsolescence through the adoption of Fuzzy Logic within an inference system. These ambitions will require datasets and analysis that are not found within literature and therefore are exposed to an unforeseeable range of critique. The reward is the opportunity to establish novel research that is applicable to the modern market of the Built Environment.

Table 25 EngD Project Risk Assessment, created by author

Probability, P	Unlikely (1)	Evens (2)	Likely (3)
Impact, I	Small (1)	Medium (2)	Large (3)
Risk, R (R = P x I)	Low (1 – 3)	Medium (4 – 6)	High (7 – 9)

Serial	Description	Probability	Impact	Risk	Mitigation	Risk
1	Internal bias from the case-study environment.	Likely	Large	3	To keep research data gathering and results secret until case-study is over.	2
2	Changing business drivers of the sponsor organisation. Causing drop in support.	Unlikely	Medium	2	Set up business relations with the data source directly, allowing for data collection remotely.	1
3	Staff turnover and fluctuating levels of competence.	Evens	Medium	4	Set up meet and greets with new staff members to implement informal training.	3
4	Risk of Supply chain changes when reliant for data.	Unlikely	Large	3	Set up meet and greets with new staff members to implement informal training.	2
5	Validation of data and quality assurance.	Likely	Small	3	Implement checks by author and sponsoring organisation.	2
6	Creation of new datasets, specifically for this thesis, being wrong.	Unlikely	Medium	2	Preliminary testing of methodology steps on test data.	1
7	Inappropriate membership functions and IF-THEN Rules for FIS.	Evens	Small	2	Seek advice from both industry and Dr. Whiter from UCL on profiles and methodology.	1

4 RESULTS

4.1 Introduction

This section will display a selected range of results, in order to efficiently demonstrate the outputs of the case-study. Full output results have been filed into appendix 8.7. This section by its very existence will confirm that the devised methodology was executed, however, it is the following Discussion section that will be used to relay to the reader the context of the results and their impact. This section will be structured by thesis aims in the following order:

1. Obsolescence indexing technique **(OAT).**
2. Obsolescence risk assessment technique **(OIT).**
3. Visual evidence of product obsolescence and the **effect on component cost.**
4. Visualisation of the **resilience trade-off** for Asset Managers/Facility Managers.

Each of the above subsections will contain an outline of their respective objectives and relevance to this research project for the reader. This will frame the narrative prior to exposure of results for both case-study assets. Whilst the above four bullet points are connected via the research questions and ultimately the research field, they fundamentally achieve different outcomes for different applications. This independence has created a Results chapter containing four subsections; however, as displayed by Figure 93, there is a common thread.

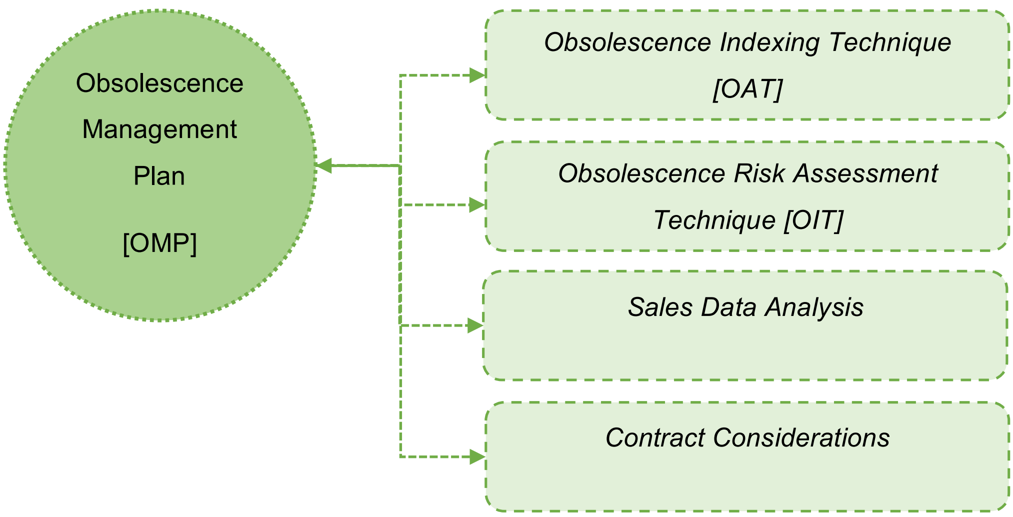


Figure 93 Results Framework, created by author

The two models (OAT and OIT) are decision-aiding tools, to be used in consideration of a wider OMP, enabling a data-driven proactive obsolescence management strategy. The following section will display results from both asset systems within each subsection, creating a repetitive format to the following literature. In the essence of page use, not all results have been displayed, and the remaining results can be found in appendix 8.7.

4.2 *Obsolescence Assessment Tool*

The purpose of Aim (1) is to enhance the original OAT algorithm, whilst adding further validity to results and migrating from Excel to MATLAB code. This following subsection will display to the reader the results of the new OAT algorithm across the case-study, as well as some preliminary thoughts by the author and component level breakdown. The Asset Health results for both asset systems will first be displayed, accompanied by wider illustrations to provide context and insight. This is then followed by the component level output from OAT, summarised in templated visualisations. To conclude the results from OAT, a direct comparison between the old and new internal algorithms will be displayed in a tabular format. The target is to provide the reader with enough information to provide a holistic insight into the amount of data created by this case-study, whilst keep information relevant and concise. To achieve this, only the Q1 2015 and Q4 2016 datasets have been used for some of the visualisations, the remaining datasets, along with the entire MATLAB code can be found in appendix 8.2.

Aim (1) produced eight data points over a two-year period for each respective asset system. Figure 94 illustrates how the outputted Asset Health (AH) score for the BMS varied over time.

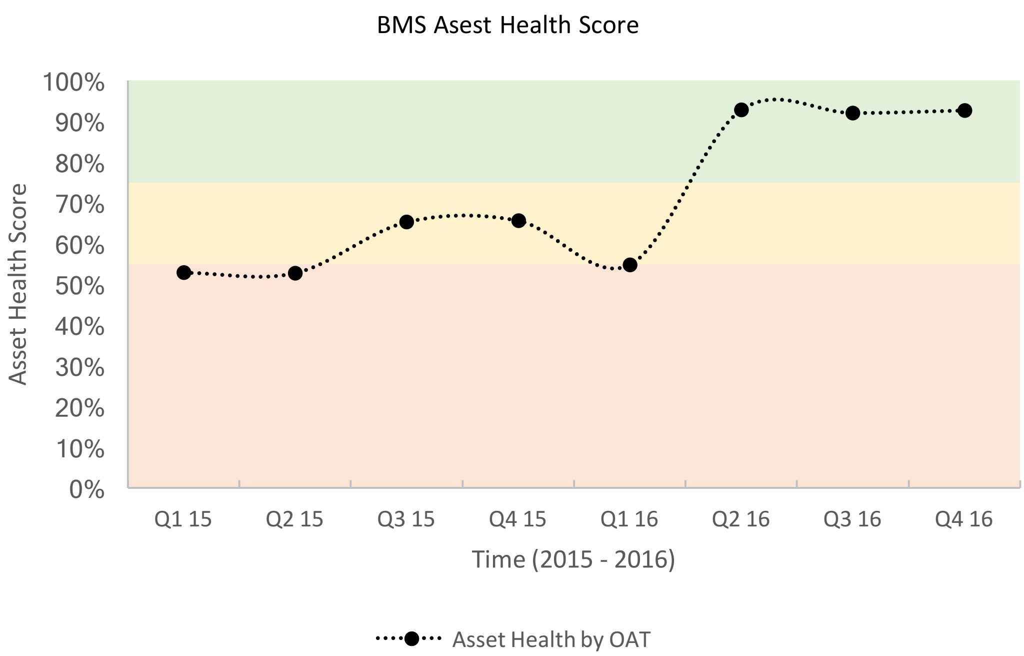


Figure 94 Building Management System Asset Health Summary, created by author

Initial observations include the gradual rise in the Asset Health score shown by OAT for the BMS within *Building A*. Without consulting the detail, which can be found in the Discussion, a comparison of the above figure and the real purchase orders (PO) made within *Building A* for the BMS during the same time period has been compiled. The full PO list for both asset systems can be found in appendix 8.8. Figure 95 contains the quantity of the POs and their combined value, within the same time frame, which as then been joined into Figure 96 for a direct cross comparison.

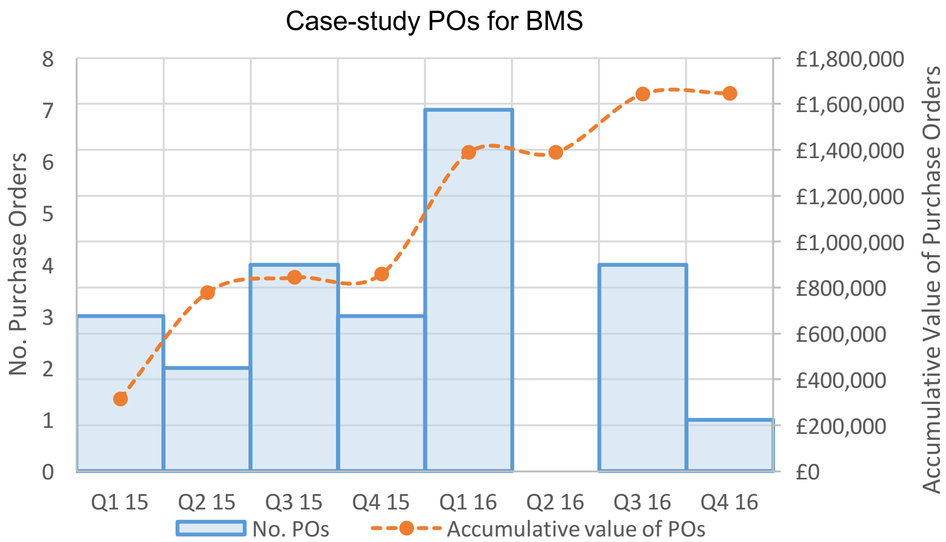


Figure 95 Building Management System Purchase Order Behaviour, created by author

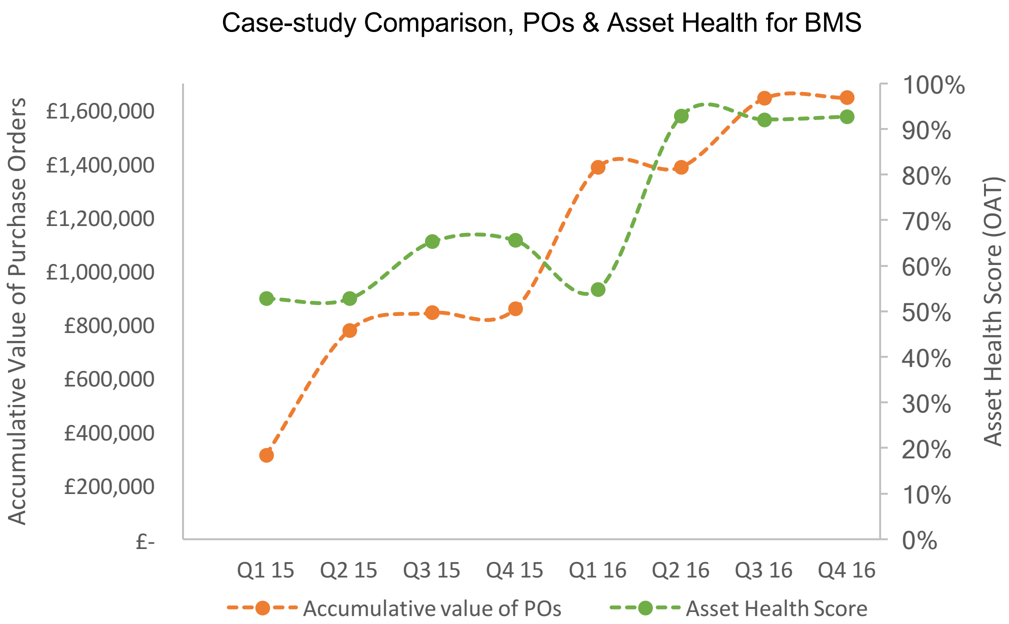


Figure 96 Building Management System Asset Health Score versus Purchase Order Behaviour, created by author

The BMS showed a positive correlation of 0.774 between the increase in accumulative lifecycle investment and resultant asset health score given by OAT. Please note, the author is of the opinion that this correlation is coincidental and not a product of a robust relationship. The investment behaviour within *Building A* is irrespective of any formal obsolescence consideration, therefore, there should not be a causal or correlated relationship. The speculated logic behind the observed correlation is - ‘a continued investment into assets is likely to replace older/obsolete components with new supported ones’. It is a logical connection; however, it is certainly not the recommendation of the author to blindly invest into assets. Some of the lifecycle investments (POs) are a pre-planned requirement due to age, irrespective of obsolescence. The results of this case-study remained anonymous to the on-site Asset Management team to not influence routine business. However, if a more robust strategy was in place in the form of an Obsolescence Management Plan, then the author would add more confidence to the correlation between the observed Asset Health and the frequency of PO’s.

Interestingly, the continued investment into the BMS throughout 2015 and then in Q1 2016 appears to lead to a heightened Asset Health score in the remaining quarters in 2016. Note that the level of investment into the BMS was significant and contributed heavily to the annual lifecycle expenditure for the entirety of *Building A*, highlighting the importance of maximising the economy of one’s life cycle expenditures. It is important to also note that some of the POs made will contain work tasks that may span more than one quarter time period. This would create a ‘lag’ or delay between the investment found within Figure 95 and the resultant impact on the asset health, seen in Figure 96.

The finer detail on a component level as to the changes caused by the POs can be found within the Discussion. However, Figure 97 was created to demonstrate the changing number of components found within the respective statuses assigned by OAT. Although this was in the desired direction, note how a considerable change is observed between Q1 and Q2 in 2016. An exchange between ‘Y2’ and ‘S’ components as shown in Figure 97 gives further evidence of the need for end-users to adopt proactive management procedures. To give the full context, please see the below-copied list of status definitions for Figure 97:

S = Two or more suppliers and no EOL

Y_1 = One supplier and no EOL notice

Y_2 = One supplier and EOL notice

A_1 = Alternative part, no EOL notice and confirmed compatibility

A_2 = Alternative part with EOL notice

B_1 = Alternative part, confirmed compatibility and EOL notice or Unknown EOL

B_2 = Alternative supplier and EOL notice

O = Obsolete part with no solution

U = Unknown status

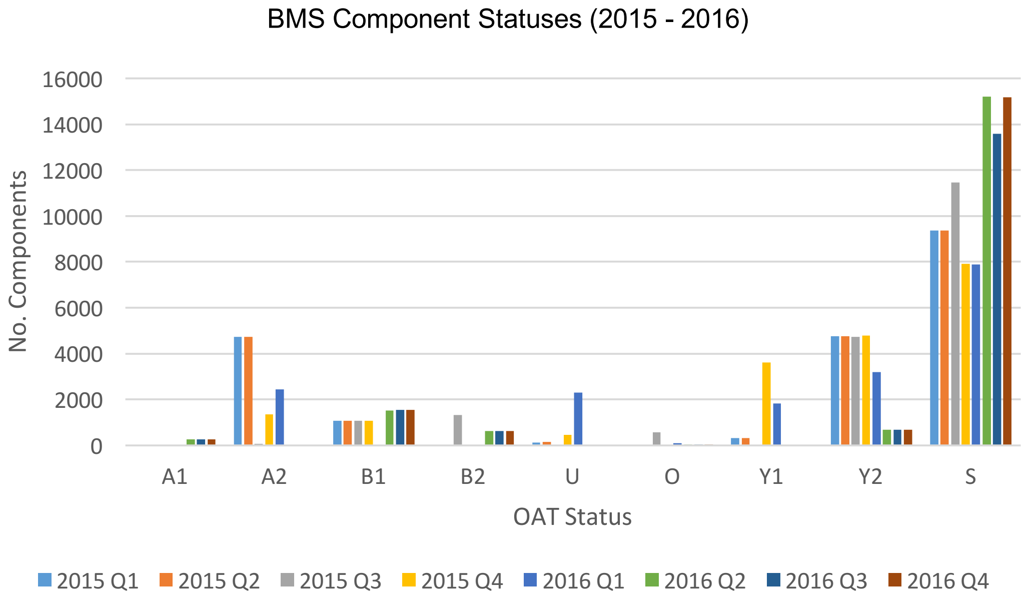


Figure 97 Building Management System Component Statuses, created by author

Figure 97 drives the creation of the asset health score given by OAT that in turn is featured in Figure 94. It is the shifting of no. components that reside within each category or status that drive an increase or decrease of the OAT output. Preliminary thoughts are the respective increase and decrease in the 'S' and 'Y2' categories.

In contrast to how the BMS behaved, the SS undertook a different set of behaviours throughout the case-study. Before further investigation within the Discussion section, one could infer from Figure 98 just how lifecycle investments irrespective of obsolescence can quickly transform an Asset Health score from within the yellow threshold to a low red threshold (Q2/Q3 2016 to Q4 2016).

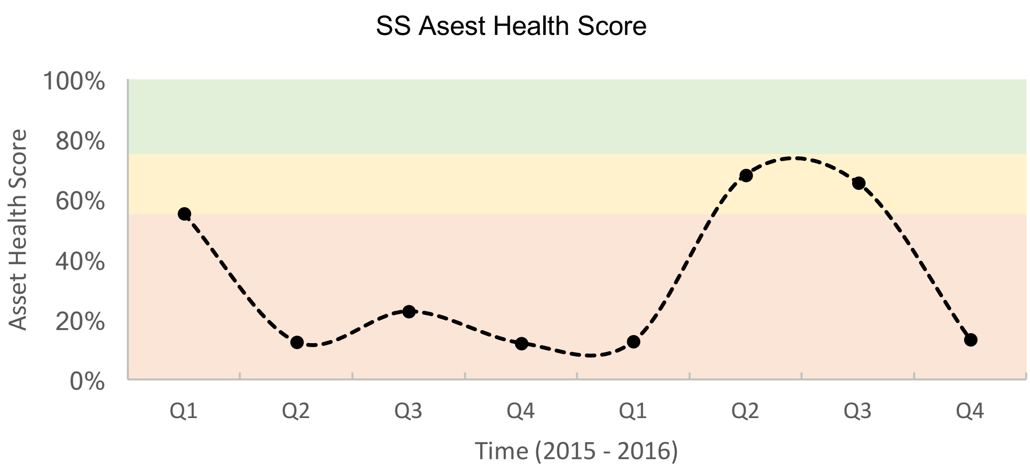


Figure 98 Security System Asset Health Summary, created by author

After reviewing the POs for the SS, it is apparent that whilst the number of POs rivals the BMS, the total value is approximately half. However, the total investment exceeds three-quarters of a million pounds, money that potentially may lead to unforeseen future lifecycle expenditure due to obsolescence. In the same manner as the BMS, Figure 99 and Figure 100 were created to directly compare how the lifecycle investment that occurred within *Building A* for the SS is reflected, if at all, in the behaviour of the Asset Health score.

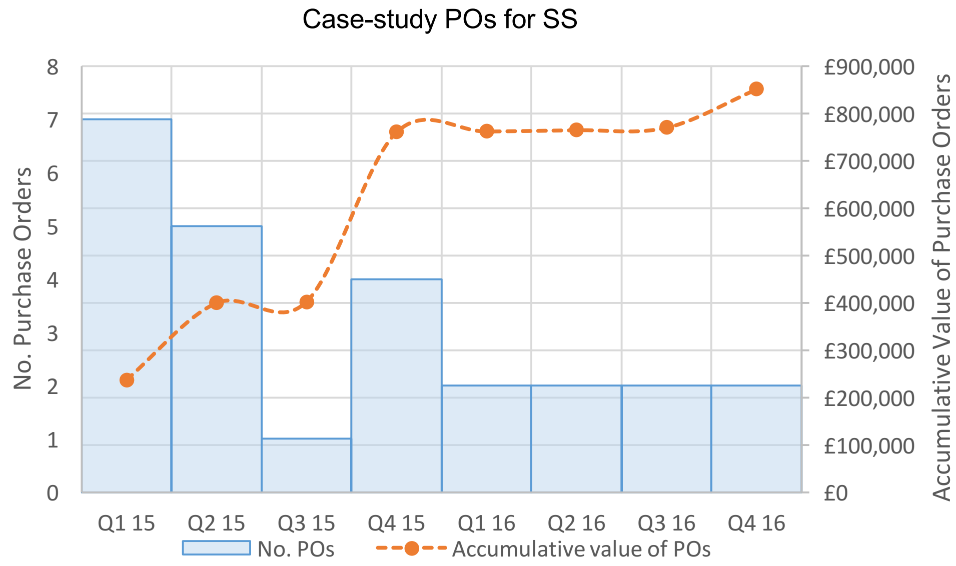


Figure 99 Security System Purchase Order Behaviour, created by author

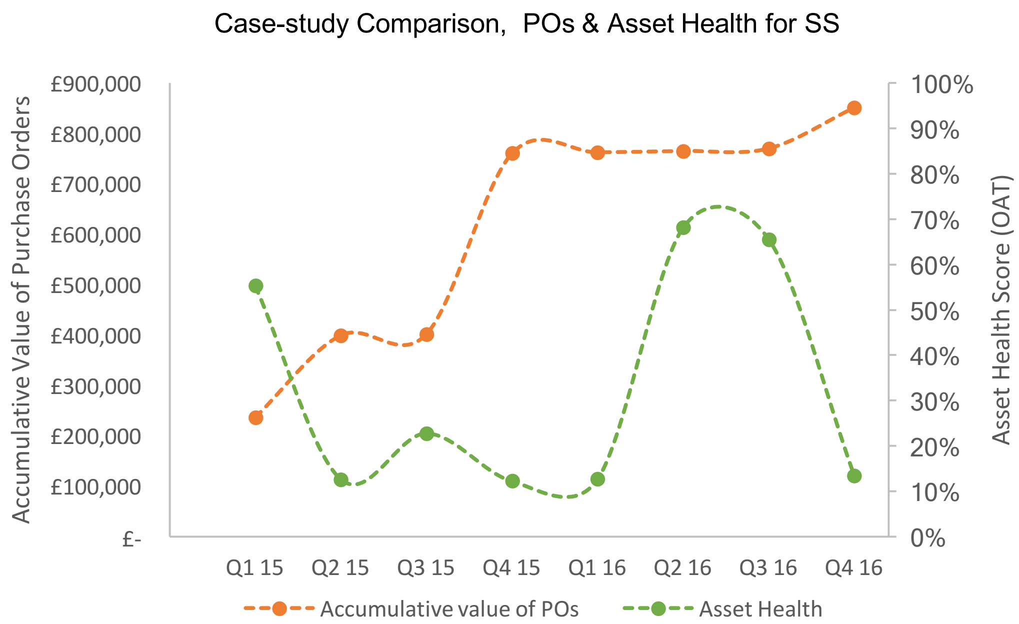


Figure 100 Security System Asset Health Score versus Purchase Order Behaviour, created by author

Whilst the front heavy investment into the SS could be a logical explanation to the peak in Q2 and Q3 in 2016 for the SS, the trough in Q4 2016 could be a result of three things;

- Either misinformation within the datasheet and/or…
- Investment into components that contain an element of obsolescence and/or…
- Components already existing within the system coincidentally becoming obsolete at Q4 2016.

This type of behaviour is a result of a lack of strategic logic that underpins the lifecycle investment in regards to obsolescence. This synopsis is reflected in a negative correlation of -0.053, no correlation. The author must note that this type of behaviour was the expected outcome due to the lack of formal process within *Building A* that considered obsolescence.

It is certainly possible that the Asset Health score contains an element of latency between the date of a purchase order, the procurement of works and the physical installation, all of which can span several weeks. It is possible, therefore, that the observed Asset Health score is a slightly shift (negatively skewed) total value curve. The Asset Health score in Figure 98 interestingly appears to show the total value curve shown in Figure 99, delayed by a quarter. Whilst this is not an objective of this thesis, it is an interesting observation.

An interesting observation between the two systems regarding the status breakdowns in Figure 97 and Figure 101 is the contrasting diversity of statuses within each respective system. The author highlights two traits; one the difference in diversity and the difference in the Asset Health Score, is there strength in diversity? Should this be an aim for Asset Managers? Equally, having a more diverse set of statuses as opposed to a polarised set between 'O' (obsolete) and 'S' allows for the spreading of lifecycle requirements as part of a mitigation strategy. The different component statuses are dictated by a different set of time frames, therefore allowing an Asset Manager to reassign parts of their Lifecycle budget in smaller amounts on an annual basis. However, with a polarised set, significant investments may be unavoidable and will, therefore, cause lifecycle spikes. In summary, it is unclear whether there is truly strength in diversity, but it is logical to see the benefits from an investment perspective with component groups who require staggered mitigation approaches i.e. lifetime buys, as opposed to grouping them together.

An earlier point was made regarding the speed of which an Asset Health can apparently change. These changes are resultant to market changes outside the sphere of control of an end-user and can be clearly observed with the significant changes within the 'S' status in Figure 101 for the SS. These changes hold the potential to enforce unforeseen lifecycle investments.

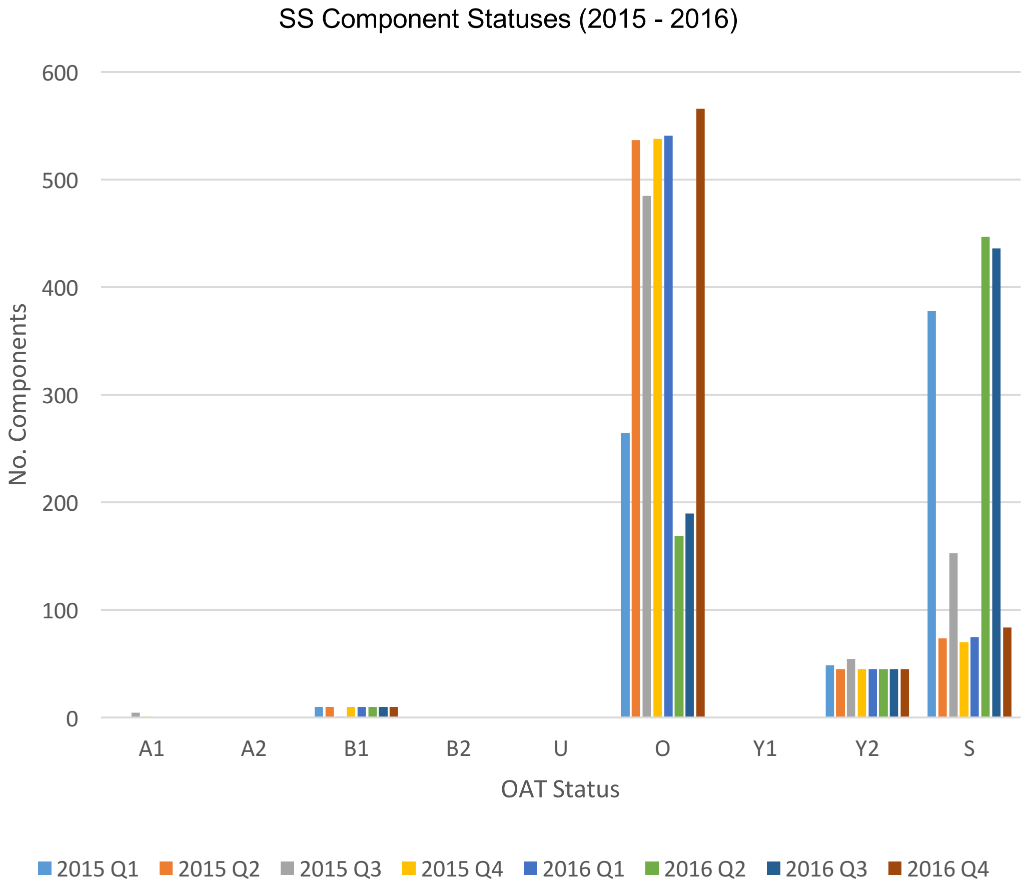


Figure 101 Security System Component Statuses, created by author

On a top level, the results produced by OAT have been displayed to the reader, however, the author will now use the first and last static visuals will be used to demonstrate how the Asset Health (AH) scores have changed from Q1 2015 to Q4 2016 for both case-study assets. The final dialogues from OAT and a breakdown of the status will be presented to illustrate the above data at a slightly more granular level. The results of the internal validity checks will also be displayed to illustrate to the reader the challenges of collective data in real time within a case-study environment.

In Q1 2015, OAT highlighted that the BMS fell into the red threshold (Asset Health = 52.83%), in order to diagnose why this is the case the user must review the statuses applied by the algorithm. When the MATLAB code for OAT is executed, there is a user interface to preselect the appropriate weighting and also locate the input Excel file. OAT will then apply the pre-programmed validity checks, algorithm and publish results into a templated visual. The visual is very similar to that used in Mulholland's (2014) dissertation and contains the primary Asset Health output, along with two weighted outputs for criticality and value, followed by an average of the three iterations. Figure 102 is the output visual from Q1 2015 dataset for the BMS, followed by the user interface results.

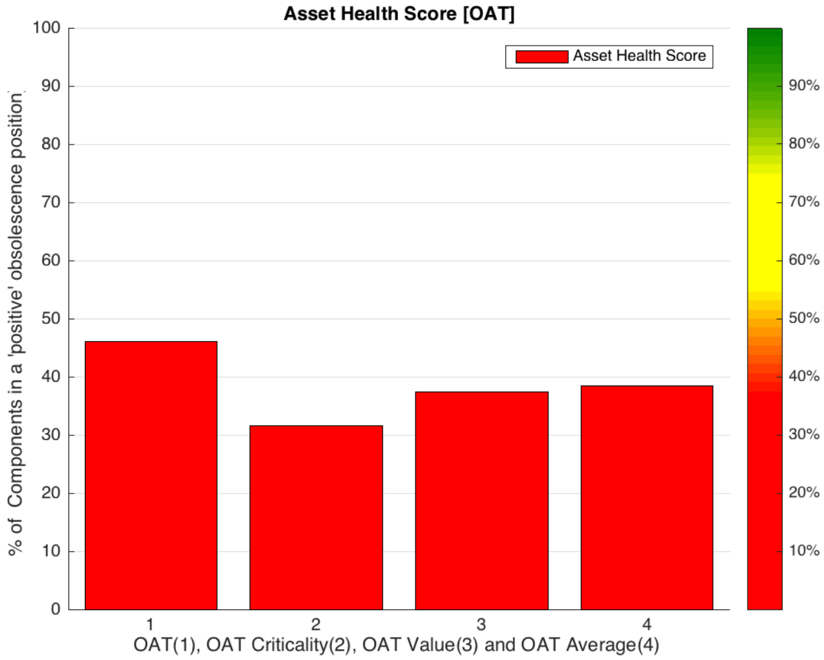


Figure 102 OAT Building Management System Results Q1 2015, created by author

The internal algorithm produced the following final dialogue screen from OAT to the user:

```
Obsolescence Assessment Tool [OAT]
Please locate the Excel data file.
191 individual components within the Building Management System were
found.

Logic Test 1:
The below components have a recorded EOL notification against them,
but no recorded date.
```

Part_Name	Part_Ref	No_Parts	EOL_Released	EOL_Date
'Valve Body 3 Port 80mm Flanged'	'VXF41.80'	9	1	NaN
'700VA UPS'	'SU700I'	9	1	NaN
'LD -64'	'LD-64'	10	1	NaN

```
Logic Test 2:
The below components should be check for errors.
They are reporting no EOL but state a date.
   empty 0-by-5 table

Logic Test 3:
The below component quantities should be checked.
   empty 0-by-5 table

Logic Test 4:
The below components should be checked for their EOL release dates.
   empty 0-by-5 table

Logic Test 5:
The below components have 6 or more missing data points. Continue?
   empty 0-by-13 table
```

In review, apart from potentially three missing data points (equating to 1% error within the dataset), the datasheet has passed the internal validity checks. Now in order to review the statuses, Figure 103 has been devised. Note this is not a standardised OAT output but is the most appropriate way to illustrate to the reader the prognosis.

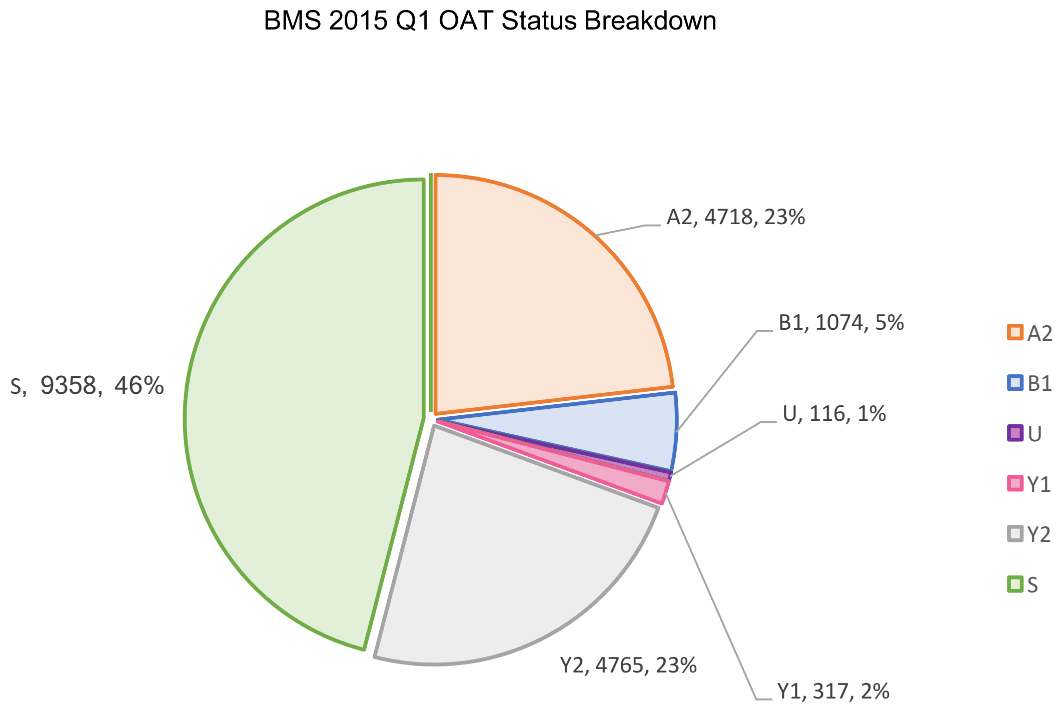


Figure 103 Summary Building Management System Results Q1 2015, created by author

In Q1 2015, the BMS had over half of its components fall into the Y_2 and A_2 categories. As a reminder, these refer to:

Y_2 = One supplier and EOL notice

A_2 = Alternative part with EOL notice

Whilst at the point of collection for Q1 2015, the 9483 components that fell into the above status groups have mitigation options available this position is not infinite. It is important to remind the reader that in order to implement a mitigation method, one must first be aware of this situation. Both of these status groups have EOL notifications against them, meaning their supportability in the coming year is at risk.

In summary, over half of the components (9,483 components) within the system have an EOL notification against them, of which 23% having just a single known supplier. Depending on further context, this may be a precarious position for the BMS in 2015. For example, from this position, it is unclear whether the components are critical to service delivery or equally whether they are expensive in value. It is this further context that OIT will aim to consider, enabling for a risk profile to be produced. Having components within statuses such as Y_2 can have a large effect on the available mitigation methods i.e. lifetime buys or cannibalisation.

Interestingly, almost half of the components in the system have no EOL notification and have more than one supplier (status ‘S’). In a real-world context, this could be an example of the difficult task Facilities Management/Asset Management have when identifying obsolescence. The almost majority of components are in an entirely robust position to obsolescence, however, a minority are not. Depending on the quality of information sharing and knowledge of the system, it is not unimaginable to envisage how this can be missed. The result is that forced unforeseen lifecycle investments into the BMS to continue support and maintenance.

In complete contrast to Q1 2015, Q4 2016 outputted an Asset Health score of 92.68% and positioned itself firmly within the green threshold band (see Figure 104). The discussion section of this thesis will begin to analyse the link between the resultant Asset Health scores and on-site POs, however, on a granular level this high score was generated via the 83% of components qualifying the ‘S’ status (see Figure 105). An important weakness of OIT that has been highlighted already is the lack of connection between these results and risk in real terms. By this, the author refers to the 19 components assigned the ‘O’ status for Q4 2016 within the BMS. From this level of scope, it is unclear whether these components are critical to the service delivery of the BMS and or whether spare parts exist already on-site for example. That is the definitive difference between a reflective index such as Asset Health and an ordinal Risk profile, as produced by OIT.

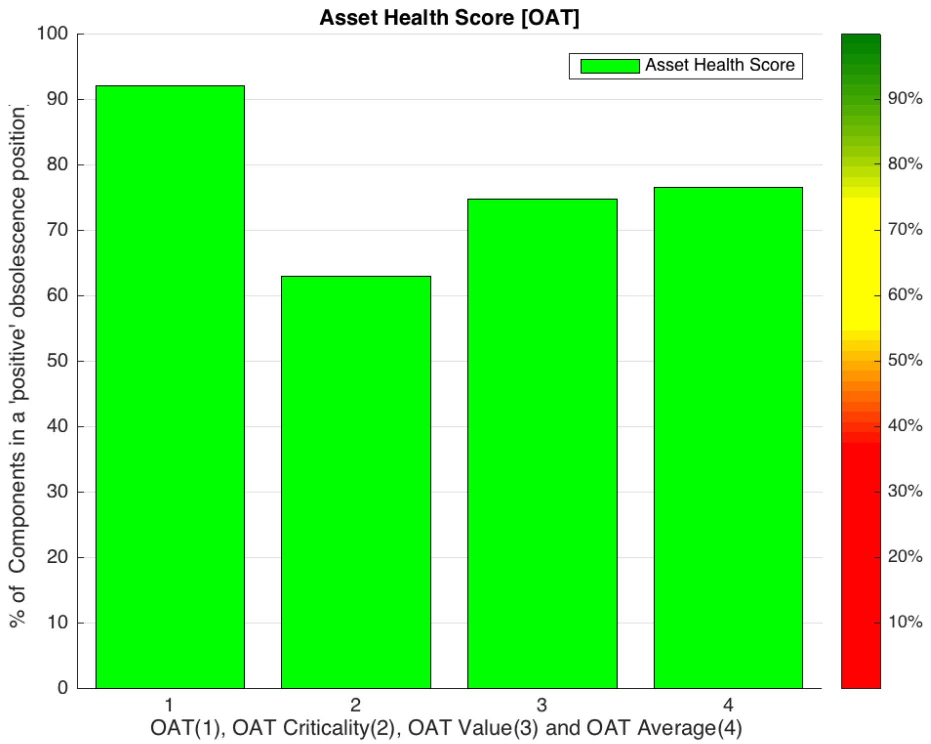


Figure 104 OAT Building Management System Results Q4 2016, created by author

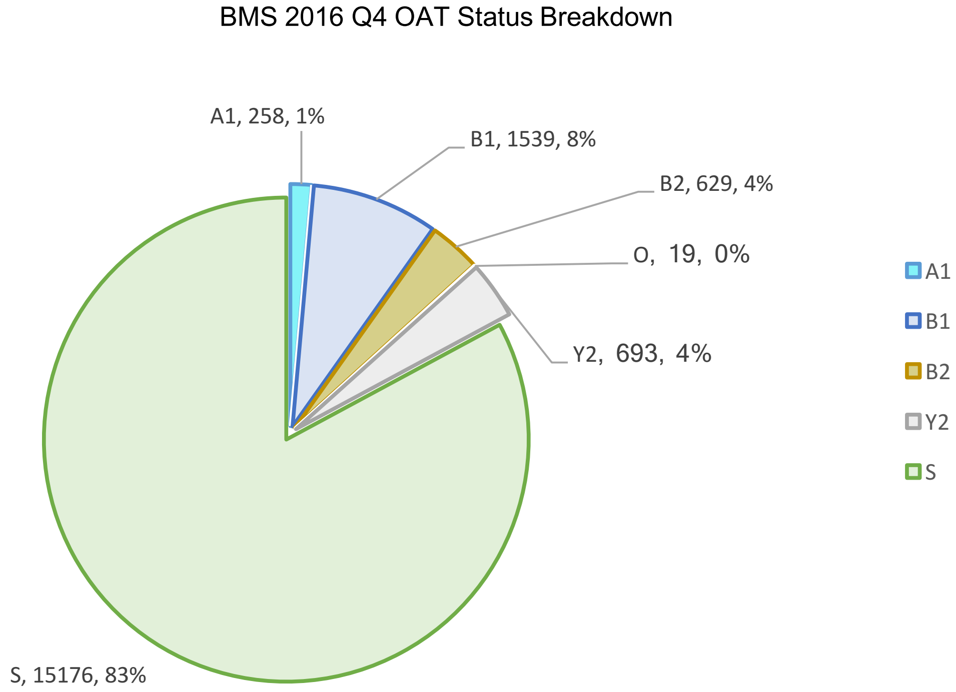


Figure 105 Summary Building Management System Results Q4 2016, created by author

Figure 106 shows the AH score for the SS in Q1 2015, the asset started within the 'yellow' threshold band but carries a large criticality weighting, which pushed it into the 'red' threshold.

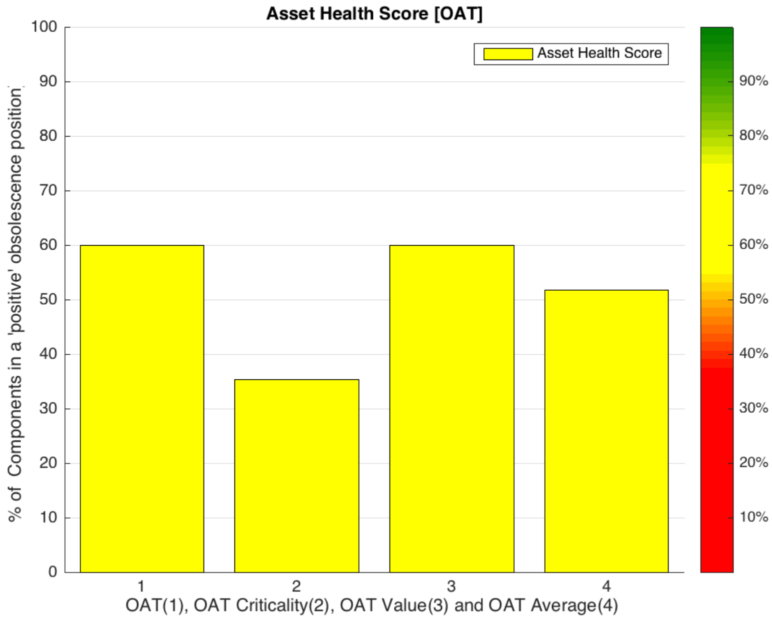


Figure 106 OAT Security System Results Q1 2015, created by author

Note that the criticality weight is applied to the total Asset Health and does not target on a component level. The following OAT output displays to the reader that one component failed the internal validity check Logic Test 1 (2% error rate). This particular error is associated with the contractor being unable to get in contact with Bosch the OEM.

```
Obsolescence Assessment Tool [OAT]
Please locate the Excel data file.

45 individual components within the Security System were found.

Logic Test 1:
The below components have a recorded EOL notification against them,
but no recorded date.
```

Part_Name	Part_Ref	No_Parts	EOL_Released	EOL_Date
'Bosch Monitor'	'UML 20'	25	1	NaN

```
Logic Test 2:
The below components should be check for errors.
They are reporting no EOL but state a date.
```

Part_Name	Part_Ref	No_Parts	EOL_Released	EOL_Date
Mic 500 Series		1	0	01/12/2023
External	Dinion	14	0	01/08/2021

Bosch Cameras	Camera			
Fibre Optic TX		12	0	01/03/2024
Fibre Optic RX		12	0	01/03/2024
Pelco domes Camera	FD5	22	0	01/12/2024
Pelco domes Camera	FD5 IR	31	0	01/08/2024
Scantronic 160 Control Panel		9	0	01/03/2024
Scantronic Keypad		9	0	01/03/2024
Expander		3	0	01/03/2024
Synectics Voll 8		5	NaN	01/06/2013
Synectics RS232		6	NaN	01/06/2013
Synectics Net 8		1	NaN	01/06/2013
Synectics Net 16		1	NaN	01/06/2013
TM Legic	A94	64	0	01/06/2019
TM Legic	A10	48	NaN	01/01/2008
Watermark Reader	WR03/1300S0/05	48	NaN	01/01/2008
APC		13	0	01/07/2013
I Star Pro		7	0	01/12/2023
I Star Edge		14	0	01/12/2023
RM4		48	0	01/08/2013
C-Cure 800	move to C-Cure 9000	1	0	01/01/2020
Camera Lens	10 - 250 Zoom	4	NaN	01/08/2013
Camera Lens	8 - 120 Zoom	11	NaN	01/08/2013
Optrex Motion Senser		28	0	01/03/2024
Vibration Sensor		4	0	01/03/2024
8 port Switch		15	0	01/03/2024
24 Port Switch		1	0	01/03/2024
24 Port Switch		1	0	01/03/2024

Logic Test 3:
The below component quantities should be checked.
empty 0-by-5 table

Logic Test 4:
The below components should be checked for their EOL release dates.
empty 0-by-5 table

Logic Test 5:
The below components have 6 or more missing data points. Continue?
empty 0-by-13 table

OAT has highlighted that a number of components have End of Life dates against them, however, they do not have formal notification of an End of Life (Logic Test 2). This can occur when the Asset Register and communication with the supply chain neglect end of life or obsolescence. The historical records of when EOL notifications were released therefore are never captured. It is entirely possible that the question regarding obsolescence has never been asked prior to this case-study, since the commissioning date in 2004 (11-year period). This is a good example of how in practice, with long-life systems, the historical information is not always consolidated enough. It is exactly this scenario that forces Facility Managers/Asset Managers to make decisions under uncertainty. This is completely avoidable with more robust data gathering and storing procedures.

In comparison to the BMS asset in Q1 2015, the SS is smaller by volume of components, however, it contains far more obsolete components. Figure 107 demonstrates whilst the majority of components are in a robust position to obsolescence (status ‘S’), over 200 components are already obsolete, with a further 69 (8%) already within their obsolescence phase of the lifecycle.

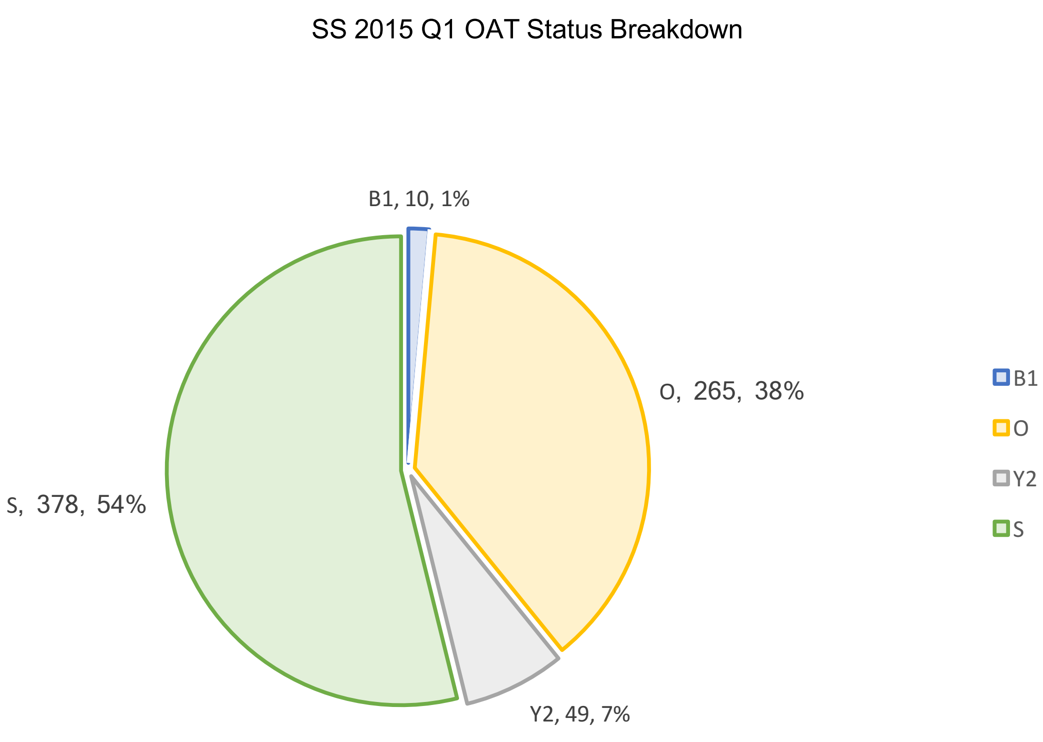


Figure 107 Summary Security System Results Q1 2015, created by author

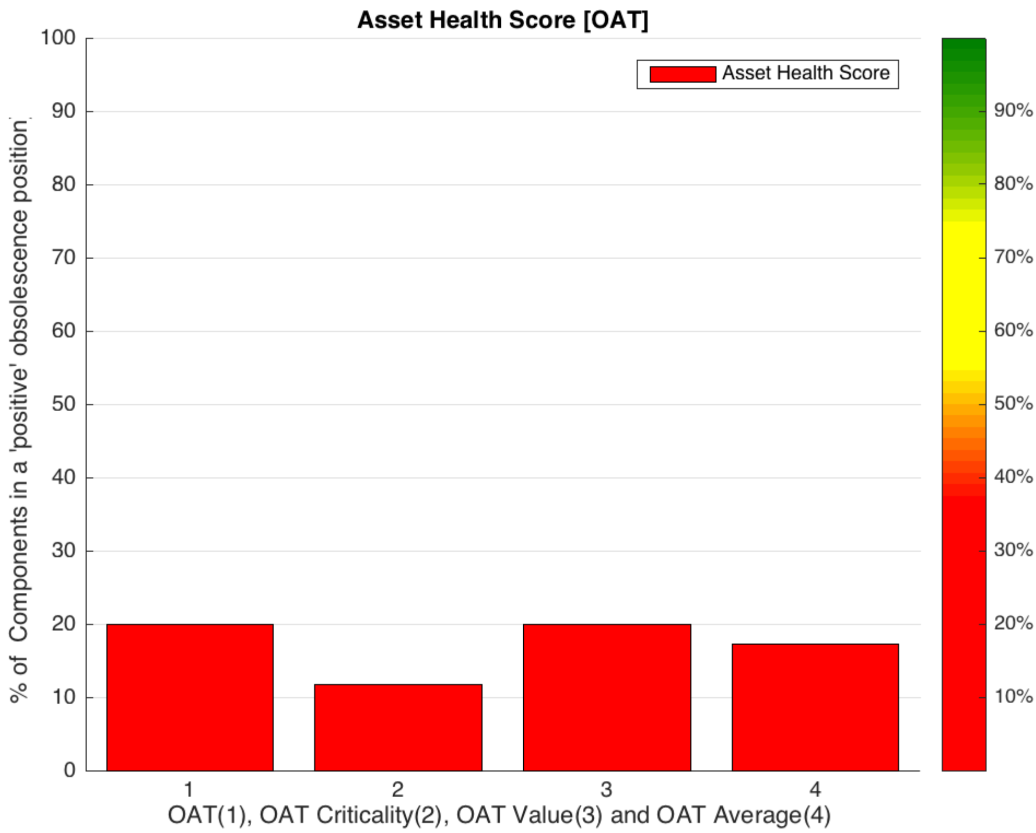


Figure 108 OAT Security System Results Q4 2016, created by author

As Figure 109 demonstrates the obsolescence found within the SS grew, subsided and grew again to culminate in 80% of components being assigned 'O' in Q4 2016. There are many potential explanations as to why the Asset Health score changed as it did; however, it is underpinned by a lack of Obsolescence Management Plan. Therefore, there is no formal reporting process for the sub-contractor, QSG Ltd in this example, to inform the Asset Management team of any obsolescence changes. The aforementioned system has its lifecycle requirements programmed out using typical commercial software packages that currently ignore obsolescence. In summary, it is foreseeable how Asset Management teams invest into asset systems, replacing components due to the consideration of age, run time, cost and maintenance, all of which are not captured by this Asset Health index. However, ultimately it is obsolescence that can immediately cease any future direct replacements.

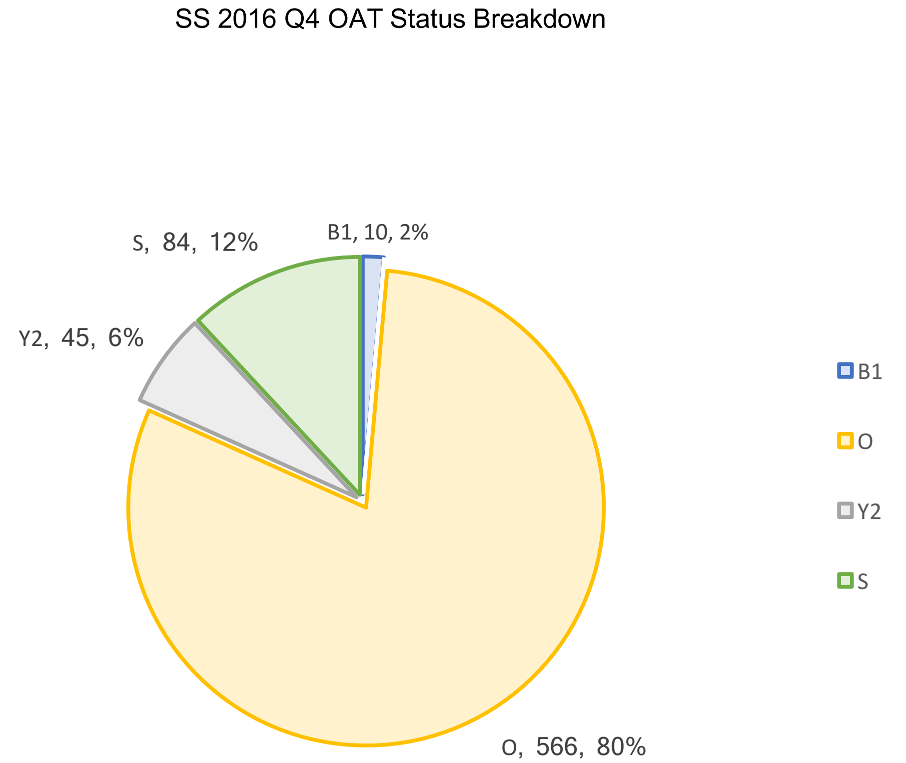


Figure 109 Summary Security System Results Q4 2016, created by author

Figure 109 illustrates an earlier point regarding the polarised set of statuses that have been observed within the SS and the likely effect this can have on both the mitigation strategies available and the lifecycle requirement. Whilst OAT is not designed to provide strategic answers, it identifies which components should be addressed first enabling for strategy development as part of an Obsolescence Management Plan.

The results in this section display the application of OAT, further illustrating its use within the Built Environment for identifying obsolescence and also enabling proactive strategies through an indexing technique. The input data sheets now go through a validation process, in addition to the quality assurance steps of in-house assessment by the Asset Management team. Aim (1) of this thesis was to further the enhancement of OAT by increasing the granularity of which the algorithm processes data. This has been displayed to the reader in the form of additional variables within the algorithm; however,

Table 26 and Table 27 have been created to simplify this point.

Table 26 and Table 27 are direct comparisons of Q4, 2016 data for both asset systems, illustrating how the algorithm now functions and assigns statuses.

Table 26 Security System Comparison of Old and New OAT Algorithm, created by author

Status	***Old OAT Algorithm***	***New OAT Algorithm***
A1	0	0
A2	0	0
B1	n/a	10
B2	n/a	0
U	0	0
O	566	566
Y1	35	0
Y2	55	45
S	49	84
Asset Health	11.92%	13.33%

Table 27 Building Management System Comparison of Old and New OAT Algorithm, created by author

Status	***Old OAT Algorithm***	***New OAT Algorithm***
A1	0	258
A2	993	0
B1	n/a	1539
B2	n/a	629
U	258	0
O	19	19
Y1	6716	0
Y2	1239	693
S	9089	15176
Asset Health	86.33%	92.68%

The highlighted cells identify the changes that now exist and also how OAT is better at categorising components, providing more information to the user and therefore further enhancing strategy development. Please note the considerable change witnessed within the BMS data; the newly-created statuses being assigned over 2000 components that previously would have resided within other statuses. This is evidence of the need to further diversify the statuses required within OAT's algorithm.

This subsection has illustrated to the reader the changing Asset Health score for both asset systems throughout the case-study. The reader was then shown analysis of the component level and PO data produced by OAT. This section then undertook a direct comparison of the old and new OAT algorithm to illustrate that all objectives within the Aim (1) were fulfilled. Further analysis and discussion of the results and speculation to their causation can be found in the Discussion section. The next subsection will bring the reader to the second key element of the Result section; the Obsolescence Impact Tool, which will explicitly quantify the risk posed by obsolescence as opposed to an indexing technique.

4.3 *Obsolescence Impact Tool*

The purpose of this section is to produce a sample of the results from the obsolescence impact tool (OIT), which in itself was a novel design, showing the changing risk profiles. Some further analysis of the highest and lowest risk components will also be isolated for review, with the remaining set of results to be found in appendix 8.7.1. Figure 110 has been repeated to illustrate the position of this subsection within the wider set of Results.

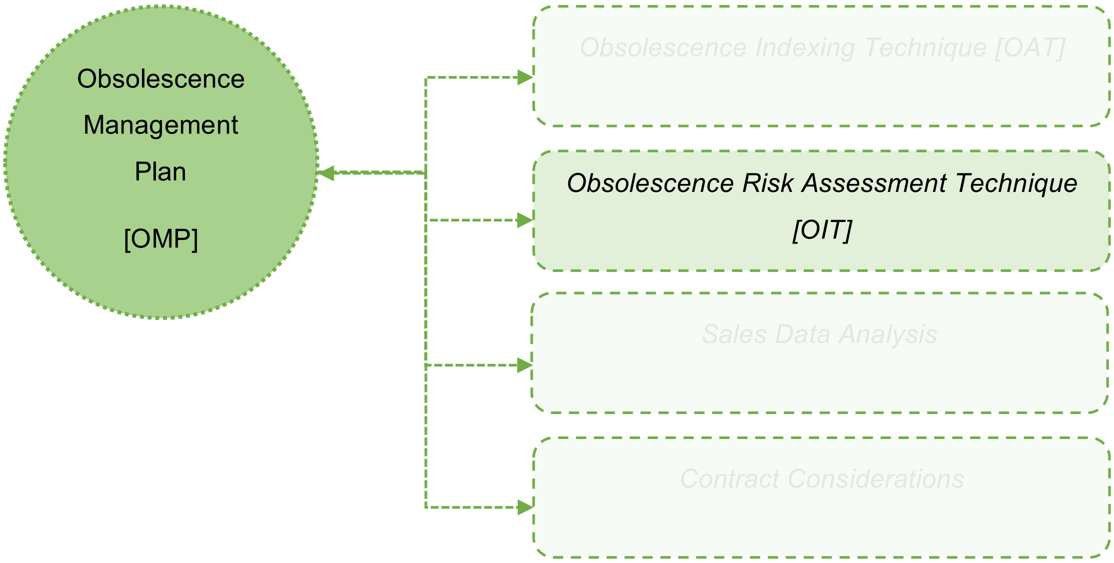


Figure 110 Results Framework, created by author

Similar to the format found in the previous subsection, here you will find the data points Q1 15 and Q4 16, along with summary charts displaying the changing ordinal risk profiles throughout the case-study for both systems. For reference, OIT is a Fuzzy System based upon an expert architecture and therefore has been designed and built with the influence of a panel of industry experts. OIT considers three inputs (stockout probability, obsolescence, and component criticality) which are passed through a set of IF-THEN rules before their output value is assigned to a range of Fuzzy Sets that contain human linguistic terms to evaluate the risk in a 'real world' context. This single output has both a crisp and fuzzy value, represented by a decimal or term i.e. 'Very Important'. The range of output terms (or Membership Functions), ordered from lowest to highest, within the Fuzzy Set are:

- Not Important
- Minor
- Low
- Moderate
- Important
- Very Important

Quarter 4, 2016 presented a highly-polarised set of risks within the BMS system, with the vast majority of components representing a 'minor' risk to the Asset Management team. Figure 111 displays the quantities of components that fall into the respective Fuzzy Sets. On initial inspection, this is a favourable position for an Asset Management team as they may be able to focus resource on the identified 2%. However, better inspection into the components and the inputs associated with them will uncover why OIT's algorithm has defined them as 'important' risks. This can be found in the Discussion section. Note also, 16 components ('MBC24 Backplate Assembly') actually have been defined as 'Very Important' risks, however, do not amount to 1% of the entire system. The same is applicable to the 27 components ('LTEC FCU Controller') that have been defined as 'Not Important' risks.

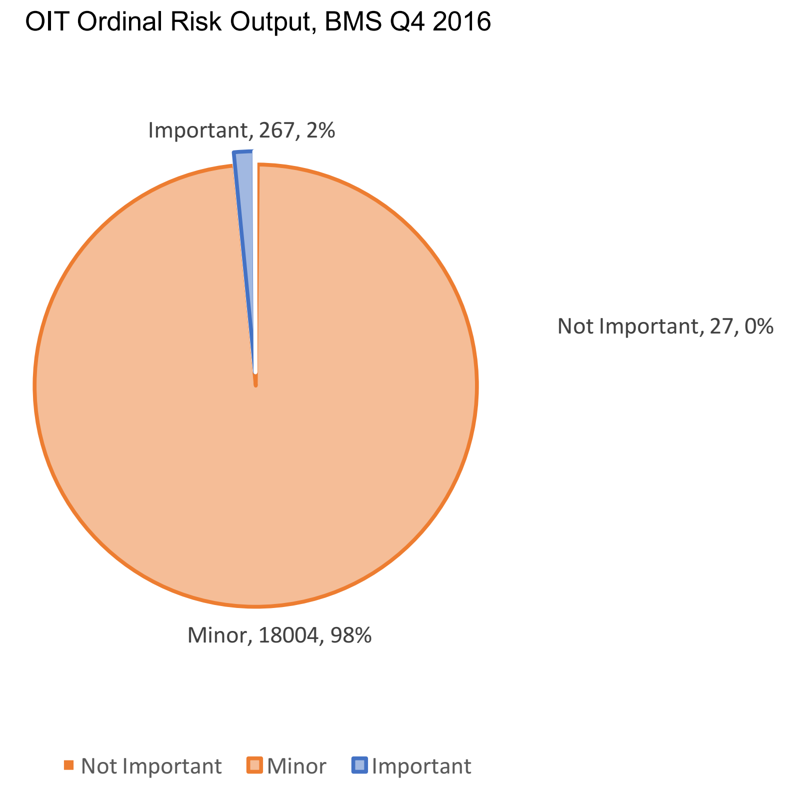


Figure 111 Building Management System Fuzzy Set Results Q4 2016, created by author

In the context of the application of such output, an Asset Management team would conceptually use the above figure to inspect the components that were posed as 'Important' risks to the business. Obsolescence can manifest in several ways and can be escalated to an 'Important' risk via several means also, meaning that each visual would need to be diagnosed as independent cases. However, the power of OIT is that it already has considered the typical demand for the said components, the on-site stores and whether it is a critical component (see Research Design for definition).

The above figure interprets the range of outputs from OIT into their Fuzzy Sets, however, the same information can be displayed as a risk profile as seen in Figure 112. The plateau within the ordinal risk profile mirrors the large percentage of components that have been identified as a 'minor' risk, equivalent to a crisp output of 0.2 by OIT. Note that as detailed within the axis title, the x-axis contains the components, which have been ranked from highest risk profile to lowest. As highlighted within Figure 112, there is a small percentage of components that have elevated levels of associated ordinal risk, which is evident from the spike in the dashed line. From the preliminary results, it has become apparent that whilst OIT does not produce an overall risk category for an entire asset system, this could be generated by the integral of the risk profile curve. The area underneath the curve is directly proportional to the levels of risk within a system i.e. the most desirable state would be a flat line of minimal or no risk and therefore having a small area.

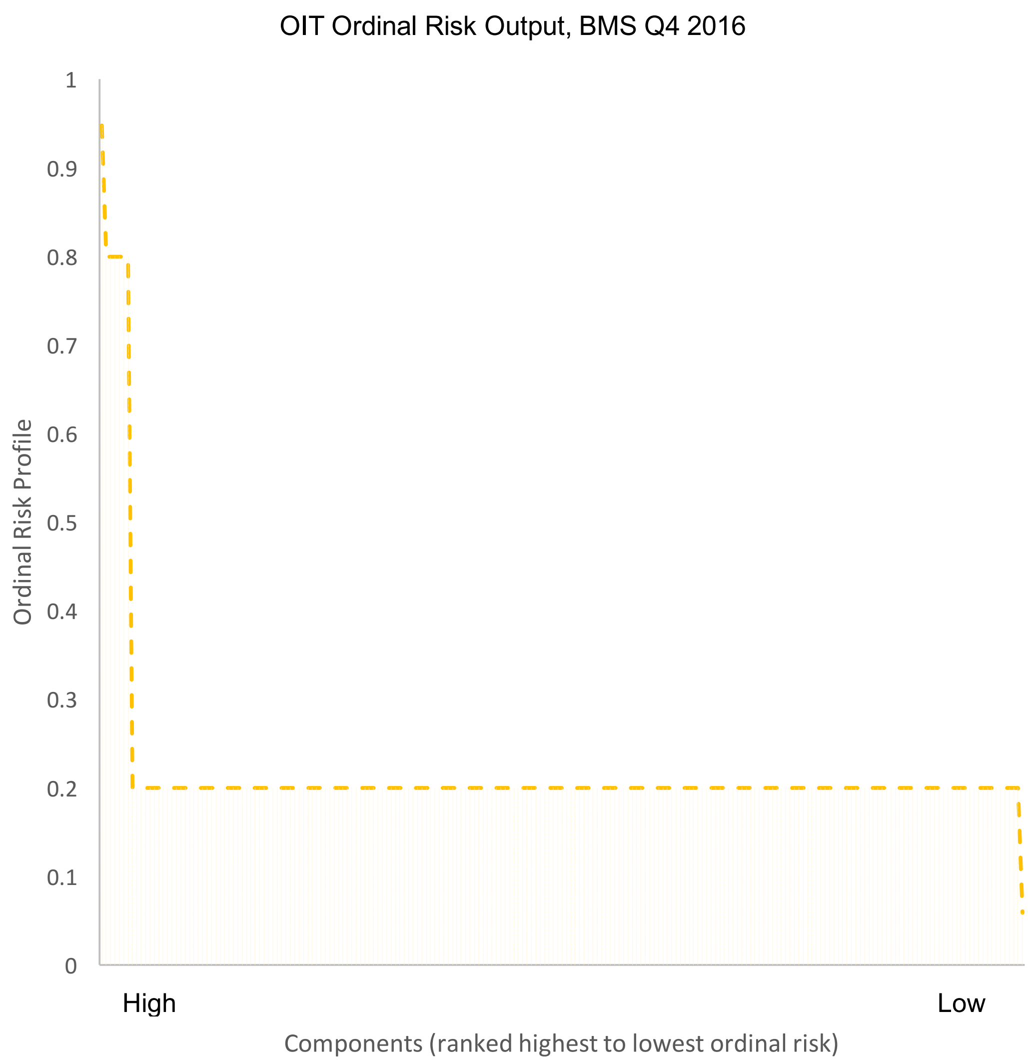


Figure 112 Building Management System Risk Results Q4 2016, created by author

In contrast, the SS appears to be more diverse in its risk profile when compared to the BMS. Interestingly, this is in opposition to the results of OAT, where the SS was far less diverse in its status allocation. The author speculates this is likely due to the added context found within OIT's algorithm, in terms of consideration for component criticality and stockout probability. This is designed to make OIT both more applicable to a real-world situation, but also give more context in terms of risk. Importantly, for the Asset Management team in Q4 16 OIT has identified a number of 'Very Important' risks along with a significant number of 'Moderate' risks. More on the context behind the numbers displayed within Figure 113 can be found within the discussion section. Depending on the function of the respective components and whether they are actually still procurable will dictate whether a reactive or proactive mitigation strategy could be designed.

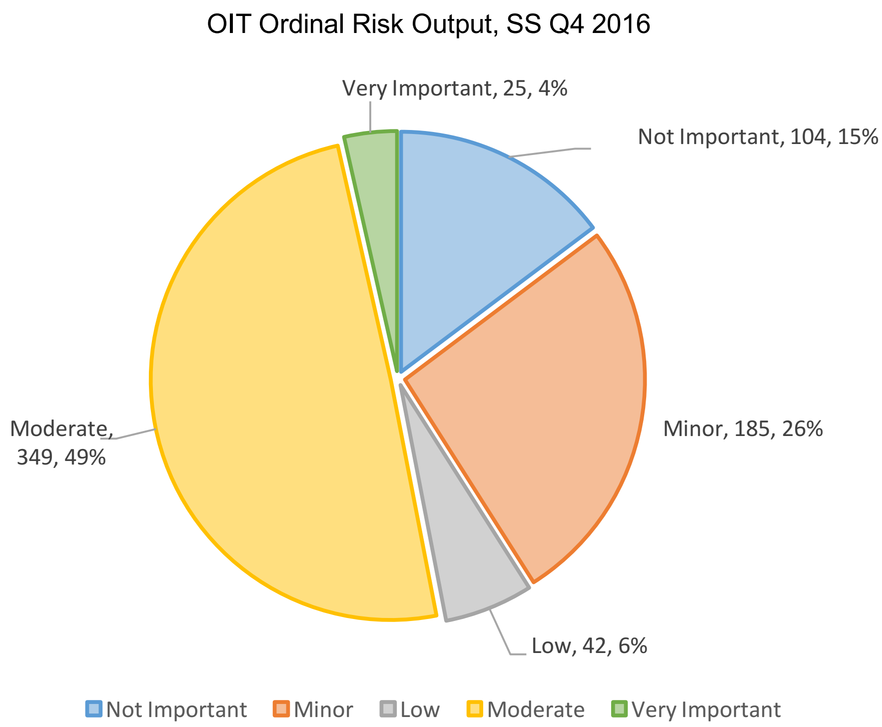


Figure 113 Security System Fuzzy Set Results Q4 2016, created by author

A result such as Figure 113 within the industry would require a lot of analysis in reaction to ensure that this diverse range of risk profiles are holistically managed within the strategy. This poses as both an opportunity and burden. It is true to say that with a range of risk profiles, they components likely exist within different time frames in regards to applying a mitigation strategy, allowing for a staggered set of investments. Staggering lifecycle investment is beneficial for budgetary control. Otherwise, there are more resources required to go through a diverse range of risks as one mitigation strategy may not be applicable to all and therefore require more elements, increasing the complexity.

The more diverse ranges of identified risks within the SS are reflected in the staggered risk profile shown in Figure 114. A key advantage of this methodology over any previous within the literature review is the case-study framework. This allows the author to not only investigate into why OITs algorithm produced the following graphs, but also how the profile changed over time and reacted to market changes. Identifying key connections between real world changes and the observed effects on the graphs, demonstrates OITs applicability within industry and validity.

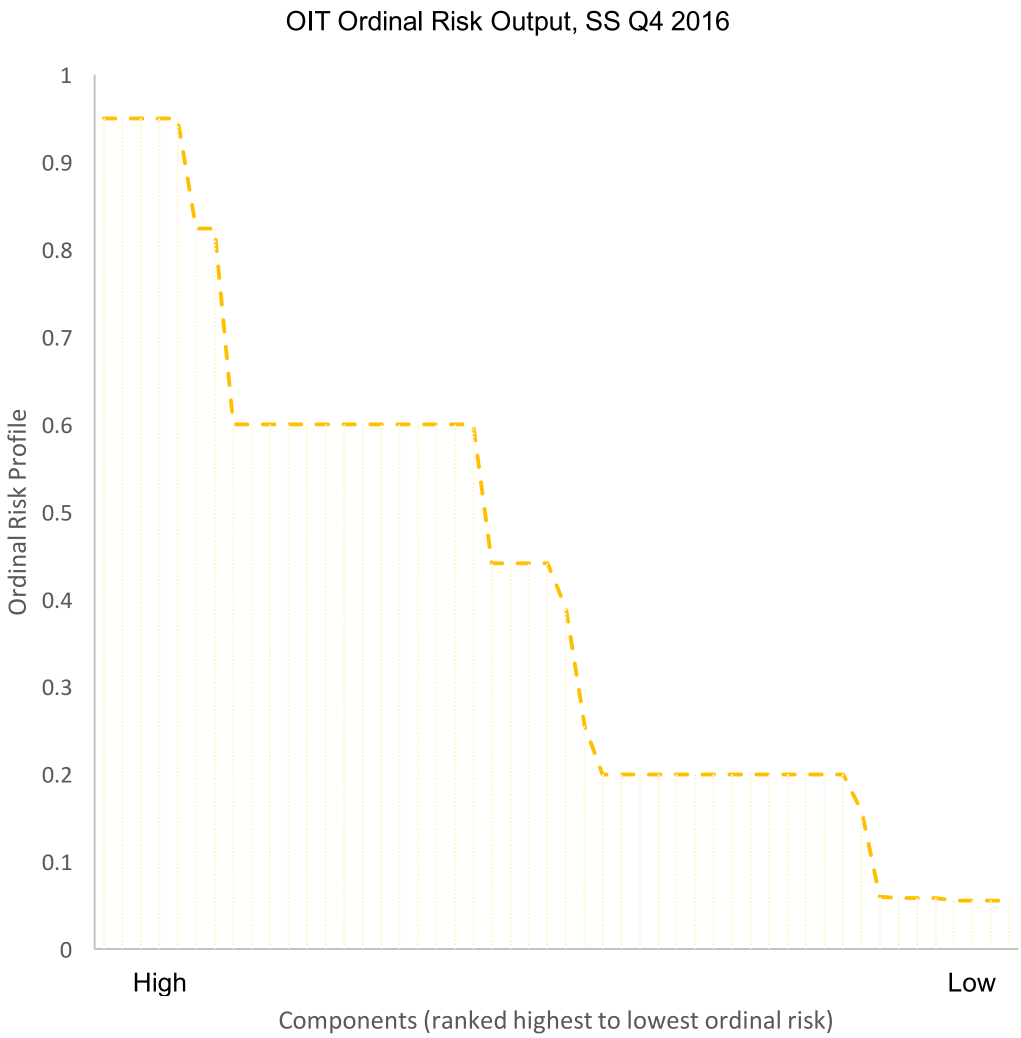


Figure 114 Security System Risk Results Q4 2016, created by author

This brings the reader back to the earlier set of figures generated by OAT, where large groups of components (38%) were assigned the ‘O’ status for being obsolete. Figure 114 illustrates how with further context; stockout probability and criticality, this large group can be further redefined. It is important to remind the reader that whilst the results from OAT and OIT can create interesting comparisons, this should be refrained from as they fundamentally produce two independent outputs. One is an index, the other a risk profile. Figure 112 and Figure 114 are the generated from the last data set within the case-study, it is now important to display to the reader just how the two asset systems scored at the beginning in Q1 2015.

Returning to the BMS and earlier Figure 111 and Figure 112, broadly, Figure 115 is a similar situation to that found within Q4 16, where the BMS appears to be polarised in its risk profile. It will be interesting to observe how if at all, this profile changed throughout the case-study alongside the lifecycle investments. This may be a key finding, illustrating that without an integrated obsolescence management plan, lifecycle investments can actually be rather ineffective with regards to the resilience of a system to obsolescence. An alternative theory is that although the lifespan of the components within the BMS are so short, that in fact, the case-study is rather tumultuous in regards to new components being added and existing ones experiencing obsolescence. This would result in a situation, regardless of lifecycle investment, where the risk profile remains rather stable.

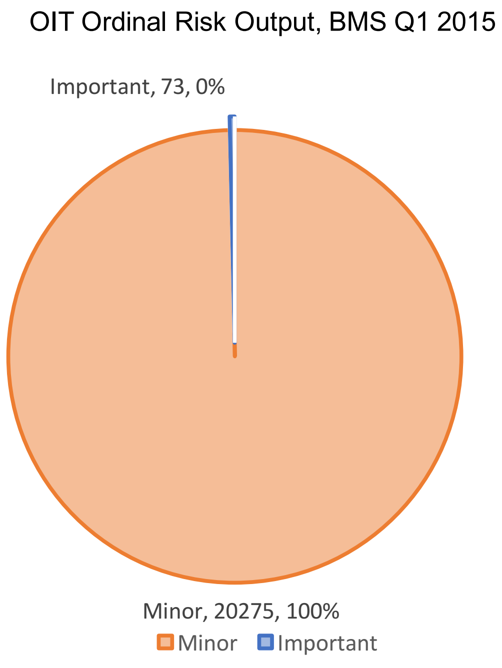


Figure 115 Building Management System Fuzzy Set Results Q1 2015, created by author

As a side analysis, the author will also inspect whether the components that have been identified as ‘minor’ risks by OIT are technically obsolete (i.e. have exceeded their last order date and therefore are not procurable). If there are components that fall into this category, then that would greatly affect the type of mitigation strategies possible for an Asset Management team. This is a potential weakness within OITs algorithm, however, the discussion section will shed more light on this insight.

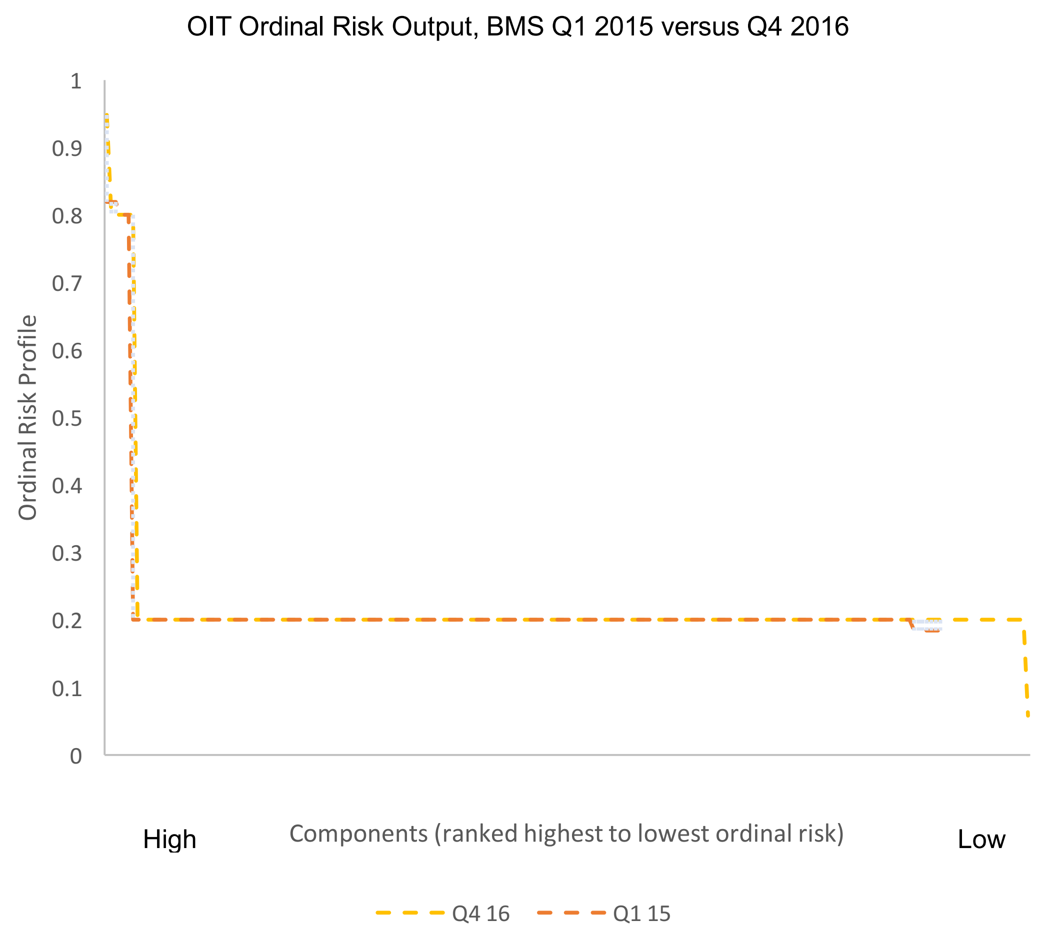


Figure 116 Building Management System Risk Comparison Results 2015 – 2016, created by author

Figure 116 contains the same plateau and spike as observed within the Q4 16 dataset, however with a slightly lower peak. The discussion section will also discover whether the components that were identified as 'Important' risks in Q1 2015 ('700VA UPS', 'Hi-Speed Trunk Isolator Extender', 'MBC24 Back Plate Assembly', 'PXC 100', 'PXC 16' and 'PXC 36') remained within the system until Q4 2016. It is likely, they did not and that in fact were upgraded/replaced via on the POs found within this section (see appendix 8.8). Between the two datasets, there has been a considerable growth in the number of components found within the BMS. This could be a result of several scenarios; system upgrades and compatibility changes, system size increase (unlikely) and or a diversification of components within the system. This section will also cover a polarised analysis on the two ends of the risk spectrum, to observe how components behaved and whether this can be connected to actions within the Asset Management team i.e. PO's. It is interesting to see that despite spending ~ £1.6 million, there are still components within the system that constitute an 'Important' risk; it will be interesting to get feedback on this point from the industry sponsor.

Previous figures had shown the SS to hold a diverse set of risk profiles in Q4 2016, which is consistent with how the case-study began as shown in Figure 117. In Q1 2015 OIT identified a significantly larger number of components as 'Moderate' risks, seeing a decrease in 'Minor', an increase in 'Low' but importantly an increase in 'Important' risks. In summary, the risks have slightly diversified, making it hard to intuitively deduce whether the risk for the system has increased or decreased. However, Figure 118 will clarify this position explicitly. Figure 118 is a perfect example of how one would iterate the development of OITs algorithm. Following this research project, it would be advisable to take a snapshot such as Q1 2015 and mine into which components have been assigned to each Fuzzy Set. Through reverse engineering the background behind each component, it would then be possible to amend the internal IF-THEN Rules. If for example, a set of components were identified that were either in a Fuzzy Set that was too high or low, along with the ordinal risk spectrum, then this could be amended by the rules. This iterative behaviour amends the sensitivity of the algorithm and further develops the accuracy of the expert model. A similar methodology as found within this research project would be advised using a diverse range of industry expertise.

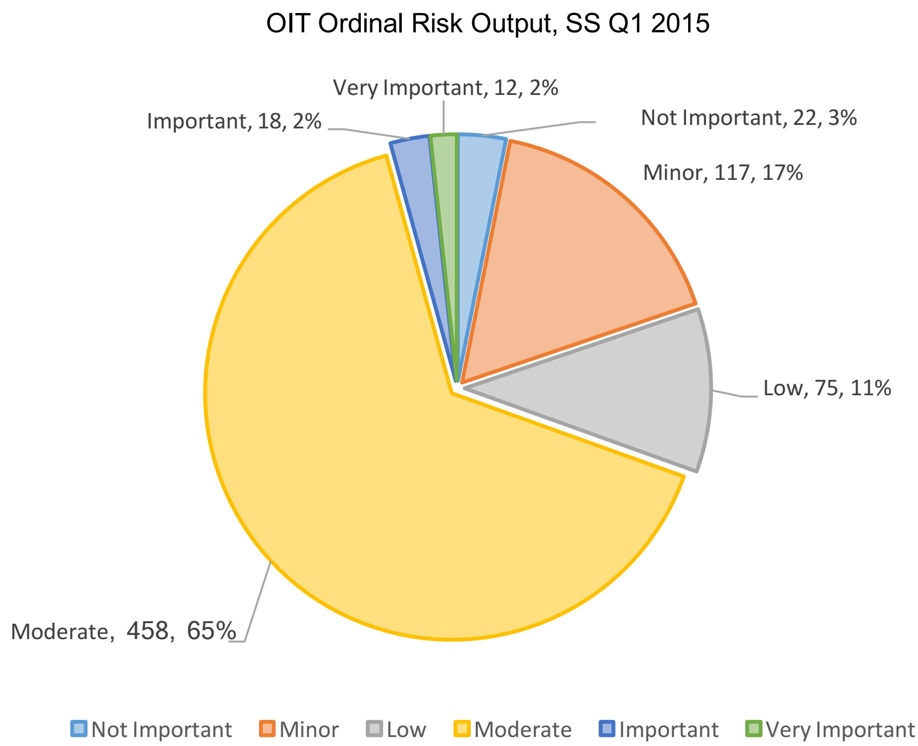


Figure 117 Security System Fuzzy Set Results Q1 2015, created by author

In order to allow the reader to quickly gauge the change of risk profile from the beginning to the end of the case-study, Figure 118 was created.

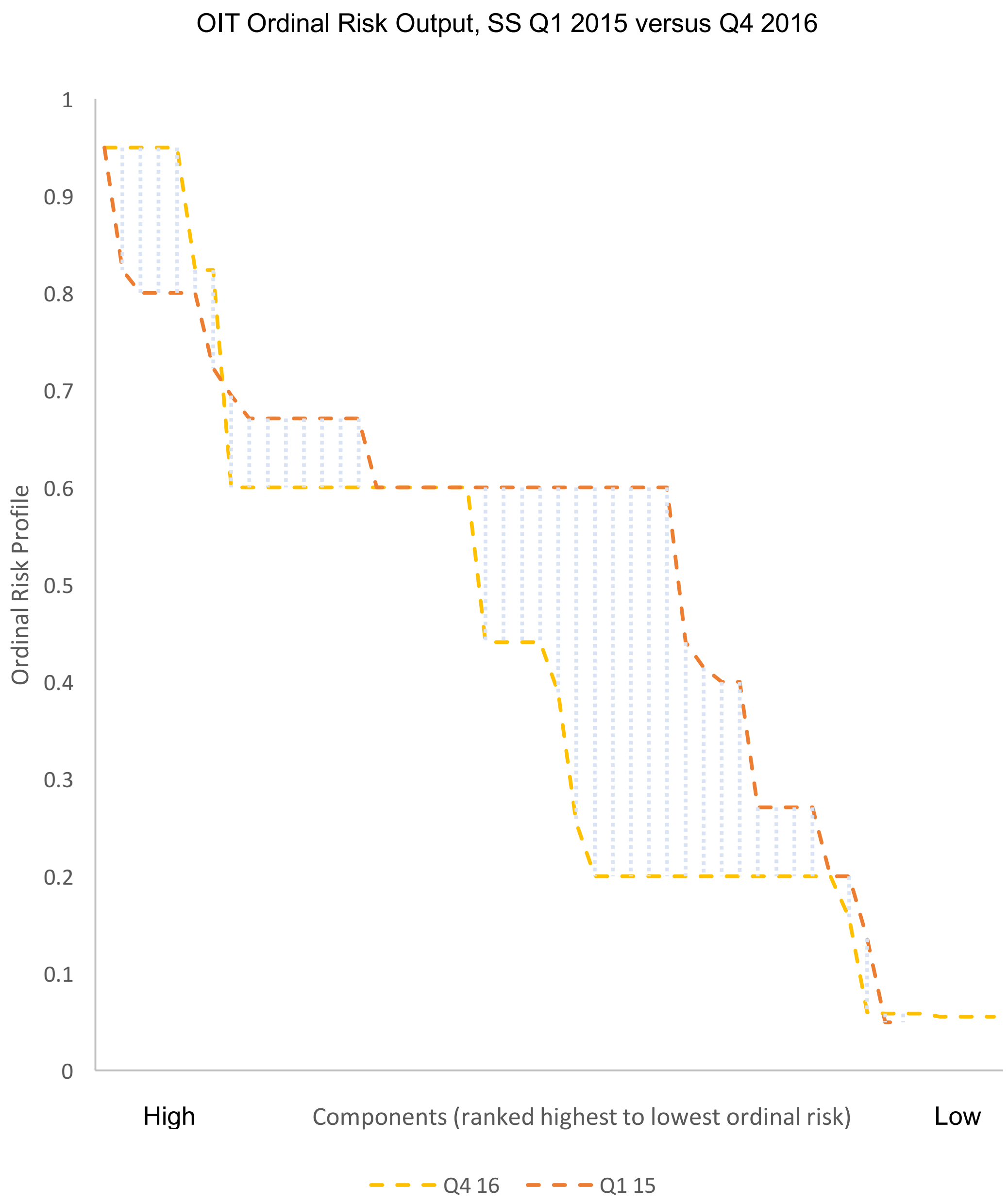


Figure 118 Security System Risk Comparison Results 2015 – 2016, created by author

OIT's algorithm indicates that there has been a reduction in the overall risk found within the SS between Q1 2015 and Q4 2016. This reduction is illustrated using 'high-low' lines between the two profiles. This is a key advantage of OIT as it allows an Asset Management team to explicitly demonstrate the effects of their decisions with regards to lifecycle expenditure and obsolescence.

As set out at the beginning of this subsection, the author will now present some component level results to investigate the behaviour of high and low-risk components from both systems. This mimic the expected behaviour of an Asset Management/Facilities Management team in response to the outputs of similar models to OAT and OIT.

Table 28 contains all of the components that at some point within the case-study fell into the 'Important' Fuzzy Set or above for the BMS. Their behaviour, regardless of Fuzzy Set, was then monitored throughout.

Table 28 Building Management System 'High Risk' Components, created by author

	Q1 15	Q2 15	Q3 15	Q4 15	Q1 16	Q2 16	Q3 16	Q4 16
700VA UPS	0.819	0.819	0.819	0.819	0.819	0.800	-	-
Hi-Speed Trunk Isolator Extender	0.819	0.819	0.800	0.819	0.819	0.800	0.800	0.800
MBC24 Back Plate Assembly	0.819	0.819	0.800	0.819	0.819	0.844	0.947	0.948
PXC 100	0.800	0.800	0.800	0.800	0.800	0.844	0.947	0.800
PXC 16	0.800	0.800	0.800	0.800	0.800	0.844	0.947	0.800
PXC 36	0.800	0.800	0.800	0.800	0.800	0.844	0.947	0.800
16 Digital Input Module	-	-	-	-	0.800	0.800	0.800	0.800
8 Digital Input Module	-	-	-	-	0.200	0.200	0.800	0.800

As displayed within Figure 119, some components remained an 'Important' risk throughout the case-study, more context behind why OIT's algorithm identified this can be found in the Discussion section. Otherwise, the other components interestingly did not exist within the system until Q4 2015 and quickly rose to become 'Important' risks to the system. The author speculates that this is possibly a result of purchasing components that were either already obsolete or had an impending EOL notification against them. This is typical of an unforeseen lifecycle investment. This contrasting set of behaviours can be observed in Figure 119.

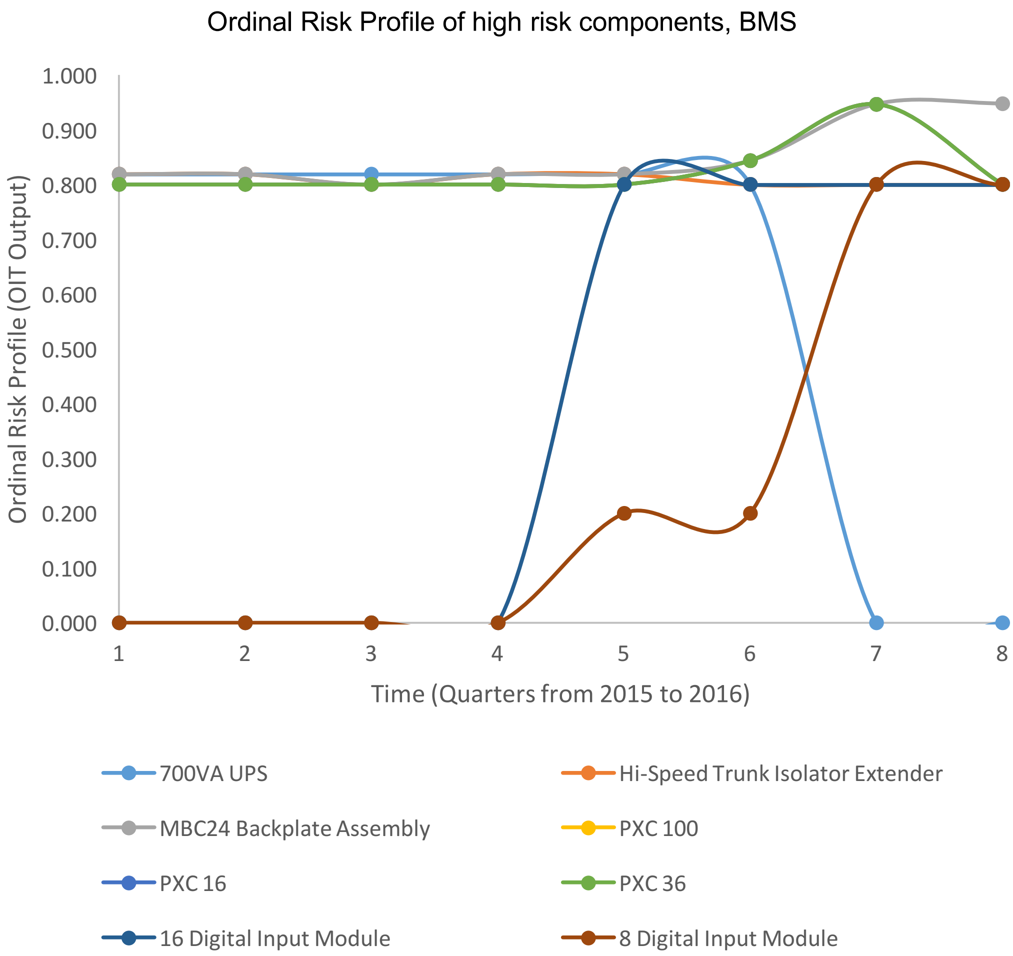


Figure 119 Building Management System 'High Risk' Components, created by author

In response to the findings within Figure 119, an Asset Management/Facilities Management team could investigate firstly why OIT identified the above components as 'Important' risks i.e. are they obsolete, high demand components, or highly critical?

Secondly, a review of current procurement processes could be called into question, when decision-makers see new components quickly rising into the 'Important' risk category. Both OAT and OIT are decision-aiding tools; it is precisely this type of output that gives decision-makers the data to make informed decisions.

Operationally an Asset Management team may only be concerned with the 'Important' risks or above, however, for the purpose of investigating results and generating a discussion, both ends of the spectrum will be assessed. Essentially, this will allow the author to reverse engineer the algorithm of OIT and illustrate why said components have been given the risk profile they have. This validates the logic behind the IF-THEN Rules of the expert model.

On a positive note, the number of components that fall into the lower end of the risk spectrum is shorter than those at the other end. However, this was to be expected after Figure 115 and Figure 116. The list shown in Table 29 consists predominantly of sensors, which are typically low-value items that are replaced regularly, which is reflected in both their criticality input and Stockout probability (see section 3.3.4.2).

Table 29 Building Management System 'Low Risk' Components, created by author

	Q1 15	Q2 15	Q3 15	Q4 15	Q1 16	Q2 16	Q3 16	Q4 16
Inverter 11kW G120P	0.184	0.189	0.200	0.200	0.200	0.200	0.200	0.200
Inverter 18.5kW G120P	0.184	0.189	0.200	0.200	0.200	0.200	0.200	0.200
Inverter 22kW G120P	0.184	0.189	0.200	0.200	0.200	0.200	0.200	0.200
Inverter 30kW G120P	0.184	0.189	0.200	0.200	0.200	0.200	0.200	0.200
Inverter 37kW G120P	0.184	0.189	0.200	0.200	0.200	0.200	0.200	0.200
Inverter 5.5kW G120P	0.184	0.189	0.200	0.200	0.200	0.200	0.200	0.200
Inverter 7.5kW G120P	0.184	0.189	0.200	0.200	0.200	0.200	0.200	0.200
Valve Actuator 24V 0-10V	0.200	0.200	0.138	0.200	0.200	0.200	0.200	0.200

Valve Actuator 24V 0-10V SR	0.200	0.200	0.138	0.200	0.200	0.200	0.200	0.200
Valve Actuator 24V 3 Point	0.200	0.200	0.138	0.200	0.200	0.200	0.200	0.200
Room Temperature Sensor	0.200	0.200	0.050	0.200	0.200	0.200	0.200	0.200
Temperature Sensor	0.200	0.200	0.050	0.200	0.200	0.200	0.200	0.200
Thyristor Controller	0.200	0.200	0.050	0.200	0.200	0.200	0.200	0.200
Strap On Temperature Sensor	0.200	0.200	0.050	0.200	0.200	0.200	0.200	0.200
Temperature Transmitter	0.200	0.200	0.050	0.200	0.200	0.200	0.200	0.200
Wind Speed & Direction Sensor	0.200	0.200	0.050	0.050	0.200	0.200	0.200	0.200
Volume Sensor	0.200	0.200	0.200	0.050	0.200	0.200	0.200	0.200
LTEC FCU Controller	0.200	0.200	0.200	0.200	0.200	0.059	0.059	0.059

Most of the components that were identified as ‘Not Important’ at some point within the case-study remained as either ‘Not Important’ or ‘Minor’, shown in Figure 120. It is an interesting insight that none of the components within Table 29 elevated at any point within the two-year period. In fact, several of them dropped and produced lower crisp ordinal risk values. These will be covered within the Discussion section.

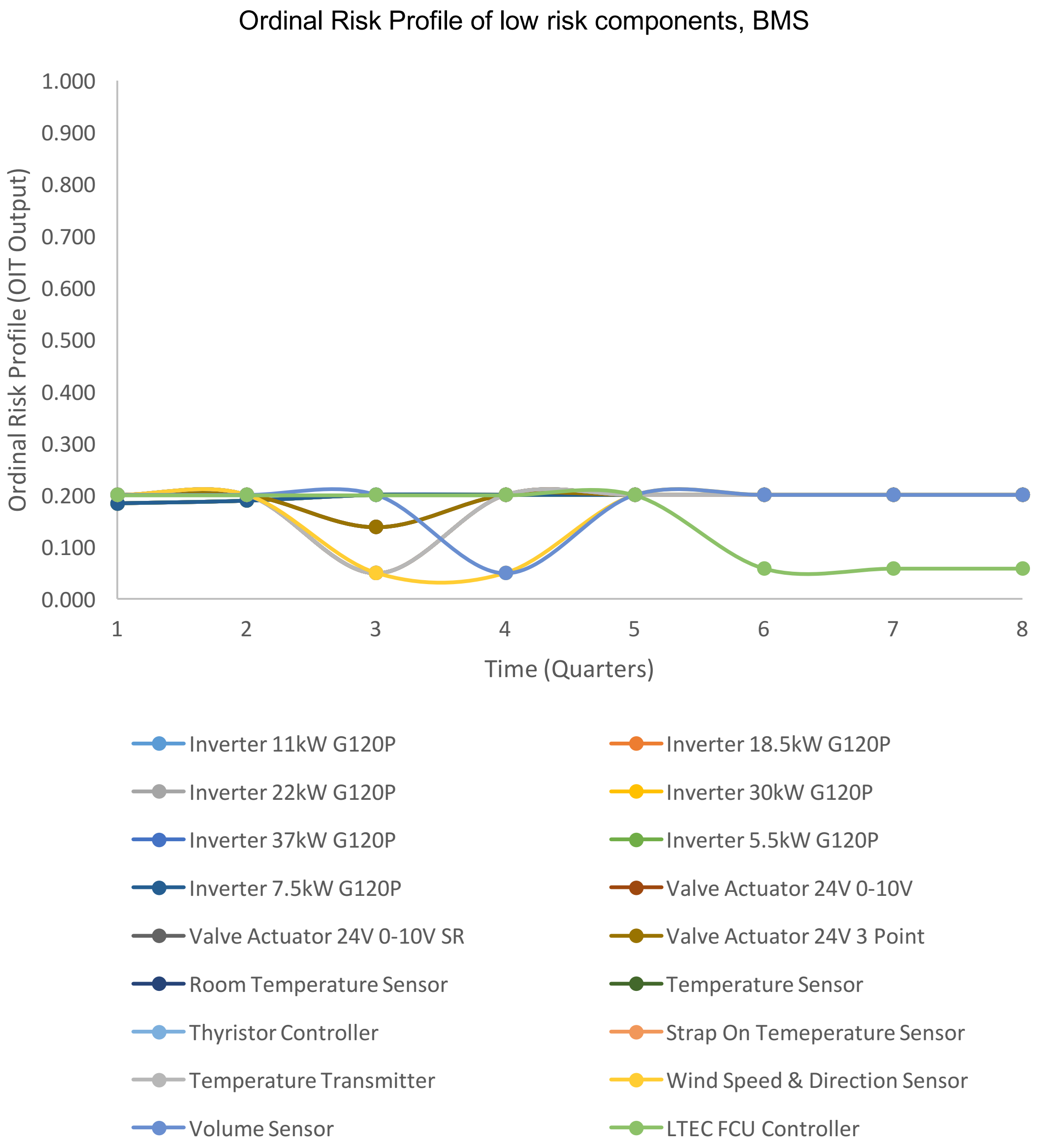


Figure 120 Building Management System ‘Low Risk’ Components, created by author

The BMS has seen the high-risk components remain in that category with little movement, including very new components to the system becoming immediate risks. Equally, the low-risk components remained within their respective categories with little movement, which is reflective of the risk profile shown in Figure 116, where the plateau of the risk profile appears to contain little change.

The same set of figures is now to be generated for the SS asset, investigating whether the high and low-risk components behaved in a similar fashion. Table 30 contains the components from within the SS that were categorised as 'Important' risks at any time and then their wider behaviour within the case-study. Firstly, although the SS is smaller in comparison to the BMS, in terms of component categories and component quantity, there are considerably more components that become an 'Important' risk to the SS, although this was first indicated by Figure 121.

Table 30 Security System 'High Risk' Components, created by author

	Q1 15	Q2 15	Q3 15	Q4 15	Q1 16	Q2 16	Q3 16	Q4 16
Synectics Net 16	0.800	0.950	0.950	0.950	0.950	0.800	0.950	0.950
Synectics Net 8	0.800	0.950	0.950	0.950	0.950	0.800	0.950	0.950
Synectics RS232	0.800	0.950	0.950	0.950	0.950	0.800	0.950	0.950
Synectics VDA's	0.950	0.950	0.950	0.950	0.950	0.950	0.950	0.950
Synectics Voll 8	0.800	0.950	0.950	0.950	0.950	0.800	0.950	0.950
TM Legic	0.600	0.824	0.824	0.824	0.824	0.671	0.824	0.824
Watermark Reader	0.671	0.824	0.824	0.824	0.824	0.671	0.824	0.824
Synectics Keyboard	0.600	0.600	0.800	0.600	0.600	0.600	0.819	0.600
Synectics matrix	0.600	0.600	0.800	0.600	0.600	0.600	0.819	0.600
synectics mini dc receiver	-	-	0.800	-	-	-	0.819	0.600
galaxy 520	-	-	-	-	-	-	0.759	0.441
C-Cure 9000	-	-	-	-	0.441	0.723	0.723	0.441
3 GS Europlex	0.671	0.747	0.747	0.747	0.747	0.747	-	-
Synectics remote matrix manager	-	-	0.800	-	-	-	-	-
JVC Monitors	0.824	0.200	0.200	0.200	0.200	0.200	0.200	0.200
C-Cure 800	0.723	0.441	0.441	0.441	-	-	-	-

Interestingly, the majority of the components within Table 30 remained an 'Important' risk throughout the case-study. However, most importantly, the succession of the Security Management Systems (C-Cure 800 to C-Cure 9000) is plainly apparent. Due to the number of components found within Table 30, the resultant figure was rather unclear for the reader. A select few components were then extracted to form Figure 121 to illustrate a set of scenarios that occurred within the dataset. More on the context of said components will be covered within the Discussion section.

Figure 121 illustrates several different pathways for components within the SS; the Synectics components VDAs and Voll 8s remained high 'Important' risks throughout. Whilst, the 3 GS Europlex alarm panel was an important risk until removed from the system in Q3 2016. Eloquently, the migration of the C-Cure Security Management System (SMS) is also captured within Figure 121 as the two curves intersect between Q4 2015 and Q1 2016. The SMS contains the highest criticality score within the system and will always, therefore, contain a reasonable risk profile.

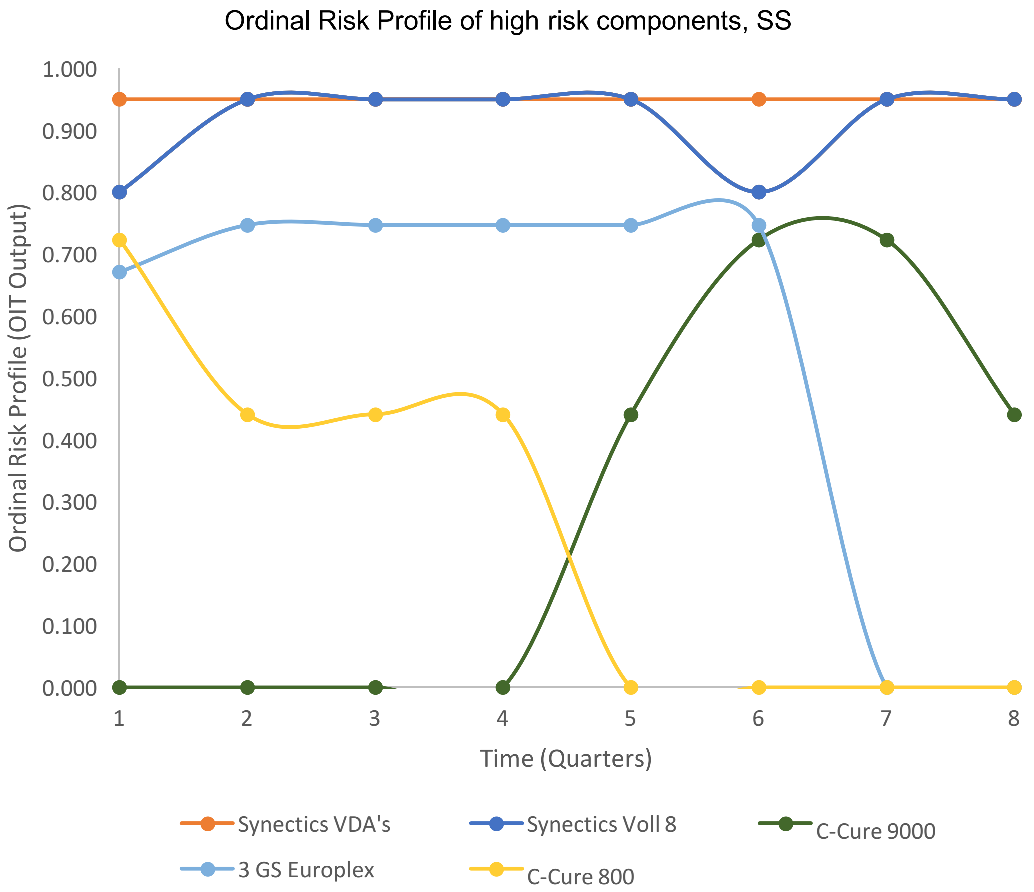


Figure 121 Security System 'High Risk' Components, created by author

The complexity represented in Figure 121 is a testament to the need for more data-driven decision-aiding tools, the above superseding of components and obsolescence risk posed by new products contain too many variables for an informal mental model to realistically comprehend. To ultimately utilise or maximise the economic life of an asset system within the Built Environment, then the above behavioural patterns must be brought to the attention of the Asset Management/Facilities Management team to undertake informed decisions.

Similar to the BMS, the low end of the risk spectrum was investigated for the SS to understand how components behaved and whether there are any comparisons to be drawn. Table 31 contains all of the components that ever held a ‘Not Important’ risk profile and their wider behaviour within the case-study. This list contains several cameras, monitors and some I/O devices. This is to be expected to their positions as peripheral items that are also very susceptible for direct replacements with alternative options.

Table 31 Security System 'Low Risk' Components, created by author

	Q1 15	Q2 15	Q3 15	Q4 15	Q1 16	Q2 16	Q3 16	Q4 16
Pelco Work Station	0.600	0.059	0.148	0.059	0.059	0.060	0.125	0.157
Bosch Monitor	0.600	0.060	0.060	0.060	0.060	0.060	0.057	0.060
External Bosch Cameras	0.415	0.059	0.059	0.059	0.059	0.199	0.200	0.059
Scantronic 160 Control Panel	0.050	0.059	0.059	0.059	0.059	0.056	0.056	0.059
Scantronic Keypad	0.050	0.059	0.059	0.059	0.059	0.056	0.056	0.059
internal Panasonic camera	-	0.271	-	-	0.200	0.056	0.200	0.056
Mic 500 Series	0.271	0.059	0.059	0.059	0.058	0.056	0.058	0.056
Pelco domes Camera	0.271	0.059	0.059	0.059	0.058	0.056	0.058	0.056
Pelco domes Camera	0.271	0.059	0.059	0.059	0.058	0.056	0.056	0.056
I Star Edge	0.200	0.200	0.200	0.200	0.145	0.136	0.200	0.200
I Star Pro	0.200	0.200	0.200	0.200	0.145	0.136	0.200	0.200
I Star Ultra	-	0.200	0.200	-	0.136	0.136	0.200	0.200
Intercoms system	0.600	0.200	-	-	0.343	0.136	0.462	0.200
PTZ Motor	0.671	0.200	0.200	0.200	0.200	0.056	0.200	0.200
Pelco NVR	0.136	0.136	0.242	0.136	0.140	0.201	0.212	0.255
Genie VDA's	-	-	0.051	-	-	-	-	-

The total number of component categories within Table 31 is large, therefore the resultant figure was difficult to interpret. A select number of components have been extracted to form Figure 122, these components display a range of behaviours found within the dataset. The

‘Pelco Work Station’, ‘Pelco NVR’ and ‘Intercoms system’ all showed signs of growing risk profiles and were selected for further analysis. The Discussion section will investigate what caused OIT’s algorithm to output this growth i.e. approaching an EOL notification. However, similar to the BMS it is interesting to note that none of the components elevated themselves into anything above a ‘Minor’ risk to the system. Is this an indication that if a system received a low all round risk profile from OIT it would retain that resilience for a guaranteed time frame?

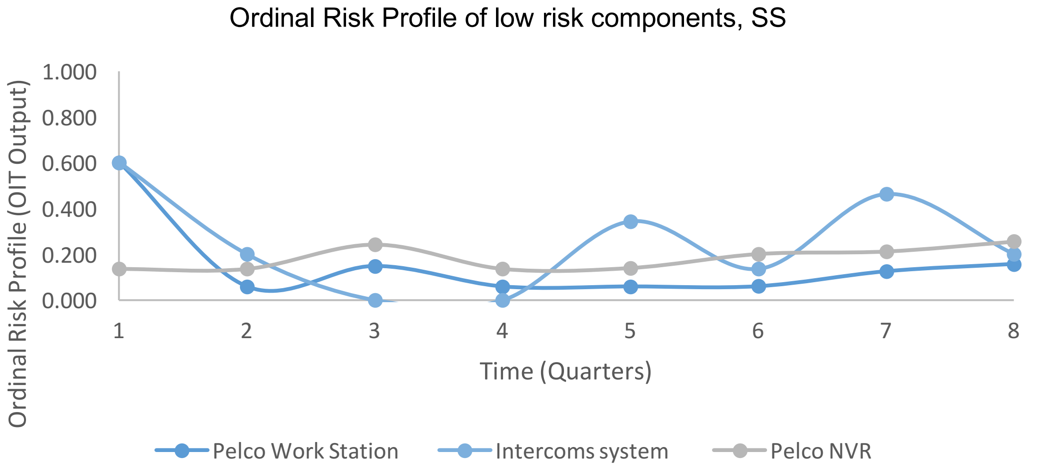


Figure 122 Security System 'Low Risk' Components, created by author

In time period 1 note the elevated risk profiles have been classed as anomalies and a result of implementing a new process for the sub-contractor. It is speculated that this may have caused some minor errors within the Q1 2015 data set, leading to high-risk profiles by OIT. Although at this stage, it is just a speculation.

This subsection has demonstrated the uses of an obsolescence risk assessment technique and illustrated the range of insights it can give to an Asset Management/Facilities Management team. All of the figures featured herein would contribute directly into an OMP, enabling data-driven decision-making. The remainder of the subsection will now portray how the risk profiles for both asset systems changed throughout the entire case study, showing the historical context. This type of insight is unique to a case-study methodology; allowing decision-makers to retrospectively appraise how their investment decisions have affected the two models (OAT and OIT). This feedback loop is an important learning process both in terms of modelling and future iterations, but also as decision-makers looking to better understand the potential applications of said models. Figure 123 summarises the changes within the BMS throughout the case study, demonstrating the relatively small changes in the ordinal risk profiles and expanding Asset register.

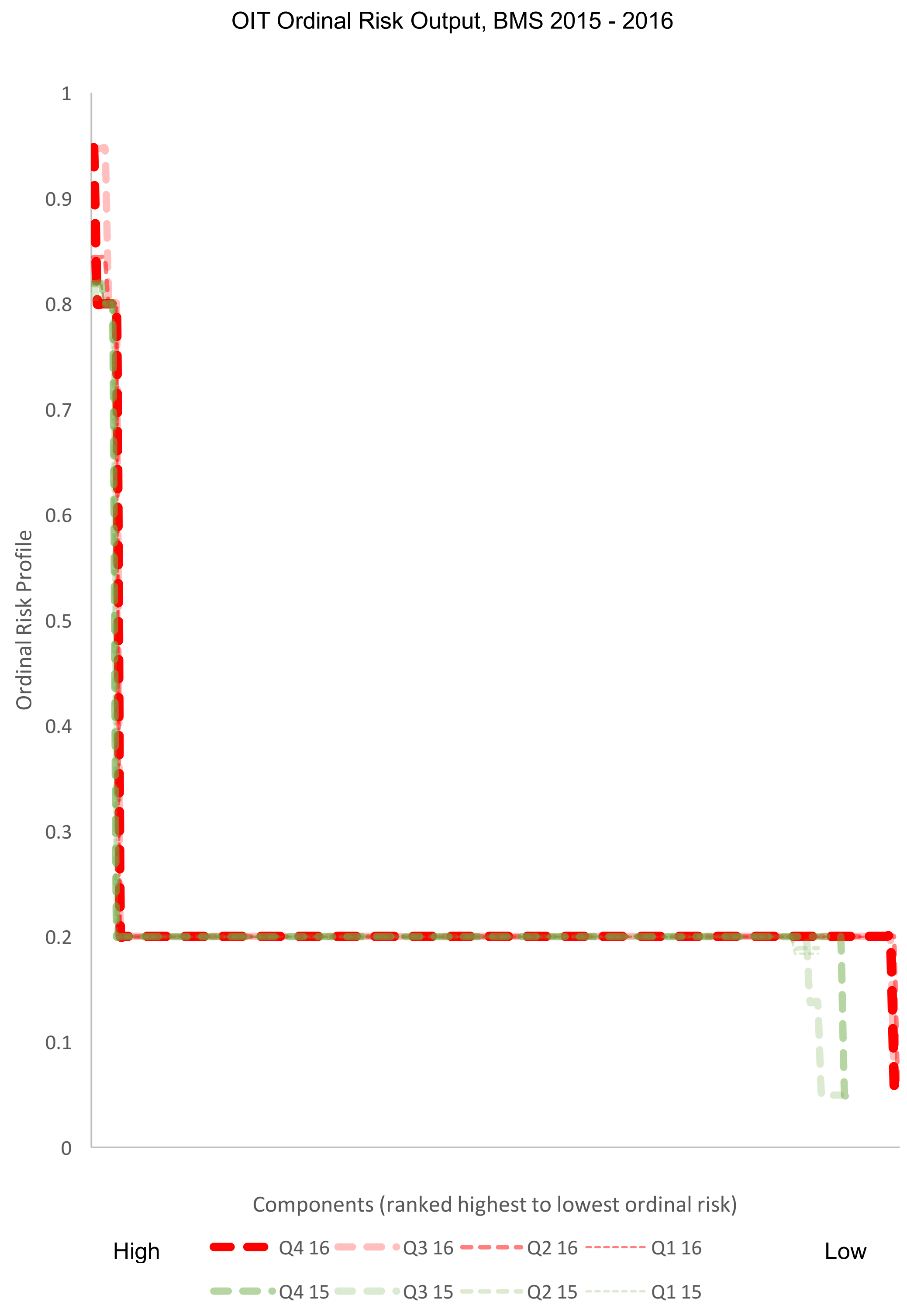


Figure 123 Building Management System Risk Summary Graphic 2015 - 2016, created by author

In contrast, the SS showed a constantly changing risk profile as illustrated in Figure 124. In the disparity between the years 2015 and 2016 are reflected within the green and red plots, it is plain to see the changing, slight reduction of the overall risk profile by area and overall number of components.

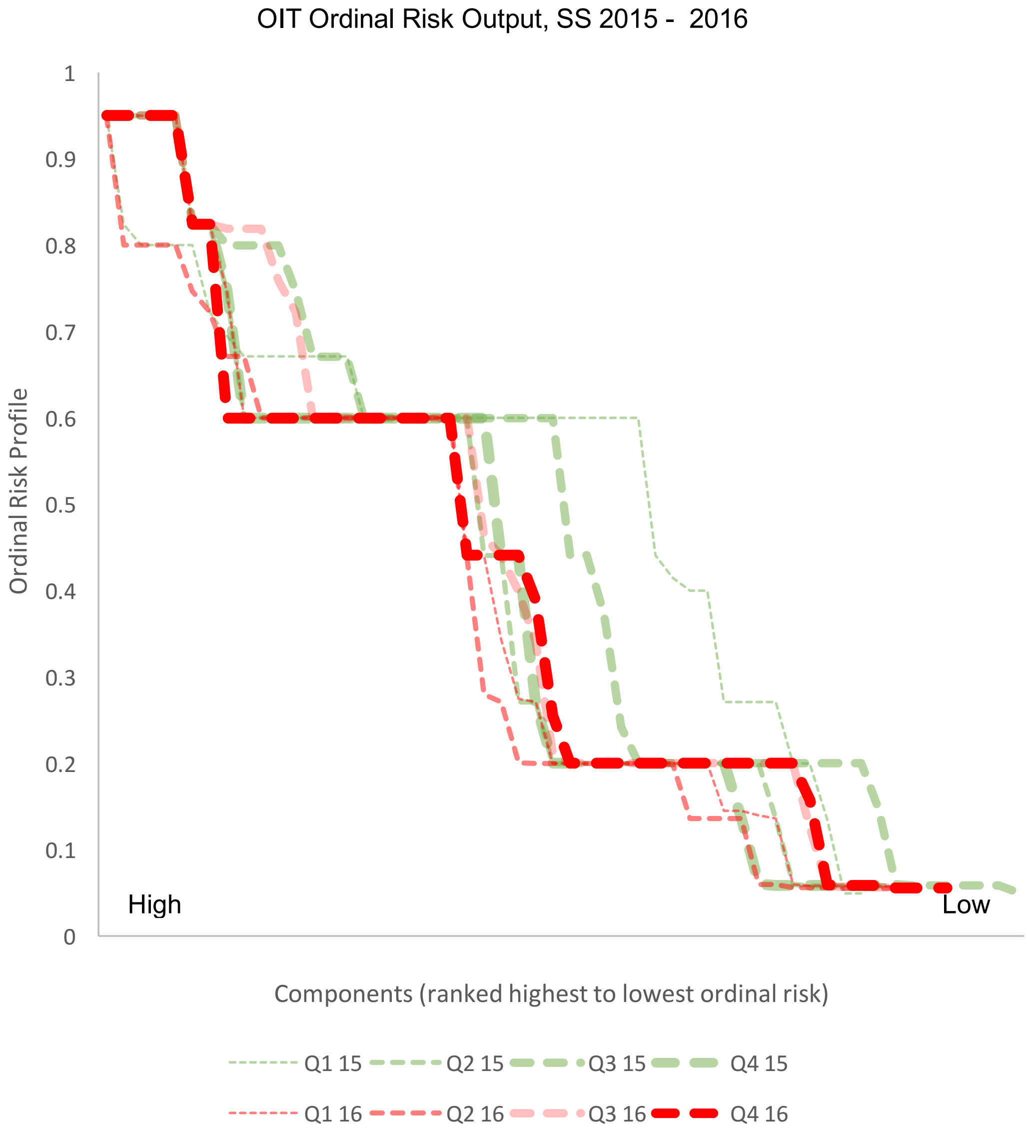


Figure 124 Security System Risk Summary Graphic 2015 - 2016, created by author

The Discussion section of this thesis will cover in more detail via a cross analysis, how the changing risk profile reflects the changing inputs into OIT's algorithm and then against the POs made within the same time frame. This subsection has comprehensively given the reader a sample of the range of insights provided by OIT, demonstrating conceptual examples of how it could be applied in industry. The two asset systems behaved very differently, illustrating how these contrasting sets of data are captured, interpreted and then illustrated to the user.

Next, the results from the reverse engineering of the sales catalogues will be presented to the reader with some brief analysis to provide some context. The impact of said results upon both the research aims of this thesis and the wider literature landscape will be covered within the Discussion section.

4.4 Sales Data Analysis

The purpose of analysing the sales catalogues is to demonstrate how an end-user can reverse engineer readily available datasets into tangible inputs for an OMP. The results displayed herein have direct benefits for both *Building A* firstly, but also any other users of a similar BMS across the Built Environment. The analysis here would exist in parallel to the outputs of OAT and OIT, enabling the Asset Management/Facilities Management team to make an informed strategy. Figure 125 has been repeated for the reader, to signpost where this section of Results sits within the wider outputs of this thesis.

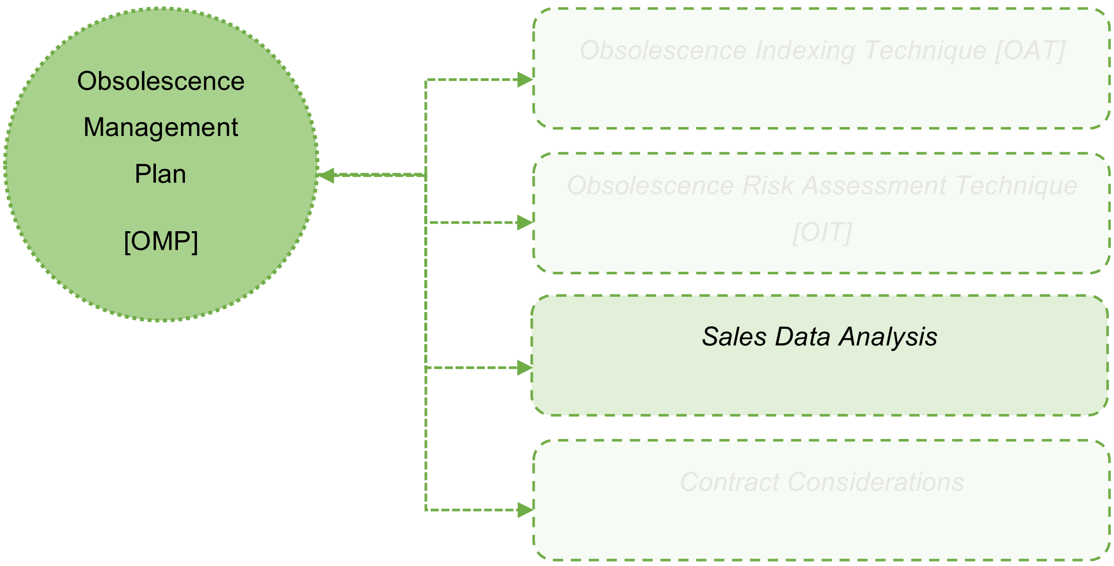


Figure 125 Results Framework, created by author

The structure of the Results will be set out as follows:

- Probability Density Functions.
- Unit Cost Fluctuations.
- Sales Strategy Identification.

All three bullet points are significant pieces of evidence that give direct insight into how one should build an OMP for this specific asset. Firstly, the probability density functions will enable the user to ascertain whether the components they rely upon will be statistically available from the OEM for the foreseeable intended supportable life. Secondly, the unit cost fluctuations will enable a CBA to consider not only when will a product cease to be available, but what is the likely range of price increase in the penultimate years. Finally, identification of a sales strategy being present from an OEM is useful, especially when the cycle of obsolete components is used to forecast or foresee where obsolescence is likely to pose a risk in the future.

SIEMENS plc provides many of the components for the BMS that features within this thesis and are a renowned global provider. Annual Controls Products and Systems (CPS) price lists are provided to customers to observe two important things; are components still procurable i.e. feature on this list and what is the unit price i.e. has it risen or fallen. In the context of this thesis research area, both of the above are insightful pieces of information that are to be investigated herein.

Aim (3) of this thesis is to provide 'Visual evidence of product obsolescence and the effect on component cost'. The first step involved the combining of all CPS sheets into a master sheet, this can be found in appendix 8.9. The master sheet indicates when a component became available, its unit price and naturally when it ceased to be available. The CPS sheets date from 2006 to 2015 and contained over 19,000 individual components and unit prices, a significant amount of data to analyse. Some of the sheets did not contain unit prices but rather were denoted with TBC, which is inherent with gathering data in the field and remained insignificant.

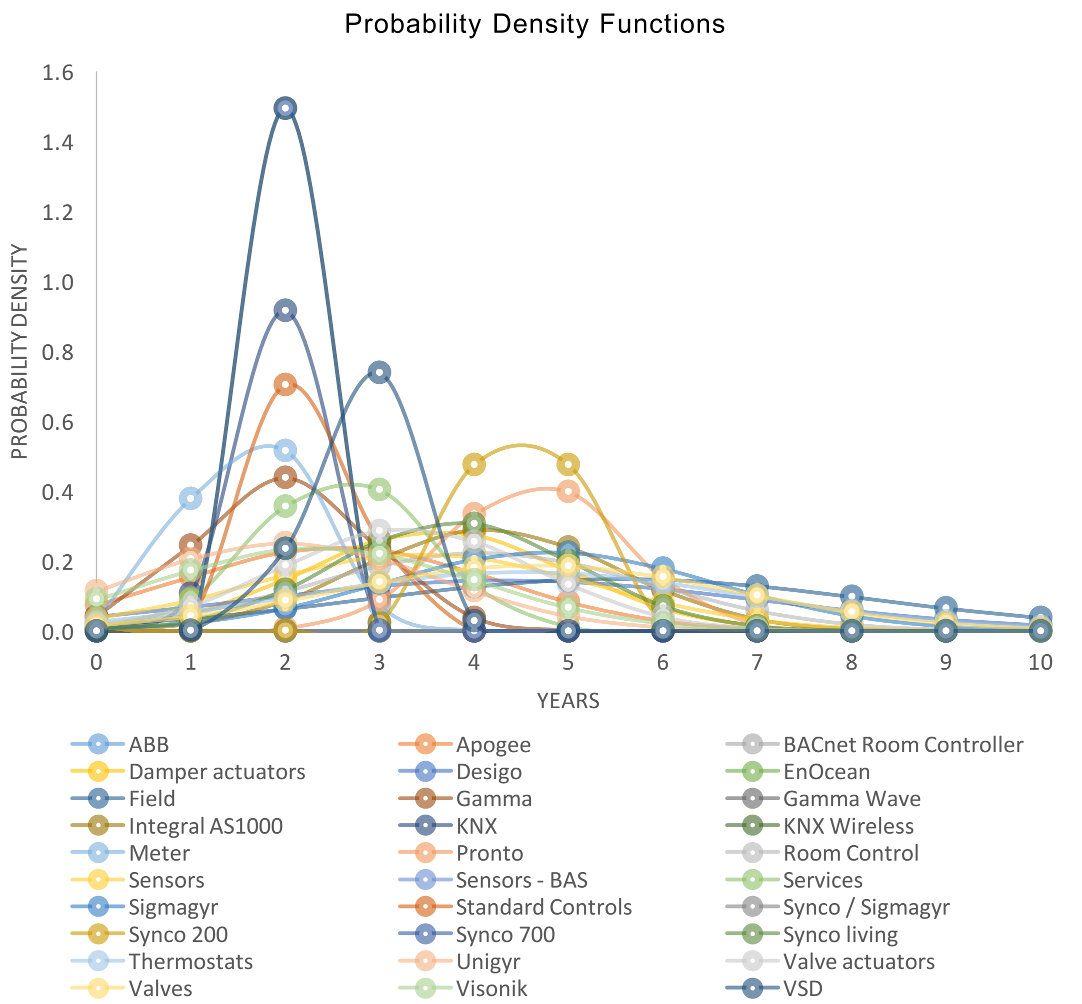


Figure 126 Probability Functions for all OEM components, created by author

The CPS sheets also contain product groups, meaning that analysis could be categorised transcending individual components and therefore retain context over time. The categories allowed for Probability Density Functions to be generated and plotted. The profiles shown in Figure 126 would allow a BMS owner to better project how long components will resist obsolescence typically. Note, this is not mechanical life but how long SIEMENS support components directly. To see further into the data and identify which components fall into the categories used here, please see the Master Sheet in appendix 8.9.

A quick top level assessment would identify the short time period all components are available on the market when compared with the intended operational life of a BMS (20+ years). Table 32 is a pivot table from the Master Sheet (see appendix 8.9) and was used to produce Figure 126. The same dataset was then mined again to split into long and medium life components to observe which components fell into each subcategory.

Table 32 Pivot Table from OEM Sales Catalogue Dataset, created by author

Row Labels	Average of Life (years)	Max of Life (years)	Min of Life (years)	StdDev of Life (years)	Count of Life (years)
ABB	1.000	1.000	1.000	0.000	38.000
Apogee	2.564	8.000	1.000	1.672	1761.000
BACnet Room Controller	2.000	4.000	1.000	1.069	8.000
Damper actuators	3.600	5.000	1.000	1.392	20.000
Desigo	4.326	9.000	1.000	2.732	350.000
EnOcean	3.000	3.000	3.000	0.000	4.000
Field	5.530	9.000	1.000	2.687	215.000
Gamma	1.986	4.000	1.000	0.912	495.000
Gamma Wave	1.000	1.000	1.000	n/a	1.000
Integral AS1000	4.143	5.000	1.000	1.377	98.000
KNX	1.868	3.000	1.000	0.414	38.000
KNX Wireless	1.933	2.000	1.000	0.258	15.000
Meter	1.638	4.000	1.000	0.667	58.000
Pronto	4.654	6.000	1.000	0.936	26.000
Room Control	4.077	6.000	1.000	1.787	26.000
Sensors	3.449	7.000	1.000	1.818	147.000
Sensors - BAS	1.000	1.000	1.000	n/a	1.000
Services	2.600	3.000	1.000	0.894	5.000
Sigmagyr	4.786	7.000	3.000	1.762	14.000
Standard Controls	2.250	3.000	2.000	0.500	4.000
Synco / Sigmagyr	4.000	4.000	4.000	n/a	1.000
Synco 200	4.500	5.000	4.000	0.577	4.000
Synco 700	1.933	2.000	1.000	0.258	15.000
Synco living	3.792	5.000	1.000	1.285	24.000

Thermostats	4.515	7.000	1.000	2.362	66.000
Unigyr	2.000	7.000	1.000	1.590	35.000
Valve actuators	3.292	7.000	1.000	1.361	113.000
Valves	4.649	7.000	1.000	2.116	373.000
Visonik	2.337	7.000	1.000	1.668	205.000
VSD	2.760	3.000	1.000	0.476	50.000

The majority of components had an average lifespan of fewer than 3.5 years and feature within Figure 127. It is precisely the short lifecycles being observed within the below figure that drives the need for end-users to adopt proactive obsolescence management methods. Even if you installed a new BMS with equally new components, you will inherit obsolescence within the systems inside the first half decade. Of course, if said components do not fail mechanically, then this risk is not realised, but rather lies dormant.

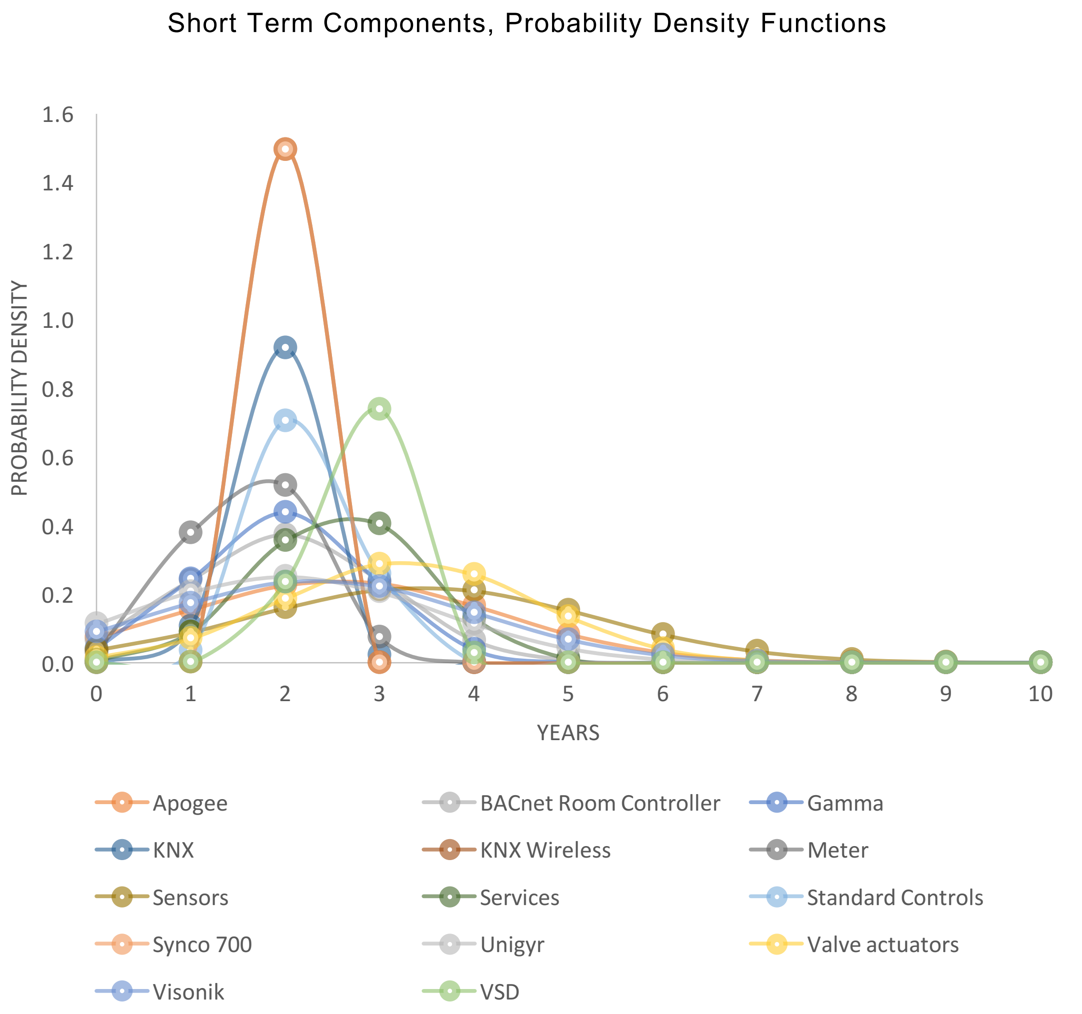


Figure 127 Probability Density Functions for Short Term OEM Components, created by author

Figure 128 contains the remaining components that had an average lifespan of more than 3.5 years. There is considerable spread in the distributions, showing that whilst the majority of components within these categories have a medium lifespan on the market, some are brief (<4 years) and some are long term (6< years). The noticeable difference in standard deviation is represented in the contrasting heights of the Probability Density Functions, both the x and y-axis have remained constant for this reason (Figure 127 and Figure 128).

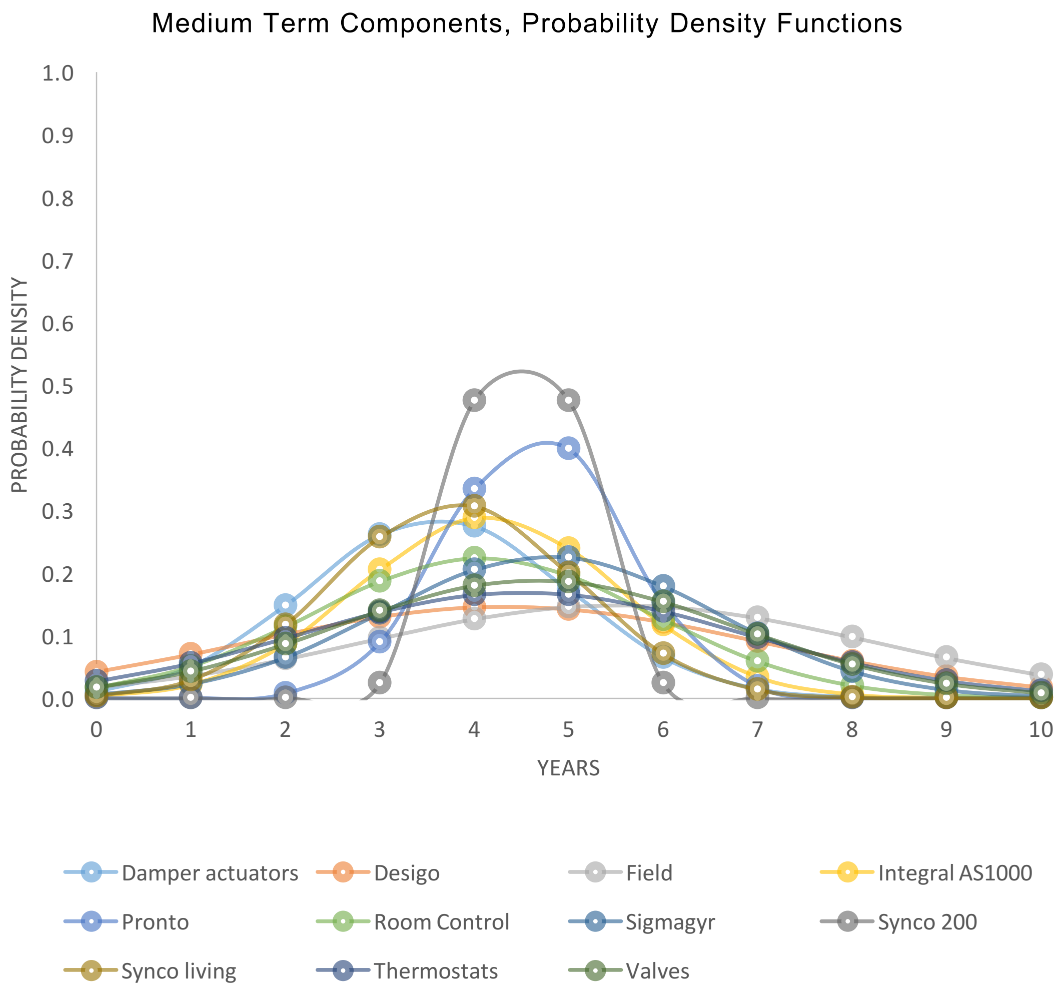


Figure 128 Probability Density Functions for Medium Term OEM Components, created by author

The visuals provided within this section illustrate in a new level of detail just how obsolescence occurs within the marketplace and the timescales associated with them. The Probability Density Functions found within this thesis have industrial application to both Facility Managers and Asset Managers who may possess some of the above components on their site. The next step with this dataset is to investigate the effect of the above obsolescence upon the unit price.

The dataset starts in 2006. There is a list of components that either were released in 2006 or pre-existed this date, many of these continued to be sold up until the end of the dataset (2015). These components represent the longest life found within the data and were extracted to observe how their unit price changed over time. Figure 129 contains the normalised price fluctuations of said components, ultimately, there are some price fluctuations but there is a general slight increase prior to becoming obsolete. This better represents how the general unit price changed. Note that a range of 30% to 60% was observed on the original unit price, a significant cost incurred if you wished to reactively undertake a 'lifetime buy' as a mitigation method. This shows that there is a premium upon proactive obsolescence management methods.

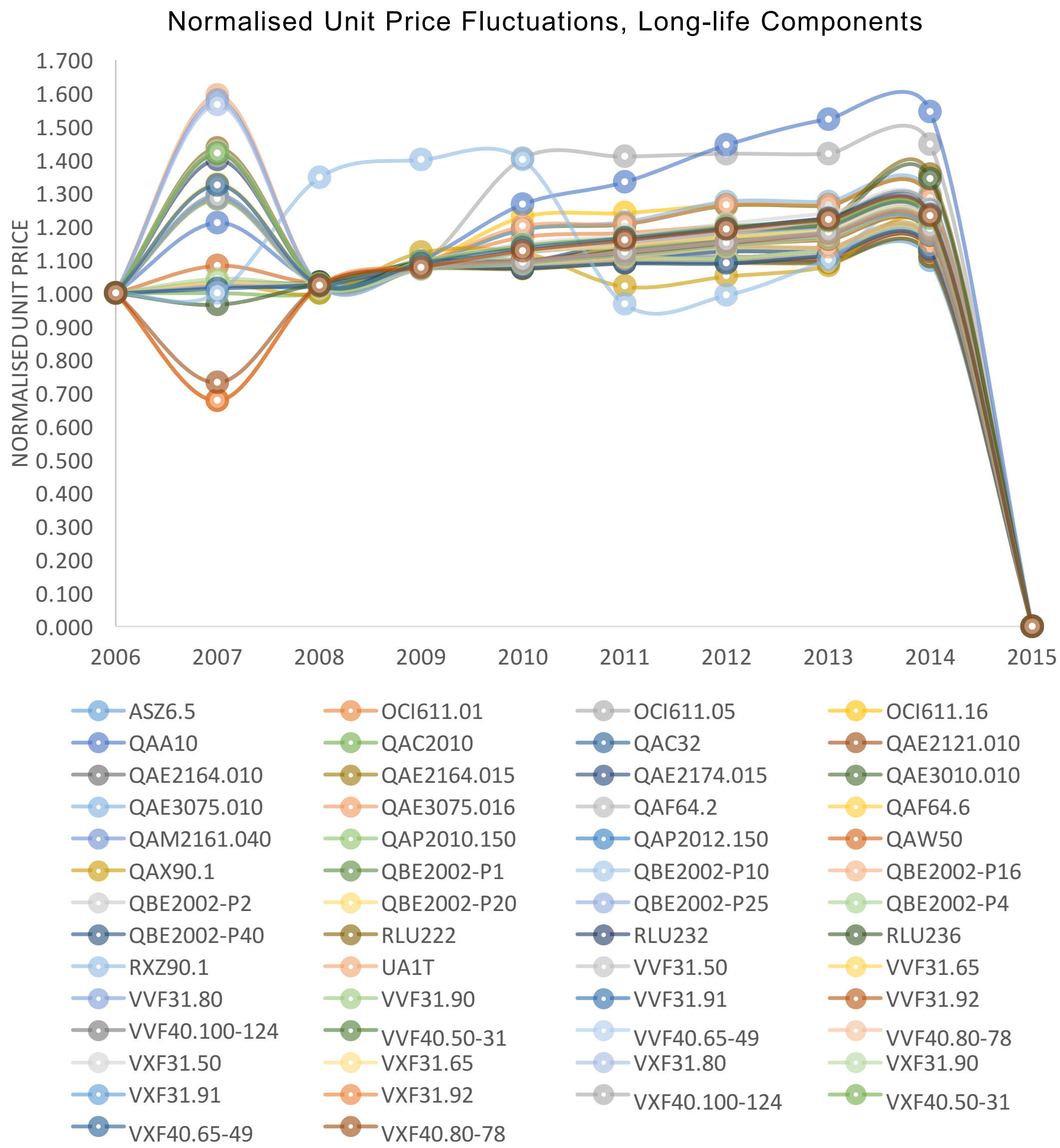


Figure 129 Normalised Unit Price of 'Long-life' OEM Components, created by author

Figure 129 demonstrates some significant fluctuations in 2007, during the same period as the global financial crisis. It is unclear whether the two are linked; however, this fluctuation aside, all of the components experience a gradual rise as they approach obsolescence. Specifically, what is unclear is whether SIEMENS were preparing to deem said components obsolete, or whether their sudden cease in existence within the catalogues was a result of buyer power.

To ensure that the components that feature within Figure 129 are not biased, it was decided that the same analysis would be applied to components that did not exist in 2006, but rather were introduced in 2007 and then ceased in 2015. The following dataset, therefore, captured their entire lifecycle within the market. On the surface, Figure 130 would appear to behave in a very similar fashion to the components found in Figure 129. However, the growth of price prior to obsolescence is far more significant and ranges from 50% to 100%; a range that is twice that found in Figure 129. This can be explained by the lack of starting unit prices for the items that pre-existed 2006.

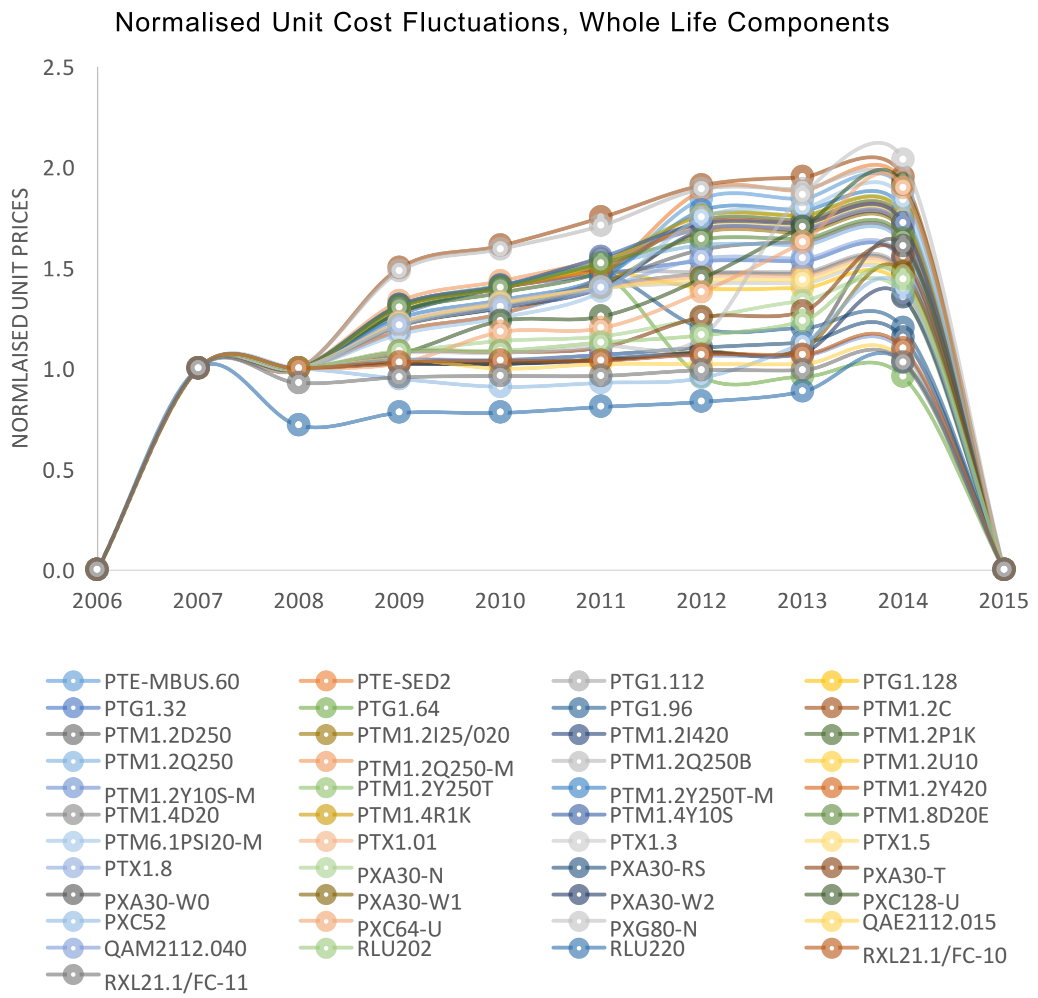


Figure 130 Normalised Unit Price of 'Whole Life' OEM Components, created by author

Note that Figure 130 had some outliers removed. VKF46.350TS, VKF46.400TS, VKF46.450TS, VKF46.500TS and VKF46.600TS are all rotary valves sold by SIEMENS, but had some missing unit prices and therefore were being skewed by the normalising process, reflected by very extreme resultant values. Figure 131 is a very important contribution to new knowledge as it explicitly details a trend as a result of obsolescence that previously had no supportive evidence. This trend has been commonly assumed within the industry, however, does not feature within any publically published literature. The rising cost throughout the time period a component is available via the OEM, along with the price spike in the penultimate year are results of an underlying sales strategy.

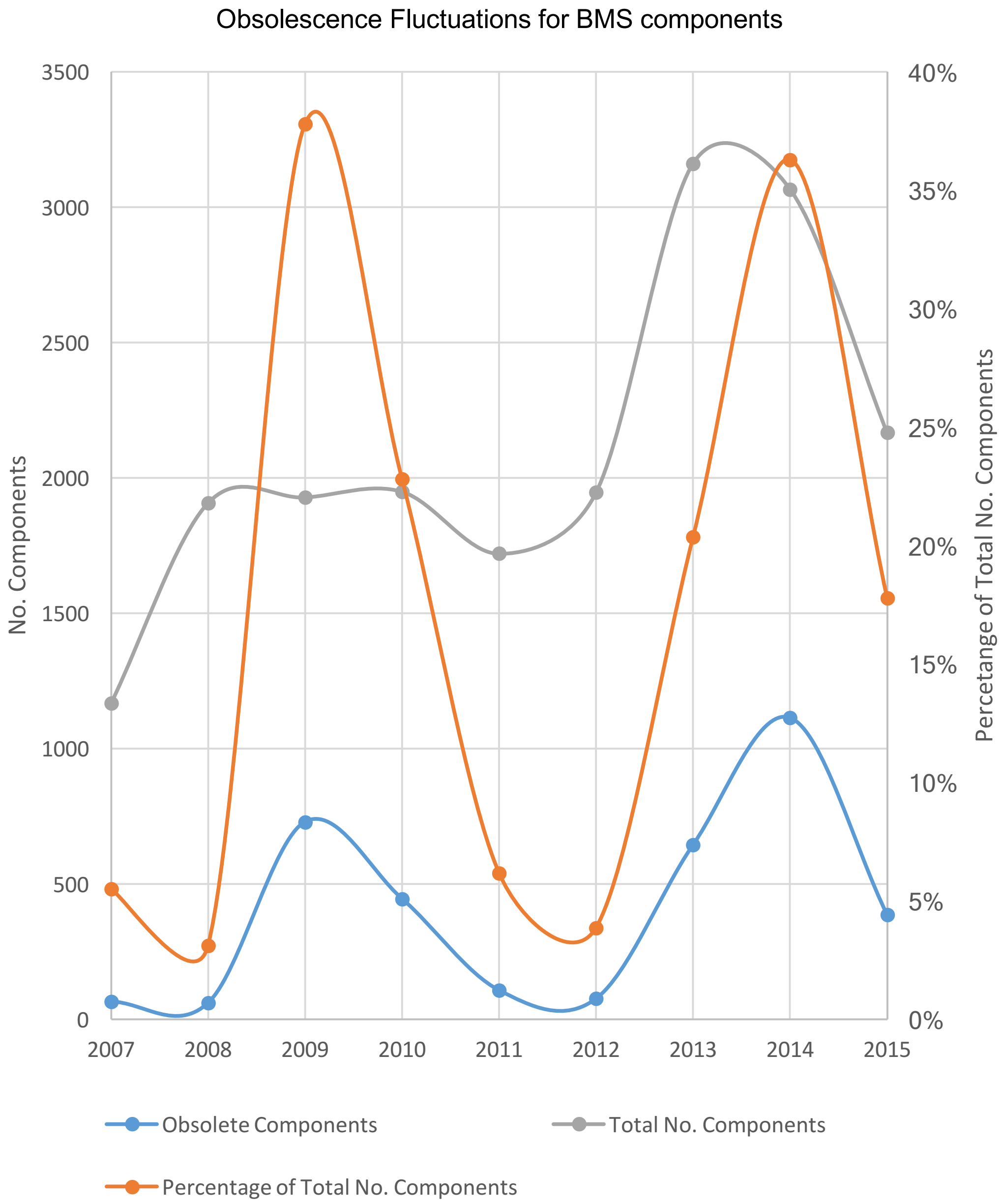


Figure 131 OEM Sales Strategy and Obsolescence, created by author

Figure 131 has been created to represent all components found within the CPS's. Interestingly, whilst the total number of components provided by SIEMENS has increased as of 2012, the ratio of said total that becomes obsolete annually continues to follow the same symmetrical pattern. Such symmetry within the data suggests there is a system in place to consistently produce this behaviour. One would speculate a sales strategy, whilst deeming products obsolete is entirely the prerogative of SIEMENS; understanding this pattern and how it will affect the system you have installed on-site is powerful. Wider information, such as the above will further support Obsolescence Management practices and enable proactive strategies. However, if the speculation is correct and there is an underlying sales strategy, then the observed unit price increases will be homogenous across all components. Adding further evidence and support for the need of proactive obsolescence management measures to avoid these premiums.

This section has uncovered trends that are not found within the existing literature landscape. The sales data analysis was provided several key pieces of evidence that not only would feed into the OMP for *Building A*, but can be directly extracted and used by other decision-makers from the Built Environment. Such analysis was not possible for the SS as they did not provide annual catalogues, however, this type of methodology – reverse engineering catalogues, could be simply adapted for other systems within the Built Environment.

Importantly, aim (3) of this thesis has now been completed and there is significant evidence here to display how obsolescence occurs and the likely cost of mitigating reactively. This analysis also provided insight into how obsolescence is forced upon an end-user and its possible resultant behaviour, stemming from underlying sales strategies.

The next and final subsection of the Results chapter will use the output from OIT to generate a hypothetical required spares list, which in turn will be used to generate a quotation as if the information found here was to be applied within the industry. The resultant cost of the quotation is to then be cross-analysed with the known penalty deductions for asset unavailability within *Building A*, which is something that is applicable to PFI contracts typically. The aim of the following section is to visualise to the reader the informal decision-making that occurs when deciding to invest into the resilience of a system with respect to obsolescence.

4.5 Resilience Trade-Off

The purpose of the resilience trade-off results is to hypothetically use some of the results found in this thesis to model the informal decision-making process undertaken within *Building A*. Currently, governed by industry standards, there are no guidelines to how one should implement an OMP, what data to consider and how to collect said data. This final subsection will create conceptual spare parts requirements list, identified by OIT, using real unit cost values to generate a quotation. This value will be cross analysed against the internal penalty mechanisms found within *Building A's* PFI contract, to illustrate a 'trade-off' point. The lead times for the requirement list and this trade-off point will conceptually indicate where the financial incentives lie, if at all. The below figure has been repeated for the reader, to help illustrate where this subsection sits within the wider Results produced by this thesis.

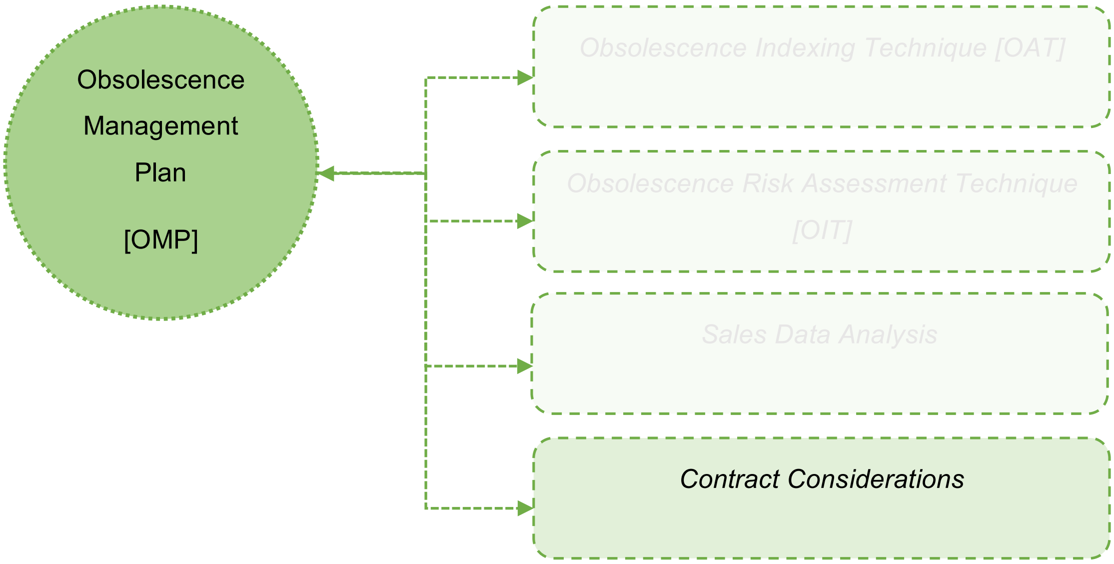


Figure 132 Results Framework, created by author

Aim (4) of this thesis was created as a peripheral exercise to simplistically illustrate the type of informal decision-making that takes place within the industry. The outputs of the models found in this thesis would allow the user to generate a cost-benefit analysis (CBA) of a range of mitigation approaches for obsolescence. Whilst the generation of a CBA is not within the scope of this thesis, it was agreed that a visualisation of the financial trade-off experienced within the context of PFI contracts would neatly illustrate the future path of obsolescence research. In order to undertake this exercise, high-risk components (from OIT Results) for the BMS were extracted to produce Table 33. SSE Ltd was contacted along with the 2015 OEM sales catalogues to compile a list of unit prices for the required components. Table 33 was then filtered for components that were already held on-site in spares, found in Table 34, and coloured green.

Table 33 Building Management System 'High Risk' Components, created by author

Part Name	Part Function	Part REF#	Part Description	No. Parts	Quotation Size
Fibre Optic Hub	Panel Equipment	LD-64	Field Device	10	1
Hi Temp Immersion Thermostat	Field Equipment	WT2254	Field Device	6	1
I/O AI Module For MBC	Panel Equipment	PTM6.2U10	BMS Controller	45	n/a
I/O AI Module For MBC	Panel Equipment	PTM6.2R1K	BMS Controller	96	n/a
I/O AI Module For MBC	Panel Equipment	PTM6.2I420	BMS Controller	6	n/a
I/O AO Module For MBC	Panel Equipment	PTM6.2Y10S-M	BMS Controller	65	n/a
I/O DI Module For MBC	Panel Equipment	PTM6.4D20	BMS Controller	186	n/a
I/O DO Module For MBC	Panel Equipment	PTM6.2Q250-M	BMS Controller	198	n/a
I/O Expansion Module For MBC	Panel Equipment	PTM6.EMK	BMS Controller	21	n/a
I/O Pulse Count Module For MBC	Panel Equipment	PTM6.2C	BMS Controller	23	n/a
Interface for McQuay Chiller	Panel Equipment	US-565359	BMS Controller	2	1
Interface for MODBUS PDU	Panel Equipment	US-565392	BMS Controller	12	1
LD -64	Westermo Fibre 485 Converter	LD-64	Fibre Hub	10	1
MBC24 Backplate Assembly	Panel Equipment	US-545077	BMS Controller	16	n/a
MBC40 Backplate Assembly	Panel Equipment	US-545078	BMS Controller	14	n/a
MEC Analogue Expansion module	Panel Equipment	US-549214	BMS Controller	88	n/a
MEC Digital Expansion module	Panel Equipment	US-549210	BMS Controller	169	n/a
MEC100 Controller	Panel Equipment	US-549021	BMS Controller	61	n/a
MEC200 Controller	Panel Equipment	US-549022	BMS Controller	108	n/a
MEC200 Controller With FLN	Panel Equipment	US-549007	BMS Controller	37	n/a
MEC200 With Lonworks	Panel Equipment	US-549407	BMS Controller	1	n/a
Open Processor (4mb)	Panel Equipment	US-545719	BMS Controller	6	1
Open Processor (8mb)	Panel Equipment	US-545730	BMS Controller	15	1
Power Module	Panel Equipment	US-545714	BMS Controller	23	1

Room Temperature Sensor	Field Equipment	TPTRJ115ML	Field Device	13	1
LTEC FCU Controller	Panel Equipment	US-550536	BMS Controller	27	1

A nominal value of 1 spare unit per component (~10%) was used to create the desired spares list. This quotation would be used to illustrate the financial trade-off for enhancing the resilience of the BMS to obsolescence. The green highlighted components in Table 33 were removed from the scope as on-site spares (see Table 34) were held for them.

Table 34 On-site Spares for Building Management System, created by author

Part	***Quantity***	***Location***
MBC24 Backplate Assembly	several	SSE Store Room
MBC40 Backplate Assembly	several	SSE Store Room
MEC Analogue Expansion module	several	SSE Store Room
MEC Digital Expansion module	several	SSE Store Room
MEC100 Controller	several	SSE Store Room
MEC200 Controller	several	SSE Store Room
MEC200 Controller With FLN	several	SSE Store Room
MEC200 With Lonworks	several	SSE Store Room
I/O AI Module For MBC	several	SSE Store Room
I/O AI Module For MBC	several	SSE Store Room
I/O AI Module For MBC	several	SSE Store Room
I/O AO Module For MBC	several	SSE Store Room
I/O DI Module For MBC	several	SSE Store Room
I/O DO Module For MBC	several	SSE Store Room
I/O Expansion Module For MBC	several	SSE Store Room
I/O Pulse Count Module For MBC	several	SSE Store Room
US-545077	several	SSE Store Room
US-545078	several	SSE Store Room
US-549214	several	SSE Store Room
US-549210	several	SSE Store Room
US-549021	several	SSE Store Room
US-549022	several	SSE Store Room
US-549007	several	SSE Store Room
US-549407	several	SSE Store Room
PTM6.2U10	several	SSE Store Room
PTM6.2R1K	several	SSE Store Room
PTM6.2I420	several	SSE Store Room
PTM6.2Y10S-M	several	SSE Store Room
PTM6.4D20	several	SSE Store Room
PTM6.2Q250-M	several	SSE Store Room
PTM6.EMK	several	SSE Store Room
PTM6.2C	several	SSE Store Room

Retired Field Panel Spare Parts	several	SSE Critical Spares Box
MBC 24 Backplane Assy 24v	1	SSE Critical Spares Box
MBC Expansion Module	1	SSE Critical Spares Box
MEC 100	1	SSE Critical Spares Box
MEC 200	1	SSE Critical Spares Box
TEC Unit	10	SSE Critical Spares Box
Trunk Interface	1	SSE Critical Spares Box
QBE61.2	2	SSE Critical Spares Box
PTM6.2C	1	SSE Critical Spares Box
FLN Expansion Card	1	SSE Critical Spares Box
PXC Modular with FLN & TXIO Support	1	SSE Critical Spares Box
24vDC Supply 1200ma	1	SSE Critical Spares Box
BUS Extension Module	1	SSE Critical Spares Box
8 Digital Input Module	1	SSE Critical Spares Box
16 Digital Input Module	1	SSE Critical Spares Box
8 Digital Input Module Universal	1	SSE Critical Spares Box
6 Digital Output Module Universal	1	SSE Critical Spares Box
Electro Controls DP Switch EP113	1	SSE Critical Spares Box
TCX/100/6/F Transformer	1	SSE Critical Spares Box

For the purpose of this analysis, the holding cost of on-site spares has been removed from the equation, depending on space availability this is potentially not representative.

The case-study PFI contract has an inbuilt service deduction mechanism, detailed within Mulholland's (2014) dissertation. Below the extracted mechanism has been adapted and broken down to re-enact the potential costs associated with service unavailability of the case-study assets.

(1) $AC_{ZONE} = \{(DC1.AC) - CT - DC2\,.\frac{(A_Z W2_Z W1_Z)}{(\sum A_Z W2_Z W1_Z)}.(0.6835)$

The deduction formula (1) can be broken down into three key elements:

a) Size of impact $DC1\,.AC$

DC1 defines the contract period, it is either 100% before the initial Unitary Payment period or 90% thereafter for the remainder. AC represents monthly unitary payment allocation for service delivery, associated with availability.

b) Financial penalty $-CT - DC2$

CT represents the financial penalty post the initial Unitary Payment period, calculated by the no. days of unavailability x £15,000. DC2 represents the financial penalty prior the initial Unitary Payment period, calculated by the no. days of unavailability x £30,000, however, is zero if not activated.

c) Weighting of Zone in respect to entire site $\frac{(A_Z W2_Z W1_Z)}{(\sum A_Z W2_Z W1_Z)}.(0.6835)$

A_Z represents the floor space of the zone in m^2, $W2_Z$ is the weighting upon the function of the space i.e. 24-hour use or core business. $W1_Z$ represents the weighting upon the zone type, set at low, medium and high, with the weighting 1, 2 and 5 respectively. The denominator in equation (c) represents the entire *Building A*. The finally weighting applied to (c) was not defined.

Formula (1) calculates the size of the impact in m^2 and then inputs into formula (2), to produce the financial deduction to the Unitary Payment.

(2) $UD_{WD} = \frac{AC_{ZONE}}{WDM}.m$

WDM represents the no. working days of unavailability and *m* is the ratchet enforced by the contract. The purpose of the ratchet is to escalate the financial deductions in accordance with how quickly service delivery is returned. Each asset system provides a difference service i.e. BMS temperature and humidity control within zones, each of these will have a unique grace and rectification period to which service must be returned.

The ratchet (*m*) ranges from 0 to 2.0 based on the following logic:

Table 35 Penalty Deduction Ratchet Mechanism, created by author

Ratchet, m	
Weighting	***Description***
0	Within grace period.
0.25	Within rectification period but outside grace period.
1	Within 7 days but outside of rectification period.
1.5	Within 20 days but more than 7.
2.0	After 20 days.

The intention set out within the Analysis section was to use this mechanism along with a set of assumptions to create a hypothetical scenario, to which compare the cost of investing into the resilience of the BMS. The assumptions used are shown in Table 36.

Table 36 Hypothetical Scenario Assumptions, created by author

Formula Serial	***Variable***	***Assumed Value***
(1)(a)	DC1	90%.
(1)(a)	AC	*Redacted.*
(1)(b)	CT	no. days of unavailability x £15,000
(1)(b)	DC2	Zero.
(1)(c)	A_Z	10,000 m^2 – entire ground floor.
(1)(c)	$W2_Z$	Core business area.
(1)(c)	$W1_Z$	Weighting 2.
(2)	WDM	A range will be used.
(2)	*m*	Dependent on WDM.

This is an example of one system in isolation, the effect of unavailability is compounded when it affects service delivery of other functions within the building i.e. access control to areas and the effect of that upon Soft FM elements. The assumptions made above were entered into the PFI contractors auditing sheets to create a scenario where the BMS availability affected the entire ground floor (either the temperature or humidity). This produced Table 37, showing how the UD_{WD} increases with time. Note, this is a simplistic view of this scenario as an unavailability of this size would have operational impacts that would also lead to further performance deductions, the below fees are solely associated with unavailability.

Table 37 Cost Comparison, created by author

Ground Floor					
	Ratchet				
	within rectification period, outside grace period (25%)	within 7 days but outside of rectification period (100%)	between 7 and 20 days (150%)	after 20 days (200%)	
	0	2	7	20	30
UD_{WD}	£-	£5,411.69	£21,646.75	£32,470.13	£43,293.50
Quotation 1	£33,038.05	£33,038.05	£33,038.05	£33,038.05	£33,038.05

To populate the value of 'Quotation 1' 2015 OEM unit costs were forecasted using linear regression by one-time unit. Note, costs for 'Fibre Optic Hub – LD 64' and 'Open Processor (8mb)' were not recoverable in the time allocated and are deemed obsolete, hence their absence in Figure 133. In addition, the 'Hi Temp Immersion Thermostat', 'Interface for McQuay Chiller' and 'Interface for MODBUS PDU' components are obsolete and were only procurable via a third party. Please note the added level of risk associated with procuring via third party channels and not via the original OEM as additional terms and conditions and/or warranties apply.

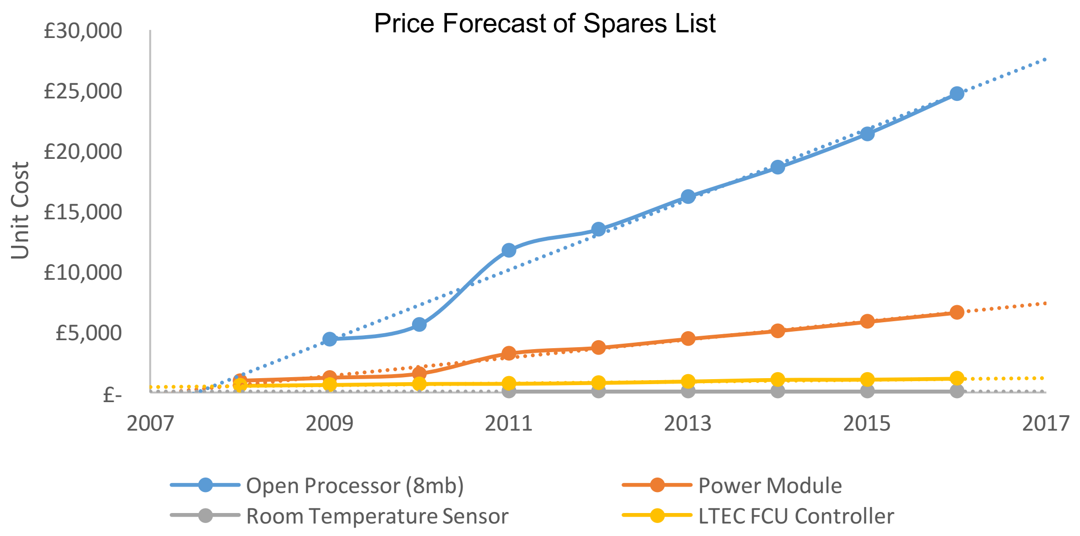


Figure 133 Component Price Projections for Analysis, created by author

Figure 134 was created using the values found in Table 37, illustrating the intersection between the resultant financial deductions and resilience investment.

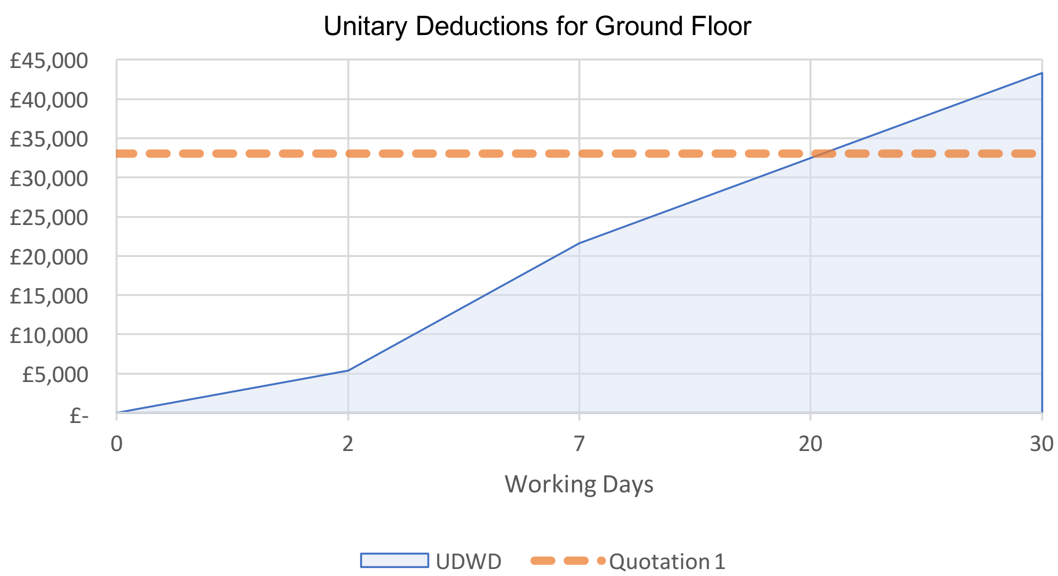


Figure 134 Resilience Trade-Off Visualisation, created by author

It is important to note the lead times of these components – if the lead time equates to deductions greater than the intersection, then there is a financial incentive (regardless of the operational benefits) to procure said components. However, for those components that have a lead time that falls under the intersection, then the associated financial risk would not suggest the need to proactively procure. However, this advice comes with a large caveat in that the procurability or whether or not a component is obsolete must be monitored to ensure that if the latter choice is taken, then it is still implementable in the future.

In the specific case of Private Finance Initiatives (PFI), the Obsolescence Management Plan could, in theory, contain Figure 134 (excluding the quotation plot) for each system for a range of scenarios. This would enable the Asset Management or Facilities Management team to contextualise the decision-making process of investing into spare parts. Precise ‘mean time between failure’ (MTBF) values will not be available within this sector; however, by presenting the information in this simplistic manner, informed decision-making is possible. For this particular PFI contract the intersect point (see Figure 134) is rather late or in other words, the time frame within which spare parts will need to be reactively procured before the cost exceeds deductions is rather large. The financial incentive to proactively invest into the resilience is low. This is a result of the cost of the at-risk components in this particular system at this particular point in time, along with the structure of this particular PFI contract.

Note also, the above visualisation also emits the rising cost of components due to scarcity, as statistically shown within section 4.4 of this thesis. Figure 134 completes Aim (4) of this thesis and is an example of the informal mental models that Asset Management professionals undertake in a reactive position. Industry standards would not provide with the information as seen within this thesis however. This is a further driver for the need to adopt proactive management methods in the form of an Obsolescence Management Plan. This is just one of the many variables that must be considered in order to holistically approach Obsolescence Management in a strategic manner.

The next section will now conclude the major findings in preparation for a formal Discussion on their validity, impact and weakness to be considered for Future Work.

4.6 Conclusion

The Results chapter was structured as shown in Figure 135, covering four very independent set of outputs for this thesis. However, they combine together as part of an OMP that would be capable of proactive obsolescence management – ultimately, quantifying the risk posed by obsolescence.

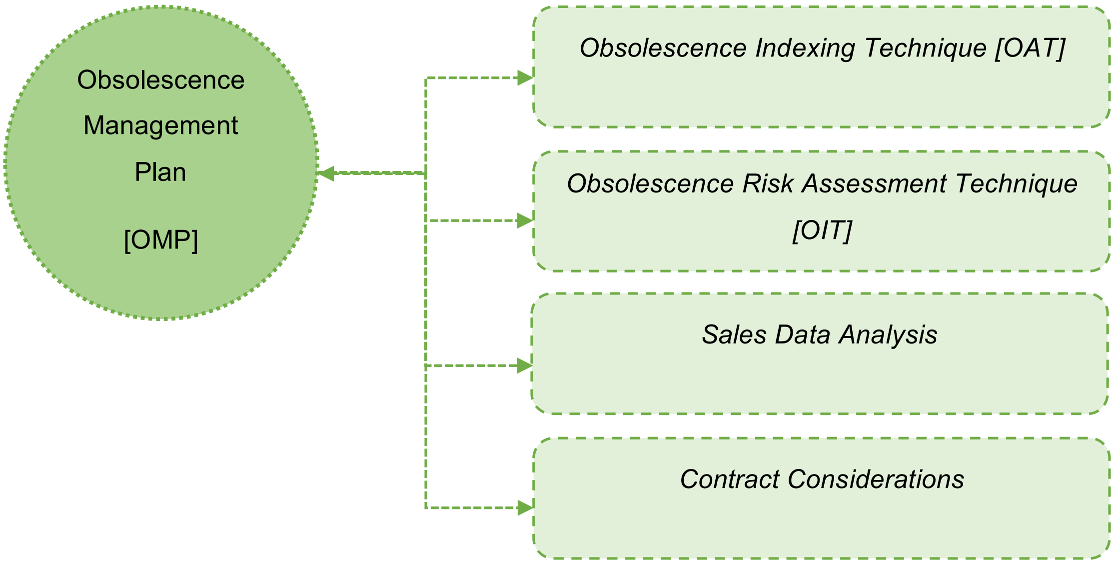


Figure 135 Results Framework, created by author

It is not within the scope of this research project to devise the most appropriate mitigation strategies; it is likely within the context of the industry that this is dealt with on a case-by-case approach. However, the methodology used within this thesis has provided a range of outputs that could be applied back into the case-study of *Building A* and influence and improve current obsolescence processes.

This section has executed all of the objectives set out in the research design in order to achieve all four aims of this Engineering Doctorate. This thesis has successfully delivered contributions to new knowledge, fulfilling an overall requirement. Now the impact and further context to the results will be covered within the Discussion section. To break down this section, the OAT, OIT, Sales Data Analysis, and Resilience Visualisation will be covered here in summary of the key elements and observations made by the author.

The internal algorithm of OAT was enhanced to add further granularity and equipped with standardised internal logic tests to improve the validity of results. In addition, the new algorithm for OAT was migrated across from Microsoft Excel into MATLAB and coded into a repeatable, transferable and scalable program. All of the above key elements are a result of both the feedback from Mulholland's (2014) dissertation and journal publication Mulholland et al. (2016a). OAT is now applicable in the industrial environment and appropriate for testing on different systems and sites. This completes objectives (1) and (2) and fulfils Aim (1). A brief discussion on preliminary observations can be found in this chapter, however, more on the Asset Health scores and system changes will be provided in the proceeding section. In summary, the new algorithm has shown to be more precise and robust to validity questions when directly compared to its predecessor.

A new risk assessment was developed and framed upon an ‘expert model’ framework that used Fuzzy Logic architecture to generate an ordinal risk output (OIT). An Importance Measure (IM) was used to categorise the component groups, formulating input (3) into OIT. A significant amount of data conversion, sanitisation and consolidation were required to convert historical PPM and UPM records from hard copy, ready for the planned analysis. A stationary Poisson Distribution method was then applied, along with on-site stock inventory figures to calculate the Stockout Probabilities against each component. This generated input (2) for OIT. The dataset required to execute OAT was reused to create input (1), indicating which components held EOL notifications and whether they were obsolete. This created the final input (1) for OIT. The Fuzzy Inference System (FIS) for OIT was then programmed using MATLAB and the IF-THEN Rules generated by the expert panel. This created the intelligence or ‘black box’ element. Creating a model using this methodology enhanced the robustness of the model’s validity and allows for future iterations of the sensitivity. The above-completed Aim (2) of this thesis via the execution of objectives (3) to (6). In summary of the results; the SS showed a diverse set of risks, whilst the BMS was rather polarised. This is a contrasting behaviour to that observed within OAT’s results. The question remains as to whether or not this the desired state? Both asset systems contained components that posed ‘low’ or ‘not important’ risks, although interestingly none of the said components elevated into high-risk categories. Does this imply that an assertion could be made upon an asset’s components that fall into these categories? Generally, the figures produced by the Results section are all novel and provide an insight into the behaviour of obsolescence that cannot be found elsewhere in the literature. For the first time, the behaviour can be cross-analysed with on-site Purchase Order behaviour, to assess OIT’s algorithm for identifying risks and changes within the Asset Register. The results will provide a substantial part of the Discussion section of this thesis.

The analysis on the OEM sales data provided several contributions to knowledge and statistical evidence to confirm some of the claims within literature. Analysing both the unit price changes and the lengths of time components were procurable gave several insights. There is evidence of an OEM using a clear sales strategy, inciting a cyclical behaviour within the market and in turn instigating a cyclical behaviour of obsolescence. This, coupled with previous evidence published within Mulholland et al. (2016b), shows that obsolescence appears to hold a cyclical behaviour within the Built Environment. However, further testing is required to add further evidence to this claim. Clear evidence was provided showing the rising costs associated by obsolescence, again supporting previous claims within literature.

The associated price increase ranges can be extracted from the figure found within, which would aid an Obsolescence Management Plan and even Cost Benefit Analysis. Price increases were systematic within all component groups provided by this particular OEM of BMS's. Through dividing the dataset into component categories, probability density functions were extracted to illustrate the length of time each would be available to the mass market. Such information has previously not been published for obvious commercial conflicts of interest. However, these profiles could directly be used to statistically support an Obsolescence Management Plan and decision-making. In summary, the graphics displayed herein hold several key insights that not only contribute to new knowledge but provide applicable industrial advice to decision-makers. All of the above complete objective (7) fulfilling Aim (3) of this thesis.

Finally, the resilience trade-off visualisation exercise created a key graphic illustrating the type of informal decision-making that occurs within management teams under uncertainty. The PFI context allows for the quantification of the unavailability costs associated with a system using its likely impact. When choosing to invest into the resilience of a system and improve its supportability against obsolescence, one must consider the cost procurement, holding costs, financial deductions, component lead times and then availability due to obsolescence. This involves a significant number of variables, containing a large amount of uncertainty, all of which is made informally using mental models predominantly. Completing objective (8) allowed for a clear intersect between selected components within *Building A*, their respective lead times and the financial risk faced by unavailability. An insight into how data-driven decision-making within Asset Management could be undertaken with the right methodology. All of the above-fulfilled Aim (4) of this thesis and concluded the planned aims and objectives of this Engineering Doctorate.

The next section will now add a discussion to the results displayed to the reader, with more context to the potential impact of this research. Whilst the contributions to the new knowledge are explicitly clear, there are further operational benefits to such work that less so defined using statistics or graphic visualisation.

5 DISCUSSION

5.1 Introduction

This Engineering Doctorate set out to answer the following three research questions:

1. Can OAT be further enhanced to consider compatibility?
2. What is the operational risk posed by obsolescence?
3. Can Fuzzy Logic be used to robustly quantify obsolescence risk?

The above research questions targeted identified gaps in the literature landscape with the aim of contributing to new knowledge and qualifying for an Engineering Doctorate. The purpose of this section is to tie in all threads of the research into a logical argument, aiming to answer the above research questions. Figure 136 has been repeated from the Results chapter as a key structure for the Discussion. Each subsection will begin with a breakdown of the topic of discussion and an example of the research application. The Discussion chapter will culminate in a Knowledge Contributions subsection, where the contributions will be formally detailed for explicit review. This will enable the reader to complete the aim of this section by appraising whether this research project delivers both answers to the research questions and the academic obligations of Doctoral Research.

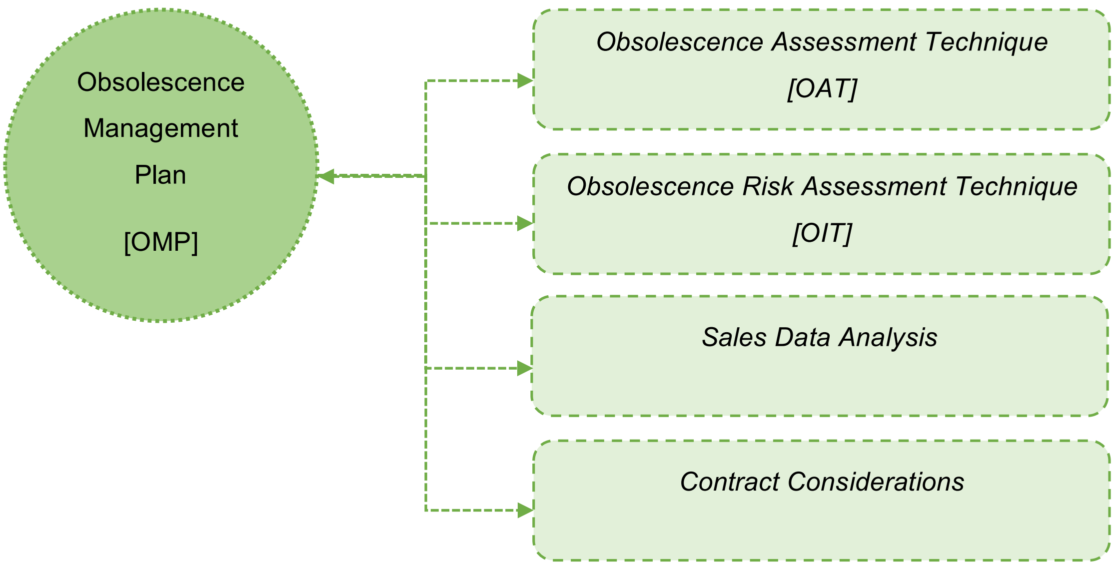


Figure 136 Results Framework, created by author

To add context to the following Discussion, the last notable research into obsolescence within the Built Environment was by Nutt (Nutt 1999; Nutt 1988; Cowan et al. 1970; Nutt et al. 1976). Since the aforementioned work, this area has not been addressed from the same research angle. Modern research has been driven by the need within manufacturing to better understand and predict obsolescence to avoid the costs of obsolete stock; good examples of this are; Pourakbar et al. (2014), Nelson III (2012), Sandborn and Myers (2008), Herald Jr. (2007), Singh et al. (2004) and Cattani and Souza (2003). All of the above-mentioned citations rely upon the type of datasets to which an end-user within the Built Environment would not be privy, i.e. Asset Management and/or Facilities Management team. It is this exact caveat that deems most of the recent research literature rather moot in the eyes of the respective Asset Management and Facilities Management industries. The research questions set out by this thesis, therefore, are both explorative and ambitious in their aims to provide two tools that would enable more proactive management methodologies and aid decision-making under uncertainty. These tools, along with the other types of analyses found within this thesis, would combine to aid a comprehensive Obsolescence Management Plan. From a research perspective, this poses challenges to the author to provide a robust and valid methodology for addressing this research problem, whilst still producing contributions to the new knowledge. In order to mitigate this research consideration, along with other highlighted risks to the project, a formal Risk Assessment was undertaken (see section 3.4) to objectively highlight and mitigate known risks. This approach is typical within the industry; however, it was felt would be applicable within the academic realm to support the research design and promote transparency within the limitations and assumptions made through this project.

Preliminary observations have indicated that the results have produced a diverse range of evidence for both the applicability of this research and the behaviour of obsolescence. Both systems behaved in a contrasting fashion, generating two sets of results that each display a contrasting scenario for Obsolescence Management. More detailed analysis and insight into exactly why said systems showed the results they did will be found herein. As previously stated, Obsolescence is a 'complex' problem; there is no silver bullet approach that fits all scenarios. Ultimately, the generic aim is to economically extend the useful life of asset systems, however, to achieve such strategic aims, more proactive and data intensive measures are required. This Discussion section will clearly demonstrate precisely why said methods are required; the sheer sizes of datasets along with the non-linear relationships between variables are not consistently handled by human heuristics. This will become apparent when the reader witnesses the scale of lifecycle investment into both systems, and the resultant effect on the level of obsolescence within both systems. The author is of the opinion that this behaviour found herein is typical of current Asset Management/Facilities Management practices and are widely felt within the industry.

As detailed within Figure 136 above, the first subsection will address the Obsolescence Assessment Tool results, show how it evidenced the increased granularity within the algorithm and improved validity. The further testing of OAT through a two-year case-study has generated more evidence of its application within the industry and the help it can provide for prioritising resource allocation.

5.2 Obsolescence Assessment Tool

This subsection will discuss the results from the use of OAT within *Building A*. As shown in Figure 137, OAT quickly identifies the components within an Asset Register that should be targeted for obsolescence mitigation techniques. OAT now contains a more precise algorithm that is compared to the previous iteration herein as well as containing an internal set of logic test to validate the input datasheets. The MATLAB script for OAT is now both scalable to either more asset systems or more components and also transferrable to other sites via email. This discussion will now cover these points in more detail, giving the context of their application within the industry.

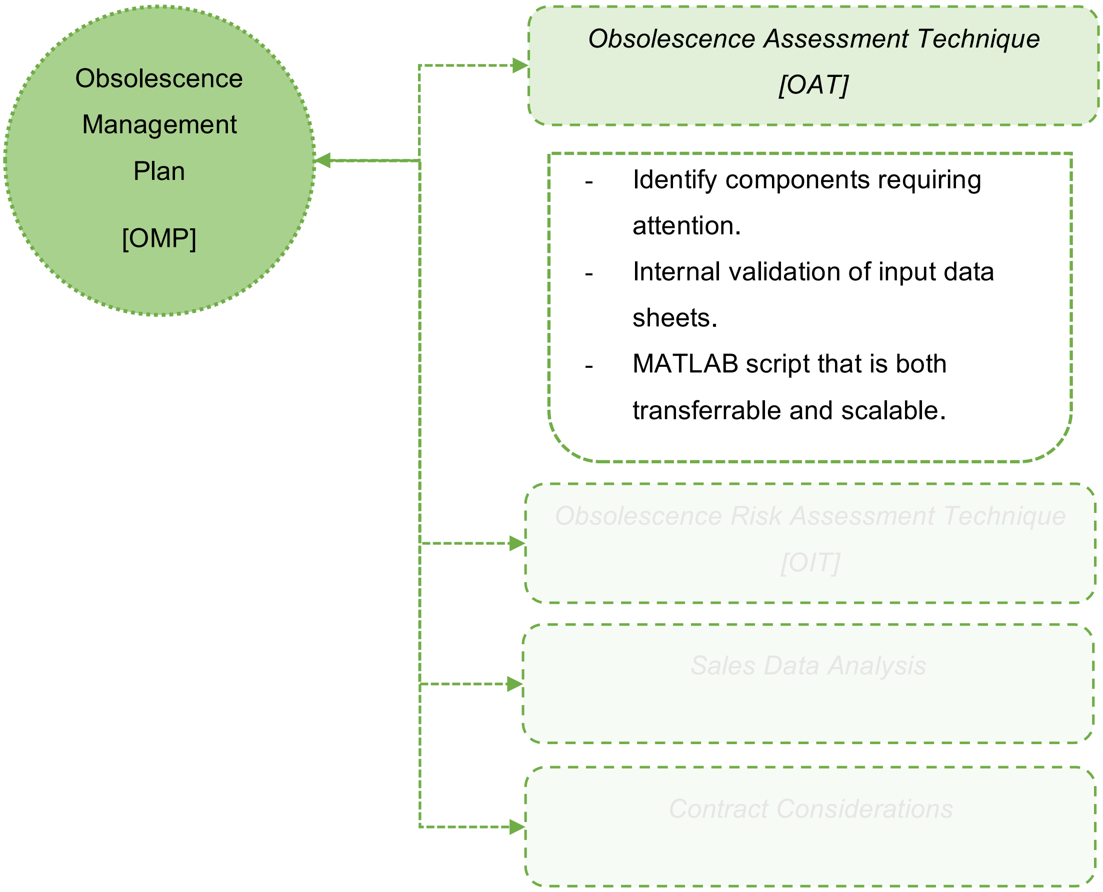


Figure 137 Results Framework, created by author

The Obsolescence Assessment Tool (OAT) was successfully used throughout the case-study and produced a range of results for both systems. Interestingly, the two systems behaved in contrasting ways and have differing amounts of investment from the Asset Management team across the two-year period. In this section, firstly, the added granularity of algorithm and validity will be discussed, followed by a discussion on the results for both systems.

The aim was to 'further develop and empirically test' OAT by 'enhancing' the internal algorithm, which was achieved by adding greater granularity. Specifically, this involved adding more statuses that could be allocated by the algorithm for a given Asset Register. This iteration of OAT now identified assets that had alternative parts on the market and confirmed their compatibility. More statuses allow for a greater diversification of an Asset Register, which in turn adds more detail and information to the output for the user. Table 38 and Table 39 illustrate how the new OAT reassigns components into the new categories when compared to the old OAT and applied on the same dataset. By adding this greater level of detail the user is now able to generate a mitigation plan that can now consider 'lifetime buys' of alternative parts, with the added assurance of their compatibility. For example, this is considered within the new OAT with a slightly higher Asset Health score. This added detail adds more value to the algorithm.

Table 38 Security System Old and New OAT Algorithm Comparison, created by author

Status	***Old OAT Algorithm***	***New OAT Algorithm***
A1	0	0
A2	0	0
B1	n/a	10
B2	n/a	0
U	0	0
O	566	566
Y1	35	0
Y2	55	45
S	49	84
Asset Health	11.92%	13.33%

It is felt by the author that this greater level of granularity achieves the aim of 'developing' and 'enhancing' OAT, with the results to be analysed later within this section. OAT is a decision-aiding tool; therefore, its sole remit is to interpret a large amount of information (the BMS had 191 individual component groups, each with 13 data fields) and provide a simple and usable output. By adding greater granularity, OAT is able to interpret said datasets, adding two new data fields, with a greater level of detail. This automates some of the decision-making that an Asset Management team would potentially undertake. Note, in practice, Asset Registers are outdated and in themselves obsolete, therefore the processes OAT executes would not be undertaken due to the poor quality of the datasets. This was only possible with the early intervention of this case-study and predefined data collections of the author.

Table 39 Building Management System Old and New OAT Algorithm Comparison, created by author

Status	***Old OAT Algorithm***	***New OAT Algorithm***
A1	0	258
A2	993	0
B1	n/a	1539
B2	n/a	629
U	258	0
O	19	19
Y1	6716	0
Y2	1239	693
S	9089	15176
Asset Health	86.33%	92.68%

In 2006, Clive Humby coined the phrase '*Data is the new oil*'. Clive later went on to develop and implement Tesco's loyalty points scheme (Arthur 2013). The Financial Times, Forbes, IBM, and Microsoft have all publically declared the same term, highlighting the importance to add value to the data through refinement, analogous with the refinement of crude oil (Deutscher 2013; Chazan 2016; Lu 2016):

"Data is just like crude. It's valuable, but if unrefined it cannot really be used. It has to be changed into gas, plastic, chemicals, etc., to create a valuable entity that drives profitable activity; so, must data be broken down, analysed for it to have value."

Rotella - Forbes (2012)

Cross-links can be made to the need to not only collect and save data in an appropriate manner within the Built Environment but to develop simple algorithms such as OAT to add value to the mountains of data that exist within our buildings. This thesis has highlighted the extensive amount of work required to retrospectively undertake such a task (a potential barrier), however, the results have shown how value and insights can still be found. Added granularity to tools such as OAT adds greater value to the same datasets and its iterative development is an important one to continue. Through analysing the results of OAT, the author has identified a potential field to add more detail to the algorithm. Currently, OAT will identify a component that is within its obsolescence phase. It will assign said component with 'O' if there are not alternative parts and suppliers etc., however, it does not distinguish between whether or not the component is already obsolete or not. In order to add this further consideration, an extra data field would be required along with a new loop level within the MATLAB code. However, this is a potential area for future work (see section 6.4).

The validity of OAT, its origins, development, and outputs are right to be questioned with any scientific development. OAT was first developed within Mulholland's (2014) dissertation, where an indexing technique from Bartels et al. (2012) was built upon. The core functionality, whilst validated by the above publication, was not empirically tested. Mulholland et al. (2016a) then published via peer-reviewed journal both OAT and the results within the dissertation. This exposed the development and structure of the algorithm to critique. The feedback from the dissertation and observations made by the industry sponsor led to the continued development of the algorithm. As detailed in section 3.3.3, the author holds the opinion that you cannot validate a model, but rather disprove the findings and compare it to like models. In the case of OAT, this involved the comparison between the original and iterated algorithm. Originally, this was the intended tests to display the validity of the model to the reader. However, in addition, internal logic tests were designed to spot-check the input datasets and display any errors to the user.

Table 40 contains the internal logic tests that were coded into the OAT MATLAB script. Each of the below contains a narrative behind its creation to display how it would benefit the user in validating the results they were seeing within the data.

Table 40 Internal Obsolescence Assessment Tool Logic Tests, created by author

Logic Test	***Narrative***
1	EOL released but no recorded date: This check identified when the EOL date is unknown, when one was present. This means that no proactive action can realistically be taken. Misinformation is common in industry.
2	EOL date is stated but not EOL notification recorded: It is illogical that a date can be recorded with no notification released; the date is contained within a notification.
3	Number of parts entered into the datasheet: This checked the number of parts is both filled with a number and not zero, this check would be invalid with an entered character for example.
4	No recorded EOL notification but a date of release: This checked for components that have no EOL notification but have a date of release. It is possible that the date of release is so recent that the full details are not all present.
5	Six or more blank data fields per component: This logic test will highlight components that hold six or more blank fields.

OAT, therefore, has been exposed to a peer-reviewed journal critique, internal review within the industry sponsor and finally, ongoing logic spot checks on all data inputs throughout the case-study.

The results for the Security System (SS) asset showed that it began with a low Asset Health score, experienced a peak in early 2016, and then a sharp decline. The following components shifted status between Q2 and Q3 in 2016, however, the overall Asset Health Score remained in a positive 60-70% range.

Table 41 Security System Component Status Change Q2 - Q3 2016, created by author

Component	Status Change
Synectics Keyboard	S to O
Intercoms system	S to O
internal Panasonic camera	S to O

The following two components were added to the Asset Register and immediately received an 'O' or obsolete status. This is an example of how through the lack of an OMP an end-user can continue to invest into obsolete components, either through negligence i.e. being unaware or through poor technology road mapping i.e. limited to no alternative solutions.

Table 42 Security System Component 'O' Status Q3 2016, created by author

Component	Status Change
Synectics mini dc receiver	O
galaxy 520	O

Table 41 and Table 42 are minimal changes to the system over a 6-month period. However, Table 43 illustrates the significant changes that were captured within the Q4 input datasheet. A swing of this nature, whilst it may seem dramatic, will contain several low-value consumables i.e. 'Bosch Monitors'. Such components are both replaceable and of low-value. However, this appropriately demonstrates the number of changes that an asset system can experience within a relatively short period of time (1 quarter = 3 months). Before the initiation of this case-study research project, the communication of such changes was left to the sub-contractor, who was not presented with a process of how to disseminate such information. Equally, there is no contractual or financial incentive to undertake such a task. The potential conflict of interest on the sharing of such information must also be considered; profit is made via the Purchase Orders raised by the Asset Management team via any sub-contractor. It is rather a complex situation to consider the stakeholders within this contractual arrangement, changing levels of obsolescence within components, and ongoing planned and unplanned maintenance requirements. Observations such as those below highlights the need for methods such as OAT and structured processes in order to implement Obsolescence Management.

Table 43 Security System Component Status Change Q3 - Q4 2016, created by author

Component	***Status Change***
Mic 500 Series	S to O
External Bosch Cameras	S to O
Bosch Monitor	S to O
Fibre Optic TX	S to O
Fibre Optic RX	S to O
Card Printer	S to O
Pelco domes Camera	S to O
Pelco domes Camera	S to O
Scantronic 160 Control Panel	S to O
Scantronic Keypad	S to O
Expander	S to O
Pelco NVR	S to O
Pelco Encoders	S to O
Pelco Work Station	S to O
Synectics Keyboard	S to O
TM Legic	S to O
I Star Pro	S to O
I Star Ultra	S to O
I Star Edge	S to O
RM4	S to O
C-Cure 9000	S to O
Optrex Motion Sensor	S to O
Vibration Sensor	S to O
8 port Switch	S to O
24 Port Switch	S to O
24 Port Switch	S to O

Due to the anonymity required within this thesis, intrinsic details of the POs raised cannot be disclosed. However, significant investment was made into the Intruder Detection System (IDS) during Q4 2015 (see Figure 99); this order replaced and upgraded a wide range of components within the SS. The author speculates this is a contributing factor into the positive curve found within Q2 and Q3 in 2016 as the works involved within this particular order stretched several months.

Interestingly, the Building Management System (BMS) displayed a completely contrasting set of behaviours within the results. The BMS showed continued improvements within its Asset Health Score, alongside continued investment. However, as already noted, the investment was almost double in value when compared to the SS. Whilst the BMS only showed the ‘Fibre Optic Hub’, ‘Liquid Differential Pressure Sensor’ and ‘LTEC FCU Controller’ as having upcoming EOL notifications; there are 65 other components that have had their EOL notifications exceeded. These components, however, contain a mixture of alternative suppliers and compatible alternative parts. Although in Q4 2016 a high Asset Health score has been reflected by OAT, the considerable investment may still be required to mitigate the obsolescence that exists within the system.

Throughout the case-study, the BMS held a more diverse range of statuses and performed markedly better than the SS (see Figure 138). Is having a diverse range of statuses a desirable trait? If so, should it not be considered when seeking to mitigate obsolescence? Although it was not within the scope of this project to answer these questions, it is felt by the author that a more diverse set of statuses would hold certain benefits. For example, a range of statuses is likely to hold a range of timelines associated with them, within which an Asset Management must implement a mitigation strategy. Through the staggering of investment, the overall lifecycle expenditure is easier to manage, as requirements within other systems can be offset by adjacent years. However, in opposition to this advantage, with a range of components requiring investment at some point, a one size fits all mitigation strategy is unlikely to work. This will likely require a more detailed Obsolescence Management Plan by the Asset Management team. This increases uncertainty and also the level of detail that will be required; a resource drain. In a more polarised set of components that are obsolete or not, the resource can be focussed and grouping of said components via a single vendor could be an attractive proposition for an Asset Management team. These results and also the above discussion is subject to a wide array of factors and no silver bullet is being suggested here, illustrating the complexity of obsolescence. However, thanks to the output of OAT this type of discussion based upon explicit detail can be held. Previously this would not have been possible.

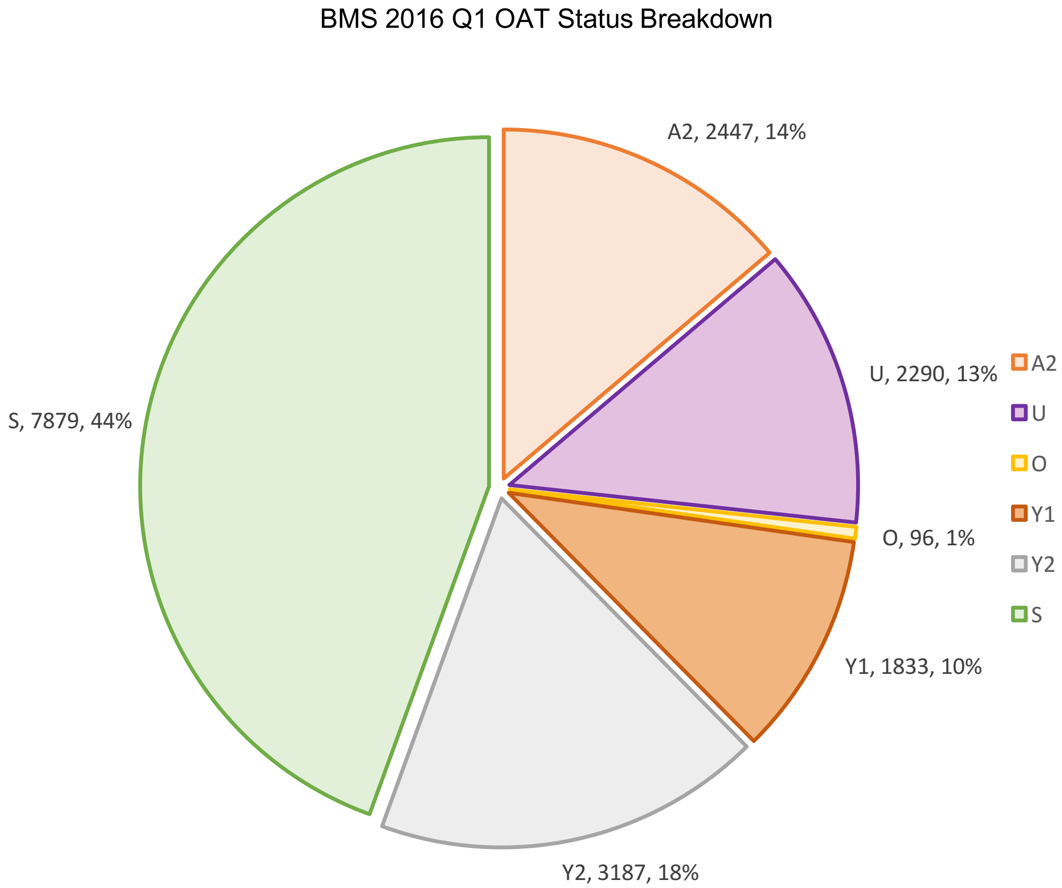


Figure 138 Building Management System OAT Status Results Q1 2016, created by author

OAT is now more detailed, adding more value to the datasets held within the Built Environment, more structurally robust via peer review and validity checking through inbuilt logic assessments. The results show two contrasting asset systems, which have received differing amounts of investment. Firstly, the results show how obsolescence can still pose a risk after significant investment. Secondly, OAT has the ability to identify the components that require further investigation and potential mitigation. However, OAT is a simple algorithm that was designed to aid decision-making. It does not contain enough context to evaluate risk, a known limitation, although its uses within industry continue to be demonstrated. The results contribute to new knowledge as continued development and testing of this indexing technique being applied within the Built Environment.

The next section will now draw the attention to the Obsolescence Impact Tool (OIT) and whether the results have successfully validated a methodology for evaluating the ordinal risk posed by obsolescence within assets from the Built Environment.

5.3 *Obsolescence Impact Tool*

The purpose of this subsection is to discuss whether the Obsolescence Impact Tool developed within this thesis successfully quantified the risk posed by obsolescence and robustly incorporated Fuzzy Logic. Figure 139 has been repeated, demonstrating in summary how the following subsection has been structured.

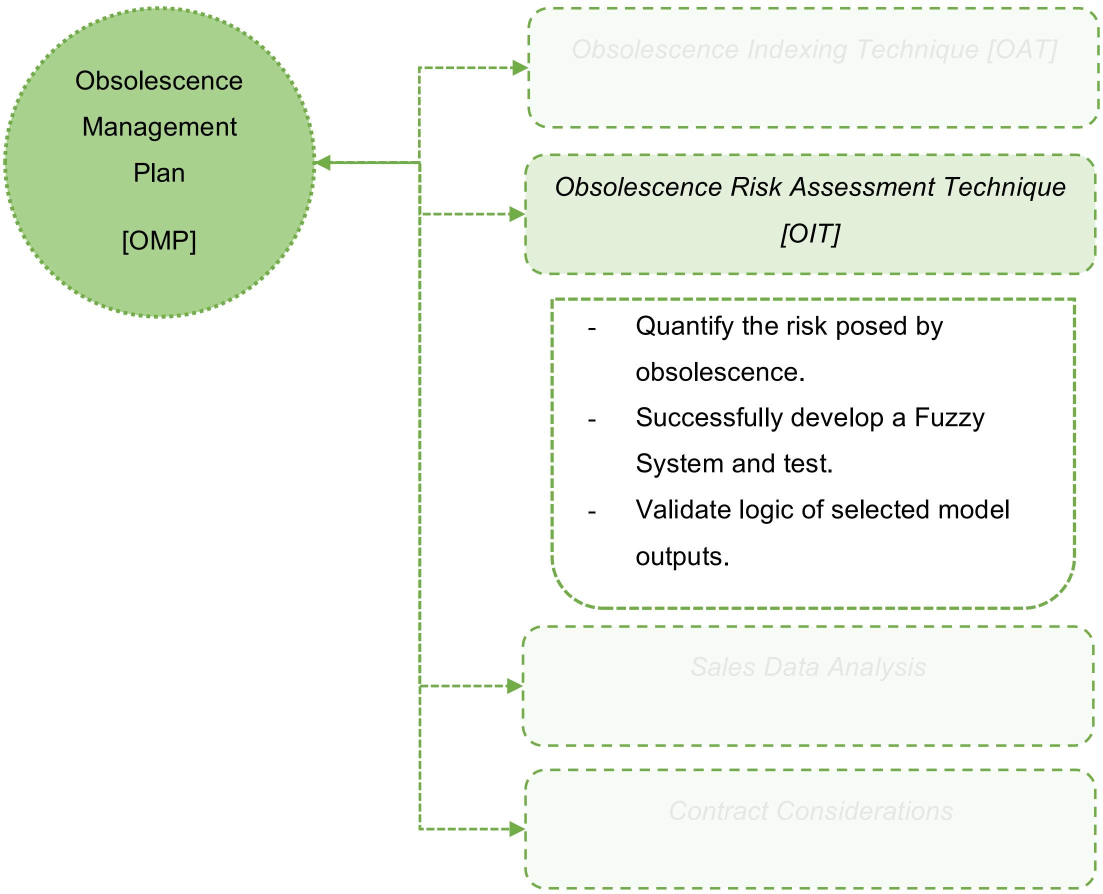


Figure 139 Results Framework, created by author

The Obsolescence Impact Tool (OIT) was fully developed and tested within the case-study, incorporating three inputs and producing a risk profile for each component within the asset system. Interestingly, some of the potential dormant risks within OAT's results, identified within the discussion were identified by OIT. The BMS and SS demonstrated risk profiles that opposed the behaviour witnessed with OAT's results. The risk profiles not only displayed contrasting results in terms of positive and negative values but also in terms of diversity, with the SS displaying a range of risk profiles across its components. The following section will cover the validity of the model and its results, discussing some of the unique trends from the Results and then cover some elements of the methodology that the author feels could fall into Future Work.

The literature review highlighted evidence of Fuzzy Systems being used to support ‘approximate reasoning’, enabling computational decision-making under uncertainty. There are several ways to develop a Fuzzy Inference System (FIS); an ‘expert model’ approach has shown robustness when seeking to map an input(s) to output space where there are no previous guidelines but intangible human knowledge and heuristics. When adopting this approach, the robustness and validity of the structure have a shared responsibility across the ‘expert’ panel used. The panel used for OIT consisted of members from both academia and industry and adopted a Delphi Method to generate the internal IF-THEN Rules. The very structure and nature in which OIT operates, from the Fuzzy Sets to the IF-THEN Rules or Algorithm to the outputted crisp values, are entirely validated by this panel. The benefits of doing it this way are:

- Viable method when there is no historical data to advise otherwise.
- Transparent approach that is also logical, promoting ‘buy-in’ by partaking stakeholders.
- A flexible process that can be iterated upon the review of results.

OIT as an expert model, by its very definition, has been validated via peer review of an expert panel, through both its conception and design to its testing phases. The review of results and repeat of the methodology would be suggested within Future Works.

Regarding the outputted ordinal risk produced by OIT, it is important to remember that Fuzzy Systems are approximators by their structure. Fuzzy Logic is adopted when ambiguous or inconsistent datasets are used between constructs where causal relationships are predominantly unknown and/or unclear. In other words, when the relationship between the input and output space is unknown, Fuzzy Logic provides a framework within which a robust approximator can be developed. Otherwise, more probabilistic methodologies would be appropriate. The crisp outputs of OIT are useful for ranking components within a system, to identify which should be addressed first. However, an output’s membership to a predefined Fuzzy Set does not constitute an automated reaction from the user. The results still require interpretation, especially, upon the first iteration of a Fuzzy System. The results are therefore not to be validated, as there is no model to benchmark against. However, the results can be reverse engineered to analyse the logic within the algorithm that produced them. To challenge the validity of the logic for the outputs of such an FIS would be to challenge the logic imposed by the expert panel in their design of the model. The accuracy, however, is a different prospect and something that should be retrospectively adjusted to align with human heuristics, again please see Future Works. For example, the sensitivity of the model can be quickly adjusted, depending on wider variables or drivers within the organisation.

The high-risk components within the BMS and SS for Q4 2016 are shown in Table 44 and Table 45. Please note, all results can be found within appendix 8.7.2; these have been shown to illustrate the logic used and to preserve space within the main body text. The inputs for each of the below components have been reviewed and then summarised in the narrative column. The Fuzzy Set column displays to the reader how OIT has interpreted the input information, which is then passed through the IF-THEN Rules and the output Fuzzy Set is shown. This in itself is one way of validating the logic behind the approximation undertaken by the FIS. Note that column two – 'MATLAB FIS Input' has been presented in the following format; 'Stockout Probability'; 'Obsolescence Status'; 'Component Criticality', this is aligned with the model design found in section 3.3.3.2 for input (1); input (2); input (3).

Table 44 Building Management System OIT High-Risk Components, created by author

Component	***MATLAB FIS Input***	***Narrative***	***Crisp Value***	***Ordinal Risk Fuzzy Set***
MBC24 Back Plate Assembly	[0.713594997113521;0.825479452054794;2]	A component of this type **'often'** requires investment, its **'EOL has been exceeded'**, but within a year and **'medium'** critical component.	0.948	'Very Important'
16 Digital Input Module	[0.713594997113521;0.5;2]	A component of this type **'often'** requires investment, it **'EOL has been released'**, but not exceeded and is a **'medium'** critical component.	0.8	'Important'
8 Digital Input Module	[0.713594997113521;0.5;2]	A component of this type **'often'** requires investment, it **'EOL has been released'**, but not exceeded and is a **'medium'** critical component.	0.8	'Important'
Hi-Speed Trunk Isolator Extender	[0.713594997113521;0.5;2]	A component of this type **'often'** requires investment, it **'EOL has been released'**, but not exceeded and is a **'medium'** critical component.	0.8	'Important'
PXC 100	[0.713594997113521;0.5;2]	A component of this type **'often'** requires investment, it **'EOL has been released'**, but not exceeded and is a **'medium'** critical component.	0.8	'Important'
PXC 16	[0.713594997113521;0.5;2]	A component of this type **'often'** requires investment, it **'EOL has been released'**, but not exceeded and is a **'medium'** critical component.	0.8	'Important'

PXC 36	[0.713594997113521;0.5;2]	A component of this type **‘often’** requires investment, it **‘EOL has been released’**, but not exceeded and is a **‘medium’** critical component.	0.8	‘Important’

The ‘MBC24 Back Plate Assembly’ within the BMS has exceeded the date provided on the EOL notification and therefore may not be procurable from the OEM. However, this did occur in the last year (from the date of calculation), which is reflected in 0.82547 as the value for input (2). The remaining components are yet to exceed the date on their EOL notifications, which is reflected in their ‘Important’ status. The logic generated by the IF-THEN Rules has clearly differentiated between this subtle but explicit difference between the components.

The SS system finished Q4 2016 with more component groups that fell into the ‘Very Important’ Fuzzy Set. However, these components had exceeded their EOL notification date by over a year. Note, due to the granularity within OIT the components that have been identified as ‘Very Important’ by OIT were not identified as risks. It is this slight difference that has led to contrasting OIT and OAT results for the respective systems. Rightly, the below component groups have been given higher crisp values, when compared to those within the BMS because of the time period that has passed since their EOL notification date.

Table 45 Security System OIT High-Risk Components, created by author

Component	***MATLAB FIS Input***	***Narrative***	***Crisp Value***	***Ordinal Risk Fuzzy Set***
Synectics Net 16	[0.713594997113521;1;2]	A component of this type **‘often’** requires investment, its **‘EOL has been exceeded’**, by more than a year and **‘medium’** critical component.	0.95	‘Very Important’
Synectics Net 8	[0.713594997113521;1;2]	A component of this type **‘often’** requires investment, its **‘EOL has been exceeded’**, by more than a year and **‘medium’** critical component.	0.95	‘Very Important’
Synectics RS232	[0.713594997113521;1;2]	A component of this type **‘often’** requires investment, its **‘EOL has been exceeded’**, by more than a year and **‘medium’** critical component.	0.95	‘Very Important’

Synectics VDA's	[0.713594997113521;1;2]	A component of this type **'often'** requires investment, its **'EOL has been exceeded'**, by more than a year and **'medium'** critical component.	0.95	'Very Important'
Synectics Voll 8	[0.713594997113521;1;2]	A component of this type **'often'** requires investment, its **'EOL has been exceeded'**, by more than a year and **'medium'** critical component.	0.95	'Very Important'
TM Legic	[0.687488308489034;1;1]	A component of this type **'often'** requires investment, its **'EOL has been exceeded'**, by more than a year and **'low'** critical component.	0.824	'Important'
Watermark Reader	[0.687488308489034;1;1]	A component of this type **'often'** requires investment, its **'EOL has been exceeded'**, by more than a year and **'low'** critical component.	0.824	'Important'

Figure 140 and Figure 141 illustrate how the SS had a more diverse range of risk profiles throughout the case-study when compared to the BMS. This type of behaviour can be the result of many scenarios, for example; continued investment into a system without the guidance of an obsolescence management plan would likely produce this behaviour. The replacement of items irrespective of obsolescence will see the risk profile fluctuate rather randomly – reflecting the random relationship between obsolescence and purchase behaviour. Equally, the two systems are patently different; in purpose and suppliers, which could affect the likely behaviour of obsolescence within these independent markets. Further case-study evidence would be required in order to confirm that speculation. Similar to the OAT results, it poses a question to the reader as to whether a more diverse risk portfolio is desirable? What does this actually mean? For example, with regards to the BMS, a small percentage of the component groups require attention in order to reduce the overall risk profile. Their respective supportability will dictate the types of mitigation available to the Asset Management team. However, it is possible that a small strategy that will deal with a small group of components may be all that is required for the time being – proving to likely be non-resource intensive.

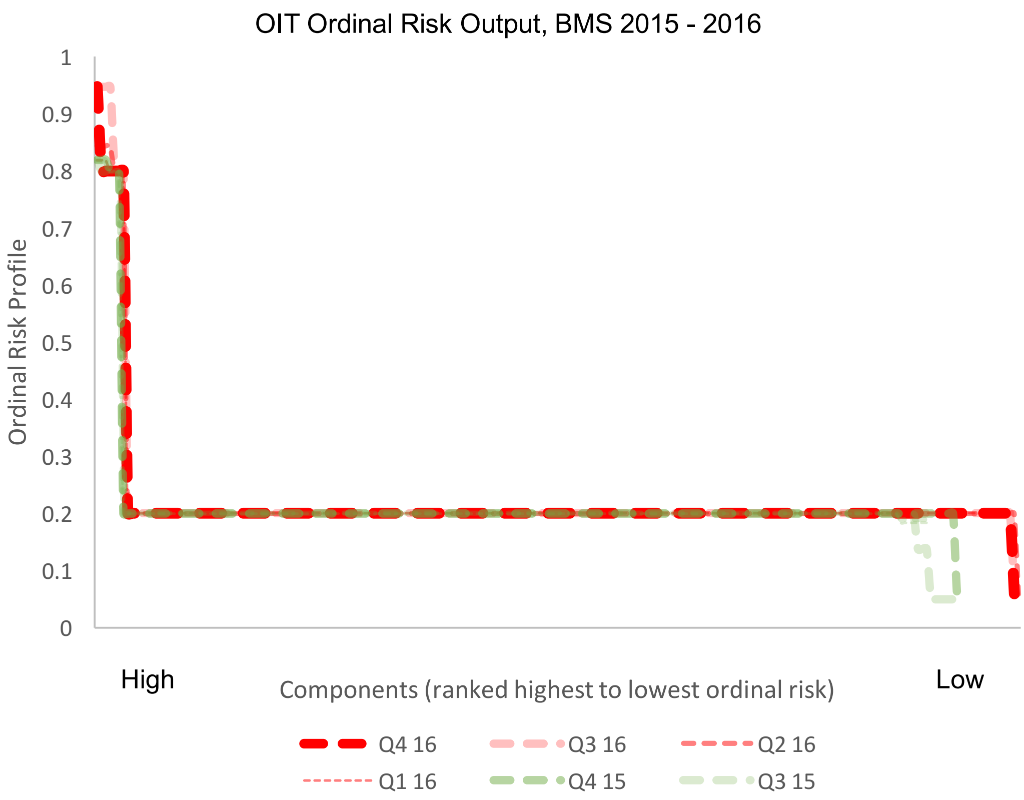


Figure 140 Building Management System Case-study Risk Results, created by author

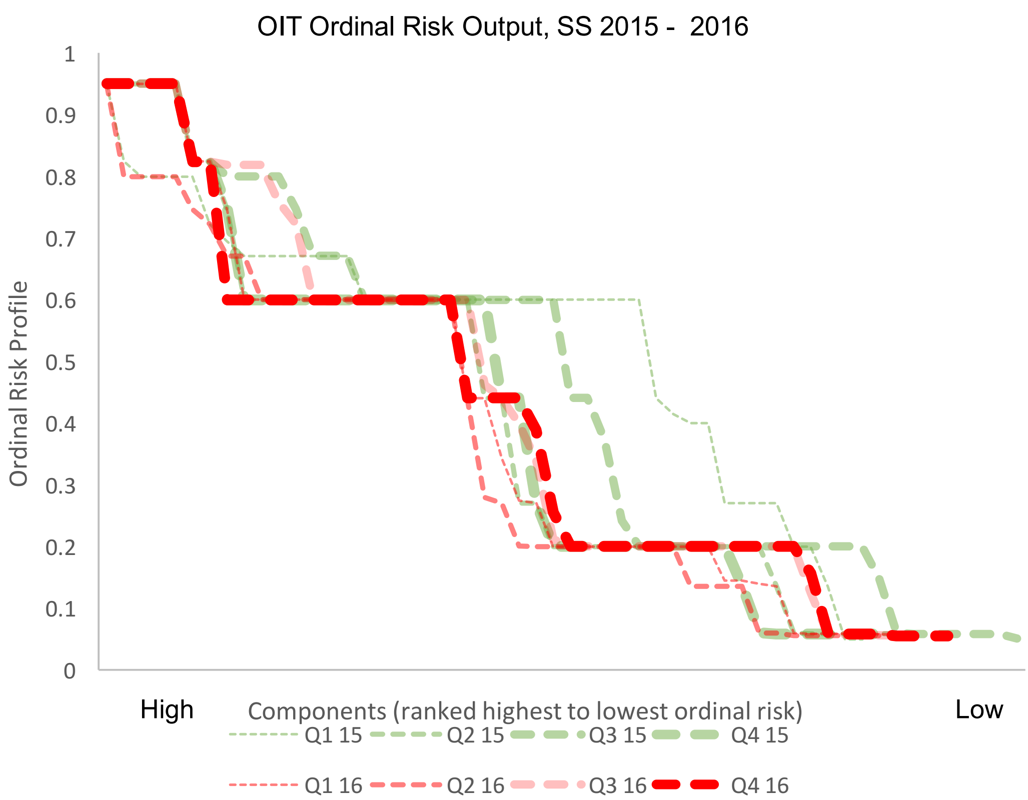


Figure 141 Security System Case-study Risk Results, created by author

Compare that with the SS, where you may require a strategy that is complicated and contains several mitigation approaches to holistically tackle obsolescence. It is unclear at this stage to speculate whether that is likely to be more expensive, as the cost is subject to more variables. However, the level of complexity and quantity of on-site spares (if lifetime buy is the adopted approach) will be greater. A further disadvantage of a more diverse risk portfolio is that you have foreseeable risks once you have mitigated the 'Most Important'. However, a significant benefit would be that with a staggered risk profile, the varied component groups are likely governed by different time periods. Meaning, any mitigation strategy could also be applied in a staggered manner, this would make the task of levelling or spreading the lifecycle investment an easier one. This holds potential benefits for budgetary control; however, a comprehensive OMP to underpin such strategy would be required. In summary, it can be speculated that in fact, the area of the curve (integral) for an entire system is the most important value, whether that be spread in a diverse manner or not. Whilst the BMS retained a similar risk profile throughout, the SS gradually reduced its risk profile, whilst retaining a small amount of 'Very Important' risks. The reduced risk profile can be observed in Figure 141, where the red plots of 2016 encroach on a smaller integral when compared to the green plots of 2015. The 'law of diminishing returns' may also be at play with these results, the SS appears to have improved its position in regards to its risk profile throughout the case-study. The BMS, with the already markedly better profile, saw little to no improvement despite the investment. However, it is likely this was needed to support and maintain the low-risk profile.

Through further mining of the low-risk components, it was identified within the Results section that in both systems across the two-year period, not a single component group elevated itself significantly once identified as a 'Not Important' risk. This is potentially an important observation because it shows robustness within the logic of OITs algorithm if it is correctly identifying low-risk components that remain low risk, providing an element of confidence. At this point, such a claim cannot be made. However, if supported by further case-study evidence would prove to be a valuable asset of OIT for an Asset Management team.

Figure 142 and Figure 143 were extracted within the Results section for further analysis, to investigate what changes, if any, were occurring on the datasheets to give more context behind why they were identified as 'Not Important' and remained that way. Of all the components that fulfilled this characteristic, three components were used to display contrasting behaviours.

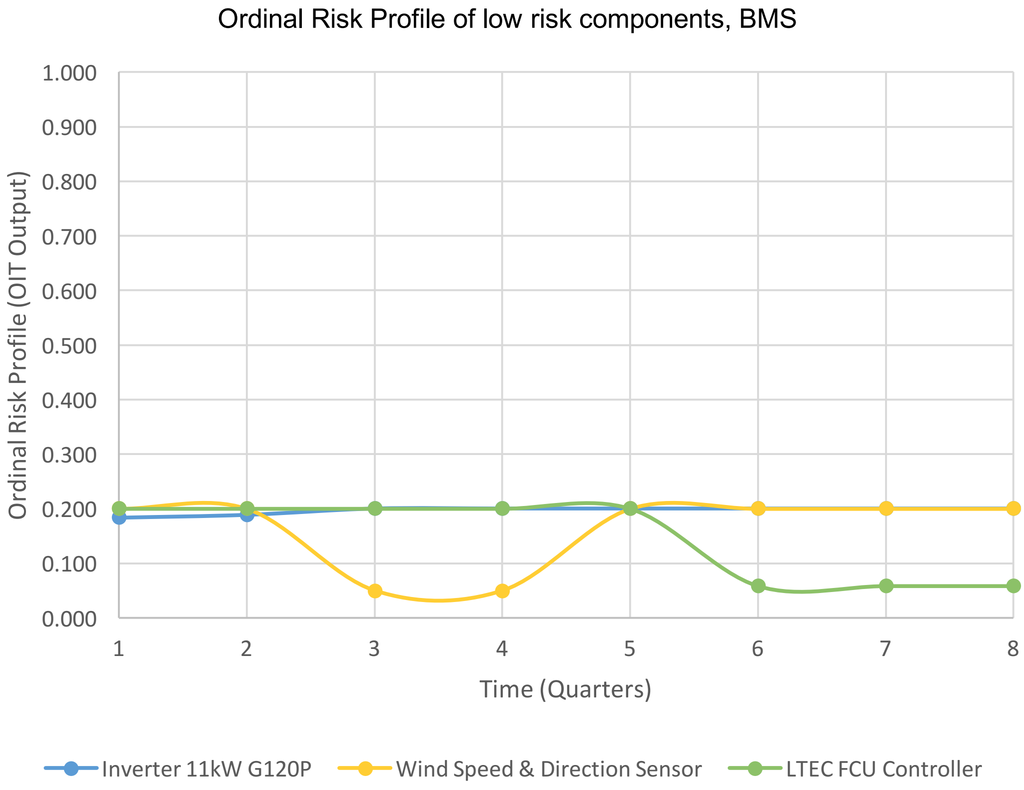


Figure 142 Building Management System 'Low Risk' Components, created by author

The narrative behind the component - 'Inverter 11kW G120P' is that it 'Never' requires an investment and although it doesn't have an EOL notification, it has been on the market for a considerable amount of time (>5 years) and therefore has been assigned into the 'EOL notification released' Fuzzy Set. This is an example of how Fuzzy Logic accounts for a potential error within the dataset, by giving this component a weak membership into an adjacent Fuzzy Set, of which it explicitly is not a part. Finally, it is a component of 'Medium' criticality and therefore produces an input of '[0.0903712731463814;0.5;2]' for the FIS in MATLAB. These inputs remained constant throughout the case-study; hence it did not elevate itself as a more important risk. It may be prudent to incorporate a follow-up process for components such as 'Inverter 11kW G120P', which have existed in the market for an extended period. The 'Wind Speed and Direction Sensor' experienced a dip of risk profile during the periods Q3 and Q4 in 2015; otherwise, it held a 'Minor' risk profile throughout. A component of this type 'Never' requires an investment and in Q2 2015 it was unknown whether an 'EOL notification was released' and was a 'Medium' criticality component. During the periods Q3 and Q4 of 2015 there was 'No EOL notification' marked against it, leading to a slightly lower risk profile of 'Not Important'. This was changed back to unknown from Q1 2016 for the remainder of the case-study with the following input for the FIS in MATLAB - [3.93941444576384E-07;0.5;2]. This slight blip in the input values can have several reasons, for example; human error by the sub-contractor that was not picked up by the Asset

Management team. Equally, an OEM holds the right to released and redact an EOL notification to the market, such movement would create a spike within the risk profile. In contrast to the two above components, the 'LTEC FCU Controller' retained a 'Minor' risk profile until Q2 2016, where it reduced to a 'Not Important' risk for the remainder of the case-study. This component 'Never' requires investment and until Q2 2016 had an 'EOL Notification' against it. In Q2 2016 the EOL notification was removed, however, due to the infancy of it, it only slightly raised the profile.

The SS appeared to have had a more active set of components that existed within the 'Minor' and 'Not Important' risk categories. Figure 143 shows the 'Pelco Work Station', 'Intercoms System' and 'Pelco NVR' oscillate throughout the case-study, with a gradual mean rise. Table 46 demonstrates how as time proceeds, whilst there was no 'EOL notification' against the 'Pelco NVR', the obsolescence input (2) gradually increased. This gradual increase reflects the increasing length of time the product has been available on the market. Therefore, the oscillating increase witnessed in the above figure is a result of Fuzzy Logic's approximating an increase in risk whilst there is no explicit or Boolean change regarding the component's obsolescence status.

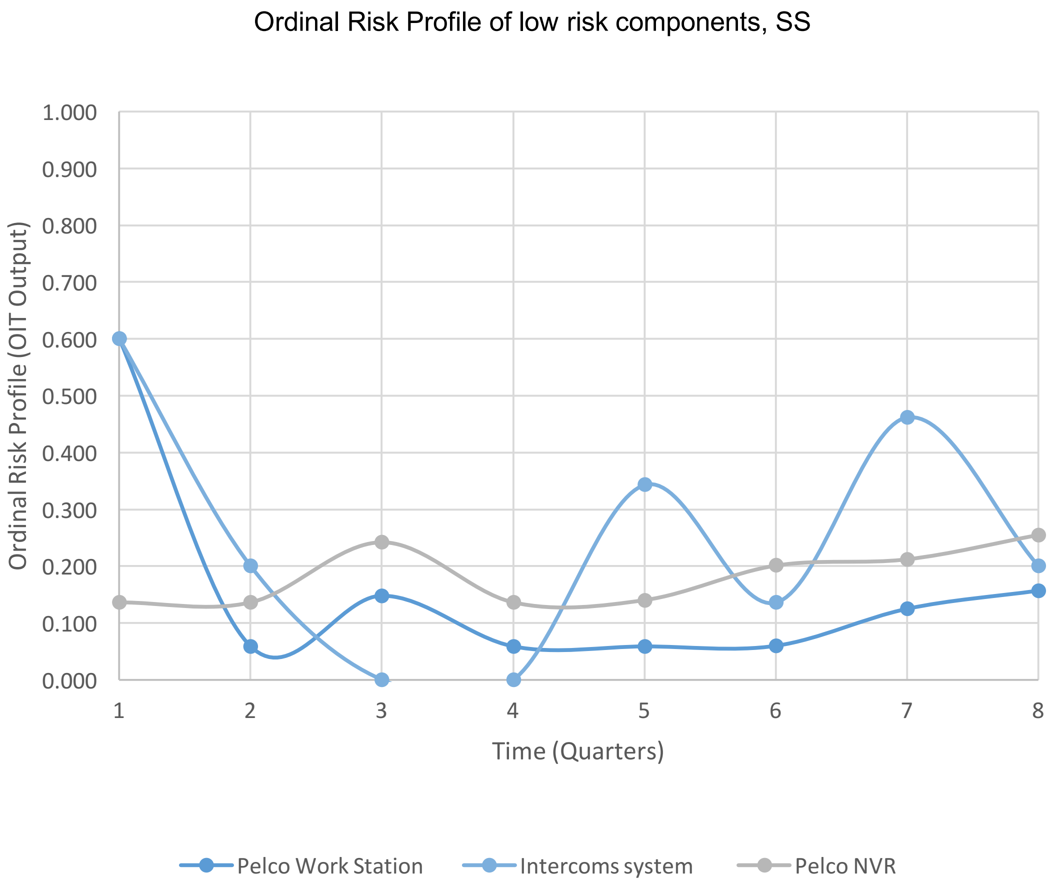


Figure 143 Security System 'Low Risk' Components, created by author

Table 46 Security System 'Pelco NVR' Analysis, created by author

	Component	**MATLAB FIS Input [(1); (2); (3)]**	**Crisp Output**	**Fuzzy Set**
Q1 15	Pelco NVR	[0.290145899175174;0.175068493150685;1]	0.136	Not Important
Q2 15	Pelco NVR	[0.290145899175174;0.2;1]	0.136	Not Important
Q3 15	Pelco NVR	[0.290145899175174;0.341917808219178;1]	0.242	Minor
Q4 15	Pelco NVR	[0.290145899175174;0.25041095890411;1]	0.136	Not Important
Q1 16	Pelco NVR	[0.290145899175174;0.275342465753425;1]	0.14	Minor
Q2 16	Pelco NVR	[0.290145899175174;0.30027397260274;2]	0.201	Minor
Q3 16	Pelco NVR	[0.290145899175174;0.325479452054795;1]	0.212	Minor
Q4 16	Pelco NVR	[0.290145899175174;0.350684931506849;1]	0.255	Minor

The ‘Pelco Work Station’ followed a similar projection as to the above ‘Pelco NVR’ component, the ‘Intercoms System’ however, showed a later more inclined rise – peaking at 0.462. An input (2) of 0.6 derives from an ‘EOL Notification’ being released against the component but with an unknown date. However, the component has been on the market for less than a year. Both of these factors increase the risk profile of the component, whilst keeping it comparatively low in the bigger context.

Figure 142 and Figure 143 both illustrate how the information being provided by the market can be incomplete and also change very quickly. It is also possible for there to be inaccurate data in the form of dates within the datasets. A Fuzzy System can, and has, mitigated these eventualities within the data through the form of Fuzzy Sets to indicate, approximately, where the risk lies. However, it is important to note that 'put rubbish in, get rubbish out' still applies and quality assurance checks are required. This research project used an in-house Asset Management team to undertake such tasks; however, it is still possible to have inaccurate dates. The approximating nature of Fuzzy Sets (in other words, their fuzzy boundaries that often overlap) reduces the impact of slightly inaccurate data – a key strength to the use of Fuzzy Logic to this field.

OIT was a novel and exploratory attempt at implementing a risk assessment model that could empirically evaluate the risk posed by obsolescence. However, from the results, there were several observations made that will feature within the Future Works section of this thesis. Input (1) represents the Stockout Probability of a component group, this statistic is reliant upon historical records held within *Building A*. More confidence can be placed upon these statistics when there is a greater depth of historical data, which is a continued exercise that should be undertaken following this thesis under Future Work. It has already been noted that Fuzzy Inference Systems built via 'expert panels' are flexible to future iterations to adapt the behaviour of the model in hindsight of results. Following this work, it is recommended that the methodology is repeated following a reverse engineering of the results to interpret whether the algorithm is reflecting the desired heuristics. This would involve the adapting of Fuzzy Set Membership Functions and IF-THEN Rules to affect the sensitivity of the model to produce a new set of results on the existing dataset. Again, the result should be appraised to ensure they are reflecting the heuristics intended and how they differed from the previous before deciding whether to adjust the model further.

Next, the discussion will move on to cover how the Resilience Analysis and Sales Data Analysis contribute towards both the research questions and the wider research field. There are some significant findings and evidence provided to the reader that clarify some of the thinking within the field on an empirical level.

5.4 Sales Data and Resilience Analysis

The purpose of this subsection is to combine the results from the Sales Data Analysis and resilience trade-off analysis to demonstrate how these wider elements of the research project contribute to the research field. The output of the Sales Data Analysis can be directly extracted from this thesis and applied into the industry to any decision maker that contains a BMS from either the same or similar OEM. This information alone can immediately enhance ones OMP. In addition, the resilience trade-off analysis begins to formulate the types of decision-making models that should occur internally within an OMP. The use of internal contractual penalty deductions against data-driven spares requirements is the elementary step required to achieving both proactive management and truly Strategic Asset Management.

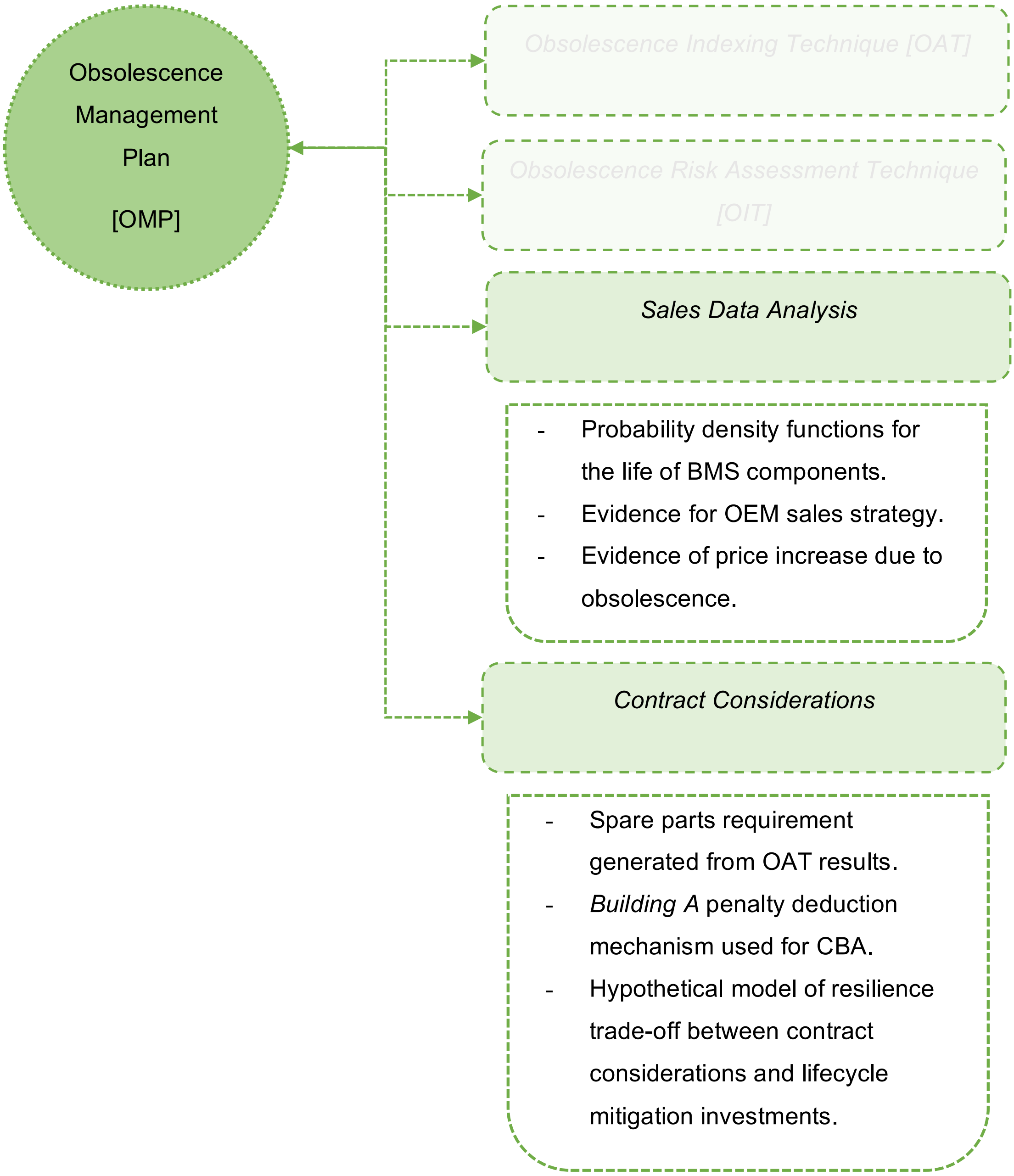


Figure 144 Results Framework, created by author

This Discussion section so far has covered the OAT and OIT tools, their results, and respective impacts upon the literature landscape and research field. Whilst the previous subsections immediately address the research questions of this thesis, the following dialogue has significant impacts on the field of Obsolescence Management (OM). The Sales

Data Analysis and Resilience ‘trade-off’ Analysis illustrate how other data streams from within the Built Environment can be utilised to aid the development of an Obsolescence Management Plan (OMP). The two aforementioned analyses are simpler by design than OAT and OIT; however, they show true merit in their application within the industry – a key characteristic for Engineering Doctorate contributions. This subsection will first discuss key findings, their impact and potential uses within both academia and industry, culminating in some observations for future works to enhance the methodology used.

It has been a long-standing suspicion within industry that certain components contain an element of ‘planned obsolescence’, this was briefly covered within the literature review following an assessment of Kessler and Brendel's (2016) interesting paper. The author is of the opinion that the term ‘planned obsolescence’ is not, in fact, a new topic in itself, but an observation of the behaviour of obsolescence as a result of a sales strategy and lack of obsolescence management plan. The underlying structure of a sales strategy will transcend and manifest itself into a non-coincidental occurrence of obsolescence and supportability issues for an end-user. These terms are not particularly surprising; however, there is no current literature that has sought to investigate the connection between a sales strategy and obsolescence. Currently, the connection between the two resides solely as theoretical one that finds itself within the core definition of obsolescence:

Obsolescence occurs when a component is no longer suitable for current demands, or is no longer supported by the manufacturer.

CMCA UK (2013); BSI (2007); Bartels et al. (2012); Singh, Peter Sandborn, et al. (2004)

To formally recognise the influence of a sales strategy upon obsolescence, followed by an analysis of the said strategy, holds the potential to predict and forecast obsolescence from an end user's perspective. This type of analysis can be loosely associated with the parametric analysis used by Solomon et al. (2000), Sandborn and Singh (2002) and Feng et al. (2007) (see section 2.2.2.2) where component attributes i.e. RAM, are plotted and extrapolated to speculate when replacement products are likely to occur.

Figure 145 shows clearly how the underlying sales strategy of this particular OEM introduces a five-year cycle within their product range. In 2013, there was a steep rise in the total number of products provided to the market (a 62% increase), however, this was directly mirrored within the annual number of obsolete components found in 2013 – 2015, maintaining the cycle ratio. Now it is important to restate to the reader that a sales strategy is expected and not the key findings within the dataset. The proof of an existing sales strategy for a set of components that you rely upon is a key piece of information for the wider OMP for the said asset system.

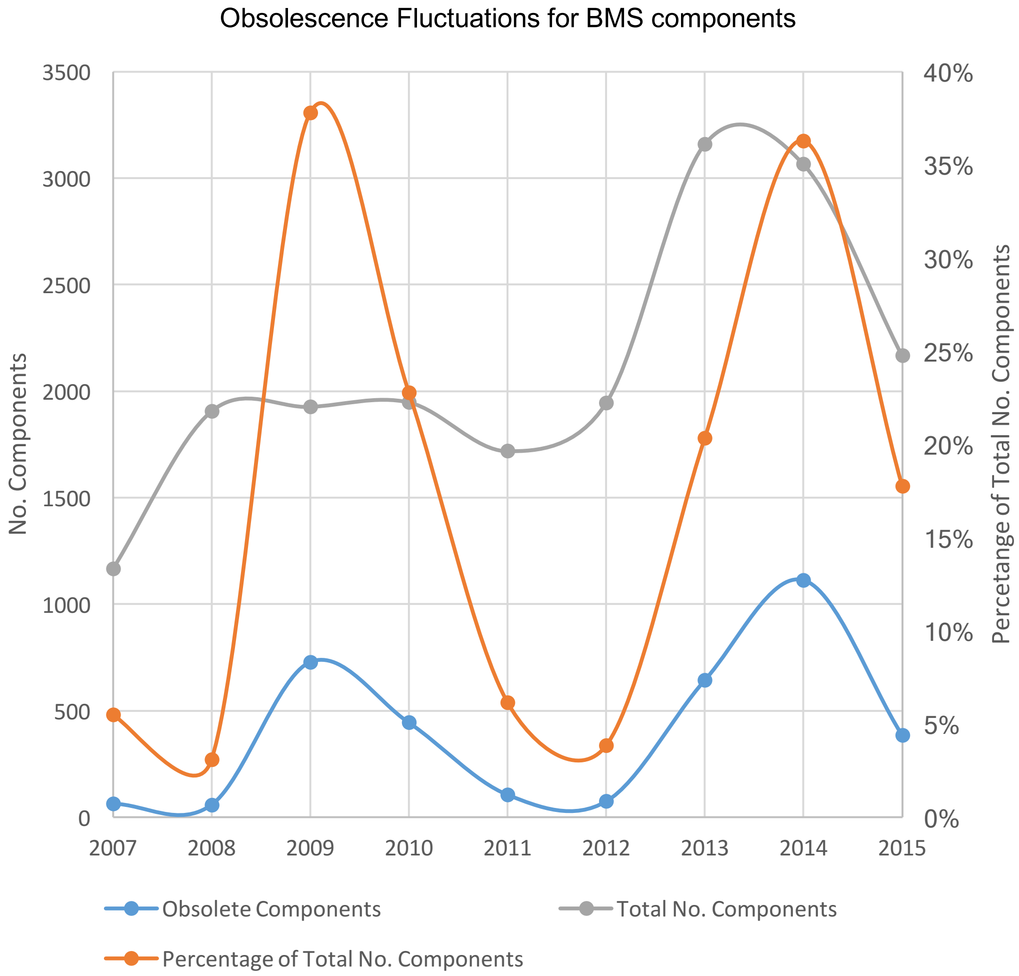


Figure 145 OEM Sales Strategy and Obsolescence, created by author

Understanding the apparent cyclical behaviour within Figure 145 would allow an Asset Management team to both strategically procure components, maximising their supportability, and predict when current components are to become obsolete. The two insights alone, both constitute to Proactive Obsolescence Management and Strategic Asset Management – valuable insights. This insight alongside the results of OIT for example would allow for a data-driven strategy to decide which components and when/if they should be procured to mitigate obsolescence. This methodology, not found within the current literature landscape, is both repeatable and scalable, and a large contribution to both academic and industry that can be adopted and implemented quickly.

Teunter and Haneveld (1998) and later Mulholland (2014) began to recognise the connection between reactive obsolescence management and rising costs associated component scarcity. Please note, there is considerably wider literature regarding component scarcity and reactive management techniques, however, none with the specific consideration of obsolescence. From this lack of literature, there is no explicit evidence of either this connection/correlation or to what extent does obsolescence increase the component cost. Again, currently this relationship, whilst widely agreed, remains conceptual as there is no published evidence to confirm. The Sales Data Analysis investigated precisely this relationship, splitting between components that were present in 2006 but with an unknown release date and components that were launched in 2007. These two datasets allow the author to investigate whether the unit prices rise or fall, and whether this heuristic is widespread or isolated within certain product groups.

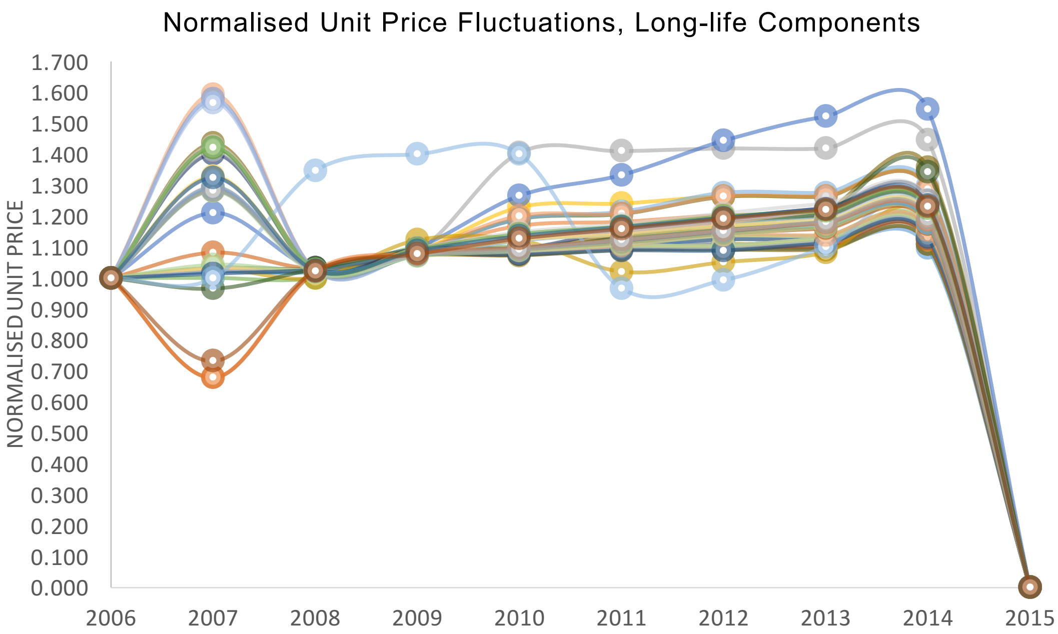


Figure 146 Normalised Unit Prices for OEM 'Long-life' Components, created by author

Figure 146 contains the components that existed in 2006 (and potentially before) and became obsolete in 2015. Note that this is the longest time period within the dataset held and that the unit prices have been normalised against their starting value (1.0). All products broadly show a gradual price increase whilst they are available via the OEM, with particular rises in the penultimate year. The price increase ranged from 0% to 54%. It is interesting to note that no products within this dataset had a reduced unit price prior to becoming obsolete. There is no evidence here that reactively purchasing is financially beneficial, there are no 'discount' or 'sale' benefits. Figure 146 and Figure 147 both contain no legend, due to the large number of components within the dataset.

The above dataset was designed to contain products covering the longest time frame possible (2006 to 2015), the next dataset contains components that were launched in 2007 and became obsolete in 2015. This will capture the entire life of the below components within the market, observing the behaviour of their unit cost.

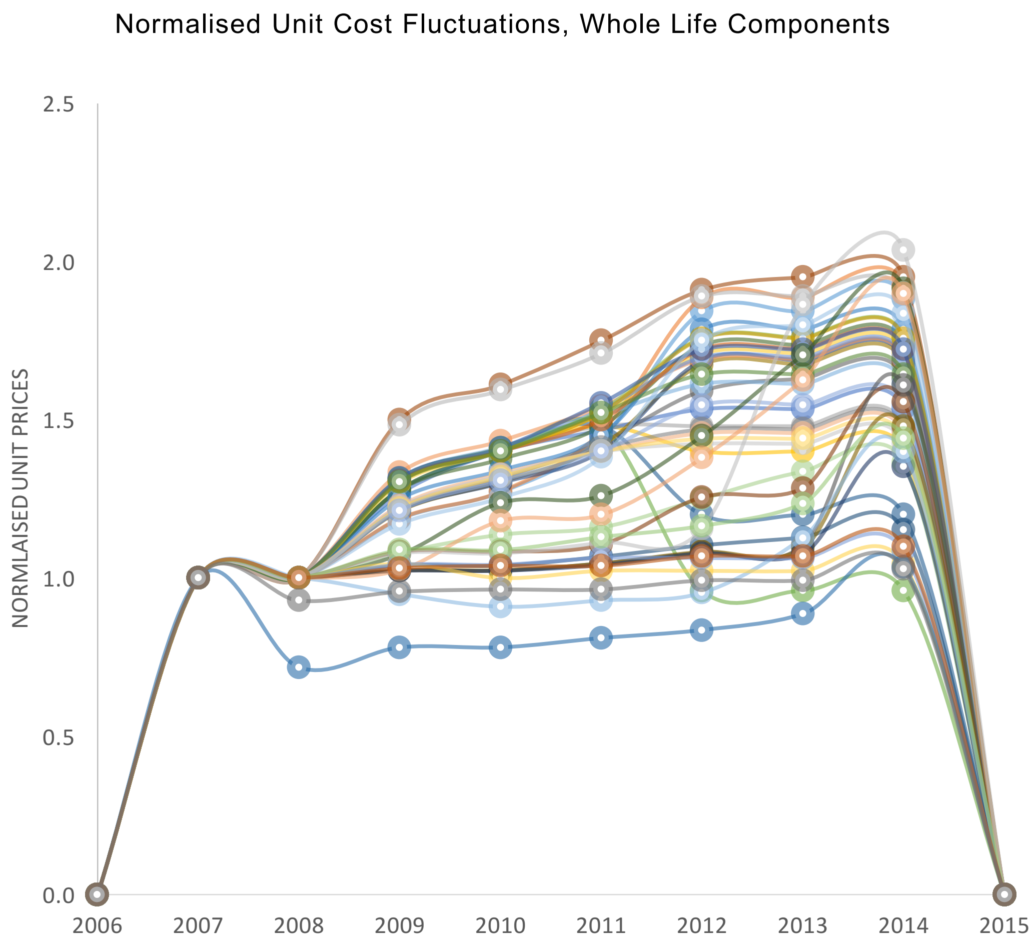


Figure 147 Normalised Unit Prices for OEM 'Whole Life' Components, created by author

Firstly, all of the components express the same trend of an increasing unit cost over time, with particular spikes in their penultimate year. This is a reassuring find, supporting the speculation in the above paragraphs that there is a real and considerable cost of reactively managing obsolescence. Perhaps the most important observation from Figure 147, when compared to Figure 146, is that the range of component cost increases ranges from 0% to 100% - this is significantly greater. It is possible that the starting component costs found within Figure 147 are in fact lower than those used to normalise the data from 2006. This finding exacerbates the claim that reactively managing obsolescence is expensive. The above two figures, for the first time, provide evidence of the effects of obsolescence upon the cost of mitigating it.

In a similar fashion to the Sales Strategy Analysis, price rises are solely the prerogative of the OEM, they have no obligation to fix the unit cost of components. However, this insight would allow an Asset Management or Facilities Management team to undertake a Cost Benefit Analysis when comparing different strategies. All of the above would feature within an Obsolescence Management Plan and allow for data-driven decision-making on a strategic level. The above two datasets were accurate as of 2015 and therefore hold real, tangible value for Asset Management teams within the industry that support systems containing components from this OEM. The third and final output from the Sales Data Analysis produced probability density functions, which would allow an Asset Management or Facilities Management team, to forecast the length of time their components or like components would be available via the OEM. It is important to highlight that this is via the OEM; alternative or secondary markets do occur, but are not considered herein.

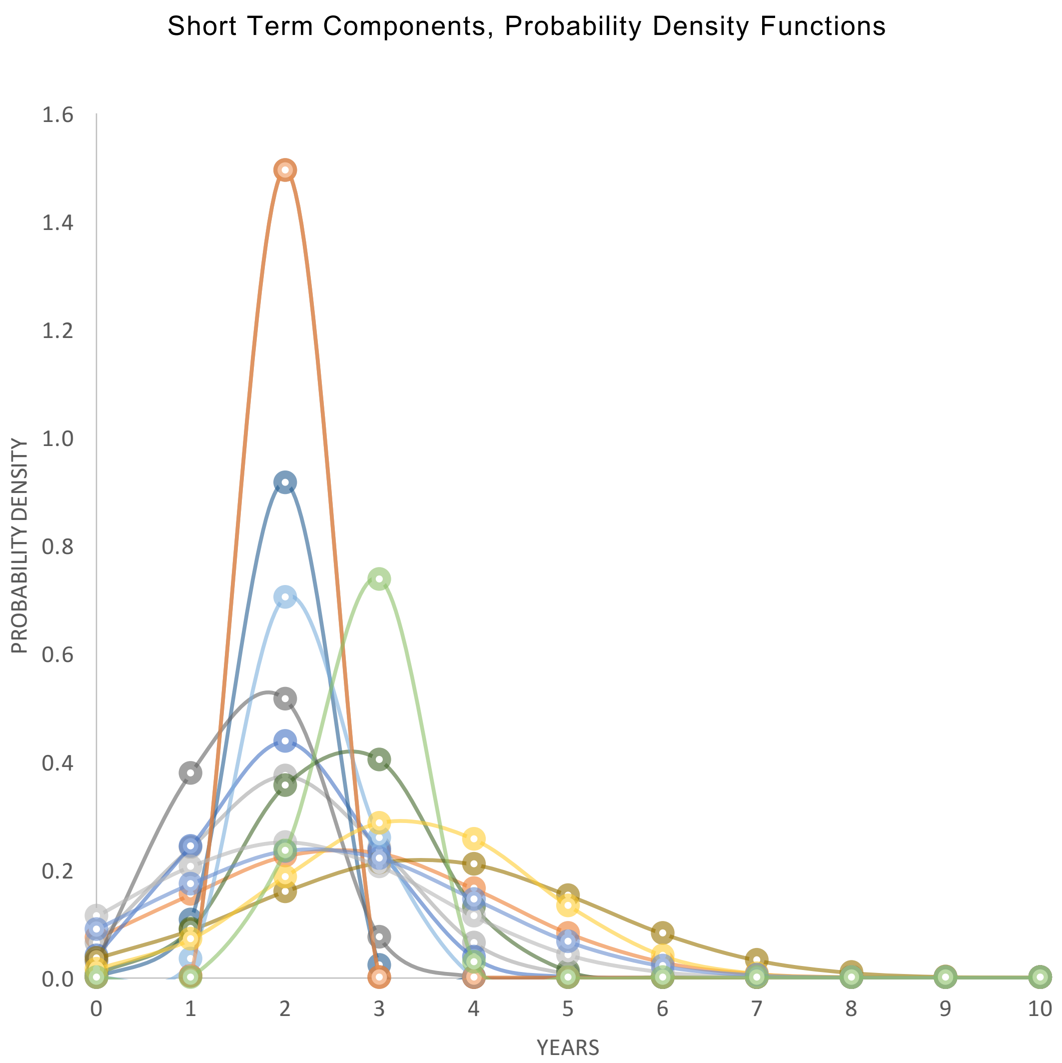


Figure 148 Probability Density Functions for 'Short Term' OEM Components, created by author

The dataset was separated into two, reflecting both short and medium length components, which appeared to broadly contain differing standard deviations. The contrasting profiles illustrate more uncertainty within medium to long-life components than with regards to when they become obsolete. Shorter life components with smaller standard deviations contain more statistical certainty of how long they will be available on the market. Note, again legends for both Figure 148 and Figure 149 have been removed in the essence of space. It is interesting to observe that regardless if the component in question is medium or short life, it will unlikely be available six or seven years beyond its introduction to the marketplace.

Medium Term Components, Probability Density Functions

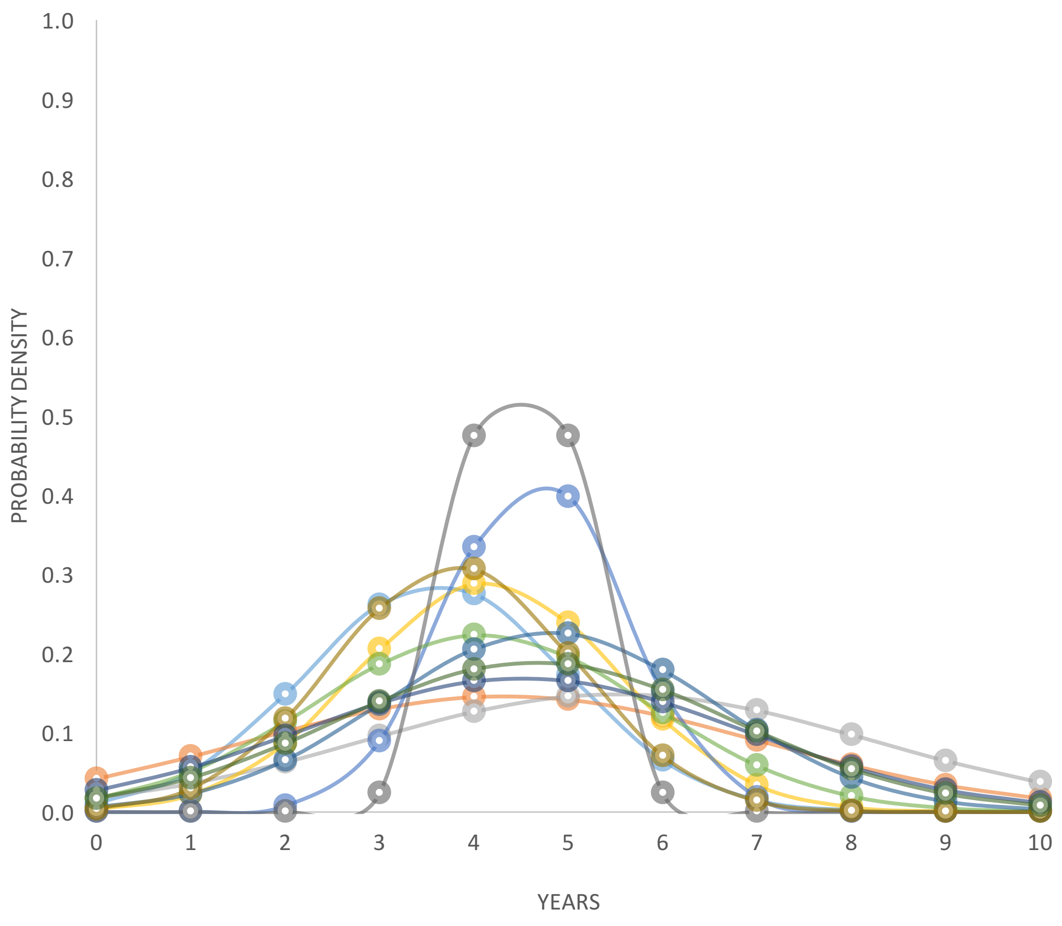


Figure 149 Probability Density Functions for 'Medium Term' OEM Components, created by author

One simple exercise of collecting annual OEM sale catalogues and then monitoring the changes over time, have provided three insights that can all directly feed into an OMP, enabling proactive OM. An informed and up-to-date OMP holds the potential to not only maximise the supportability of assets but avoid unforeseen obsolescence driven investments. It is important to remember that these three separate insights have cost the end-user nothing, but hold the potential to add significant value.

The above discussion holds benefits across the Built Environment, however, within the context of Private Finance Initiatives (PFI) there are clear drivers for formalising some of the decision-making models. *Building A,* for example, has an internal Asset Management team who are responsible for the lifecycle of all the assets. They make the decision as to whether to invest or not and into what they should invest when seeking to economically support their assets and meet service delivery. Currently, the above decisions are completely reliant upon informal mental models, directed by the experience and knowledge of the employees. As already covered within the literature review, it is not that this is inadequate, but rather it can be enhanced if made aware of certain trends within relevant datasets. For example, if the said Asset Management team were aware of the underlying sales strategy and rising component costs, they would likely change their behaviour.

To give further context to the scale of the impact, the UK PFI market consisted of 728 live contracts, amounting to a total of £56.5bn in capital value and would peak to £10bn in annual unitary payments to the private sector (Partnerships UK 2006; Mulholland et al. 2016c). Figure 150 illustrates the market, interestingly although the department of education (denoted 1) hold the most concentrated number of contracts; it is the department of health (denoted 2) that hold the highest capital value. Logically these contracts contain large healthcare sites i.e. hospitals and contain large asset systems of significant monetary value.

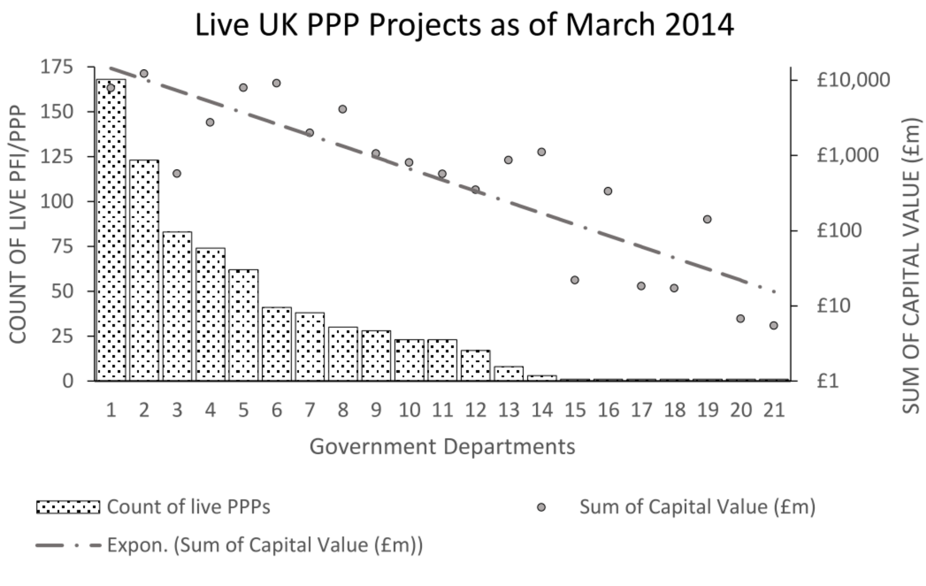


Figure 150 UK Private Finance Initiative Market, from Mulholland et al. (2016c)

The Resilience ‘Trade-off’ Analysis formalised the decision-making process currently undertaken via heuristics and informal mental models, as to whether to invest into spare components proactively. The aim of this analysis was to illustrate this ‘trade-off’ to the reader, no to design a fully fledge strategy for *Building A*. It would form the basis of the Cost Benefit Analysis to be found within an OMP for a system. This type of exercise was possible due to the service delivery obligations within PFI’s that formalise the deductions made upon the Unitary Payments from the public to private sector. This exercise appropriately ties up the underlying narrative of this entire Discussion section. Firstly, OAT (an indexing technique) was evaluated for identifying components within asset registers that should be highlighted for further investigation. Secondly, OIT (a risk assessment method) was developed to evaluate the risk posed by obsolescence to the operational status of an asset. The outputs of both models would be supported by wider market information, such as that provided by the Sales Data Analysis. This would enable data-driven decision-making within an OMP. Finally, with information regarding which components were a risk and why, when they would likely become obsolete (if not already) and the possible increase in unit costs, one would be able to undertake a CBA or ‘trade-off’ visualisation to decide whether to invest or not. This narrative was underpinned by the research questions set out and tested a methodology that enables proactive obsolescence management.

As a result of the Sales Data Analysis and Resilience Analysis, observations were made for Future Works in order to continue this line of research and add further evidence. It is recommended by the author that an OMP is produced for *Building A*, using the evidence found in this thesis. The OMP would contain forecasts and projections on both when obsolescence may occur and also the likely costs. A review can then be held in a year or two, evaluating the accuracy of the methodology proposed herein. This exercise was not possible within the timeframe governed by an Engineering Doctorate, however, would be appropriate for any follow-up research. As a separate exercise, the formal ratification of the Sales Data Analysis methodology for more OEMs would be an interesting piece of research. Continued investigation into how OEMs influence the market with sales strategies and the resultant obsolescence, would be widely beneficial.

The next section will culminate the ongoing discussion into the explicit contributions to new knowledge held within this thesis. As an Engineering Doctorate requirement, it is important that contributions are explicitly stated and also supported. Added context via the Gap Analysis (see section 2.6.1) is important in order to benchmark the contributions of this piece of research. This final subsection of the Discussion will create the foundation upon which the author will provide a conclusion of all research questions, research aims, and objectives, allowing the reader to holistically evaluate this project.

5.5 Knowledge Contributions

It is felt by the author that a concise summary of the key contributions reviewed within this Discussion section would be appropriate to both satisfy this requirement and set a grounding for the Conclusion. In advance of both the Results and Discussion sections, the research design used the Gap Analysis (see section 2.6.1) to identify the following four areas that would contribute to new knowledge either through the discovery of new knowledge or the connection of unrelated facts.

- Further development and empirical testing of obsolescence indexing technique.
- Development and empirical testing of a new obsolescence risk assessment technique.
- Visual evidence of product obsolescence and the effect on component cost.
- Visualisation of the resilience trade-off for Asset Managers/Facility Managers.

The following subsection will discuss how the above identified gaps were ratified into deliverables in the form of aims and objectives for the methodology to deliver. This will create the datum against which the success of this thesis will be judged. The above four gaps were converted into the following four aims for this thesis.

Table 47 Thesis Aims, created by author

Aim (1)	To further develop and empirically test the obsolescence indexing technique (OAT), then to benchmark the new iteration against the previous to illustrate the added precision to the model and validate its use.
Aim (2)	To develop and empirical test a new obsolescence risk assessment technique herein called OIT. OIT is an 'expert model' and will be developed via an expert panel to ensure robustness within the methodology and model behaviour.
Aim (3)	Critical analysis on sales catalogues from an original equipment manufacturer (OEM). The outputted visuals will provide evidence of the influence of obsolescence upon both unit costs over time and also generate density probability functions for the life of components on the market.
Aim (4)	Visualising the conceptual resilience trade-off for Asset Managers/Facility Managers. This novel visual will attempt to demonstrate the informal decisions made when seeking to mitigate obsolescence and improve resilience.

Aim (1) involved the further development of the previously published indexing technique of OAT (Mulholland et al. 2016b). Technically this involved added granularity of the internal algorithm and inbuilt validity checks for input files. This new tool was then migrated over to

MATLAB as a complete script, allowing it to be both transferrable and scalable. The new OAT was then implemented into a case-study environment for two years and benchmarked against the previous iteration of the algorithm. This aim held several new technical elements undertaken by this research project, culminating in a new comprehensive Obsolescence Indexing Technique that has had empirical testing.

Table 48 contains the four objectives created to ensure that this contribution to new knowledge was executed. This contribution falls under the 'revision of older views' category, whilst providing further empirical evidence of the impact of obsolescence.

Table 48 Aim (1) Objectives, created by author

Objective (1)	Enhance OAT's internal algorithm to now consider additional parts and confirmed compatibility. This will enable OAT to provide a more accurate characterisation of obsolescence.
Objective (2)	To enhance validity and increase industrial application of OAT, internal validity checks for the input dataset will be developed. This increases the transparency and validity of the model.

Aim (2) involved the creation of a completely new Obsolescence Impact Tool, OIT. In order to compute the sometimes subjective and ambiguous data sets, an alternative to Boolean methods was sought. Fuzzy Logic was chosen for its merit as a tool for approximate reasoning and risk assessments (Markowski & Mannan 2008; Ross 2010). Fuzzy Systems are adaptable as 'expert models' allowing for the author to incorporate the knowledge held within the industry sponsor management team. The three inputs to OIT required separate bits of analysis to organise the data into the expected form for the Fuzzy Inference System (FIS) to correctly interpret the data and provide a single ordinal risk output. Whilst Fuzzy Systems have been widely used within the context of Risk Assessments, this was the first to be designed for obsolescence within the Built Environment. This aim of creating OIT and testing it within a live case-study environment is a significant 'discovery of new knowledge' as a way of quantifying the risk posed by obsolescence.

Table 49 contains the subsequent objectives required to deliver Aim (2), note that the three inputs required several steps prior to being analysed by OIT. Most noticeably, the Stockout Probability input was extensive. The design of OIT relied heavily upon previous literature and guidance for designing similar Fuzzy Systems and the consultation of an 'expert panel' to validate the 'black box' or intelligence element of the model. When designing a model in this manner, it is advised to iterate the process under Future Works to adapt, if required, the sensitivity of the model.

Table 49 Aim (2) Objectives, created by author

Objective (3)	An Importance Measure (IM) to be used for categorisation of case-study asset systems. This will identify the most critical components and add context to the model output. The output will then be used as input (1) for the Obsolescence Impact Tool (OIT).
Objective (4)	Stockout probability calculations are to be undertaken using data from onsite UPM records and stock inventory data. This will be used as input (2) into OIT. Stockout probabilities use the statistical forecast demands, essential for risk calculation.
Objective (5)	Data collected for Aim (1) will be used to act as input (3), concerning the obsolescence status of each asset system.
Objective (6)	A Delphi methodology will be used amongst industry experts to create the internal IF-THEN rules to govern the FIS rules. This will now enable the testing of OIT on real world data. It also adds robustness to the validity of the model and its behaviour.

Aim (3) was centred around directly contributing to the field of Obsolescence Management (OM) in the ‘connecting of two previously unrelated facts’, by reverse engineering annual sales catalogues of an OEM. This exercise technically involved the collating of datasets from 2006 to 2015 and then organising the data so that it was ready for parallel analysis. The collection of this data and analysis in itself was not novel, but the results provided evidence of relationships that previously were only conceptually claimed. Aim (3) provided evidence that had not been published prior to this thesis that comprehensively supports what was previously believed.

The contribution to new knowledge, therefore, is more the methodology designed and implemented that led to the outputted graphs. This simple set of analyses has demonstrated that great insight can be created, cheaply and across many systems. The process is detailed in Table 50 in the form of two objectives. The contribution will widely benefit the field of OM as Asset Management and Facilities Management teams will be able to adopt data-driven decision-making. This step further enables Strategic or Proactive Obsolescence Management.

Table 50 Aim (3) Objectives, created by author

Objective (7)	Annual catalogues from a key OEM will be reverse engineered to extract the price change both when a product is new and becoming obsolete. This dataset spans over a decade and will provide a robust foundation for analysis.

Aim (4) was also orientated towards the field of OM and seeks to demonstrate to the user the type of informal 'trade-off' decisions that occur when decision-makers choose to invest or not into the resilience of an asset. Lifetime buys are the most prominent obsolescence mitigation technique; this involves the calculation of required spares to continue maintenance and supportability of a system throughout its intended life. By using a real scenario from the case-study, a visual trade-off between the resultant costs of asset unavailability against a spares quotation was created. Similar to Aim (3) this simple methodology encourages data-driven OM, illustrating an approach for Proactive OM. It is debatable whether this is a 'discovery of new knowledge' but more likely a 'revision of older views'.

Table 51 Aim (4) Objectives, created by author

Objective (8)	The case-study PFI penalty mechanism will be extracted and simplified to illustrate how costs rise over time with asset downtime. This is cross referenced with a quotation from the OEM for identified spare parts.

In summary of the above discussion, the author has concluded the key elements into the following contributions to new knowledge and their definition, shown in Table 52.

Table 52 Contributions to New Knowledge, created by author

Serial	Contribution	Definition
1	**Obsolescence Assessment Tool (OAT)** New algorithm, added validity and further empirical testing.	'revision of older views'
2	**Obsolescence Impact Tool (OIT)** New methodology and empirical testing.	'discovery of new knowledge'
3	**OEM Sales Data Analysis** Evidence confirming and connecting previous conceptual theories.	'connecting of two previously unrelated facts'
4	**Resilience Analysis** Evidence of existing theory to support proactive obsolescence management.	'revision of older views'

Table 52 appropriately and plainly details the contributions of this thesis to both academia and industry and when combined, addresses the title of this thesis - 'The Resilience of Asset Systems to the Operational Risk of Obsolescence: Using Fuzzy Logic to Quantify Risk Profiles'. The next section will formally conclude the findings and include future works to both learn from this project and continue research into this field.

6 CONCLUSION

6.1 Introduction

The purpose of this conclusion is to formally combine all of the strands of narrative that exist within this research project into a unified argument. This project contained several research questions, which in turn produced several contributions to new knowledge that need clarifying in order to holistically assess the output of this thesis. This section is not to be read in isolation from the other main chapters, however, there will be supporting words to guide the reader through, in brief, the path this thesis has taken.

This conclusion will deliver three key things; a critical analysis of the contributions to new knowledge, an objective appraisal, and then a comparative analysis of this chapter and the thesis title. These three substantial elements, shown in Figure 151, will construct the flow of the conclusion, whilst the author will provide a synopsis of the orthogonal pieces that combine and continue the narrative of the argument.

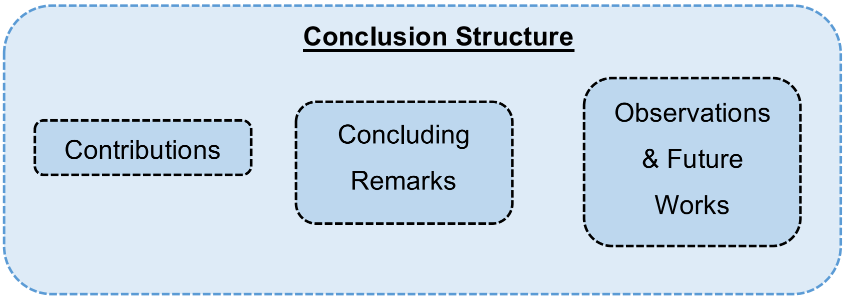


Figure 151 Conclusion Structure, created by author

The aim of this section is to enable the reader to assess whether this thesis achieves the requirements of an Engineering Doctorate as stated by the University College London's 'Academic Manual' (University College London 2016a). After reading the conclusion, the reader should be in a position to assess whether this project has delivered upon the research questions and ultimately answered the thesis title. In addition to undertaking the above assessment, this chapter will provide any wider elements required for the reader to decide whether the requirements for a doctorate have been met.

The first subsection of the conclusion will bring forward the contributions to new knowledge found within the previous chapter, and critically assess their impact and whether they have or are applicable for publication. By starting with the contributions, accompanied with a short synopsis, conclusions can be drawn to generate a coherent narrative to the reader. This is an important step before the author collates all of the observations and comments upon the methodology found within this thesis into a subsection for Future Works.

6.2 Contributions

Table 53 has been taken from the Discussion section of this thesis. This subsection will now provide a synopsis behind each one, which will contain extracts from the Results section to provide context and evidence of their achievement. Each contribution will express the overarching narrative, which will ultimately combine and compliment the other contributions, formulating the concluding findings and thoughts of this thesis.

Table 53 Contributions to New Knowledge, created by author

Serial	***Contribution***	***Definition***
1	**Obsolescence Assessment Tool (OAT)** New algorithm, added validity and further empirical testing.	'revision of older views'
2	**Obsolescence Impact Tool (OIT)** New methodology and empirical testing.	'discovery of new knowledge'
3	**OEM Sales Data Analysis** Evidence confirming and connecting previous conceptual theories.	'connecting of two previously unrelated facts'
4	**Resilience Analysis** Evidence of existing theory to support proactive obsolescence management.	'revision of older views'

Contribution (1) was achieved following changes suggested in the feedback from Mulholland's (2014) dissertation and a successful migration from Microsoft Excel to MATLAB. Enhancements included three additional statuses for the internal algorithm to assign to components within an Asset Register. The below formula depicts how this was achieved:

$$H = 100\frac{(\sum S + \sum Y_1 + \sum A_1 + \sum B_1)}{(\sum S + \sum Y_1 + \sum Y_2 + \sum O + \sum U + \sum A_1 + \sum A_2 + \sum B_1 + \sum B_2)}$$

AH = Asset Health

S = Two or more suppliers and no EOL

Y_1 = One supplier and no EOL notice

Y_2 = One supplier and EOL notice

A_1 = Alternative part, no EOL notice and confirmed compatibility

A_2 = Alternative part with EOL notice

B_1 = Alternative part, confirmed compatibility and EOL notice or Unknown EOL

B_2 = Alternative supplier and EOL notice

O = Obsolete part with no solution

U = Unknown status

The additional statuses added granularity and in turn a further level of precision from the internal algorithm. This was displayed with a comparative analysis between the old and new algorithms (see Table 54).

Table 54 Building Management System Old and New OAT Algorithm Comparison, created by author

Status	***Old OAT Algorithm***	***New OAT Algorithm***
A1	0	258
A2	993	0
B1	n/a	1539
B2	n/a	629
U	258	0
O	19	19
Y1	6716	0
Y2	1239	693
S	9089	15176
Asset Health	86.33%	92.68%

To add further validity to the algorithm before it was retested within a new case-study, five internal spot checks were embedded into the MATLAB script to check input datasheets. These independent checks validate the logic of the datasheets for common errors, and they were designed following the experience gained from the initial case-study in 2013 for Mulholland's (2014) dissertation. The next internal algorithm and preliminary observations made by OAT were published in the 'Journal of Facilities Management', a testament to the methodology used as it underwent peer review (Mulholland et al. 2016b). OAT further demonstrated the need for a simple algorithm to assess Asset Registers for obsolescence, as a continuous process, in order to keep Asset Registers up to date and correct. OAT is novel in design, as it was developed upon an original previous design; the added inbuilt validity increases its applicability to the industry. It is a 'low-tech' obsolescence indexing tool that could be quickly adopted by Asset Management and Facilities Management teams. In theory, OAT could be connected to automated decision-making in the form of Risk Management and issue escalation.

The need for contribution (2) was first identified in the literature review within Mulholland's (2014) dissertation, where there existed a gap for a tool to quantify the risk posed by obsolescence (OIT). The methodology provided within this thesis to build OIT relied upon Fuzzy Logic theory to design an 'expert' Fuzzy System, which could infer risk profiles upon ambiguous inputs (obsolescence, Stockout probability and criticality). This methodology, whilst in itself was deduced from several pieces of literature, was a contribution to new knowledge for applying it to obsolescence within the Built Environment for the first time. The internal algorithm inside the Fuzzy Inference System is visualised using a 'surface' diagram, as shown in Figure 152, Figure 153 and Figure 154. This demonstrates the achievement of building the Fuzzy System, in preparation for data analysis.

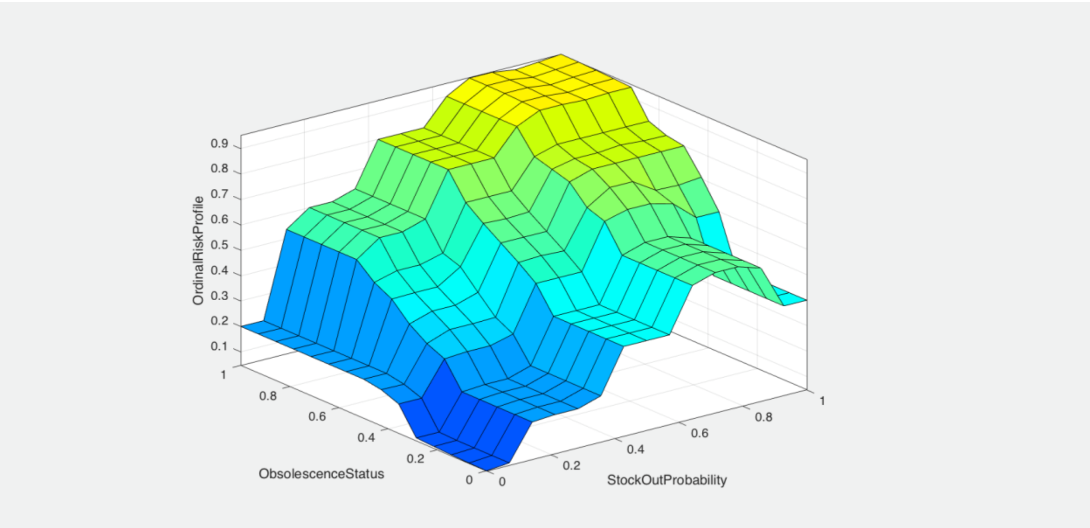


Figure 152 OIT Input (1) and Input (2) Surface Map Graphic, created by author

Figure 152 consists of the Stockout Probability input (1) and Obsolescence input (2), against the Ordinal Risk output from OIT. In addition, Figure 153 demonstrates how the surface created by the Obsolescence input (2) and Component Criticality (3) differs in profile. The combination of these three figures creates the overall surface that reflects the internal decision-making undertaken by the algorithm within OIT. OIT contained triangular membership function profiles for the Fuzzy Sets, which creates a linear step change surface. More complex relationships are possible with non-linear membership profile functions.

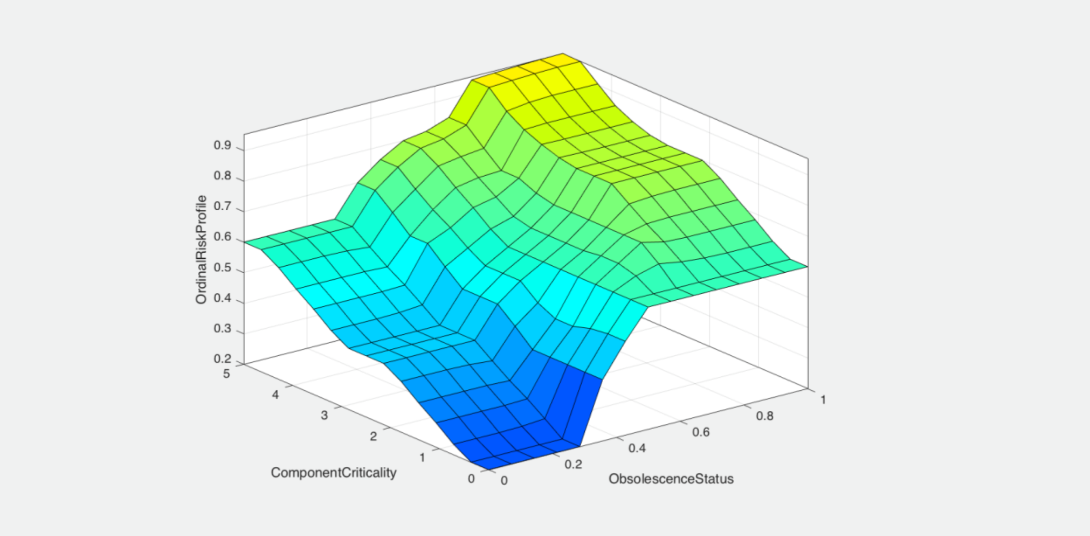


Figure 153 OIT Input (2) and Input (3) Surface Map Graphic, created by author

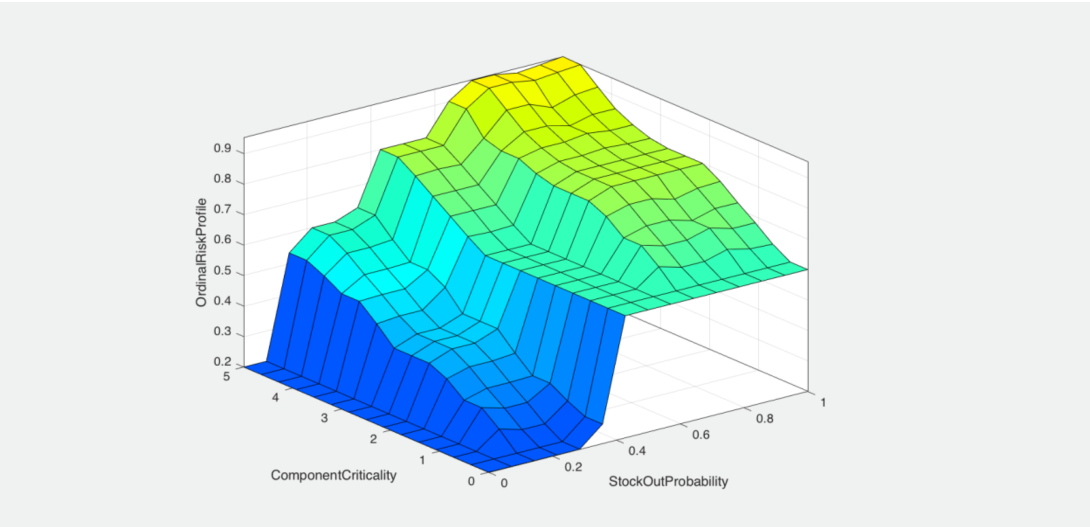


Figure 154 OIT Input (1) and Input (3) Surface Map Graphic, created by author

Once OIT had been fully programmed into MATLAB, a two-year case study was implemented to assess its ability to compute three independent variables and logically deduce risk profiles. The completion of said case-study and the quarterly graphics generated are an additional contribution as evidence that can be used for further iterations of the model. Figure 155 is evidence of the achievement of contribution (2) as an example of the insight that OIT can provide and the now possible analysis that can be undertaken. OITs structure and the methodology found within this thesis, at the time of writing, was yet to be submitted for publication. OIT is a more advanced tool that could be adopted by Asset Management and Facilities Management teams to quantify the risk posed by obsolescence to the operations of major asset systems. A risk assessment of this nature had not been previously published and has clear utility within the industry for end-users with good data management processes in place.

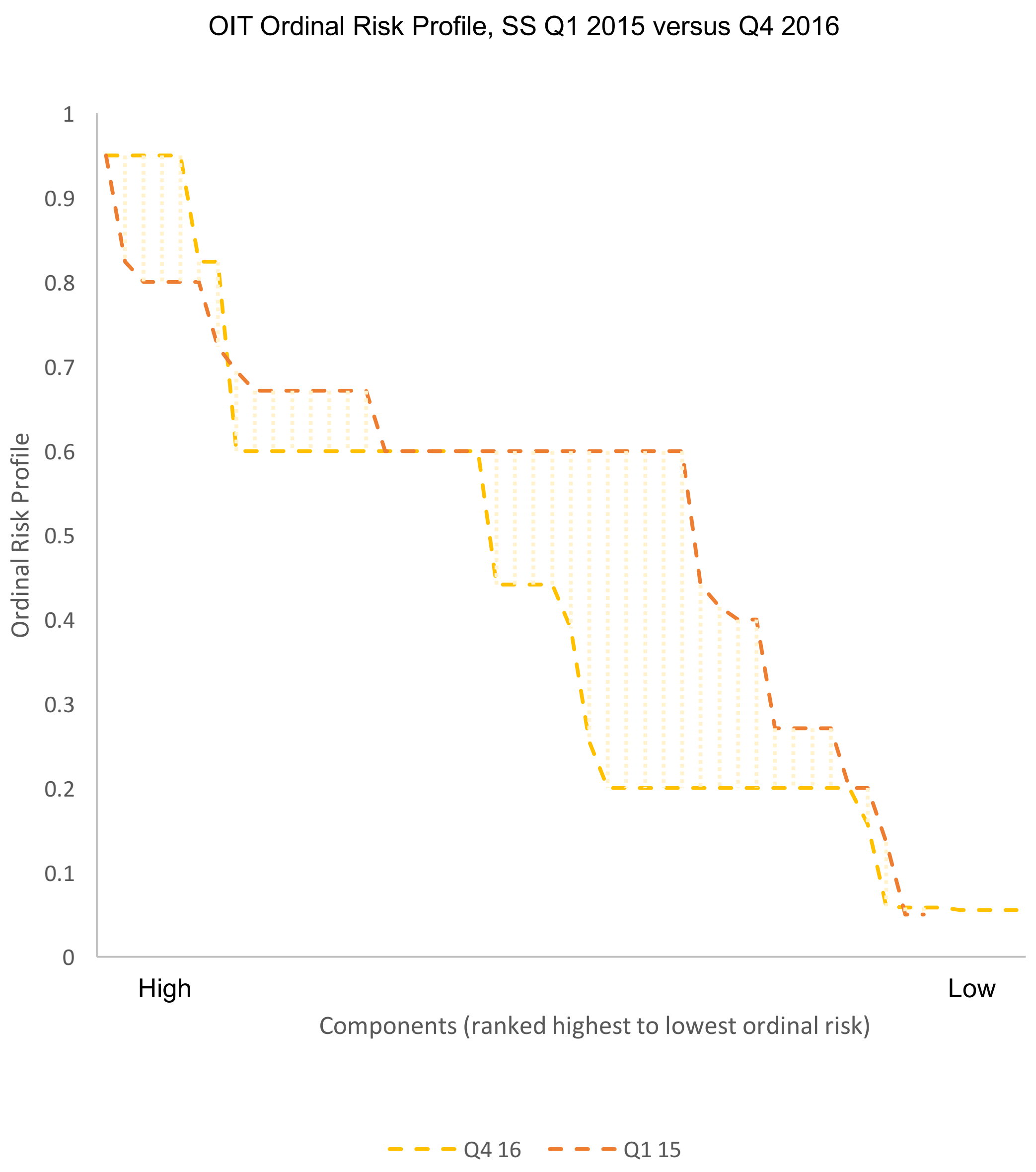


Figure 155 Security System OIT Risk Results Q1 2015 versus Q4 2016, created by author

Contribution (3) entailed the detailed analysis of OEM sales data, spanning several years. Figure 156 is an example of one of the resultant graphics created, illustrating to the reader the effects of an underlying Sales Strategy upon obsolescence. This analysis contributed to new knowledge in the form of confirmed previously speculated theories and/or connected two unrelated facts. This dataset identified proof of the effect of obsolescence upon the unit cost of components, with a set of price ranges that could theoretically be applied to current components to project final costs. Probability density functions were generated for component groups to reflect the time period this OEM made them available before inducing obsolescence. This type of information can be directly used to enhance an OMP and allow an Asset Management or Facilities Management team to proactively plan for obsolescence. At the time of writing this, the results from this analysis have not been published.

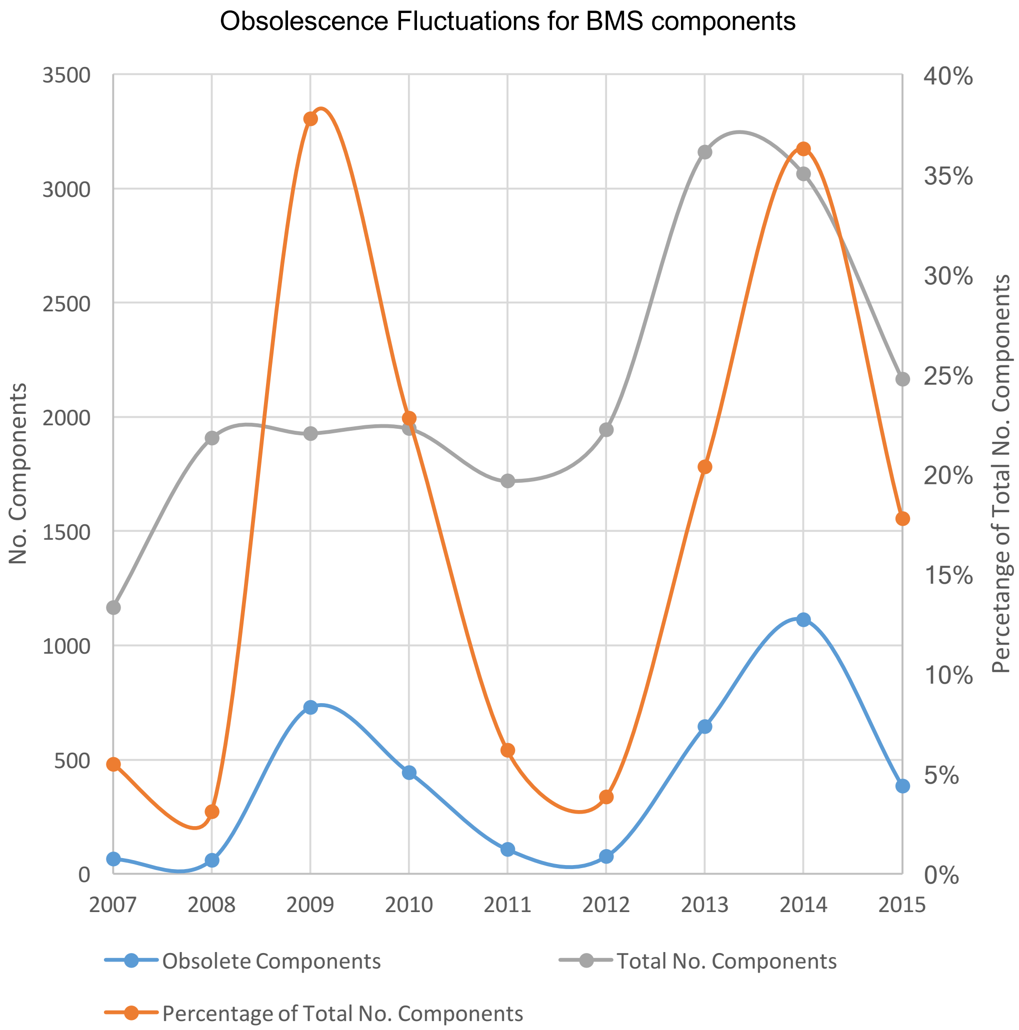


Figure 156 OEM Sales Strategy and Obsolescence, created by author

Figure 157 was created to demonstrate how one would use the information from the observed sales strategy. Through extrapolating the witnessed trends, leading up to 2015, forward to 2020 (assuming the sales strategy remains consistent) Figure 157 illustrates a likely rise in 2018/19 of obsolete components. This will likely be a result of the apparent five-year cycle of deeming a number of components obsolete.

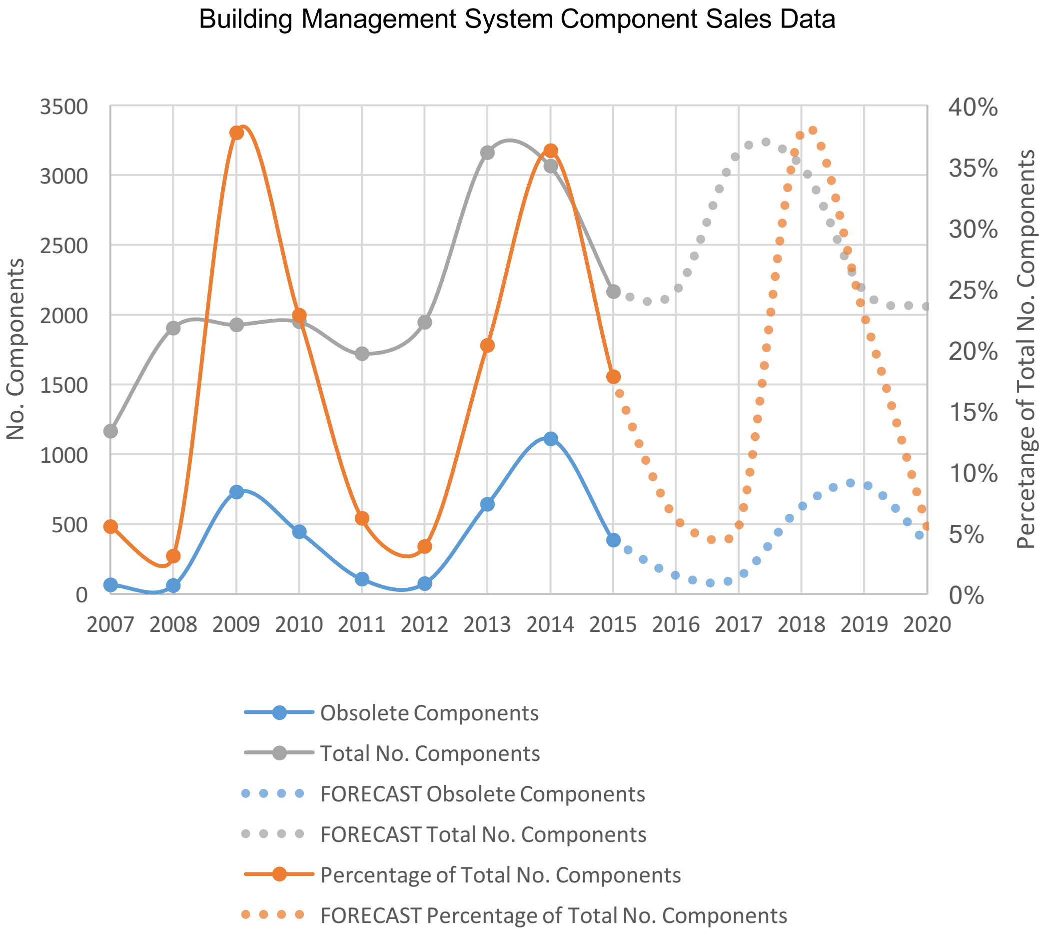


Figure 157 Projected OEM Sales Strategy and Obsolescence, created by author

Whilst this type of analysis does not identify which components are likely to fall into that wave of obsolete components, the probability density functions can be used to help indicate. This insight is potentially invaluable and is a robust piece of evidence to frame an Obsolescence Management Plan upon. Proactively being aware of future supportability issues is the first step to developing a mitigation strategy to avoid unnecessary lifecycle investments and ultimately extend the useful life of the assets within the Built Environment.

The fourth and final contribution to new knowledge involved visualising the trade-off between investing in the resilience of an asset system against obsolescence and the financial risk of unavailability. This involved combining the observed rising component costs with the financial penalties associated with asset unavailability for Private Finance Initiative (PFI) contracts. Using real case-study contract mechanisms, true values could be used to set up this scenario experiment. Industry OEM sales catalogues and third-party suppliers were used to evaluate the real costs of procurement for the year 2016. The intersect shown in Figure 158 is important in terms of decision-making, as it is representative of the financial incentives involved.

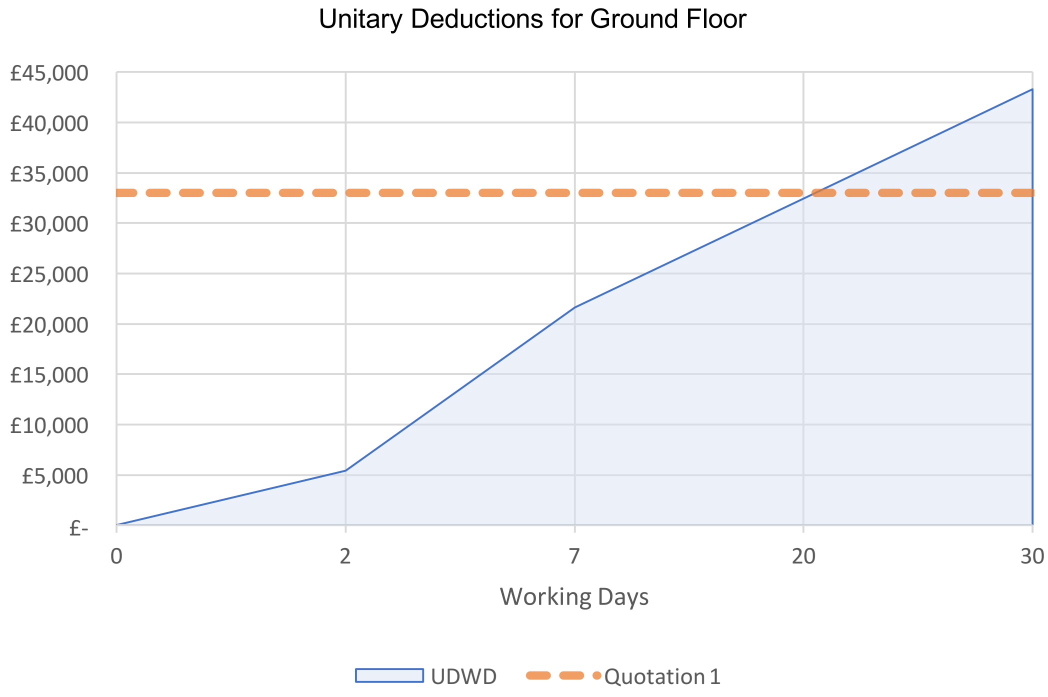


Figure 158 Resilience Trade-Off Visualisation, created by author

The time period prior to the intersect point (20 working days), is the time frame in which if a component could be procured (i.e. lead time < 20 working days) within, then the incentive is to reactively manage said components. If there were any long-lead items, beyond the intersect point, then the incentive would be to proactively procure and avoid the Unitary Deductions. This type of analysis would be appropriate within an OMP, enabling Asset Management and Facilities Management teams to incorporate data-driven decision-making. Note that the horizontal line in Figure 158 represents the value of the entire spares investment, from the point of investment, which spare is to be required is unknown and therefore it is recommended to invest in the selected group of components. Additionally, the above informal mental model does not consider the operational impacts of such a failure of this size. The impact on business users and the likely repercussions are an additional variable that holds value.

The contributions to new knowledge presented within this subsection provide several tools, applicable within the Built Environment, for Asset Management and Facilities Management teams. Through the combination of OAT, OIT, and the insights provided by OEM sales analysis and proactive resilience trade-off, comprehensive advances of Obsolescence Management are possible. All of the above should feature within an Obsolescence Management Plan, enabling proactive management techniques. Ultimately, whilst the above contributed to Obsolescence Management as a whole, OIT specifically quantified the risk posed by obsolescence in a manner that had not previously been attempted.

6.3 Concluding Remarks

Have the findings within this research project addressed the title of this thesis?

'The resilience of asset systems to the operational risk of obsolescence: using fuzzy logic to quantify risk profiles'

The author is of the opinion that the collective contributions practically enable an Asset Management or Facilities Management team to implement proactive Obsolescence Management techniques. An Obsolescence Management Plan containing the above findings would enable the assessment of an asset system's resilience to the risk of obsolescence.

The resilience in this context refers to one's ability to maintain and support an asset system, avoiding unnecessary downtime due to obsolete components. The MCEER framework definition for resilience has been adopted by the author (see section 2.3), containing two key concepts:

- Robustness - the ability to withstand a given level of stress without suffering degradation or loss of function.
- Rapidity - the capacity to meet priorities and achieve goals in a timely manner in order to contain losses and avoid future disruption.

In the scenario of component failure and obsolescence combining into asset downtime, both the robustness and rapidity of the asset system to restore normal performance is directly related to the availability of components. Contributions (1), (2), and (3) all directly monitor how the changes of obsolescence impact upon the resilience of an asset system, in the context of robustness and rapidity. Contribution (4) however, visualises the current informal mental model that decision-makers undertake in regards to lifecycle investment. It is important to highlight that typical modern lifecycle practices do not account for obsolescence. The trade-off, therefore, displayed within Figure 158 is a more advanced decision-making exercise than typically occurs; typical lifecycle software packages work on the basis of predefined lifecycle requirements (irrespective of obsolescence).

The need to measure the risk posed by obsolescence has both operational and financial drivers (see section 2.2). The impact of successfully achieving this element of the research title can avoid lifecycle investments that have shown to enter the hundreds of thousands in annual expenditure per system (Mulholland et al. 2016c). Adapting a risk assessment methodology to begin measuring this risk was an innovative approach, however, an essential one. Contribution (2) solely addressed this specific element of the research title, combining previously unrelated fields to design and test a new model, and provides the first set of evidence.

The second element of the research title – *'using fuzzy logic to quantify risk profiles'* stems from the requirement to use Fuzzy Logic identified within Mulholland's (2014) dissertation. Fuzzy Logic enables a model to sufficiently process ambiguous data sets and adopts 'expert' inference rules, which enables a robust approximator to be created whose heuristics are a direct reflection of those within industry experts. The Fuzzy Inference System (FIS) created is evidence to the aforementioned methodology meeting the requirements of the research title.

The *'risk profiles'* element of the research title was addressed using the output Fuzzy Sets assigned within the Fuzzy Inference System (FIS). The output Fuzzy Sets contained six separate Membership Functions (see Figure 159), 'Not Important' to 'Very Important', categorising the ordinal risk deduced from the inputs using the FIS governed by industry experts. These 'categories' or 'Fuzzy Sets' use human language to contextualise the output/risk profiles.

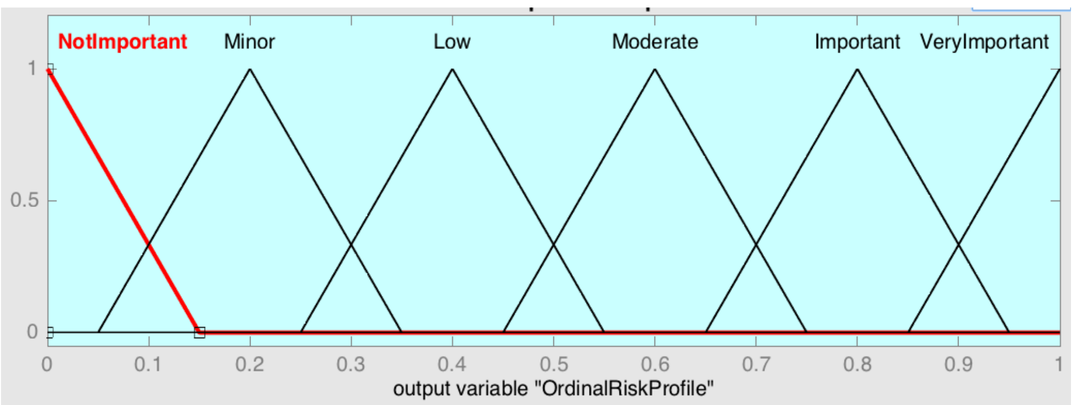


Figure 159 OIT Output (1) Membership Functions and Fuzzy Sets, created by author

Ultimately, following the above breakdown and the appraisal of the research questions within the Discussion section, the author is of the opinion that the research title was holistically delivered. To answer the question set by the author on the previous page; yes, the findings within this project have addressed the research title.

The nature of undertaking research in the field brings many alternative parallels, sometimes tangent, methodologies for answering the research questions set out in section 3.2. Throughout the undertaking of this research project, decisions have been made and observations have been noted in other ways or reasons to why this approach was adopted. The following subsection will clarify said decisions and detail to the reader alternative approaches that may now be possible to adopt.

6.4 Observations and Future Work

This subsection will reassess the observations made throughout this research project for either improvements or alternative ways to approach this methodology. The benefits of alternative approaches can only be speculated as they were not actioned within this thesis. It is important, in order to create a balanced view of both the methodology and findings, to openly critique the approach used and display the narrative behind the choices made.

The reader will find comments in the following pages on the general structure of Engineering Doctorate (EngD) research, the Obsolescence Assessment Tool (OAT), and the Obsolescence Impact Tool (OIT). The observations have been extracted from the main body of text within the respective chapters, which will be elaborated here to provide more detail.

The key topics of this subsection are:

- Engineering Doctorate (EngD).
    - Time Frame.
    - Behaviour Change.
    - ‘Real World’ Research.
- Obsolescence Assessment Tool (OAT).
    - Further Status Definition.
- Obsolescence Impact Tool (OIT).
    - Multistate Modelling (better Stockout probability analysis).
    - ‘Type 2’ Fuzzy Sets.
    - Adaptive Techniques.
    - Methodology Iteration.

The above key topics will provide some elements that can be extracted for future work in new research projects. Some of the above observations were considered and decided against for various reasons, which will be detailed within this section. Others posed as constraints upon the current methodology, which may now be alleviated for future research projects.

This section will act as a key contributor to the transparency of this research project by consolidating the conscious decisions made throughout into a concise single body of text for the reader to appraise. At this point within the research project, there are now ‘knowns’ that were ‘unknown’ at the commissioning stage, creating hindsight bias to possible changes and amendments. It is important to comprehensively feature a ‘lessons learnt’ exercise to ensure that later research into this field is progressive. The first key topic for consideration of future work is regarding research undertaken within the framework of a sponsored Engineering Doctorate position at University College London. This is relevant as it differs slightly from other frameworks, which affect the research design selection.

Research within the EngD framework has some inherent characteristics, which distinguishes it from a PhD programme and governs the type of research undertaken. 'An EngD is an enhanced PhD designed by the Engineering and Physical Sciences Research Council (EPSRC) to provide a new generation of research engineers' (University College London 2016b). Each engineering doctorate project is focused on producing the following two results (University College London 2016b):

- future leaders in innovative research and development (R&D) with outstanding academic and industrial perspectives.
- a significant industry-focused research project that creates a step change in the company's knowledge and capability.

Other key characteristics to consider are that an EngD programme consists of a one-year Master of Research (MRes) technical training course followed by a full-time three-year research project, as well as an industry-based placement. Case-study methodologies can be improved in correlation to the length of time used; *Building A* provided data over a two-year period. Whilst the author is of the opinion that sufficient data was collected, further testing within a longer case-study will only improve the confidence of findings. In addition, the diversity of the case studies used will aid the support of the transferability of the techniques found herein. This consideration for future work can immediately be adopted and implemented in either isolation from other observations or in cooperation. As noted within EngD research there is a requirement to embed the researcher into the industry, typically at the sponsor's organisation to undertake the research first hand. One effect of undertaking said placement is the 'Hawthorne Effect' – where the subject changes their behaviour in response to being observed. This is particularly a risk when undertaking case-study research; as members of staff (subjects) are aware you are undertaking research and likely know the target research field. To avoid this within *Building A*, the details of this project were kept on a need-to-know basis, with sub-contractors not being briefed, an important step to get a fair reflection of the conditions. This is an important consideration for any similar future work. That being said, undertaking research in a 'real world' context is likely to bring up anomalies within the results that can be difficult to explain. The workplace environment within the industry is not a sanitised laboratory, things go wrong, human error is common and ultimately priorities of subjects within the case-study change. The above three points are all considerations for anyone undertaking either a similar project or a general project within the EngD programme. Whilst some of the above points are in hindrance to the quality of this research project, if correctly identified in the form of a Risk Assessment, they can be appropriately mitigated (see Risk Assessment in section 3.4).

The Obsolescence Assessment Tool (OAT) was a 'revision of older views' and following the results found herein and the insight that OIT produced, the author has identified a further enhancement now possible. Currently, the algorithm does not distinguish between a component being within its 'obsolescence phase' i.e. an EOL notification released, nor a component that is 'obsolete' i.e. exceeded its last order date. In essence, both scenarios are negative and undesirable. However, there is a categorical difference that could be added to enhance the precision of OAT even further. Below is an example of how the added input would feature within the algorithm:

$$H = 100\frac{(\sum S + \sum Y_1 + \sum A_1 + \sum B_1)}{(\sum S + \sum Y_1 + \sum Y_2 + \sum O_1 + \sum O_2 + \sum U + \sum A_1 + \sum A_2 + \sum B_1 + \sum B_2)}$$

AH = Asset Health

S = Two or more suppliers and no EOL

Y_1 = One supplier and no EOL notice

Y_2 = One supplier and EOL notice

A_1 = Alternative part, no EOL notice and confirmed compatibility

A_2 = Alternative part with EOL notice

B_1 = Alternative part, confirmed compatibility and EOL notice or Unknown EOL

B_2 = Alternative supplier and EOL notice

O_1 = Obsolescence Phase

O_2 = Obsolete. Exceed EOL notification date.

U = Unknown status

This added status would allow the end-user to quickly assess whether there was an opportunity to reactively mitigate the effects of the components that have been assigned 'O_1' status, or whether it was likely too late with the status 'O_2'. The above is a direct change that could be adopted and tested within future work, contributing to another new piece of knowledge.

Mulholland (2014) identified the need to develop a model that could quantify the risk posed by obsolescence, in order to do so the 'probability' and 'impact' elements of the 'risk' needed to be incorporated. However, it was apparent from the initial case-study that industry was not collecting and preserving datasets to the appropriate level of accuracy or precision to adopt a probabilistic methodology. In order words, statistically we do not know when obsolescence will occur and to add to that, it will differ for separate systems and will change over time. It is certainly a complex problem. In an ideal world, the Asset Management team or Facilities Management team would diligently record every piece of data in a format that would accommodate Big Data and allow retrospective analysis. There is considerable value in doing so. Large, precise datasets are required if the end-user is to generate probabilities to reflect changes of state. This would enable more probabilistic methodologies, such as multi-state analysis i.e. Markov Chains.

Discrete Markov Chains are a possible stochastic methodology that could be adopted to simulate the progression of obsolescence within a system; however, there are fundamental reasons why it is not viable for this exercise. Markov Chains require crisp categories or 'States', which are a central element to the model. The author has created a hypothetical example of how this could be applied to obsolescence; Figure 160 is a conceptual Markov Chain. The three 'States' have been defined as; #1 – Not Obsolete, #2 – Obsolescence Phase and #3 – Obsolete. These are three technical states of which a component can exist as part of an Asset System. The arrows represent the pathways in which a component's 'State' can change, note that chain accounts for an EOL notification to be revoked and therefore return from State #2 to #1. This is a simplified chain, and it is likely that there are more 'States' and pathways in reality. The recursive arrows represent how a component retains within a 'State' after an iteration of the Markov Chain.

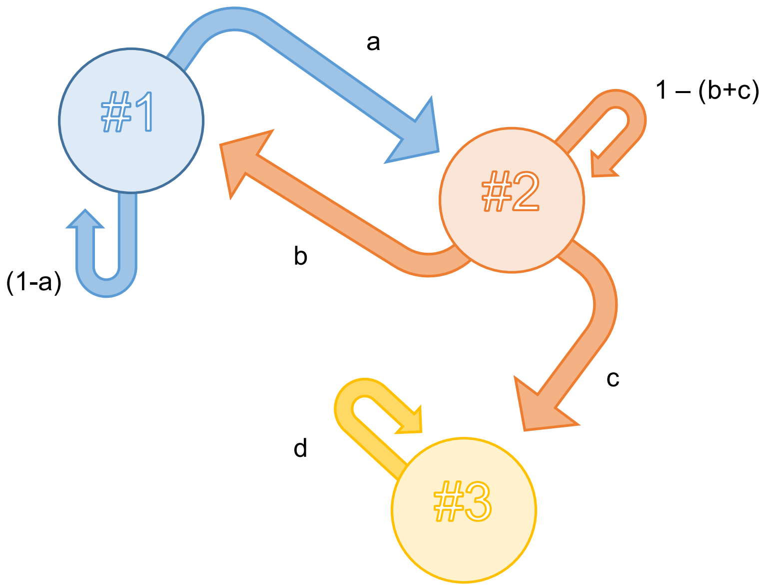


Figure 160 Markov Chain Example, created by author

Markov Chains have the ability, in a discrete manner, to iterate a model to observe how states behave over time in the conceptual future. This type of exercise is a 'step process type of modelling' and is reliant upon the Transitional Matrix of today, irrespective of the recent past. If the Transitional Matrix is accurate and the 'States' are representative of a scenario, then very insightful models can be created and quickly iterated through thousands of computations. There are two fundamental reasons why this type of modelling is not appropriate for obsolescence:

- The probabilistic values that reflect how component transitions from one state to another are completely unknown. The data and evidence provided by this thesis begin to enable such method; however, currently this would be no better than guessing.

- Obsolescence appears to change over time. The transitional matrix should therefore also change to reflect this reality. However, how one should change the matrix and importantly when are two unanswerable questions at this stage.

Markov Chains or related probabilistic modelling techniques are extremely powerful. However, their strength is primarily centred on the accuracy of the probabilities used. As said before, put rubbish in and get rubbish out. In the immature research field of obsolescence, this foundation of evidence as to what probabilities should be used in the above example does not yet exist. The advantages of using such insight are obvious, forecasting or planning when statistically you should be removing or upgrading an asset enables proactive management. This is certainly a project that constitutes future work following this thesis. Markov Chains have been used in inventory and reliability management, see White (1993), Somani et al. (1993) and Joglekar and Lee (1993), Haviv (2013) also has a useful book on Markov Chains and other finite modelling methods.

The Fuzzy System that was used within this thesis would be defined as a 'Type 1' Fuzzy System (FS). Type 1 FSs are appropriate for handling data where ambiguity lies and crisp sets are not suitable (Karnik & Mendel 1998). Type 2 FSs were first developed by Zadeh (1975) as a way of protecting the system from uncertainty within the decision rules, typically 'IF-THEN Rules' (Mendel & John 2002; Mendel et al. 2006). Karnik and Mendel (1998) highlighted that Type 1 FSs could possibly carry over uncertainty in the following four scenarios:

1. The meanings of the words that are used in the antecedents and consequents of rules can be uncertain (words mean different things to different people).
2. Consequents may have a histogram of values associated with them, especially when knowledge is extracted from a group of experts who do not all agree.
3. Measurements that activate a type-1 FS may be noisy and therefore uncertain.
4. The data that are used to tune the parameters of a type-1 FLS may also be noisy.

The above uncertainties translate into uncertainties about fuzzy set membership functions (Karnik & Mendel 1998; Mendel et al. 2006). A Type 1 Fuzzy Set is crisp by definition as it involves a single line, along which membership values are assigned. Type 2 Fuzzy Sets are able to model the above uncertainties because their membership functions are themselves fuzzy, existing within a third dimension. It is this added dimension that provides a new layer of degree that accounts for the known uncertainty within the data (Karnik & Mendel 1998; Mendel et al. 2006). As Karnik and Mendel (1998) report, Type 2 Fuzzy Systems have been applied to the following areas; classification of coded video streams, control of mobile robots, decision-making, equalisation of nonlinear fading channels, and transport scheduling.

Figure 161, in a 2D space, illustrates the 'Fuzziness' of a Type 2 Fuzzy Set, imagine the shaded area was created by taking the Type 1 Fuzzy Set and moving it side to side to create a spread. In a new third dimension (into the page) there are probability distributions to reflect the certainty or uncertainty of each membership value.

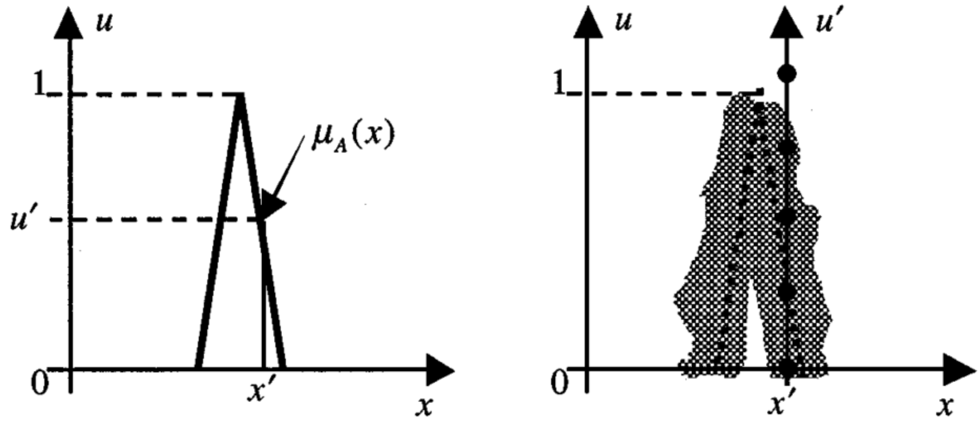


Figure 161 Type 1 and Type 2 Fuzzy Sets, from Mendel et al. (2006)

It is precisely the aforementioned distribution profiles that create the shaded area, otherwise coined the 'Footprint of Uncertainty (FOU)'. When uncertainty is removed and assumed all certain then a Type 2 Fuzzy Set instantly becomes a Type 1. Karnik and Mendel (1998) created Figure 162, which neatly illustrates a Gaussian distribution of certainty that created the Type 2 Fuzzy Set in the top figure. The density of the FOU reflects the certainty within the data, weakening at further standard deviations from the mean.

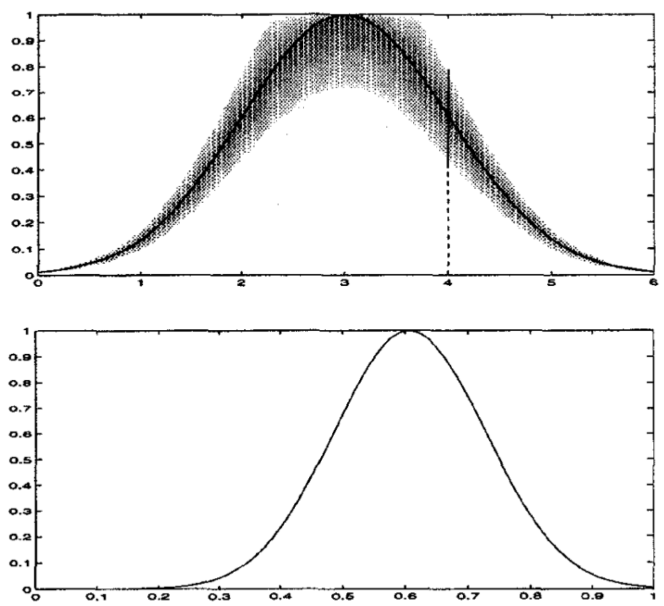


Figure 162 Type 2 Fuzzy Set with Gaussian Uncertainty Profile, from Mendel et al. (2006)

Note that the profile of uncertainty, if in a step fashion, will create a homogenous FOU as seen in Figure 163. Mendel et al. (2000) created Figure 163, directly comparing how the two profiles would influence the FOU.

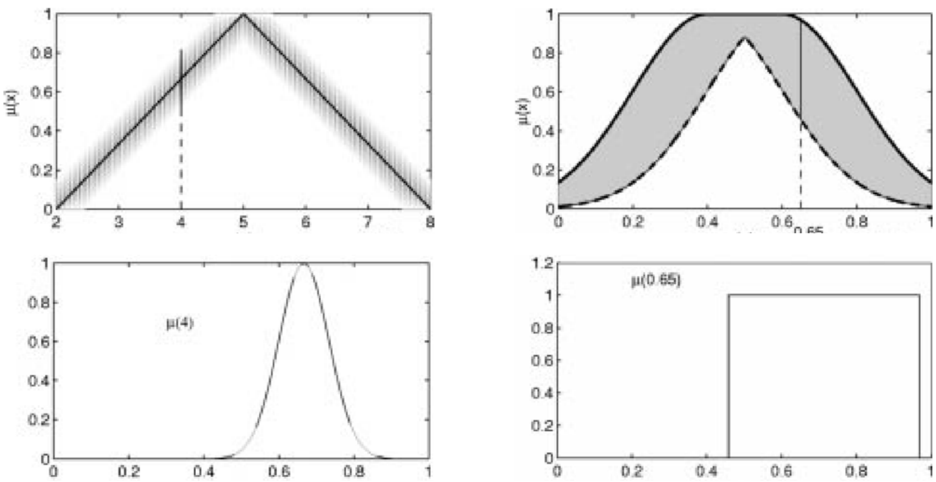


Figure 163 Type 2 Comparison of Profiles, adapted from Mendel et al. (2000)

Otherwise, as Figure 164 depicts the internal of the Fuzzy Inference System is comparable to a Type 1 Fuzzy System (Karnik & Mendel 1998). It is within the 'Defuzzification' steps where there is a difference in the analysis. As the below figure demonstrates, the initial Defuzzification produces a 'Type Reduced Set', which is otherwise a Type 1 Fuzzy Set. The process is repeated in order to generate a crisp output.

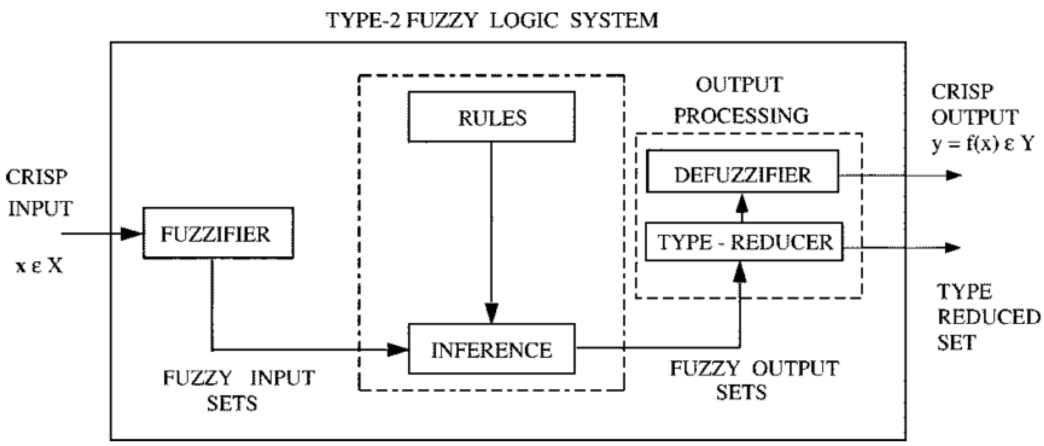


Figure 164 Type 2 Fuzzy Inference System, from Karnik & Mendel (1998)

Adopting a Type 2 approach to the Fuzzy System design would be a way of reducing the risk of carrying unnecessary uncertainty through the model. However, this is without assuming a generic profile i.e. Gaussian, as seen in the above examples. A new scientifically robust method would be required to calculate the known uncertainty within the data. At the time of undertaking this research project, this was not possible. A piece of future work could, in theory, take the Fuzzy Inference System found within this thesis and convert it into a Type 2 Fuzzy System for analysis.

When designing membership functions for an FIS, Ross (2010) highlights several methods that can be used:

- Intuition
- Inference
- Rank Ordering
- Neural Networks
- Genetic Algorithms
- Inductive Reasoning

Neural Networks and Genetic Algorithms would both be described as 'adaptive learning methods' (The MathWorks Inc. 2015). Neural Networks can be utilised to map the membership functions between the input and output data for the FIS (Cox 1999; Ross 2010), MATLAB has an inbuilt 'adaptive neuro-fuzzy inference system' (ANFIS) tool to implement such a method (The MathWorks Inc. 2015). ANFIS uses a back-propagation algorithm and/or least squares method to adjust the membership function profiles to best map the data (The MathWorks Inc. 2015). Typically, this is undertaken with a training and testing set of data, created from the same source. This enables the designer to build a Neural Network, train it on a random portion of the dataset, then use the remaining dataset to test its performance (Ross 2010; The MathWorks Inc. 2015). In many ways, this 'automates the Fuzzy Set and Membership Function designing stages of an FIS' (Cox 1999). Neural Networks require very large datasets, however, in order to discover non-linear relationships. See Lee (1991), Schouten et al. (2002) and Wang and Elhag (2008) for examples of Neural Networks being used for Fuzzy Inference Systems.

Another method is the use of Genetic Algorithms (GA), which are framed upon the 'survival of the fittest' theory from Darwinism within the natural world (Ross 2010). Through the reproduction, crossover and mutation of existing solutions, whilst comparing their performances, GAs search for an ideal solution in a more 'natural' way (Ross 2010). The best solutions are continually combined and modified to produce an infinite number of new solutions until there is a convergence within a generation (Ross 2010). GAs use binary strings to represent their parameters, which are then manipulated using three genetic operators; reproduction, crossover and mutation. The total population of strings within each generation is constant, with 'fitness' values assigned to the best performing strings for the problem. Each generation contains the strongest strings from the previous, with the weakest being disregarded and replaced by new possible solutions via the genetic operators. GAs can be utilised to amend Membership Functions (MF), firstly assumed MF and Profiles are required. The MFs are then converted into a binary string that is then concatenated (combined into one single long string). The above mentioned ‘fitness’ values are used until a convergence is found for an optimised Membership Function profile via the GA. Examples of how the above two Adaptive Techniques could be adopted can be found within Ross' (2010) book. GAs are one of the most commonly used optimisation methods and within the context of the Built Environment they have been used for Life Cycle Costing (LCC) and Life Cycle Assessments (LCA) (Schwartz et al. 2016). Schwartz et al. (2016) are an example of the use of multi-objective GAs for decision makers in the design stage to reduce the carbon footprint and lifecycle cost of refurbishments.

Adaptive Techniques are particularly powerful when data within the problem space is present; however, the underlying relationships between certain elements are unknown. The above techniques would reverse engineer the observed data to create the missing relationships, which could then be tested on other datasets. These datasets do not exist within the field of obsolescence currently, however, going forward this is the type of methodology required to design a more accurate model using the observed data. The weakness is still that the strength of the resultant models is reliant upon the designer’s ability to sanitise the training and testing datasets of all bias. However, where expert panels are either not present or in complete disagreement on how the internal algorithm of the FIS should appear or operate, adaptive methods can provide an alternative. There is well-documented literature on the two above methods, both of which could be adopted as a piece of future work within the field of obsolescence for someone looking to further OIT.

In summary, this subsection has covered some of the author’s thoughts upon how future pieces of work could learn from this research project and contribute to further pieces of new knowledge, beginning with the EngD programme structure and the specific types of bias witnessed herein. Thereafter was suggested an explicit change for the OAT algorithm, adding further precision in future iterations of the model. Finally, the author covered briefly the potential use of Type 2 Fuzzy Sets as well as two adaptive learning techniques for building an FIS. All of the above suggestions would produce more accurate models, however, the narrative behind why such decisions were not taken has also been provided.

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8 APPENDICES

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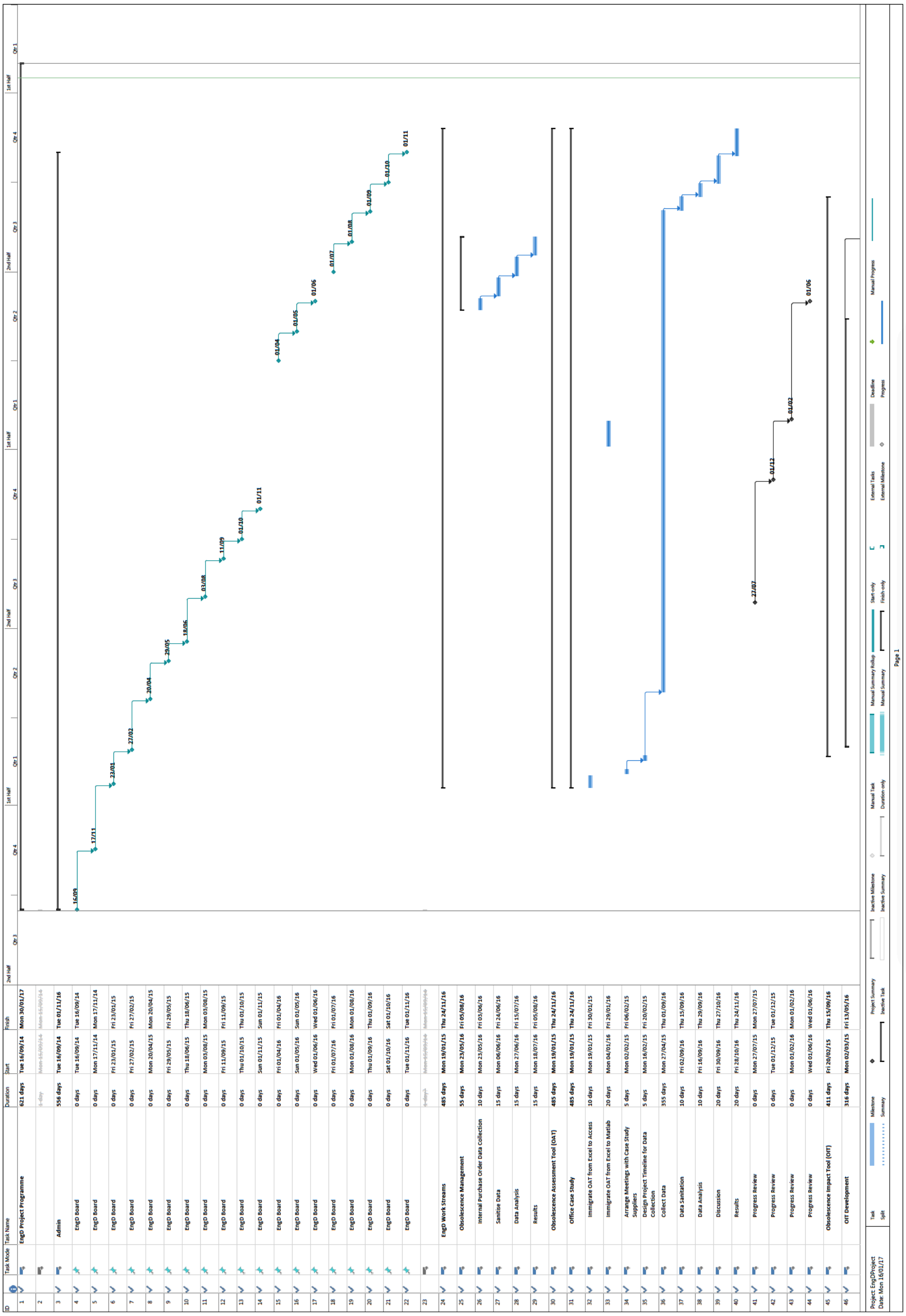
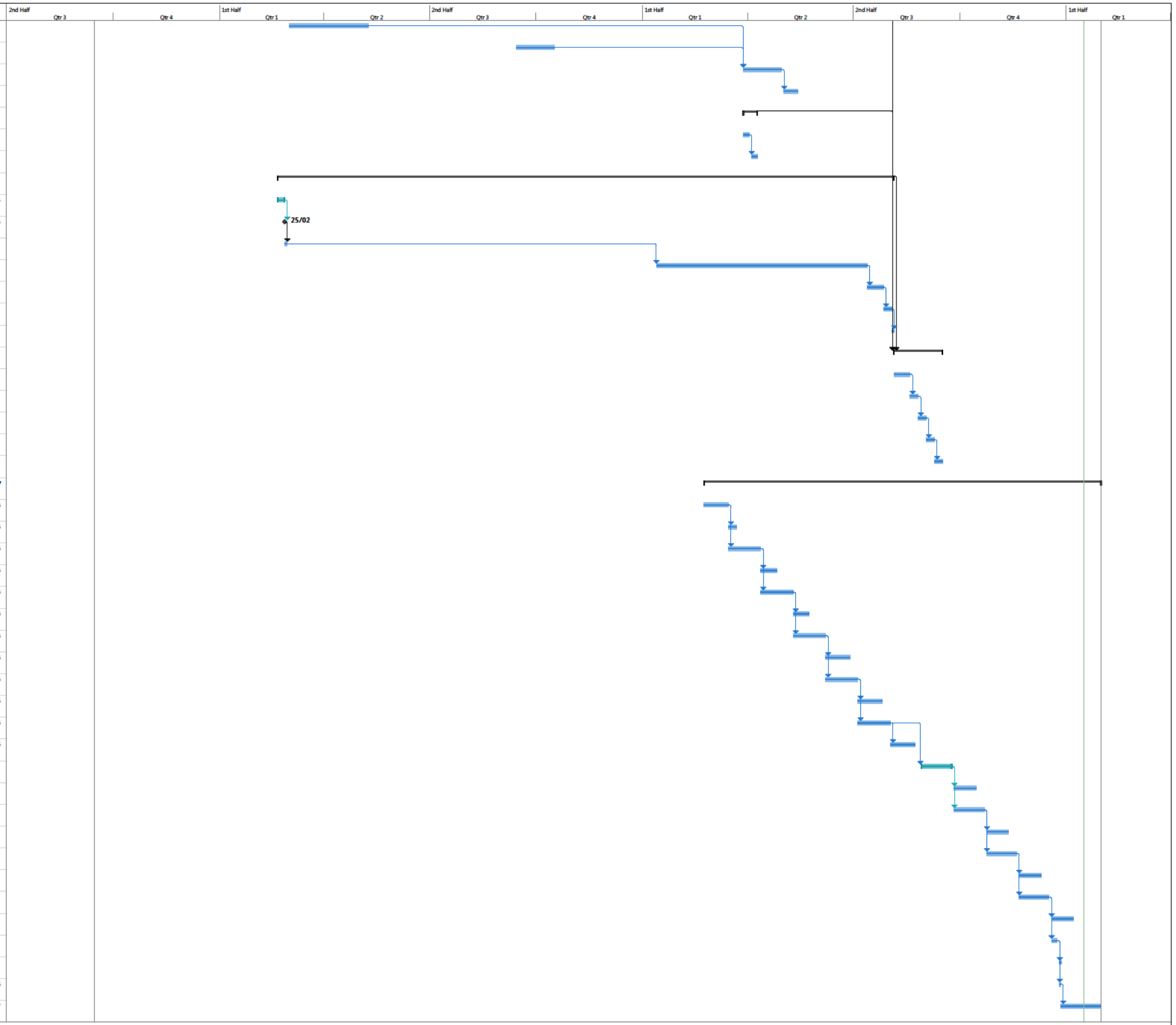
8.1 MS Project Programme



ID	Task Mode	Task Name	Duration	Start	Finish
47		Develop Fuzzy Logic Understanding	50 days	Mon 02/03/15	Fri 08/05/15
48		Develop MatLab Understanding	25 days	Mon 14/09/15	Fri 16/10/15
49		Build Model	25 days	Mon 28/03/16	Fri 29/04/16
50		Test with Dummy Data	10 days	Mon 02/05/16	Fri 13/05/16
51		**Component Criticality Methodology**	**10 days**	**Mon 28/03/16**	**Fri 08/04/16**
52		Design Methodology	5 days	Mon 28/03/16	Fri 01/04/16
53		Implement	5 days	Mon 04/04/16	Fri 08/04/16
54		**Service Level Methodology**	**381 days**	**Fri 20/02/15**	**Thu 04/08/16**
55		Data Collection Design	4 days	Fri 20/02/15	Wed 25/02/15
56		Meeting with Supply Chain	0 days	Wed 25/02/15	Wed 25/02/15
57		Agreement on data collection method	2 days	Thu 26/02/15	Fri 27/02/15
58		Data Collection	130 days	Wed 13/01/16	Tue 12/07/16
59		Sanitisation of Data	10 days	Wed 13/07/16	Tue 26/07/16
60		Analysis	5 days	Wed 27/07/16	Tue 02/08/16
61		Review	2 days	Wed 03/08/16	Thu 04/08/16
62		**OIT Testing**	**30 days**	**Fri 05/08/16**	**Thu 15/09/16**
63		Data Compilation	10 days	Fri 05/08/16	Thu 18/08/16
64		Data Sanitation	5 days	Fri 19/08/16	Thu 25/08/16
65		Data Analysis	5 days	Fri 26/08/16	Thu 01/09/16
66		Discussion	5 days	Fri 02/09/16	Thu 08/09/16
67		Results	5 days	Fri 09/09/16	Thu 15/09/16
68		**Thesis Writing**	**245 days**	**Tue 23/02/16**	**Mon 30/01/17**
69		Introduction Draft	15 days	Tue 23/02/16	Mon 14/03/16
70		Review	5 days	Tue 15/03/16	Mon 21/03/16
71		Background Draft	20 days	Tue 15/03/16	Mon 11/04/16
72		Review	10 days	Tue 12/04/16	Mon 25/04/16
73		Related Work Draft	20 days	Tue 12/04/16	Mon 09/05/16
74		Review	10 days	Tue 10/05/16	Mon 23/05/16
75		Analysis Draft	20 days	Tue 10/05/16	Mon 06/06/16
76		Review	15 days	Tue 07/06/16	Mon 27/06/16
77		Design Draft	20 days	Tue 07/06/16	Mon 04/07/16
78		Review	15 days	Tue 05/07/16	Mon 25/07/16
79		Implementation Draft	20 days	Tue 05/07/16	Mon 01/08/16
80		Review	15 days	Tue 02/08/16	Mon 22/08/16
81		Interpretation of Results Draft	20 days	Mon 29/08/16	Fri 23/09/16
82		Review	15 days	Mon 26/09/16	Fri 14/10/16
83		Critical Assessment of Work Draft	20 days	Mon 26/09/16	Fri 21/10/16
84		Review	15 days	Mon 24/10/16	Fri 11/11/16
85		Further Work Draft	20 days	Mon 24/10/16	Fri 18/11/16
86		Review	15 days	Mon 21/11/16	Fri 09/12/16
87		Summary Conclusions Draft	20 days	Mon 21/11/16	Fri 16/12/16
88		Review	15 days	Mon 19/12/16	Fri 06/01/17
89		Appendices Draft	5 days	Mon 19/12/16	Fri 23/12/16
90		Review	2 days	Mon 26/12/16	Tue 27/12/16
91		Bibliography	1 day	Mon 26/12/16	Mon 26/12/16
92		Review Thesis	25 days	Tue 27/12/16	Mon 30/01/17

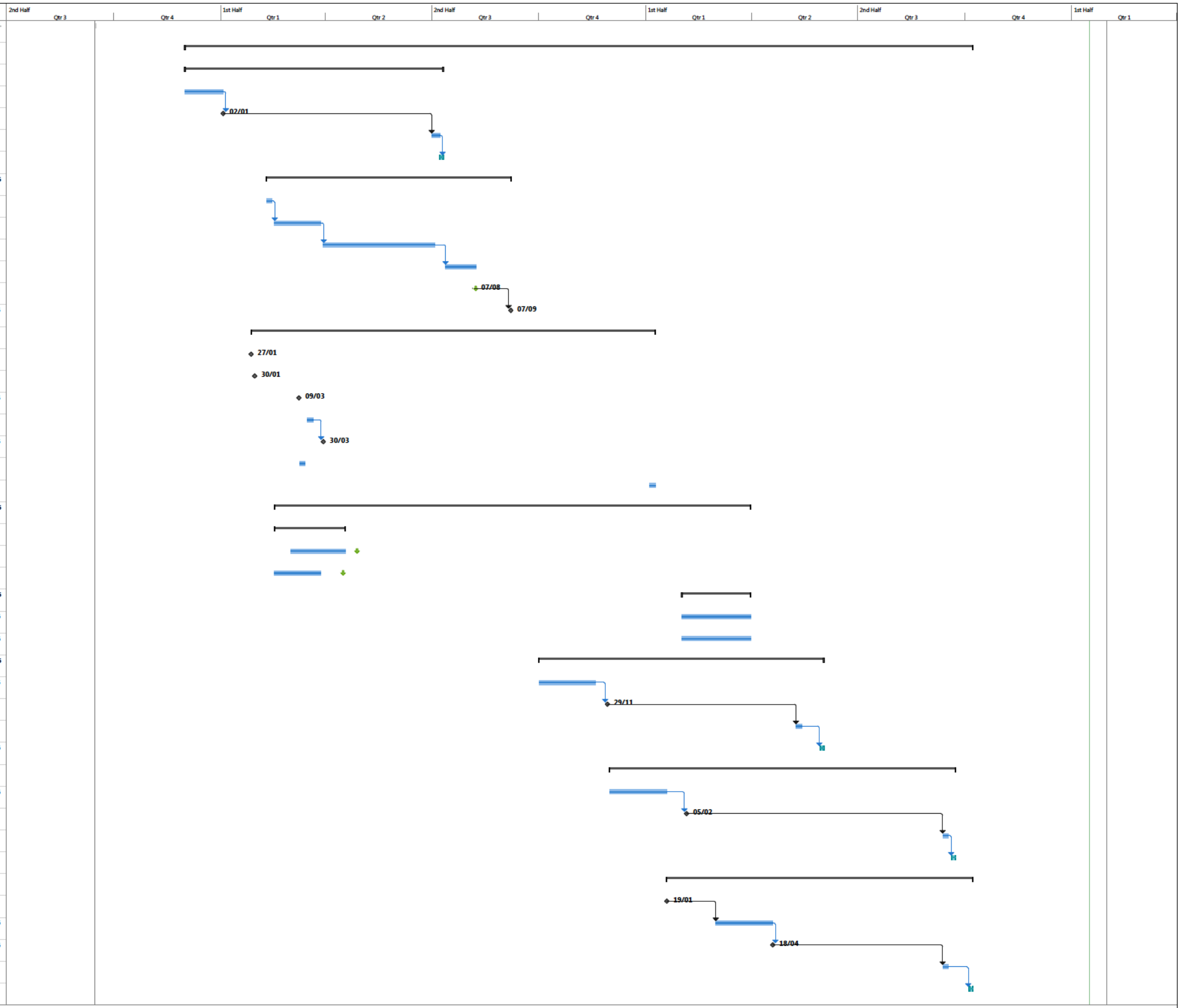


Project: EngDProject
Date: Mon 16/01/17

Task, Split, Milestone, Summary, Project Summary, Inactive Task, Inactive Milestone, Inactive Summary, Manual Task, Duration-only, Manual Summary Rollup, Manual Summary, Start-only, Finish-only, External Tasks, External Milestone, Deadline, Progress, Manual Progress

8.2

ID		Task Mode	Task Name	Duration	Start	Finish
93			~~<New Task>~~	~~1 day?~~	~~Mon 15/09/14~~	~~Mon 15/09/14~~
94	✓		**UCL Work Streams**	**486 days**	**Mon 01/12/14**	**Fri 07/10/16**
95	✓		**COBRA Conference 2015**	**160 days**	**Mon 01/12/14**	**Fri 10/07/15**
96	✓		Write Paper	25 days	Mon 01/12/14	Fri 02/01/15
97	✓		Submit Paper	0 days	Fri 02/01/15	Fri 02/01/15
98	✓		Prepare Presentation	5 days	Wed 01/07/15	Tue 07/07/15
99	✓		Conference	3 days	Wed 08/07/15	Fri 10/07/15
100	✓		**VIVA Upgrade**	**150 days**	**Mon 09/02/15**	**Mon 07/09/15**
101	✓		Create Report Skeleton	5 days	Mon 09/02/15	Fri 13/02/15
102	✓		Review with Supervisors	30 days	Mon 16/02/15	Fri 27/03/15
103	✓		Write Report	70 days	Mon 30/03/15	Fri 03/07/15
104	✓		Review Report	20 days	Mon 13/07/15	Fri 07/08/15
105	✓		Submit	0 days	Fri 07/08/15	Fri 07/08/15
106	✓		Presentation	0 days	Mon 07/09/15	Mon 07/09/15
107	✓		**Training**	**250 days**	**Tue 27/01/15**	**Fri 08/01/16**
108	✓		UCL Microsoft Access	0 days	Tue 27/01/15	Tue 27/01/15
109	✓		UCL Microsoft Word (Large Documents)	0 days	Fri 30/01/15	Fri 30/01/15
110	✓		Matlab Course (UCL)	0 days	Mon 09/03/15	Mon 09/03/15
111	✓		APMP Project Management	5 days	Mon 16/03/15	Fri 20/03/15
112	✓		APMP Project Management Exam	0 days	Mon 30/03/15	Mon 30/03/15
113	✓		UCL Python Training Course	4 days	Tue 10/03/15	Fri 13/03/15
114	✓		Matlab Fundamentals	5 days	Mon 04/01/16	Fri 08/01/16
115	✓		**UCL Modules**	**294 days**	**Mon 16/02/15**	**Wed 30/03/16**
116	✓		**UCL Modules 2014/15 Semester 2**	**45 days**	**Mon 16/02/15**	**Fri 17/04/15**
117	✓		Resilience Module Coursework	35 days	Mon 02/03/15	Fri 17/04/15
118	✓		FM Module Coursework	30 days	Mon 16/02/15	Fri 27/03/15
119	✓		**UCL Modules 2015/2016 Semester 2**	**43 days**	**Mon 01/02/16**	**Wed 30/03/16**
120	✓		System Dynamics Modelling in the Built Environment	43 days	Mon 01/02/16	Wed 30/03/16
121	✓		Environmental Sustainability in the Construction Sector	43 days	Mon 01/02/16	Wed 30/03/16
122	✓		**CIB Conference 2016**	**176 days**	**Thu 01/10/15**	**Wed 01/06/16**
123	✓		Write Paper	35 days	Thu 01/10/15	Wed 18/11/15
124	✓		Submit Paper	0 days	Sun 29/11/15	Sun 29/11/15
125	✓		Prepare Presentation	5 days	Mon 09/05/16	Fri 13/05/16
126	✓		Conference	3 days	Mon 30/05/16	Wed 01/06/16
127	✓		**COBRA Conference 2016**	**213 days**	**Tue 01/12/15**	**Thu 22/09/16**
128	✓		Write Paper	35 days	Tue 01/12/15	Mon 18/01/16
129	✓		Submit Paper	0 days	Fri 05/02/16	Fri 05/02/16
130	✓		Prepare Presentation	5 days	Mon 12/09/16	Fri 16/09/16
131	✓		Conference	3 days	Tue 20/09/16	Thu 22/09/16
132	✓		**IFMA Conference 2016**	**189 days**	**Tue 19/01/16**	**Fri 07/10/16**
133	✓		Register	0 days	Tue 19/01/16	Tue 19/01/16
134	✓		Write Paper	35 days	Tue 01/03/16	Mon 18/04/16
135	✓		Submit Paper	0 days	Mon 18/04/16	Mon 18/04/16
136	✓		Prepare Presentation	5 days	Mon 12/09/16	Fri 16/09/16
137	✓		Conference	3 days	Wed 05/10/16	Fri 07/10/16



Project: EngDProject
Date: Mon 16/01/17

Task | Split | Milestone | Summary | Project Summary | Inactive Task | Inactive Milestone | Inactive Summary | Manual Task | Duration-only | Manual Summary Rollup | Manual Summary | Start-only | Finish-only | External Tasks | External Milestone | Deadline | Progress | Manual Progress

Page 3

OAT MATLAB Script Report

Contents


```
clear; close all; clc %Clean Me Code.

%%Welcome

display('Obsolescence Assessment Tool [OAT]')

display('Please locate the Excel data file.')
```

```
Obsolescence Assessment Tool [OAT]

Please locate the Excel data file.
```

OAT Script 1

```
%Objective:

%This script will operate the import function of OAT. Allowing the user to

%select an excel file for import. Excel files will already be structured in

%a specific way, these will be imported as tables within Matlab. This

%script will then extract the data from the table and create variables for

%each column.
```

```
file = uigetfile('.xlsx','.xls');

data = readtable(file);

data.Properties.VariableNames =
{'Part_Name','Part_Function','Part_Ref','Part_Description','No_Parts','Intr
oduction_Date','EOL_Released','Date_of_Release','EOL_Date','Current_Supplie
r','Alternative_Supplier','Alternative_Parts','Confirmed_Compatability'};


%The first two lines will allow the user to select an excel file, which is

%then imported as a table and stored within the data variable.
```

```
label = menu('Obsolescence Assessment Tool, select the asset:','BMS','Fire','Security');

if label == 1
    label = 'Building Management System';
elseif label == 2
    label = 'Fire Alarm System';
else
    label = 'Security System';
end

%This short for loop allows the user to identify the sytem being imported.
%By storing this into a variable, I can then use this later for plotting.

Part_Name=data{:,1};
Part_Function=data{:,2};
Part_Ref=data{:,3};
Part_Description=data{:,4};
No_Parts=data{:,5};
Introduction_Date=data{:,6};
EOL_Released=data{:,7};
Date_Of_Release=data{:,8};
EOL_Date=data{:,9};
Current_Supplier=data{:,10};
Alternative_Supplier=data{:,11};
Alternative_Parts=data{:,12};
Confirmed_Compatibility=data{:,13};
```

```
%The above lines extract the data from the table, converting it into cells,
%doubles and timedate variables. These can now be individually santised,
%plotted and applied through a logic.
```

```
By_No_Parts = sortrows(data,'No_Parts','descend');
```

```
%This script does not sanitise any of the input data. It has been decided

%the default presentation of the data will be sorted by quantity. Showing

%the most abundent components within an asset at the top of the register.
```

```
Data_Size = size(data);

DataSummary = [num2str(Data_Size(1)),' individual components within the ', label, ' were found.'];

disp(DataSummary)
```

```
%This final piece of code returns to the user the number of individual

%components found within the excel file.
```

```
Warning: Variable names were modified to make them valid MATLAB identifiers.

211 individual components within the Building Management System were found.
```

OAT Script 2

```
%Objective:

%The objective of script 2 is to sanitise the data that has now been

%imported and stored within variables. It is important that date/time

%format here is consistant and that NaN data points are not deleted, but

%ignored when plotting and also extracted for reference to the user.
```

```
san_Introduction_Date = datetime(Introduction_Date,'ConvertFrom','excel','InputFormat','dd/mm/yyyy');

isnat(san_Introduction_Date);

san_Date_Of_Release = datetime(Date_Of_Release,'ConvertFrom','excel','InputFormat','dd/mm/yyyy');

isnat(san_Date_Of_Release);

san_EOL_Date = datetime(EOL_Date,'ConvertFrom','excel','InputFormat','dd/mm/yyyy');
```

```
isnat(san_EOL_Date);
```

```
%This converts the excel formatted datetime and converts the vector into a
%datetime variable. Important for doing any between date calcs or
%plotting.
```

```

```

```
% Logic Tests On Data Input
%1. EOL Released but no recorded date. This poses a risk to the user as you
%are unable to plan for obsolete parts.
```

```
san_EOL_Released = ~isnan(EOL_Released);
Ssan_EOL_Released = san_EOL_Released == 1;
newdata = data(Ssan_EOL_Released,:);
newtable = newdata(:,[1,3,5,7,9]);
Date_Released = isnan(newtable.EOL_Date);
```

```
%This first set of code removes NaN from the EOL Released column and then
%creates a new table. It then identifies NaN or blank entries within the
%EOL date column.
```

```
disp('Logic Test 1: ')
disp('The below components have a recorded EOL notification against them, but no recorded date.')

Logic1Testa = newtable.EOL_Released== 1;
Logic1Testb = Date_Released == 1;
Logic1Test = Logic1Testa & Logic1Testb;
newtable.Properties.VariableNames = {'Part_Name','Part_Ref','No_Parts','EOL_Released','EOL_Date'};
Logic1Result = newtable(Logic1Test,:);
disp(Logic1Result)
```

```
%
%2. A slight reverse of logic1, EOL Date is not blank and EOL released is
%blank or false. The results of this test would suggest that there is a
%quality issue with the data being recieved. Logically, you cannot have an
%EOL date without acknowledgement of an EOL notification.
```

```
disp('Logic Test 2: ')
display('The below components should be check for errors.')
display('They are reporting no EOL but state a date.')
Nonblank_EOL_Date = ~isnan(EOL_Date);
NoEOL = EOL_Released == 0;
BlankEOL = isnan(EOL_Released);
BlankEOL_or_NoEOL = BlankEOL | NoEOL;
LogicTest2 = Nonblank_EOL_Date & BlankEOL_or_NoEOL;
LogicIndex2 = find(LogicTest2);
Logic2Result = data(LogicIndex2,[1,3,5,7,9]);
disp(Logic2Result)

%
% 3.This is a simple check on the data, which would likely be a typo error.
%
Logic3Testa = isnan(No_Parts);
Logic3Testb = No_Parts == 0;
Logic3Test = Logic3Testa | Logic3Testb;
LogicIndex3 = find(Logic3Test);
Logic3Result = data(LogicIndex3,[1,3,5,7,9]);
disp('The below component quantities should be checked.')
disp(Logic3Result)

%
% 4. This logic test identifies components with no recorded EOL
% notification but with a  Date of Release filed.
%
```

```
Logic4Testa = EOL_Released == 0;

Logic4Testb = ~isnan(Date_Of_Release);

Logic4Test = Logic4Testa & Logic4Testb;

LogicIndex4 = find(Logic4Test);

Logic4Result = data(LogicIndex4,[1,3,5,7,8]);

disp('The below components should be checked for their EOL release dates.')

disp(Logic4Result)


%

% 5. This is a data quality test for blank fields, if 6 or more fields

% within an observation are blank, then they are flagged.

%

Logic5Test = ismissing(data);

rowsum = sum(Logic5Test,2);

Logic5TestIndex = find(rowsum>=6);

Logic5Result = data(Logic5TestIndex,:);

disp('The below components have 6 or more missing data points. Continue?')

disp(Logic5Result)
```

```
Logic Test 1:

The below components have a recorded EOL notification against them, but no
recorded date.

      Part_Name                     Part_Ref        No_Parts      EOL_Released
EOL_Date

   _____________________       ____________      ________      ____________
________



   'Room  Temperature  Sensor'       'TPTRJ115ML'       13                   1
NaN



Logic Test 2:

The below components should be check for errors.
```

```
They are reporting no EOL but state a date.

   empty 0-by-5 table
```

```
The below component quantities should be checked.

        Part_Name                   Part_Ref         No_Parts      EOL_Released
EOL_Date

    __________________       ____________       ________       ____________
________

    '50VA Transformer'    'TCX/50/6/F'    0            0                NaN
```

```
The below components should be checked for their EOL release dates.

   empty 0-by-5 table
```

```
The below components have 6 or more missing data points. Continue?

   empty 0-by-13 table
```

OAT Script 3

```
%Objective:
%The objective of script 3 is to embed the core OAT formula and assign
%components statuses. The results will then need to be grouped and counted.
%Finally there needs to be a weighting element applied before final results
%can be published.
```

```
% Status assignment - Logic Loop
```

```
%A loop is needed to pass along each observation and apply IF then logic,
%resulting in an a status assignment.
```

```
%I still require a Loop which I am unsure of. to loop the logic along each
%row.

%A table is created, extracting just the fields required for the logic.
oattable = data(:,[7,11:13]);
```

```
%The dimensions of the matrix is gathered using the size function and then
%an empty cell array is created using these dimensions. This will be used
%to store the statuses.
```

```
[m, n] = size(oattable);
result = cell(m,1);

%A for loop is created, to iterate from 1 to the end of the number of rows
%assigned to m in this case.
for i = 1:m

    testtable = oattable(i,:);

    %Level 1
    %The first level of the decision tree is assigned either a true, false
    %or U status. This is assigned into variable level1, which will be
    %required later for the logic test.
    if testtable.EOL_Released == 0
        level1 = 0;
    elseif testtable.EOL_Released == 1
        level1 = 1;
    else level1 = 'U';
    end
```

```
%Level 2
%Level 2 of the decision tree ascertains whether an alternative
%supplier is available. This is either true or false and then assigned
%under the variable level2.
if testtable.Alternative_Supplier == 0
    level2 = 0;
elseif testtable.Alternative_Supplier == 1
    level2 = 1;
end

%Level 3
%Similarly level 3 collects whether there are alternative parts
%available. The result is assigned under varialbe level3.
if testtable.Alternative_Parts == 0
    level3 = 0;
elseif testtable.Alternative_Parts == 1
    level3 = 1;
end

%Level 4
%The compatibility of the alternative components is then either
%confirmed or unknown. The result assigned under variable level4.
if testtable.Confirmed_Compatability == 0
    level4 = 0;
elseif testtable.Confirmed_Compatability == 1
    level4 = 1;
end

%This if statement combines all of the levels to assign a status.
%branch 1 within the logic
if level1 && level2 && level3 && level4 == 1
    status = 'B1';
```

```
    elseif level1 && level2 && level3 == 1 && level4 == 0
        status = 'A2';
    elseif level1 && level2 == 1 && level3 == 0
        status = 'B2';
    elseif level1 == 1 && level2 == 0 && level3 && level4 == 1
        status = 'B1';
    elseif level1 == 1 && level2 == 0 && level3 == 1 && level4 == 0
        status = 'Y2';
    elseif level1 == 1 && level2 == 0 && level3 == 0
        status = 'O';

        %branch two within the logic
    elseif level1 == 0 && level2 && level3 && level4 == 1
        status = 'A1';
    elseif level1 == 0 && level2 && level3 == 1 && level4 == 0
        status = 'S';
    elseif level1 == 0 && level2 == 1 && level3 == 0
        status = 'S';
    elseif level1 == 0 && level2 == 0 && level3 && level4 == 1
        status = 'A1';
    elseif level1 == 0 && level2 == 0 && level3 == 1 && level4 == 0
        status = 'Y1';
    elseif level1 == 0 && level2 == 0 && level3 == 0
        status = 'S';

        %branch three within the logic
    elseif level1 == 'U' && level2 && level3 && level4 == 1
        status = 'B1';
    elseif level1 == 'U' && level2 && level3 == 1 && level4 == 0
        status = 'U';
    elseif level1 == 'U' && level2 == 1 && level3 == 0
        status = 'U';
    elseif level1 == 'U' && level2 == 0 && level3 && level4 == 1
```

```
        status = 'B1';
    elseif level1 == 'U' && level2 == 0 && level3 == 1 && level4 == 0
        status = 'U';
    elseif level1 == 'U' && level2 == 0 && level3 == 0
        status = 'O';
    end

    %Each loop will pass along a single component and apply the above
    %logic. This index (i) is then assigned into the empty cell array
    %'status'. The loop will then iterate to the next component until m or
    %the end of the components is reached.

    result{i} =  status;
end
```

```
% Status Counting
%Now that the logic has been applied to the input data and a status has
```

```
%been applied, the results need to be returned to the user. For this, I
%have extracted the most relevent information and then sorted by status.

statuscolumn = cell2table(result);
oattable2 = data(:,[1:3,5]);
finalstatustable = [oattable2,statuscolumn];
finalstatustable.Properties.VariableNames                              =
{'Part_Name','Part_Function','Part_Ref','No_Parts','OAT_Status'};
sortedfinalstatustable = sortrows(finalstatustable,'OAT_Status','descend');
disp(sortedfinalstatustable)
```

```
%The next lines of code will search and then sum the statuses, putting the
%value into a variable. This can then be used to enter into the OAT
%equation.
```

```
u = strfind(result,'U');
u = cell2mat(u);
[u,~] = size(u);

o = strfind(result,'O');
o = cell2mat(o);
[o,~] = size(o);

s = strfind(result,'S');
s = cell2mat(s);
[s,~] = size(s);

b1 = strfind(result,'B1');
b1 = cell2mat(b1);
[b1,~] = size(b1);
b2 = strfind(result,'B2');
b2 = cell2mat(b2);
[b2,~] = size(b2);

y1 = strfind(result,'Y1');
y1 = cell2mat(y1);
[y1,~] = size(y1);
y2 = strfind(result,'Y2');
y2 = cell2mat(y2);
[y2,~] = size(y2);

a1 = strfind(result,'A1');
a1 = cell2mat(a1);
[a1,~] = size(a1);
a2 = strfind(result,'A2');
a2 = cell2mat(a2);
[a2,~] = size(a2);
```

```
% OAT Formula and Weighting

%The core OAT forumula.

positive = (s+y1+a1+b1);

negative = (s+y1+y2+o+u+a1+a2+b1+b2);

OAT = 100*(positive/negative);
```

```
%The weighting now needs to be applied for critical and high value asset

%systems. This will involve two menus, which will then create the four

%output Asset Health values to then be used for visualisations.
```

```
criticalityweighting = menu('Asset Criticality Weighting:','1.0','1.23','1.46','1.7');


if criticalityweighting == 1

    criticalityweighting = 1;

elseif criticalityweighting == 2

    criticalityweighting = 1.23;

elseif criticalityweighting == 3

    criticalityweighting = 1.46;

else

    criticalityweighting = 1.7;

end


OATcriticality = 100*(positive/(negative*criticalityweighting));
```

```
%The weighting is applied to the 'negative' or the denominator of the OAT

%core formula.
```

```
valueweighting = menu('Asset Value Weighting:','1.0','1.23','1.46','1.7');


if valueweighting == 1

    valueweighting = 1;
```

```
elseif valueweighting == 2
    valueweighting = 1.23;
elseif valueweighting == 3
    valueweighting = 1.46;
else
    valueweighting = 1.7;
end

OATvalue = 100*(positive/(negative*valueweighting));
OATaverage = (OAT+OATcriticality+OATvalue)/3;
```

```
%Finally, two last variables are created leaving the user with four OAT
%results. OAT running in isolation, two weighted results and an average of
%the three.
```

```
Part_Name              Part_Function                   Part_Ref        No_Parts
OAT_Status


____________________________________________________________________________
________

I/O   AI   Module
For MBC             Panel Equipment             PTM6.2U10                45   Y2

I/O   AI   Module
For MBC             Panel Equipment             PTM6.2R1K                96   Y2

I/O   AI   Module
For MBC             Panel Equipment             PTM6.2I420                6   Y2

I/O   AO   Module
For MBC             Panel Equipment             PTM6.2Y10S-M             65   Y2

I/O   DI   Module
For MBC             Panel Equipment             PTM6.4D20               186   Y2

I/O   DO   Module
For MBC             Panel Equipment             PTM6.2Q250-M            198   Y2

I/O     Expansion
Module For MBC      Panel Equipment             PTM6.EMK                 21   Y2
```

I/O Pulse Count Module For MBC	Panel Equipment	PTM6.2C	23	Y2
LD -64	Westermo Fibre 485 Converter	LD-64	10	Y2
LTEC FCU Controller	Panel Equipment	US-550536	27	Y2
MBC24 Backplate Assembly	Panel Equipment	US-545077	16	Y2
1000VA UPS	Panel Equipment	SUA100I	37	S
100VA Transformer	Field Equipment	TCX/100/6/F	43	S
2000VA UPS	Panel Equipment	A2000	1	S
240V Actuator 0-10V	Valve Bodies, Valve Actuators and Damper Actuators	OA15	1	S
240V Actuator 0-10V	Valve Bodies, Valve Actuators and Damper Actuators	AS50	1	S
240V Actuator 2 Position SR	Valve Bodies, Valve Actuators and Damper Actuators	FQ30	12	S
240V Actuator 2 Position SR	Valve Bodies, Valve Actuators and Damper Actuators	FQ18	8	S
240V Actuator 2 Position SR	Valve Bodies, Valve Actuators and Damper Actuators	FQ12	4	S
24V Actuator 2 Position SR	Valve Bodies, Valve Actuators and Damper Actuators	OAP	18	S
24V Actuator 2 Position SR	Valve Bodies, Valve Actuators and Damper Actuators	OA15	19	S
24V Actuator 2 Position SR	Valve Bodies, Valve Actuators and Damper Actuators	BS100	3	S
24V Actuator 2	Valve Bodies, Valve	ASP25	3	S

Position SR	Actuators and Damper Actuators			
420VA UPS	Panel Equipment	SU420I	2	S
50VA Transformer	Field Equipment	TCX/50/6/F	0	S
Air Pressure Switch	Field Equipment	CPS1100	4	S
Air Quality Sensor	Sensor	QPA63.1	4	S
Butterfly Valve Flanged 100mm	Valve Bodies, Valve Actuators and Damper Actuators	970BZ 100mm	2	S
Butterfly Valve Flanged 100mm	Valve Bodies, Valve Actuators and Damper Actuators	4990BZ 100mm	12	S
Butterfly Valve Flanged 150mm	Valve Bodies, Valve Actuators and Damper Actuators	150MS0970JNDBOA	12	S
Butterfly Valve Flanged 150mm	Valve Bodies, Valve Actuators and Damper Actuators	970BZ 150mm	4	S
Butterfly Valve Flanged 200mm	Valve Bodies, Valve Actuators and Damper Actuators	200MS0970JNDEVD	1	S
Butterfly Valve Flanged 200mm	Valve Bodies, Valve Actuators and Damper Actuators	200MS0970JNDBOD	13	S
Butterfly Valve Flanged 200mm	Valve Bodies, Valve Actuators and Damper Actuators	970BZ 200mm	6	S
Butterfly Valve Flanged 250mm	Valve Bodies, Valve Actuators and Damper Actuators	970BZ 250mm	3	S
Butterfly Valve Flanged 300mm	Valve Bodies, Valve Actuators and Damper Actuators	970BZ 300mm	3	S
Butterfly Valve Flanged 300mm	Valve Bodies, Valve Actuators and Damper	4970BZ 300mm	1	S

	Actuators			
Butterfly Valve Flanged 65mm	Valve Bodies, Valve Actuators and Damper Actuators	4990BZ 65mm	4	S
Butterfly Valve Flanged 80mm	Valve Bodies, Valve Actuators and Damper Actuators	4990BZ 80mm	8	S
Current Switch	Field Equipment	H800	523	S
Damper Actuator	Valve Bodies, Valve Actuators and Damper Actuators	GMA126.1E	119	S
Damper Actuator	Valve Bodies, Valve Actuators and Damper Actuators	GLB131.1E	43	S
Damper Actuator	Valve Bodies, Valve Actuators and Damper Actuators	GCA161.1E	37	S
Damper Actuator	Valve Bodies, Valve Actuators and Damper Actuators	GCA126.1E	148	S
Duct Pressure Switch	DP Switch	QBM81.3	176	S
Flue Gas Temperature Sensor	Field Equipment	TT342	24	S
Frost Thermostat	Thermostat	QAF81.6	44	S
Gas Valve	Valve Bodies, Valve Actuators and Damper Actuators	VMR72/SW	1	S
High Temp Air Pressure Switch	Field Equipment	EFS-02-HT	56	S
Hi-Speed Trunk Isolator Extender	Panel Equipment	US-538960	8	S
Humidity Sensor	Field Equipment	TPVRH	214	S
8 Universal I/O Module	Panel Equipment	TXM1.8U	126	S

16 Digital Input Module	Panel Equipment	TXM1.16D	138	S
6 Relay Output Module w/ Ovd	Panel Equipment	TXM1.6R-M	113	S
8 Univ I/O Module w/4-20mA	Panel Equipment	TXM1.8X	29	S
8 Univ I/O Module w/ Ovd&LCD	Panel Equipment	TXM1.8U-ML	85	S
6 Relay Output Module	Panel Equipment	TXM1.6R	42	S
8 Digital Input Module	Panel Equipment	TXM1.8D	32	S
Immersion Thermostat	Thermostat	RAK-TW-1200B	6	S
Immersion Thermostat	Field Equipment	KR80.207	12	S
Inverter 1.1kW G120P	Variable Speed Drive	G120P-1.1/35A	1	S
Inverter 1.5kW G120P	Variable Speed Drive	G120P-1.5/35A	2	S
Inverter 11kW G120P	Variable Speed Drive	G120P-11/35A	7	S
Inverter 15.0kW G120P	Variable Speed Drive	G120P-15/35A	5	S
Inverter 18.5kW G120P	Variable Speed Drive	G120P-18.5/35A	10	S
Inverter 2.2kW G120P	Variable Speed Drive	G120P-2.2/35A	1	S
Inverter 22kW G120P	Variable Speed Drive	G120P-22/35A	11	S
Inverter 3.0kW G120P	Variable Speed Drive	G120P-3.0/35A	8	S
Inverter 30kW G120P	Variable Speed Drive	G120P-30/35A	11	S
Inverter 37kW	Variable Speed Drive	G120P-37/35A	8	S

G120P				
Inverter 4.0kW G120P	Variable Speed Drive	G120P-4.0/35A	7	S
Inverter 45kW G120P	Variable Speed Drive	G120P-45/35A	1	S
Inverter 5.5kW G120P	Variable Speed Drive	G120P-5.5/35A	10	S
Inverter 55.0kW G120P	Variable Speed Drive	G120P-55/35A	6	S
Inverter 7.5kW G120P	Variable Speed Drive	G120P-7.5/35A	6	S
Inverter 75kW G120P	Variable Speed Drive	G120P-75/35A	4	S
IP65 Air Pressure Switch	Field Equipment	DL10K-4W	24	S
ODW- 730-F2	Westermo Fibre 485 Converter	LD-64	10	S
Leak Detection Alarm & Sensor	Field Equipment	WD-AMX WD-PS	2	S
Liquid Differential Pressure Sensor	Sensor	QBE61.3-DP10	10	S
Liquid Differnetial Pressure Switch	Field Equipment	EP-113	58	S
Liquid Differnetial Pressure Switch	Field Equipment	EP-100	12	S
Liquid Pressure Switch	Field Equipment	EP-2	10	S
LTEC 3 Port Repeater	Panel Equipment	US-587455	1	S
Mechancial Control Valve Set	Valve Bodies, Valve Actuators and Damper Actuators	Mech Valve Set More Details Required	6	S
Mode 5 Smoke	Valve Bodies, Valve Actuators and Damper	BAM 24-1	272	S

Damper Actuator	Actuators			
Output Filter	Variable Speed Drive	FN5010 (More Details Required)	17	S
PXC 100	Panel Equipment	PXC100-PE96.A	67	S
PXC 16	Panel Equipment	PXC 16- Compact	4	S
PXC 36	Panel Equipment	PXC 36- Compact	18	S
Refrigerant Gas Detection	Field Equipment	Chillgard McQuay to Advise	1	S
Room Temperature Sensor	Field Equipment	TPPT3RS	18	S
Room Temperature Sensor	Field Equipment	SPL0033	1728	S
Room Temperature Sensor	Sensor	QAA24	44	S
S/S Button Sensor	Field Equipment	TPSSBS	5	S
Strap On Temeperature Sensor	Field Equipment	TT351	36	S
TEC Controller	Panel Equipment	US-540110	1920	S
TEC Controller	Panel Equipment	US-540100	70	S
Temp Sensor with Flying Lead	Field Equipment	TT555	193	S
Temperature Transmitter	Field Equipment	TC614	24	S
Thyristor Controller	Field Equipment	MPR1-9-RL	3	S
Thyristor Controller	Field Equipment	MPR1-2-RL	345	S
Thyristor Controller	Field Equipment	EH7	27	S
Thyristor Controller	Field Equipment	AX-MPR1-2.0	193	S
Valve Actuator 24V 0-10V	Valve Bodies, Valve Actuators and Damper	SSB81	3429	S

	Actuators			
Valve Actuator 24V 0-10V	Valve Bodies, Valve Actuators and Damper Actuators	SSB61	221	S
Valve Actuator 24V 0-10V	Valve Bodies, Valve Actuators and Damper Actuators	SQS65	166	S
Valve Actuator 24V 0-10V SR	Valve Bodies, Valve Actuators and Damper Actuators	SQS65.5	10	S
Valve Actuator 24V 0-10V SR	Valve Bodies, Valve Actuators and Damper Actuators	SKD62	13	S
Valve Actuator 24V 0-10V SR	Valve Bodies, Valve Actuators and Damper Actuators	SKC62	33	S
Valve Actuator 24V 0-10V SR	Valve Bodies, Valve Actuators and Damper Actuators	SKB62	13	S
Valve Actuator 24V 3 Point	Valve Bodies, Valve Actuators and Damper Actuators	SSP81	50	S
Valve Actuator 24V 3 Point	Valve Bodies, Valve Actuators and Damper Actuators	SSB81.1	196	S
Valve Actuator 24V 3 Point	Valve Bodies, Valve Actuators and Damper Actuators	SQS85.00	40	S
Valve Body 2 Port 10mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VVP45.15-2.5	44	S
Valve Body 2 Port 10mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VVP45.10-1.6	442	S
Valve Body 2 Port 10mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VVP45.10-1	628	S
Valve Body 2	Valve Bodies, Valve	VVP45.10-0.63	46	S

Port 10mm Screwed	Actuators and Damper Actuators			
Valve Body 2 Port 10mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VVP45.10-0.4	32	S
Valve Body 2 Port 10mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VVP45.10-0.25	4	S
Valve Body 2 Port 20mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VVP45.20-4	193	S
Valve Body 2 Port 32mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VVG44.32-16	4	S
Valve Body 2 Port 40mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VVG44.40-25	26	S
Valve Body 2 Port 50mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VVG41.50	19	S
Valve Body 2 Port 65mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VVF41.65-4	2	S
Valve Body 3 Port 1/2in	Valve Bodies, Valve Actuators and Damper Actuators	VXP45.10-1	35	S
Valve Body 3 Port 1/2in	Valve Bodies, Valve Actuators and Damper Actuators	VXP45.10-0.63	20	S
Valve Body 3 Port 100mm Flanged	Valve Bodies, Valve Actuators and Damper Actuators	VXF41.90 Now VXF 42	10	S
Valve Body 3 Port 125mm Flanged	Valve Bodies, Valve Actuators and Damper Actuators	VXF41.91 Now VXF 42	1	S
Valve Body 3 Port 15mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VXG44.15-4	23	S

Valve Body 3 Port 15mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VXG44.15-2.5	13	S
Valve Body 3 Port 15mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VXG44.15-1.6	8	S
Valve Body 3 Port 15mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VXG44.15-1.0	4	S
Valve Body 3 Port 20mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VXG44.20-6.3	15	S
Valve Body 3 Port 25mm Flanged	Valve Bodies, Valve Actuators and Damper Actuators	VXG41.25	4	S
Valve Body 3 Port 25mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VXG44.25-10	60	S
Valve Body 3 Port 32mm Flanged	Valve Bodies, Valve Actuators and Damper Actuators	VXG41.32	7	S
Valve Body 3 Port 32mm Flanged	Valve Bodies, Valve Actuators and Damper Actuators	VXF61.39	2	S
Valve Body 3 Port 32mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VXG44.40-25	16	S
Valve Body 3 Port 32mm Screwed	Valve Bodies, Valve Actuators and Damper Actuators	VXG44.32-16	27	S
Valve Body 3 Port 50mm Flanged	Valve Bodies, Valve Actuators and Damper Actuators	VXG41.50	14	S
Valve Body 3 Port 50mm Flanged	Valve Bodies, Valve Actuators and Damper Actuators	VXF61.50	4	S
Valve Body 3 Port 65mm	Valve Bodies, Valve Actuators and Damper	VXF41.65 Now VXF 42 range	6	S

Flanged	Actuators			
Valve Body 3 Port 80mm Flanged	Valve Bodies, Valve Actuators and Damper Actuators	VXF61.80	6	S
Valve Body 3 Port 80mm Flanged	Valve Bodies, Valve Actuators and Damper Actuators	VXF41.80 VXF 42 Range	9	S
Valve Body 4 Port 1/2in	Valve Bodies, Valve Actuators and Damper Actuators	VMP45.10-1.6	12	S
Valve Body 4 Port 3/4in	Valve Bodies, Valve Actuators and Damper Actuators	VMP47.10-0.63	10	S
Valve Body 4 Port 3/4in	Valve Bodies, Valve Actuators and Damper Actuators	VMP45.20-4	15	S
Valve Body 4 Port 3/4in	Valve Bodies, Valve Actuators and Damper Actuators	VMP45.15-2.5	181	S
Volume Sensor	Field Equipment	V-Sensor	20	S
VVP45…(Rad	VVP45.xxxx		1601	S
Wilson Flow Grid	Field Equipment	Flow Grid	20	S
Wind Speed & Direction Sensor	Field Equipment	WSD1	1	S
Hi Temp Immersion Thermostat	Field Equipment	WT2254	6	O
Room Temperature Sensor	Field Equipment	TPTRJ115ML	13	O
Valve Body 4 Port 1/2in	Valve Bodies, Valve Actuators and Damper Actuators	VMK45.10-1.6	65	B2
Valve Body 4 Port 1/2in	Valve Bodies, Valve Actuators and Damper Actuators	VMK45.10-1	489	B2
Valve Body 4 Port 1/2in	Valve Bodies, Valve Actuators and Damper	VMK45.10-0.63	12	B2

	Actuators			
Valve Body 4 Port 1/2in	Valve Bodies, Valve Actuators and Damper Actuators	VMK45.10-0.4	63	B2
Air Differential Pressure Detector	Sensor	QBM62.203	16	B1
Air Differential Pressure Detector	Sensor	QBM62.202	126	B1
Duct Temp / Humidity Sensor	Sensor	QFM66	33	B1
Duct Temp / Humidity Sensor	Sensor	QFM65	67	B1
Duct Temperature Sensor	Sensor	QAM22.6	106	B1
Duct Temperature Sensor	Sensor	QAM22.2	7	B1
Duct Temperature Sensor	Sensor	QAM22	23	B1
Fibre Optic Hub	Panel Equipment	LD-64	10	B1
Immersion Temperature Sensor	Sensor	QAE22A	251	B1
Immersion Temperature Sensor	Sensor	QAE22.5A	1	B1
Interface For McQuay Chiller	Panel Equipment	US-565359	2	B1
Interface For MODBUS PDU	Panel Equipment	US-565392	12	B1
Inverter 1.1kW	Variable Speed Drive	SED2-1.1/35B	1	B1
Inverter 1.5kW	Variable Speed Drive	SED2-1.5/35B	2	B1
Inverter 110kW	Variable Speed Drive	ECO1-110K/3	12	B1
Inverter 11kW	Variable Speed Drive	SED2-11/35B	8	B1

Inverter 132kW	Variable Speed Drive	ECO1-132K/3	3	B1
Inverter 15kW	Variable Speed Drive	SED2-15/35B	2	B1
Inverter 160kW	Variable Speed Drive	ECO1-160K/3	2	B1
Inverter 18.5kW	Variable Speed Drive	SED2-18.5/35B	6	B1
Inverter 2.2kW	Variable Speed Drive	SED2-2.2/35B	1	B1
Inverter 22kW	Variable Speed Drive	SED2-22/35B	10	B1
Inverter 3kW	Variable Speed Drive	SED2-3/35B	6	B1
Inverter 30kW	Variable Speed Drive	SED2-30/35B	8	B1
Inverter 37kW	Variable Speed Drive	SED2-37/35B	8	B1
Inverter 45kW	Variable Speed Drive	SED2-45/35B	1	B1
Inverter 4kW	Variable Speed Drive	SED2-4/35B	6	B1
Inverter 5.5kW	Variable Speed Drive	SED2-5.5/35B	5	B1
Inverter 55kW	Variable Speed Drive	SED2-55/35B	4	B1
Inverter 7.5kW	Variable Speed Drive	SED2-7.5/35B	10	B1
Inverter 75kW	Variable Speed Drive	SED2-75/35B	4	B1
Inverter 110kW ECO1 - 110K/3	Variable Speed Drive	SED2-110/35B	12	B1
Inverter 160kW ECO1 - 110K/3	Variable Speed Drive	SED2-160/35B	2	B1
Inverter 132kW ECO1 - 110K/3	Variable Speed Drive	SED2-132/35B	3	B1
Liquid Differential Pressure Sensor	Sensor	QBE64-DP4	13	B1
Liquid Pressure Sensor	Sensor	QBE620-P10	11	B1
Liquid Pressure Sensor	Sensor	QBE620-P1	9	B1
MBC40 Backplate Assembly	Panel Equipment	US-545078	14	B1
MEC Analogue Expansion module	Panel Equipment	US-549214	88	B1
MEC Digital	Panel Equipment	US-549210	169	B1

Expansion module				
MEC100 Controller	Panel Equipment	US-549021	61	B1
MEC200 Controller	Panel Equipment	US-549022	108	B1
MEC200 Controller With FLN	Panel Equipment	US-549007	37	B1
MEC200 With Lonworks	Panel Equipment	US-549407	1	B1
Open Processor (4mb)	Panel Equipment	US-545719	6	B1
Open Processor (8mb)	Panel Equipment	US-545730	15	B1
Power Module	Panel Equipment	US-545714	23	B1
Room Temp / Humidity Sensor	Sensor	QFA66	12	B1
Room Temp / Humidity Sensor	Sensor	QFA65	140	B1
Valve Actuator 24V 0-10V	Valve Bodies, Valve Actuators and Damper Actuators	SQX62	8	B1
Valve Actuator 24V 3 Point	Valve Bodies, Valve Actuators and Damper Actuators	SQX82.00	54	B1
Temperature Sensor	Sensor	US-540128	258	A1

OAT Script 4

```
%Objective:
%The objective of script 4 is to use the variables created earlier by OAT
%to create templated output visualisations. This will include a top level
%Asset Health indicator with weighting. It will also include Unknown or
%Obsolete components for attention to the user. The final visualisation
%will be an annual summary report for the user, featuring all components
```

```
%due to become obsolete within the coming year.
```

```

```

```
% Top Level Asset Health

%Firstly, a small line of code to change the colour of the bars used within

%the charts to reflect the Asset Health score.
```

```
AH = [OAT,OATcriticality,OATvalue, OATaverage];


if OAT <= 55

    colour = 'r';

elseif OAT <= 80

    colour = 'y';

else colour = 'g';

end


AHplot = figure('Name','Asset Health Score',...

    'Colormap',[1          0.00196078442968428          0.00196078442968428;1
0.00196078442968428          0.00196078442968428;1          0.00196078442968428
0.00196078442968428;1          0.00196078442968428          0.00196078442968428;1
0.00196078442968428          0.00196078442968428;1          0.00196078442968428
0.00196078442968428;1          0.00196078442968428          0.00196078442968428;1
0.00196078442968428          0.00196078442968428;1          0.00196078442968428
0.00196078442968428;1          0.00196078442968428          0.00196078442968428;1
0.00196078442968428          0.00196078442968428;1          0.00196078442968428
0.00196078442968428;1          0.00196078442968428          0.00196078442968428;1
0.00196078442968428          0.00196078442968428;1          0.00196078442968428
0.00196078442968428;1          0.00196078442968428          0.00196078442968428;1
0.00196078442968428          0.00196078442968428;1          0.00196078442968428
0.00196078442968428;1          0.00196078442968428          0.00196078442968428;1
0.00196078442968428          0.00196078442968428;1          0.00196078442968428
0.00196078442968428;1          0.0852941200137138          0.00196078442968428;1
0.168627455830574          0.00196078442968428;1          0.251960784196854
0.00196078442968428;1          0.335294127464294          0.00196078442968428;1
0.418627440929413          0.00196078442968428;1          0.501960813999176
0.00196078442968428;1          0.585294127464294          0.00196078442968428;1
0.668627440929413          0.00196078442968428;1          0.751960813999176
0.00196078442968428;1          0.835294127464294          0.00196078442968428;1
0.918627440929413     0.00196078442968428;1     1     0.00196078442968428;1     1
0.00196078442968428;1  1   0.00196078442968428;1  1   0.00196078442968428;1  1
0.00196078442968428;1  1   0.00196078442968428;1  1   0.00196078442968428;1  1
0.00196078442968428;1  1   0.00196078442968428;1  1   0.00196078442968428;1  1
```

```
0.00196078442968428;1          1          0.00196078442968428;1          1
0.00196078442968428;0.906885981559753                    0.958935558795929
0.00196078442968428;0.816491425037384                    0.915910363197327
0.00196078442968428;0.730777144432068                    0.872885167598724
0.00196078442968428;0.649743139743805                    0.829859972000122
0.00196078442968428;0.573389410972595                     0.78683477640152
0.00196078442968428;0.504182636737823                    0.760758876800537
0.00196078442968428;0.438427597284317                    0.734682977199554
0.00196078442968428;0.376124292612076                    0.708607077598572
0.00196078442968428;0.317272752523422                    0.682531177997589
0.00196078442968428;0.261872977018356                    0.656455338001251
0.00196078442968428;0.209924906492233                    0.630379438400269
0.00196078442968428;0.161428600549698                    0.604303538799286
0.00196078442968428;0.116384029388428                    0.578227639198303
0.00196078442968428;0.074791207909584                    0.552151799201965
0.00196078442968428;0.0366501249372959                   0.526075899600983
0.00196078442968428;0.00196078442968428 0.5 0.00196078442968428]);


% Create axes

axes1 = axes('Parent',AHplot,...

       'Position',[0.101910828025478   0.114893617021277   0.770700636942675
0.797872340425532]);

hold(axes1,'on');


% Create bar

bar(1:4,AH,'DisplayName','Asset Health Score',...

    'FaceColor',colour);


% Create xlabel

xlabel('OAT(1), OAT Criticality(2), OAT Value(3) and OAT Average(4) ');


% Create ylabel

ylabel('% of     Components in a ''positive'' obsolescence position)        ');


% Create title

title('Asset Health Score [OAT]');


xlim(axes1,[0.5 4.5]);

ylim(axes1,[0 100]);

% Set the remaining axes properties
```

```
set(axes1,'XTick',[1 2 3 4],'YGrid','on');
% Create legend
legend(axes1,'show');

% Create colorbar
colorbar('peer',axes1,'Ticks',[1.1,1.2,1.3,1.4,1.5,1.6,1.7,1.8,1.9],...
    'TickLabels',{'10%','20%','30%','40%','50%','60%','70%','80%','90%'});
```

```
%The above code will produce a figure to reflec the inputted excel file.
%this is to be saved locally by the user before uploading a different excel
%file for analysis.
```

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8.3 OAT Input Sheet Template

Part Name				
Part Function				
Part REF#				
Part Description				
No. Parts				
Introduction Date				
EOL Released?				
Date of Release				
EOL Date (Real or Estimated)				
Current Supplier				
Alternative Supplier (Y/N)				
Alternative Parts (Y/N)				
Confirmed Compatibility (Y/N)				

8.4 OIT MATLAB Script Report

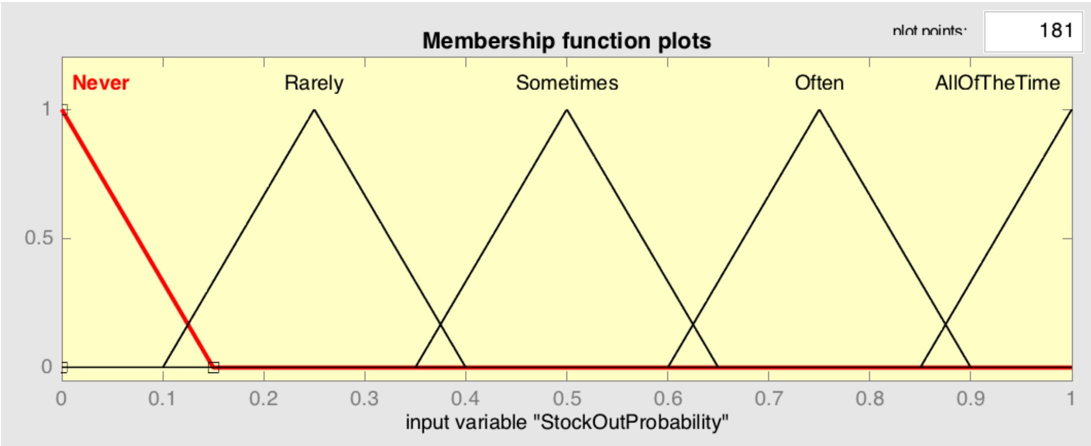
The following code was used to generate the Fuzzy Inference System, used for OIT. The screenshots illustrate the three ‘inputs’ and ‘output’ cited within the code.

```
[System]
Name='OIT'
Type='mamdani'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=45
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='StockOutProbability'
Range=[0 1]
NumMFs=5
MF1='Never':'trimf',[0 0 0.15]
MF2='Rarely':'trimf',[0.1 0.25 0.4]
MF3='AllOfTheTime':'trimf',[0.85 1 1]
MF4='Sometimes':'trimf',[0.35 0.5 0.65]
MF5='Often':'trimf',[0.6 0.75 0.9]

[Input2]
Name='ObsolescenceStatus'
Range=[0 1]
NumMFs=3
MF1='NoEOL':'trapmf',[0 0 0 0.5]
MF2='EOLReleased':'trimf',[0.3 0.5 0.7]
MF3='EOLExceeded':'trapmf',[0.5 1 1 1]

[Input3]
```

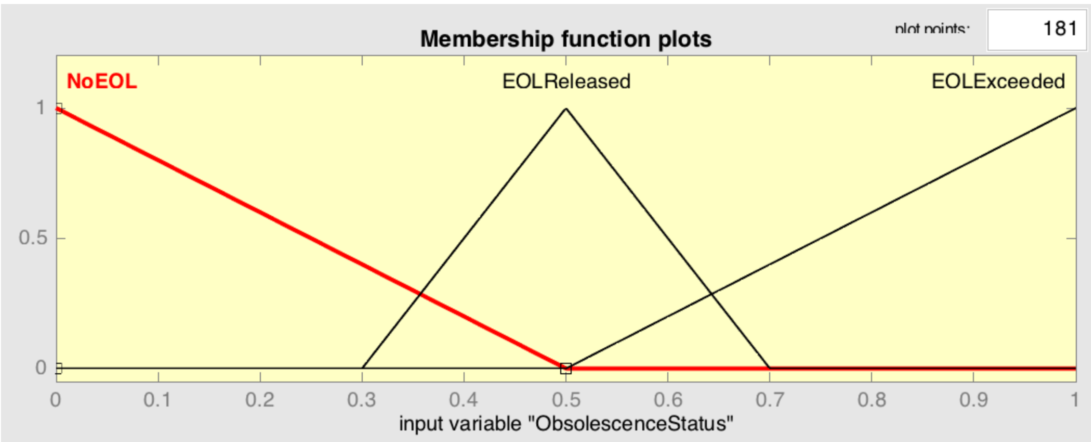
```
Name='ComponentCriticality'
Range=[0 5]
NumMFs=3
MF1='Low':'trimf',[-2 0 2]
MF2='Medium':'trimf',[0.5 2.5 4.5]
MF3='High':'trimf',[3 5 7]

[Output1]
Name='OrdinalRiskProfile'
Range=[0 1]
NumMFs=6
MF1='NotImportant':'trimf',[0 0 0.15]
MF2='Low':'trimf',[0.25 0.4 0.55]
MF3='VeryImportant':'trimf',[0.85 1 1]
MF4='Minor':'trimf',[0.05 0.2 0.35]
MF5='Moderate':'trimf',[0.45 0.6 0.75]
MF6='Important':'trimf',[0.65 0.8 0.95]

[Rules]
1 1 1, 1 (1) : 1
1 1 2, 1 (1) : 1
1 1 3, 1 (1) : 1
1 2 1, 4 (1) : 1
1 2 2, 4 (1) : 1
1 2 3, 4 (1) : 1
1 3 1, 4 (1) : 1
1 3 2, 4 (1) : 1
1 3 3, 2 (1) : 1
2 1 1, 1 (1) : 1
2 1 2, 4 (1) : 1
2 1 3, 4 (1) : 1
2 2 1, 4 (1) : 1
2 2 2, 2 (1) : 1
2 2 3, 5 (1) : 1
2 3 1, 5 (1) : 1
2 3 2, 5 (1) : 1
```

```
2 3 3, 5 (1) : 1
3 1 1, 2 (1) : 1
3 1 2, 2 (1) : 1
3 1 3, 6 (1) : 1
3 2 1, 5 (1) : 1
3 2 2, 6 (1) : 1
3 2 3, 3 (1) : 1
3 3 1, 6 (1) : 1
3 3 2, 3 (1) : 1
3 3 3, 3 (1) : 1
4 1 1, 4 (1) : 1
4 1 2, 2 (1) : 1
4 1 3, 5 (1) : 1
4 2 1, 5 (1) : 1
4 2 2, 5 (1) : 1
4 2 3, 6 (1) : 1
4 3 1, 5 (1) : 1
4 3 2, 6 (1) : 1
4 3 3, 3 (1) : 1
5 1 1, 5 (1) : 1
5 1 2, 5 (1) : 1
5 1 3, 6 (1) : 1
5 2 1, 5 (1) : 1
5 2 2, 6 (1) : 1
5 2 3, 3 (1) : 1
5 3 1, 6 (1) : 1
5 3 2, 3 (1) : 1
5 3 3, 3 (1) : 1
```

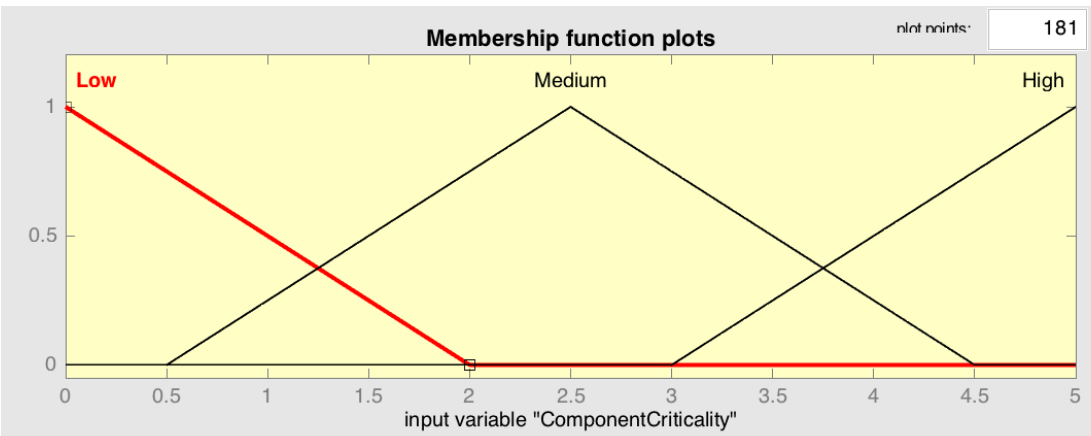
Input1



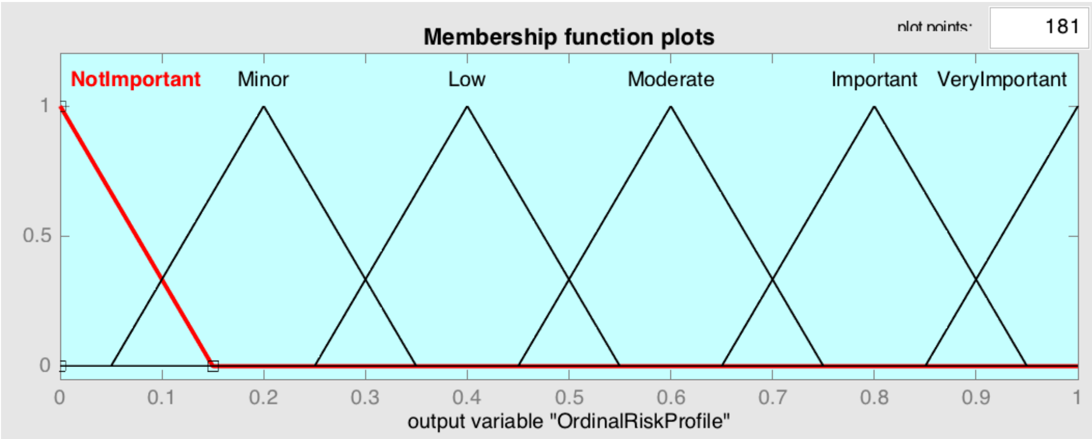
Input2



Input3



Output1



Membership function plots
plot points:
181
NotImportant
Minor
Low
Moderate
Important
VeryImportant
1
0.5
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
output variable "OrdinalRiskProfile"

8.5 OIT Stockout Probability Input Sheet Template

UPM and PPM records were grouped into a single Excel worksheet, the below table is how Excel formulae was used to extract demand profiles for the respect component groups within the case study.

Time Periods (months)	59
Actuator	=(SUMIF(D2:D60,AE1,C2:C60))/AD2
Sensors	=(SUMIF(F2:F60,AF1,E2:E60))/AD2
Headend	=(SUMIF(H2:H60,AG1,G2:G60))/AD2
Outstation	=(SUMIF(J2:J60,AH1,I2:I60))/AD2
Security Management System (SMS)	=(SUMIF(L2:L60,AI1,K2:K60))/$AD$2
Access Control	=(SUMIF(N2:N60,AJ1,M2:M60))/$AD$2
Cameras	=(SUMIF(P2:P60,AK1,O2:O60))/$AD$2
Intruder Detection Systems (IDS)	=(SUMIF(R2:R60,AL1,Q2:Q60))/$AD$2
Synectics Matrix	=(SUMIF(T2:T60,AM1,S2:S60))/$AD$2
Digital Video Recording System	=(SUMIF(V2:V60,AN1,U2:U60))/$AD$2
I/O Devices	=(SUMIF(X2:X60,AO1,W2:W60))/$AD$2
Controller	=(SUMIF(Z2:Z60,AP1,Y2:Y60))/$AD$2
Monitors	=(SUMIF(AB2:AB60,AQ1,AA2:AA60))/$AD$2

In order to anonymise the dataset, the below table was used to extract the date, quantity and component parts from the onsite records.

Year	2010										
Month	January	February	March	April	May	June	July	August	September	October	November
Demand											
Part Descriptio											
Demand											25
Part Descriptio											Sensors
Demand											
Part Descriptio											
Demand				2						2	
Part Descriptio				Outstation						Outstation	
Demand											
Part Descriptio											
Demand											
Part Descriptio											
Demand											
Part Descriptio											
Demand											
Part Descriptio											
Demand											
Part Descriptio											
Demand											
Part Descriptio											
Demand											
Part Descriptio											
Demand											
Part Descriptio											
Demand											
Part Descriptio											

											2011	
December	November	October	Septembe r	August	July	June	May	April	March	February	January	December
						1		2				10
						Sensors		Sensors				Sensors
					3		1					
					Headend		Headend					
		3	1		1			2			2	
		Outstation	Outstation		Outstation			Outstation			Outstation	
						1						
						Managem ent						
												10
												I/O Devices
									1	1			
								Monitors	Monitors			

2013												2012
January	December	November	October	Septembe r	August	July	June	May	April	March	February	January
		1	2	3					2			
		Actuator	Actuator	Actuator					Actuator			
			18									
			Sensors									
1												
Headend												
1		7	2	2		1	1	3	2			
Outstation		Outstation	Outstation	Outstation		Outstation	Outstation	Outstation	Outstation			
				1		3						
				Access Control		Access Control						
6	2	1		1					1			
Cameras	Cameras	Cameras		Cameras					Cameras			
			18									
			Detection Systems									
		1										
		Synectics Matrix										
1	4					1						
Video Recording	Video Recording					Video Recording						
						12						
						I/O Devices						
											1	
											Controller	
5												
Monitors												

	2014											
February	January	December	November	October	Septembe r	August	July	June	May	April	March	February
								2	2	1		
								Actuator	Actuator	Actuator		
			10	3	2	1	7					
			Sensors	Sensors	Sensors	Sensors	Sensors					
			2	2	1			1				
			Headend	Headend	Headend			Headend				
1	2	3		32	4	5	5	4	5		1	1
Outstation	Outstation	Outstation		Outstation	Outstation	Outstation	Outstation	Outstation	Outstation		Outstation	Outstation
			10								1	
			Managem ent								Managem ent	
												5
												Access Control
			3	3								
			Cameras	Cameras								
						1		1		1		
						Video Recording		Video Recording		Video Recording		
				2							5	
				Monitors							Monitors	

Year									
Month	November	October	Septembe r	August	July	June	May	April	March
Demand									
Part Descriptio									
Demand				4			3	1	
Part Descriptio				Sensors			Sensors	Sensors	
Demand		6			2	6			2
Part Descriptio		Headend			Headend	Headend			Headend
Demand	2		2	2	2	5		3	1
Part Descriptio	Outstation		Outstation	Outstation	Outstation	Outstation		Outstation	Outstation
Demand									
Part Descriptio									
Demand									
Part Descriptio									
Demand									
Part Descriptio									
Demand				4					
Part Descriptio				Detection Systems					
Demand		6		9	2	6			
Part Descriptio		Synectics Matrix		Synectics Matrix	Synectics Matrix	Synectics Matrix			
Demand									
Part Descriptio									
Demand	1								
Part Descriptio	I/O Devices								
Demand									
Part Descriptio									
Demand	8	3							
Part Descriptio	Monitors	Monitors							

The next table illustrates the Excel code that was used to generate Stockout Probabilities for each component group that created input (1) for OIT.

Serial	1
Component	EXAMPLE NAME
	EXAMPLE
Category	EXAMPLE
Stock	2
Lead Time	0.25
Demand over Lead (6m)	=H2*F2
Demand	=D2="OUTSTATION" '/Users/kieranmulholland/Documents/UCL Work/MATLAB/OIT/Input Files/Stockout Input (1)/[BlueBookDatav1.xlsx]Sheet1'!$AK$2 D2="ACTUATORS"
Validation Check	=IF(E2>5,"FAILED","PASSED")
1	=IF($J$1=E2,"",IF($J$1<E2,"",($J$1-E2)*(POISSON.DIST($J$1,H2,FALSE))))
2	=IF($K$1=E2,"",IF($K$1<E2,"",($K$1-E2)*POISSON.DIST($K$1,H2,FALSE)))
3	=IF($L$1=E2,"",IF($L$1<E2,"",($L$1-E2)*POISSON.DIST($L$1,H2,FALSE)))
4	=IF($M$1=E2,"",IF($M$1<E2,"",($M$1-E2)*POISSON.DIST($M$1,H2,FALSE)))
5	=IF($N$1=E2,"",IF($N$1<E2,"",($N$1-E2)*POISSON.DIST($N$1,H2,FALSE)))
6	=IF($O$1=E2,"",IF($O$1<E2,"",($O$1-E2)*POISSON.DIST($O$1,H2,FALSE)))
Stockout Probability	=IF(O2=0,0,(1-(1-(SUM(J2:O2)/G2))))

8.6 OIT Obsolescence Input Sheet Template

Part Name	EXAMPLE
Date of Assessment	EXAMPLE DATE
Introduction Date.	
Market Age	=IF(C2="","",((B2-C2)/365))
EOL Released.	FALSE
EOL Date.	
Time to Exceed	=IF(F2="","",IF(F2<B2,"",(F2-B2)/365))
Exceeded?	=IF(F2="","",IF(F2>B2,"No","Yes"))
Exceeded By	=IF(H2="Yes",(B2-F2)/365,"")
NoEOL Range	0.5
EOL Range	0.2
Exceeded Range (1)	0.2
Exceeded Range (2)	0.3
EOL L Limit	0.3
Exceeded L Limit (1)	0.5
Exceeded L Limit (2)	0.7
No EOL Arbitrary Value	5
EOL Arbitrary Value	1
Exceeded Arbitrary Value	3
NoEOL Input Score	=IF(E2=FALSE,IF(D2>Q2,J2,(D2/Q2)*J2),"")
EOL Input Score	=IF(H2="No",IF(AND(E2=TRUE,F2<>""),IF(G2>R2,N2,(G2*K2)+N2),""),IF(AND(E2=TRUE,F2=""),0.6,""))
Exceeded Input Score	=IF(H2="Yes",IF(I2>S2,1,IF(I2<1,(I2*L2)+O2,((I2/S2)*M2)+P2)),"")
INPUT	=IF(T2="",IF(U2="",V2,U2),T2)

8.7 Results

Note the below appendix will contain summary data tables and final graphics. Full data tables have been moved into an attached CD.

8.7.1 OAT

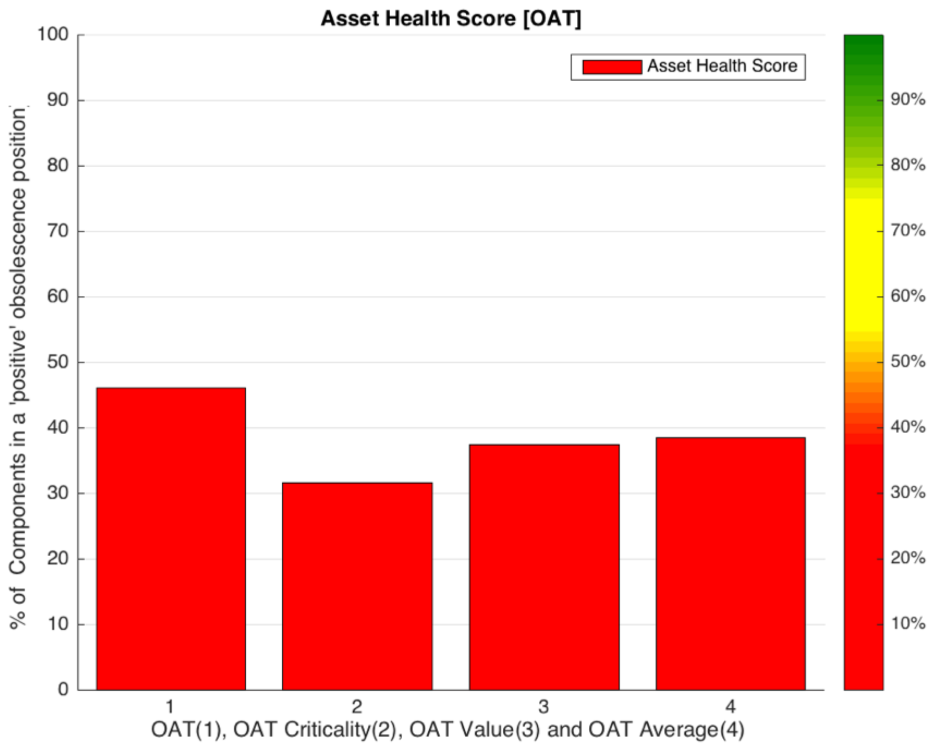
8.7.1.1 Q1 2015

BMS Results.

Summary data table.

A1	A2	B1	B2	U	O	Y1	Y2	S
0	4718	1074	0	116	0	317	4765	9358

OAT output graphic.

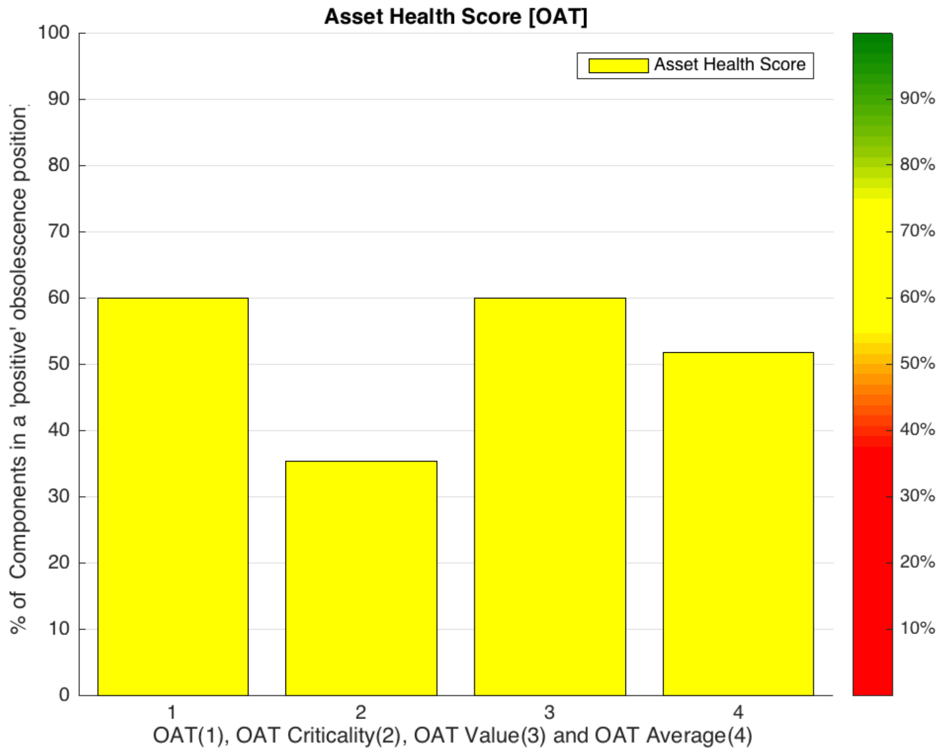


SS Results.

Summary data table.

A1	A2	B1	B2	U	O	Y1	Y2	S
0	0	10	0	0	265	0	49	378

OAT output graphic.



8.7.1.2 Q2 2015

BMS Results.

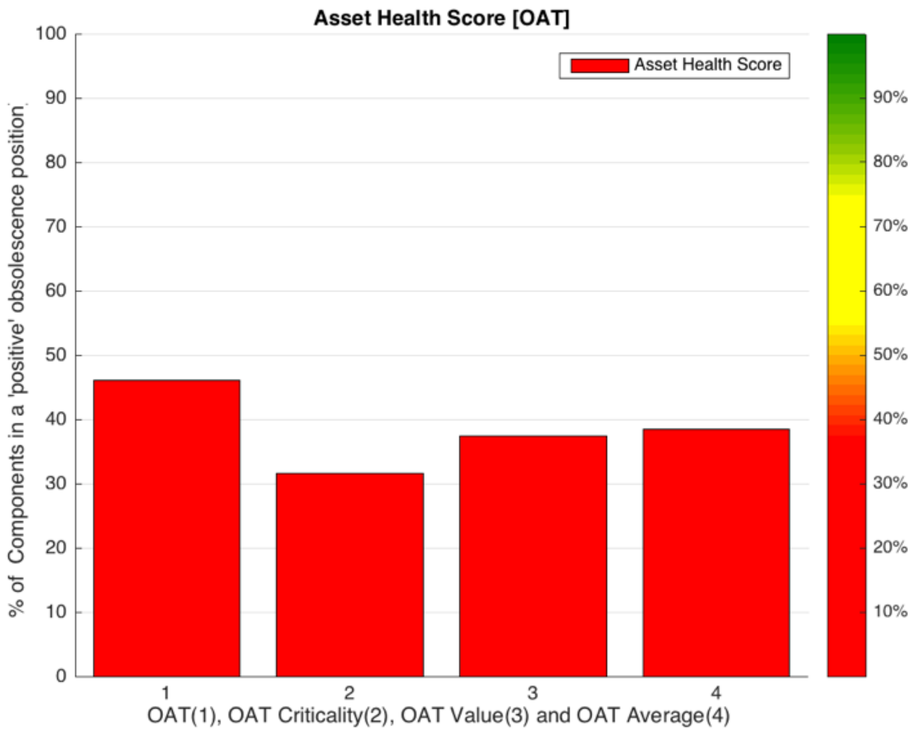
Summary data table.

A1	A2	B1	B2	U	O	Y1	Y2	S
0	4718	1074	0	153	0	317	4765	9357

Logic test results.

Logic 1				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
700VA UPS	SU700I	9	1	NaN
LD -64	LD-64	10	1	NaN
Valve Body 3 Port 80mm Flanged	VXF41.80	9	1	NaN

OAT output graphic.



SS Results.

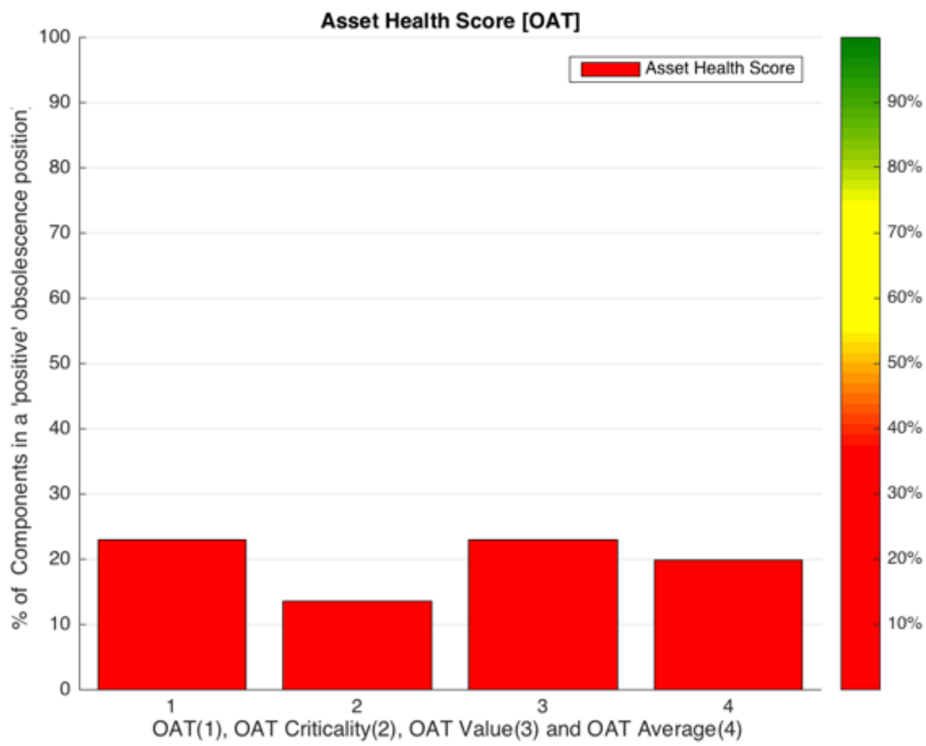
Summary data table.

A1	A2	B1	B2	U	O	Y1	Y2	S
0	0	10	0	0	537	0	45	74

Logic test results.

Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
Logic 1				
Bosch Monitor	UML 20	25	1	NaN
Logic 3				
TM Legic	A10	0	NaN	01/01/2008
Watermark Reader	WR03/1300S0/05	0	NaN	01/01/2008
Logic 4				
Intercoms system		1	0	01/01/2015
internal panosonic camera	WV-CF600	1	0	01/01/2015

OAT output graphic.



8.7.1.3 Q3 2015

BMS Results.

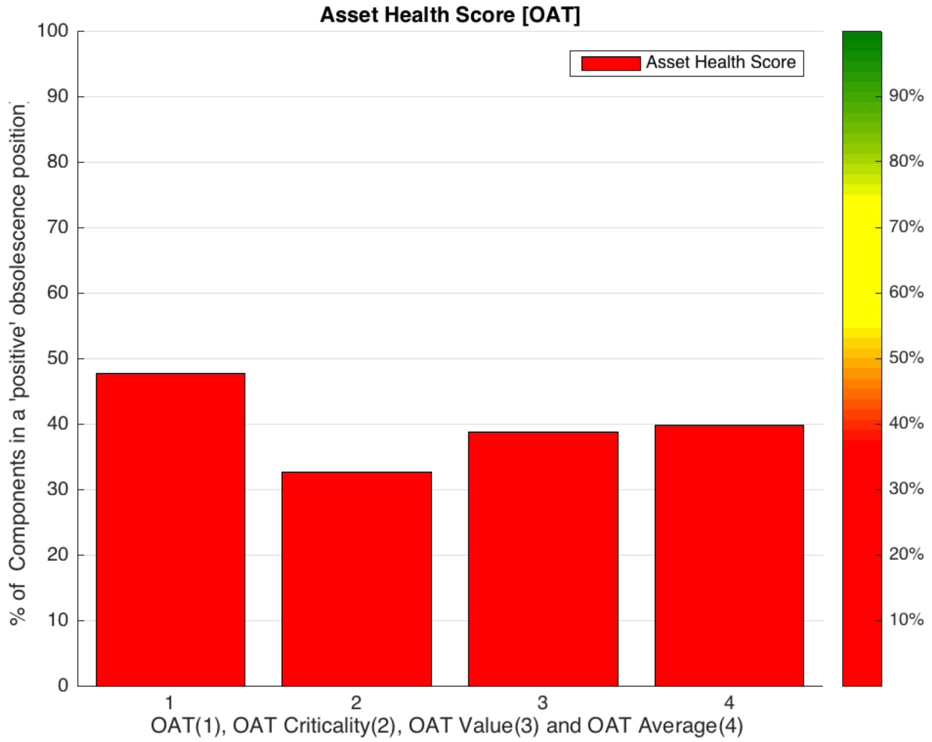
Summary data table

A1	A2	B1	B2	U	O	Y1	Y2	S
0	79	1074	1309	0	564	0	4720	11458

Logic test results.

Logic 1				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
420VA UPS	SU420I	26	1	NaN
700VA UPS	SU700I	9	1	NaN
Inverter 1.1kW	SED2-1.1/35B	0	1	NaN
Inverter 110kW	ECO1-110K/3	12	1	NaN
Inverter 11kW G120P	G120P-11/35A	7	1	NaN
Inverter 132kW	ECO1-132K/3	3	1	NaN
Inverter 15kW	SED2-15/35B	9	1	NaN
Inverter 160kW	ECO1-160K/3	2	1	NaN
Inverter 18.5kW	SED2-18.5/35B	6	1	NaN
Inverter 2.2kW	SED2-2.2/35B	13	1	NaN
Inverter 22kW	SED2-22/35B	17	1	NaN
Inverter 30kW	SED2-30/35B	16	1	NaN
Inverter 37kW	SED2-37/35B	13	1	NaN
Inverter 3kW	SED2-3/35B	0	1	NaN
Inverter 45kW	SED2-45/35B	2	1	NaN
Inverter 4kW	SED2-4/35B	9	1	NaN
Inverter 5.5kW	SED2-5.5/35B	12	1	NaN
Inverter 55kW	SED2-55/35B	6	1	NaN
Inverter 7.5kW	SED2-7.5/35B	9	1	NaN
Inverter 75kW	SED2-75/35B	8	1	NaN
LD -64	LD-64	10	1	NaN
Valve Body 3 Port 80mm Flanged	VXF41.80	9	1	NaN
Logic 3				
Inverter 1.1kW	SED2-1.1/35B	0	1	NaN
Inverter 3kW	SED2-3/35B	0	1	NaN
50VA Transformer	TCX/50/6/F	0	NaN	NaN

OAT output graphic.



SS Results.

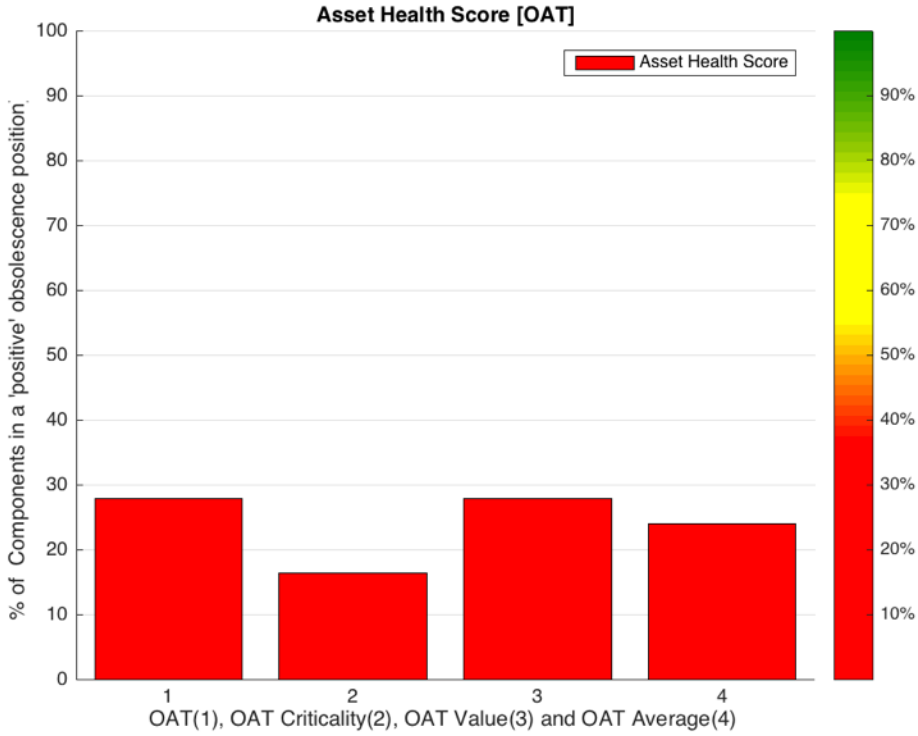
Summary data table.

A1	A2	B1	B2	U	O	Y1	Y2	S
5	0	1	0	0	485	0	55	153

Logic test results.

Logic 1				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
Bosch Monitor	UML 20	25	TRUE	NaN
3GS Europlex keypad		10	TRUE	NaN

OAT output graphic.



8.7.1.4 Q4 2015

BMS Results.

Summary data table.

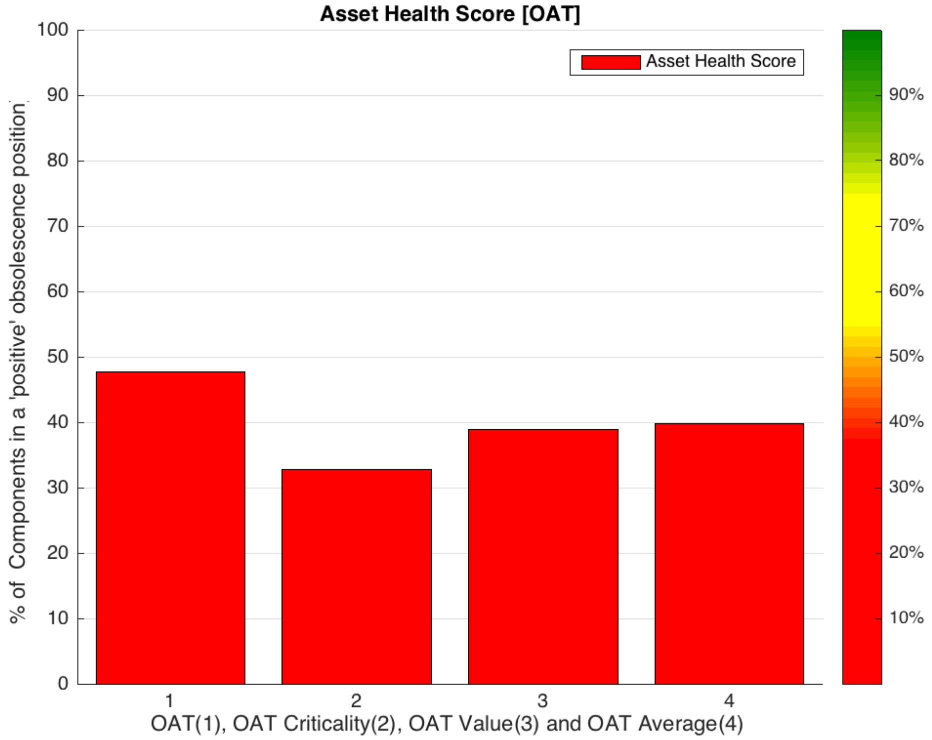
A1	A2	B1	B2	U	O	Y1	Y2	S
0	1362	1074	0	464	0	3627	4785	7906

Logic test results.

Logic 1				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
420VA UPS	SU420I	26	1	NaN
700VA UPS	SU700I	9	1	NaN
Inverter 1.1kW	SED2-1.1/35B	0	1	NaN
Inverter 110kW	ECO1-110K/3	12	1	NaN
Inverter 11kW	SED2-11/35B	12	1	NaN
Inverter 132kW	ECO1-132K/3	3	1	NaN
Inverter 15.0kW G120P	G120P-15/35A	3	1	NaN
Inverter 15kW	SED2-15/35B	9	1	NaN
Inverter 160kW	ECO1-160K/3	2	1	NaN
Inverter 18.5kW	SED2-18.5/35B	6	1	NaN
Inverter 2.2kW	SED2-2.2/35B	13	1	NaN
Inverter 22kW	SED2-22/35B	17	1	NaN
Inverter 3.0kW G120P	G120P-3.0/35A	6	1	NaN
Inverter 30kW	SED2-30/35B	16	1	NaN
Inverter 37kW	SED2-37/35B	12	1	NaN
Inverter 3kW	SED2-3/35B	0	1	NaN
Inverter 4.0kW G120P	G120P-4.0/35A	6	1	NaN
Inverter 45kW	SED2-45/35B	2	1	NaN
Inverter 4kW	SED2-4/35B	9	1	NaN
Inverter 5.5kW	SED2-5.5/35B	12	1	NaN
Inverter 55.0kW G120P	G120P-55/35A	3	1	NaN
Inverter 55kW	SED2-55/35B	6	1	NaN
Inverter 7.5kW	SED2-7.5/35B	9	1	NaN
Inverter 75kW	SED2-75/35B	8	1	NaN
Inverter 75kW G120P	G120P-75/35A	4	1	NaN
LD -64	LD-64	10	1	NaN
Valve Actuator 24V 0-10V	SQX62	8	1	NaN
Valve Actuator 24V 0-10V	SQS65	166	1	NaN
Valve Actuator	SQS65.5	10	1	NaN

24V 0-10V SR				
Valve Actuator 24V 3 Point	SQX82.00	54	1	NaN
Valve Actuator 24V 3 Point	SQS85.00	40	1	NaN
Valve Body 3 Port 100mm Flanged	VXF41.90	10	1	NaN
Valve Body 3 Port 125mm Flanged	VXF41.91	1	1	NaN
Valve Body 3 Port 65mm Flanged	VXF41.65	6	1	NaN
Valve Body 3 Port 80mm Flanged	VXF41.80	9	1	NaN
Valve Body 4 Port 1/2in	VMP45.10-1.6	12	1	NaN
Valve Body 4 Port 1/2in	VMK45.10-1.6	65	1	NaN
Valve Body 4 Port 1/2in	VMK45.10-1	489	1	NaN
Valve Body 4 Port 1/2in	VMK45.10-0.4	63	1	NaN
Wilson Flow Grid	Flow Grid	20	1	NaN
Logic 3				
50VA Transformer	TCX/50/6/F	0	NaN	NaN
Inverter 1.1kW	SED2-1.1/35B	0	1	NaN
Inverter 3kW	SED2-3/35B	0	1	NaN

OAT output graphic.



SS Results.

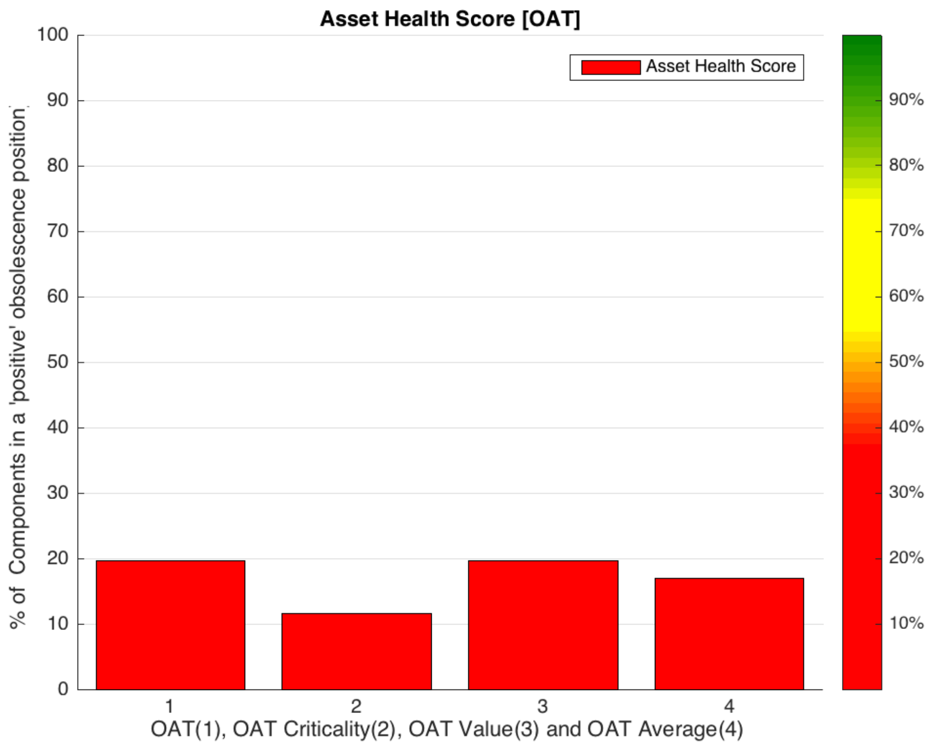
Summary data table.

A1	A2	B1	B2	U	O	Y1	Y2	S
1	0	10	0	0	538	0	45	70

Logic test results.

Logic 1				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
Bosch Monitor	UML 20	25	1	NaN
Logic 3				
TM Legic	A10	0	NaN	01/01/2008
Watermark Reader	WR03/1300S0/05	0	NaN	01/01/2008

OAT output graphic.



8.7.1.5 Q1 2016

BMS Results.

Data summary table.

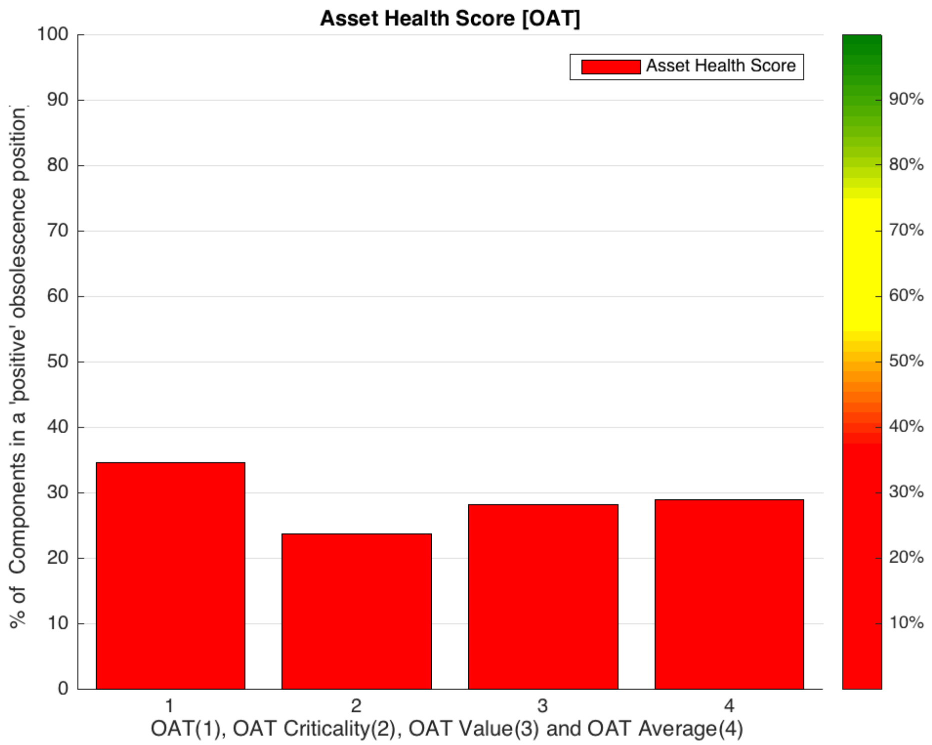
A1	A2	B1	B2	U	O	Y1	Y2	S
0	2447	0	0	2290	96	1833	3187	7879

Logic test results.

Logic 1				
Part_Name	**Part_Ref**	**No_Parts**	**EOL_Released**	**EOL_Date**
420VA UPS	SU420I	26	1	NaN
700VA UPS	SU700I	9	1	NaN
LD -64	LD-64	10	1	NaN
Valve Actuator 24V 0-10V	SQS65	166	1	NaN
Valve Body 3 Port 80mm Flanged	VXF41.80	9	1	NaN
Wilson Flow Grid	Flow Grid	20	1	NaN
Logic 2				
Inverter 2.2kW G120P	G120P-2.2/35A	2	NaN	06/01/2014
Inverter 22kW G120P	G120P-22/35A	10	0	06/01/2014
Inverter 45kW G120P	G120P-45/35A	NaN	NaN	12/01/2014
Inverter 5.5kW G120P	G120P-5.5/35A	10	0	02/01/2014
Valve Actuator 24V 0-10V	SSB61	221	0	01/01/2011
Valve Body 4 Port 1/2in	VMK45.10-0.63	12	0	01/01/2005
Logic 3				
16 Digital Input Module	TXM1.16D	NaN	NaN	NaN
50VA Transformer	TCX/50/6/F	0	NaN	NaN
6 Relay Output Module	TXM1.6R	NaN	NaN	NaN
6 Relay Output Module w/ Ovd	TXM1.6R-M	NaN	NaN	NaN
8 Digital Input Module	TXM1.8D	NaN	NaN	NaN
8 Univ I/O Module w/ Ovd&LCD	TXM1.8U-ML	NaN	NaN	NaN
8 Univ I/O	TXM1.8X	NaN	NaN	NaN

Module w/4-20mA				
8 Universal I/O Module	TXM1.8U	NaN	NaN	NaN
Inverter 1.1kW	SED2-1.1/35B	0	1	15/01/2014
Inverter 1.5kW	SED2-1.5/35B	NaN	NaN	NaN
Inverter 45kW G120P	G120P-45/35A	NaN	NaN	12/01/2014
Logic 4				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***Date_of_Release***
Valve Actuator 24V 0-10V	SSB61	221	0	01/01/2010

OAT output graphic.



SS Results.

Data summary table.

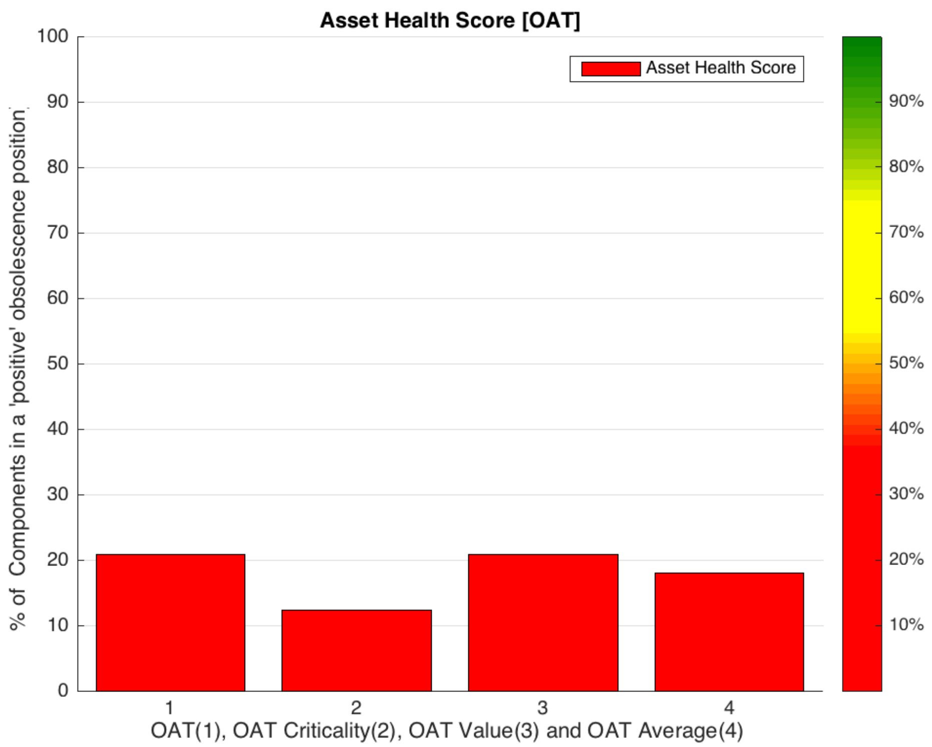
A1	A2	B1	B2	U	O	Y1	Y2	S
0	0	10	0	0	541	0	45	75

Logic test results.

Logic 1				

Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
Bosch Monitor	UML 20	25	TRUE	NaN
Intercoms system	3	TRUE	NaN	
internal panosonic camera	WV-CF600	1	TRUE	NaN
Logic 3				
TM Legic	A10	0	NaN	01/01/2008
Watermark Reader	WR03/1300S0/05	0	NaN	01/01/2008

OAT output graphic.



8.7.1.6 Q2 2016

BMS Results.

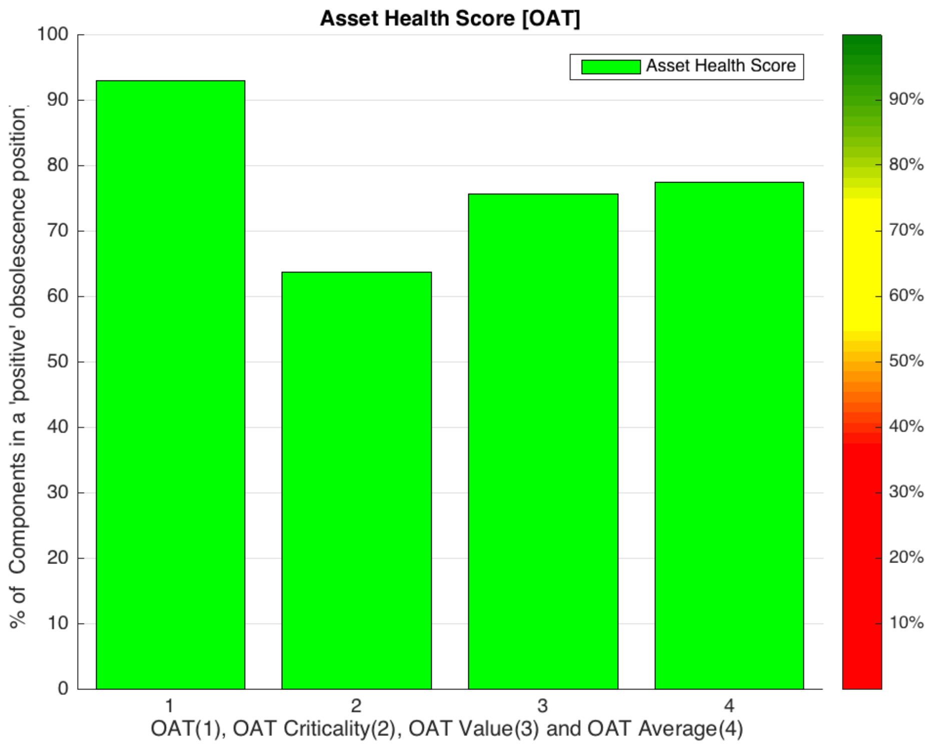
Summary data table.

A1	A2	B1	B2	U	O	Y1	Y2	S
268	0	1529	629	0	6	0	683	15196

Logic test results.

Logic 3				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
50VA Transformer	TCX/50/6/F	0	FALSE	NaN
Logic 4				
Fibre Optic Hub	LD-64	10	FALSE	01/03/2015

OAT output graphic.



SS Results.

Summary data table.

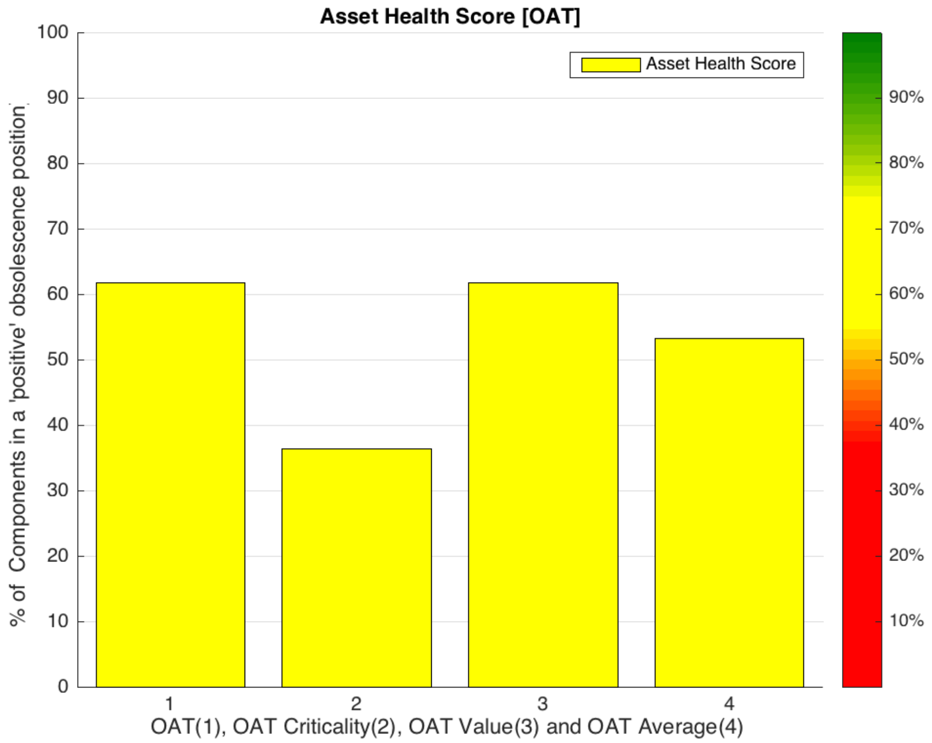
A1	A2	B1	B2	U	O	Y1	Y2	S
0	0	10	0	0	169	0	45	447

Logic test results.

Logic 1				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
Bosch Monitor	UML 20	25	1	NaN
Logic 2				
Mic 500 Series	Dinion Camera	7	0	01/12/2023
External Bosch Cameras	Dinion Camera	14	0	01/08/2021
Fibre Optic TX		12	0	01/03/2024
Fibre Optic RX		12	0	01/03/2024
Pelco domes Camera	FD5	23	0	01/12/2024
Pelco domes Camera	FD5 IR	31	0	01/08/2024
Scantronic 160 Control Panel		9	0	01/03/2024
Scantronic Keypad		9	0	01/03/2024
Expander		3	0	01/03/2024
Synectics Voll 8		5	NaN	01/06/2013
Synectics RS232		6	NaN	01/06/2013
Synectics Net 8		1	NaN	01/06/2013
Synectics Net 16		1	NaN	01/06/2013
TM Legic	A94	112	0	01/06/2019
TM Legic	A10	0	NaN	01/01/2008
Watermark Reader	WR03/1300S0/05	0	NaN	01/01/2008
I Star Pro		7	0	01/12/2023
I Star Edge		22	0	01/12/2023
RM4		48	0	01/08/2013
C-Cure 9000	C-Cure 9000	1	0	01/01/2020
Camera Lens	10 - 250 Zoom	4	NaN	01/08/2013
Camera Lens	8 - 120 Zoom	11	NaN	01/08/2013
Optrex Motion Senser		28	0	01/03/2024
Vibration Sensor		4	0	01/03/2024
8 port Switch		26	0	01/03/2024
24 Port Switch		1	0	01/03/2024
24 Port Switch		1	0	01/03/2024

Logic 3				
TM Legic	A10	0	NaN	01/01/2008
Watermark Reader	WR03/1300S0/ 05	0	NaN	01/01/2008
Logic 4				
Intercoms system	3	0	01/01/2015	
internal panosonic camera	WV-CF600	1	0	01/01/2015

OAT output graphic.



8.7.1.7 Q3 2016

BMS Results.

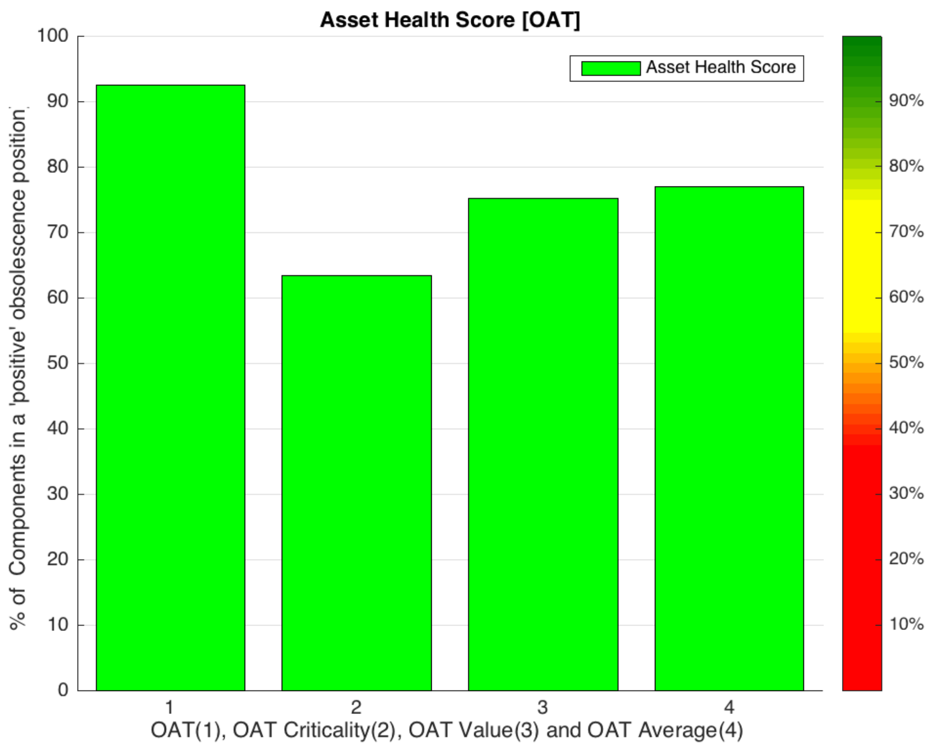
Data summary table.

A1	A2	B1	B2	U	O	Y1	Y2	S
258	0	1549	629	0	19	0	683	13575

Logic test results.

Logic 1				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
Room Temperature Sensor	TPTRJ115ML	4	1	NaN
Logic 3				
50VA Transformer	TCX/50/6/F	0	0	NaN

OAT output graphic.



SS Results.

Data summary table.

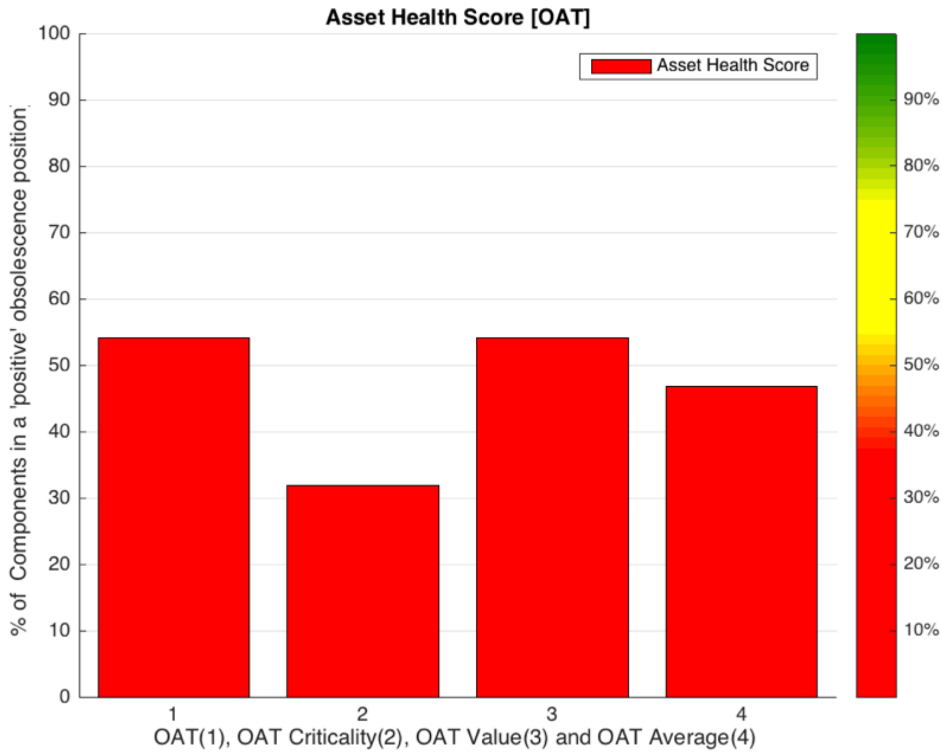
A1	A2	B1	B2	U	O	Y1	Y2	S
0	0	10	0	0	190	0	45	436

Logic test results.

Logic 1				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
Bosch Monitor	UML 20	25	1	NaN
Synectics Keyboard		7	1	NaN
Synectics matrix		1	1	NaN
synectics mini dc reciever		10	1	NaN
Intercoms system		3	1	NaN
internal panosonic camera	WV-CF600	1	1	NaN
galaxy 520		5	1	NaN
Logic 2				
Mic 500 Series	Dinion Camera	7	0	01/12/2023
External Bosch Cameras	Dinion Camera	14	0	01/08/2021
Fibre Optic TX		12	0	01/03/2024
Fibre Optic RX		12	0	01/03/2024
Pelco domes Camera	FD5	23	0	01/12/2024
Pelco domes Camera	FD5 IR	31	0	01/08/2024
Scantronic 160 Control Panel		9	0	01/03/2024
Scantronic Keypad		9	0	01/03/2024
Expander		3	0	01/03/2024
TM Legic	A94	112	0	01/06/2019
I Star Pro		7	0	01/12/2023
I Star Edge		22	0	01/12/2023
RM4		48	0	01/08/2013
C-Cure 9000	C-Cure 9000	1	0	01/01/2020
Optrex Motion Senser		28	0	01/03/2024
Vibration Sensor		4	0	01/03/2024
8 port Switch		26	0	01/03/2024
24 Port Switch		1	0	01/03/2024
24 Port Switch		1	0	01/03/2024

Logic 3				
TM Legic	A10	0	1	01/01/2008
Watermark Reader	WR03/1300S0/ 05	0	1	01/01/2008

OAT output graphic.



8.7.1.8 Q4 2016

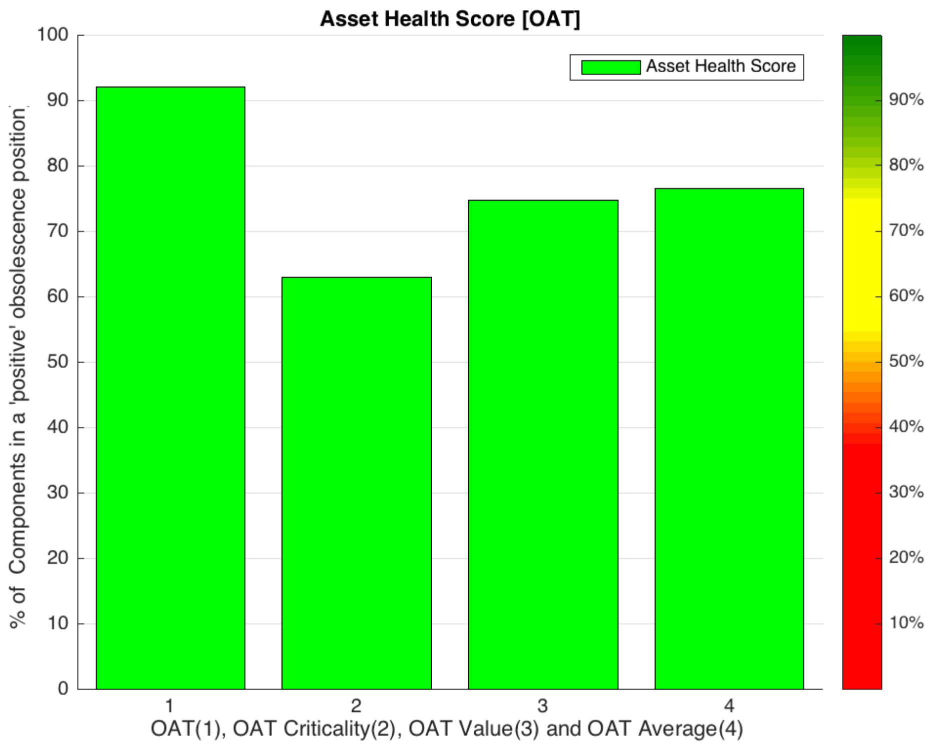
BMS Results.

Data summary table.

A1	A2	B1	B2	U	O	Y1	Y2	S
258	0	1539	629	0	19	0	693	15176

Logic test results.

Logic 1				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
Room Temperature Sensor	TPTRJ115ML	13	1	NaN
Logic 3				
50VA Transformer'	'TCX/50/6/F'	0	0	NaN



SS Results.

Data summary table.

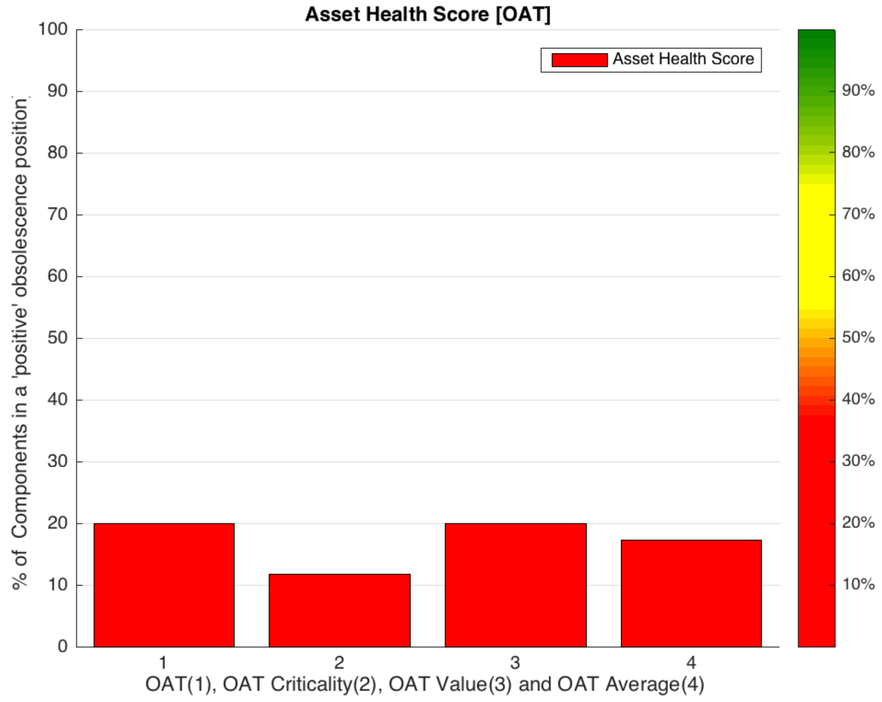
A1	A2	B1	B2	U	O	Y1	Y2	S
0	0	10	0	0	566	0	45	84

Logic test results.

Logic 1				
Part_Name	***Part_Ref***	***No_Parts***	***EOL_Released***	***EOL_Date***
Bosch Monitor	UML 20	25	1	NaN
Synectics Keyboard		7	1	NaN
Synectics matrix		1	1	NaN
synectics mini dc reciever		10	1	NaN
pelco ip camera		2	1	NaN
Logic 3				
TM Legic	A10	0	1	39448
Watermark Reader	WR03/1300S0/05	0	1	39448
Logic 4				
Intercoms system		3	0	42005
internal panosonic camera	WV-CF600	1	0	42005
galaxy 520		5	0	42370

Logic 5												
Part_Name	***Part_Function***	***Part_Ref***	***Part_Description***	***No_Parts***	***Introduction_Date***	***EOL_Released***	***Date_of_Release***	***EOL_Date***	***Current_Supplier***	***Alternative_Supplier***	***Alternative_Parts***	***Confirmed_Compatability***
galaxy 48	Alarm system		NaN	13	NaN	0	NaN	NaN		0	0	0

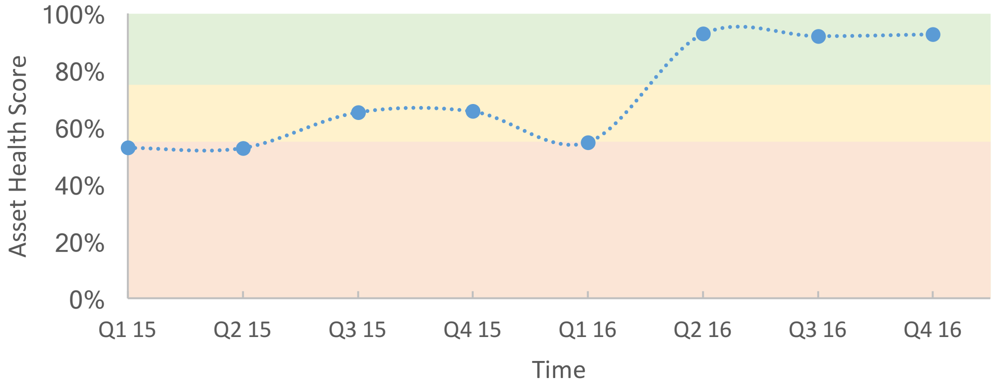
OAT output graphic.



8.7.1.9 BMS Summary

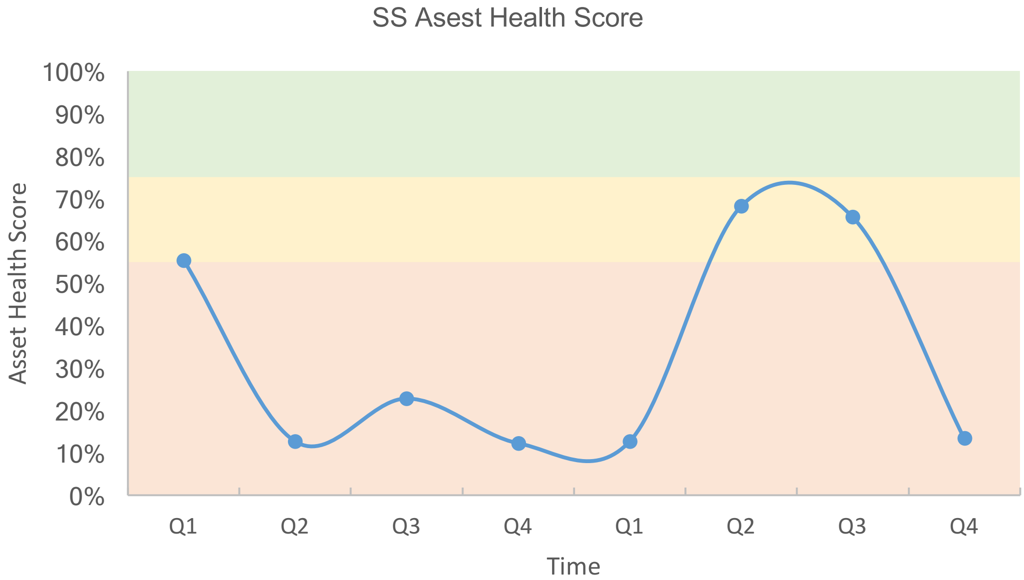
		A1	A2	B1	B2	U	O	Y1	Y2	S	AH
2015	Q1 15	0	4718	1074	0	116	0	317	4765	9358	52.83%
	Q2 15	0	4718	1074	0	153	0	317	4765	9357	52.73%
	Q3 15	0	79	1074	1309	0	564	0	4720	11458	65.26%
	Q4 15	0	1362	1074	0	464	0	3627	4785	7906	65.60%
2016	Q1 16	0	2447	0	0	2290	96	1833	3187	7879	54.77%
	Q2 16	268	0	1529	629	0	6	0	683	15196	92.80%
	Q3 16	258	0	1549	629	0	19	0	683	13575	92.04%
	Q4 16	258	0	1539	629	0	19	0	693	15176	92.68%

BMS Asest Health Score



8.7.1.10 SS Summary

		A1	A2	B1	B2	U	O	Y1	Y2	S	AH
2015	Q1	0	0	10	0	0	265	0	49	378	55.27%
	Q2	0	0	10	0	0	537	0	45	74	12.61%
	Q3	5	0	1	0	0	485	0	55	153	22.75%
	Q4	1	0	10	0	0	538	0	45	70	12.20%
2016	Q1	0	0	10	0	0	541	0	45	75	12.67%
	Q2	0	0	10	0	0	169	0	45	447	68.11%
	Q3	0	0	10	0	0	190	0	45	436	65.49%
	Q4	0	0	10	0	0	566	0	45	84	13.33%



8.7.2 OIT

Note this appendix will contain summary data tables and summary graphics. Full data tables are held within the attached CD for reference.

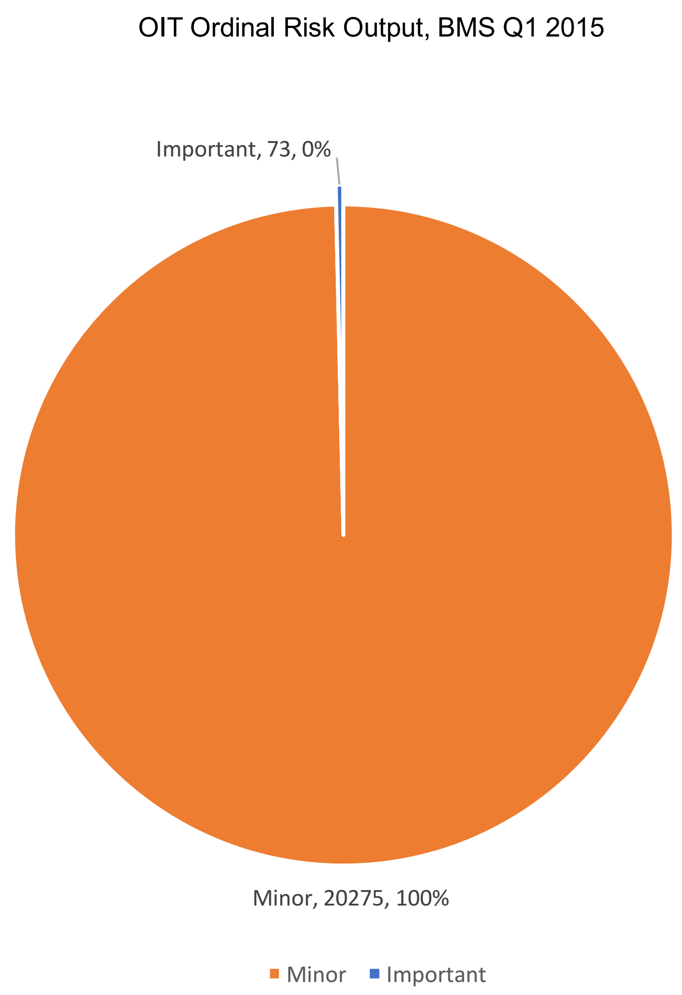
8.7.2.1 Q1 2015

BMS Results.

Data summary tables.

Not Important	Minor	Low	Moderate	Important	Very Important
0	20275	0	0	73	0

OIT summary graphic.

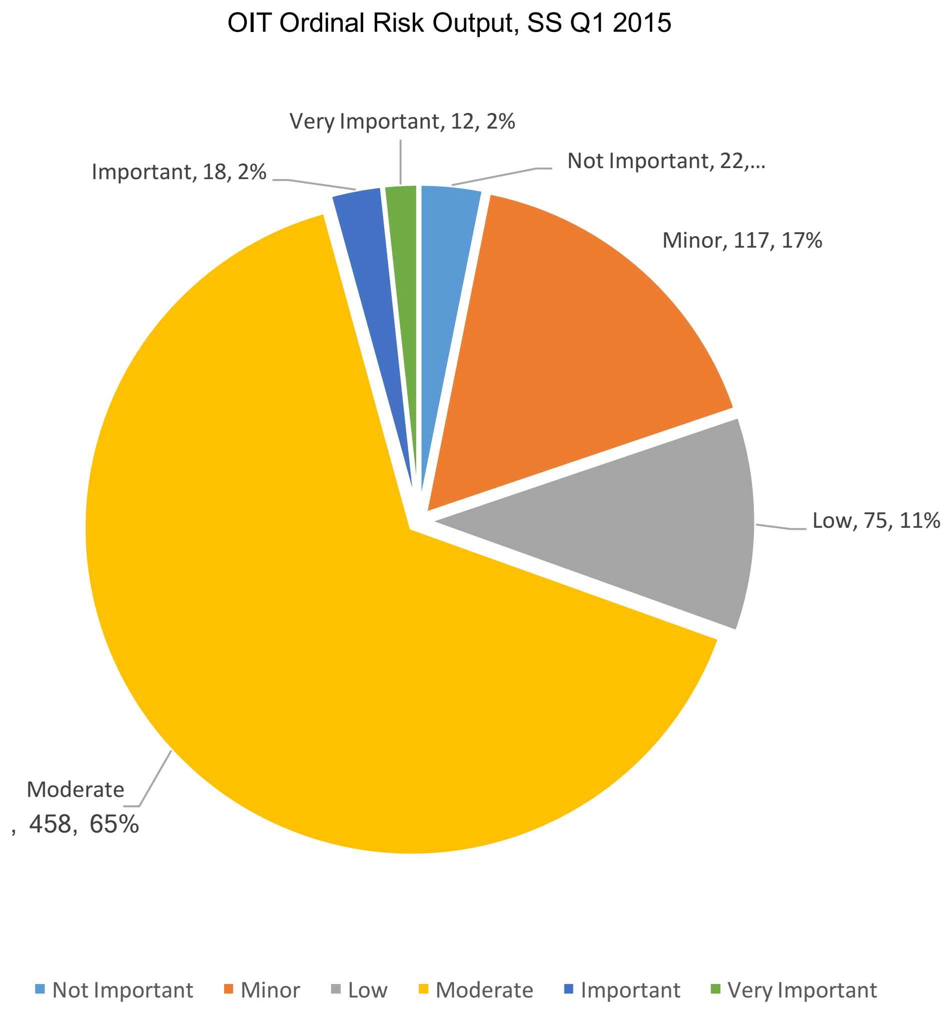


SS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
22	117	75	458	18	12

OIT summary graphic.



8.7.2.2 Q2 2015

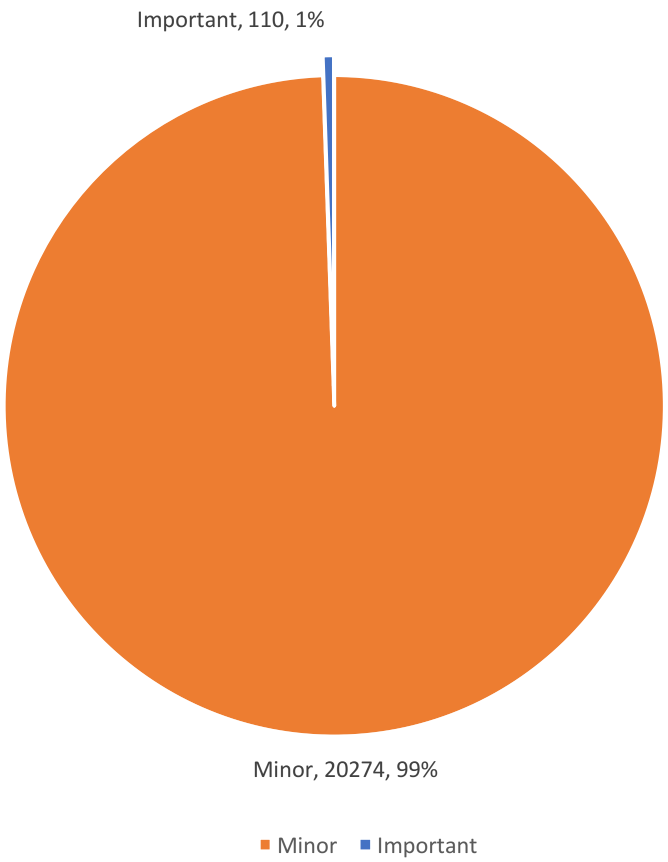
BMS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
0	20274	0	0	110	0

OIT summary graphic.

OIT Ordinal Risk Output, BMS Q2 2015

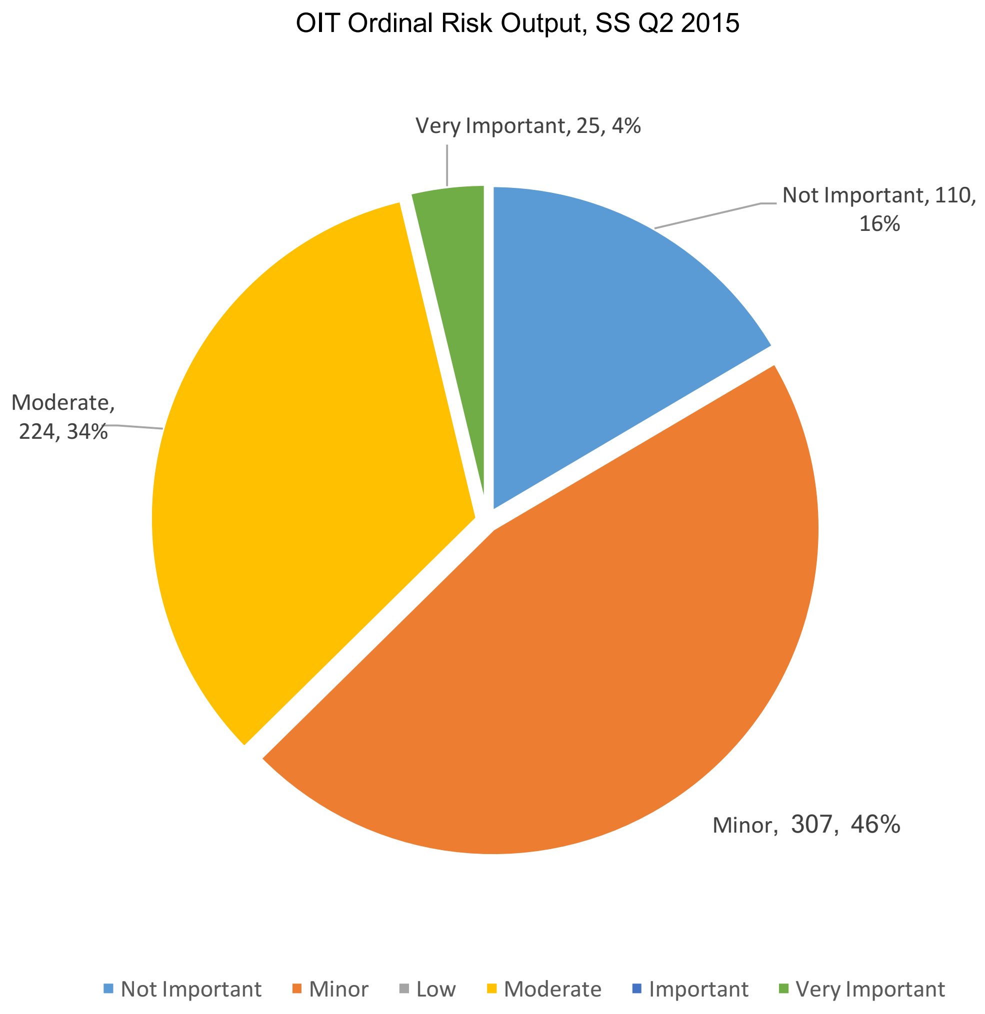


SS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
110	307	0	224	0	25

OIT summary graphic.



8.7.2.3 Q3 2015

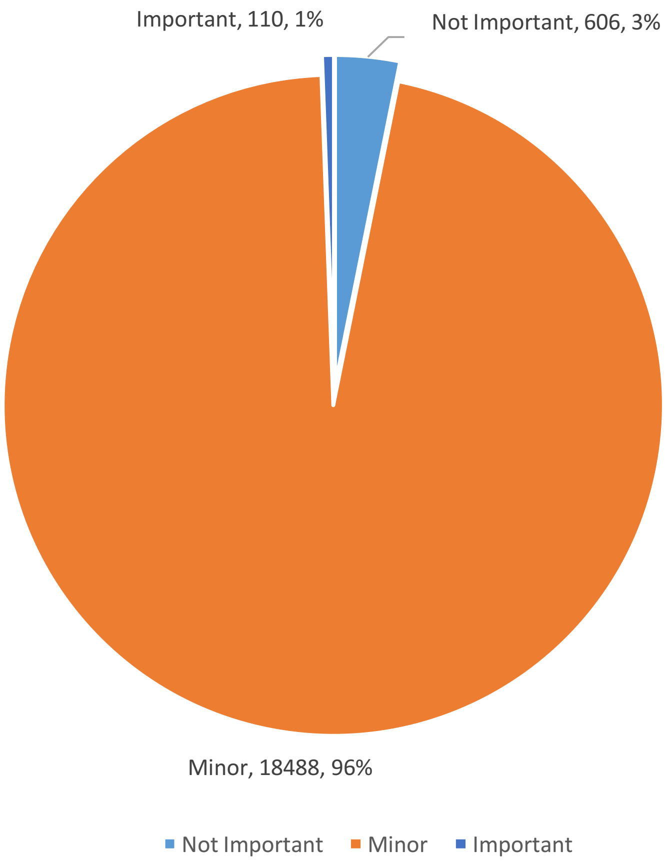
BMS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
606	18488	0	0	110	0

OIT summary graphic.

OIT Ordinal Risk Output, BMS Q3 2015

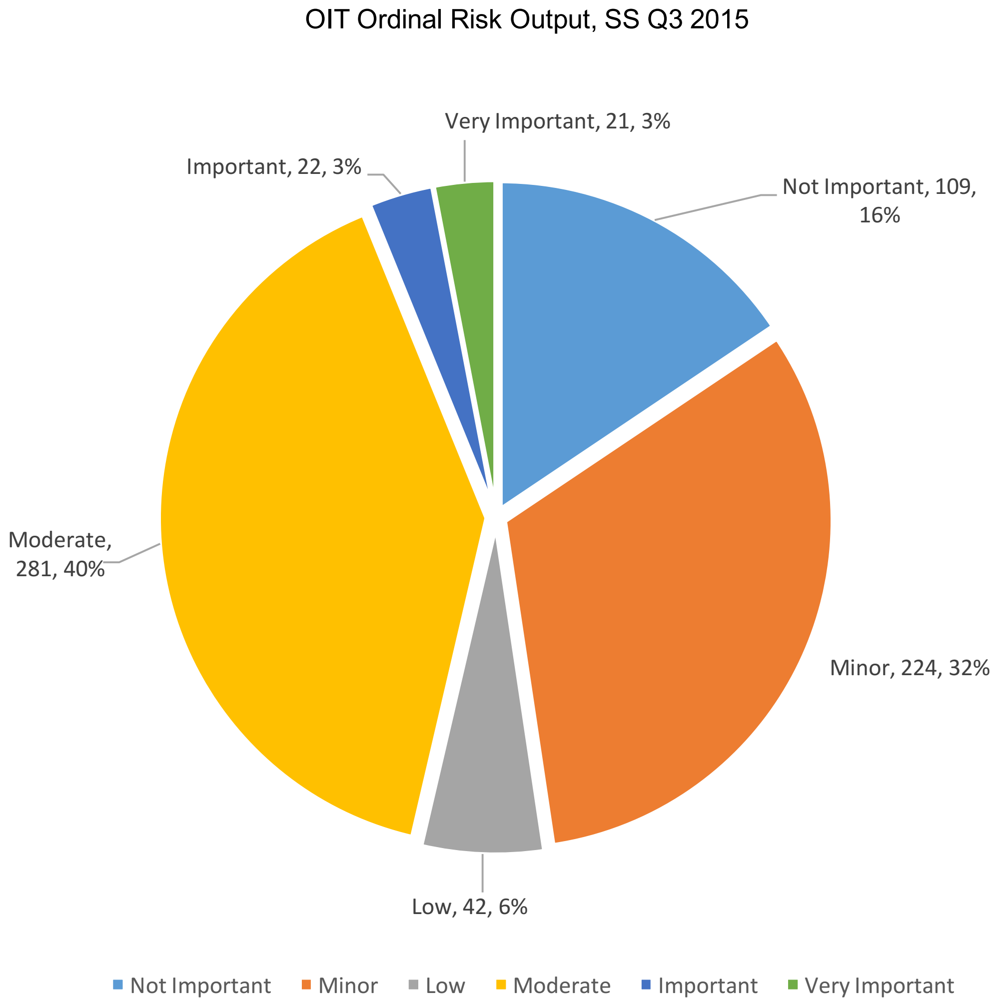


SS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
109	224	42	281	22	21

OIT summary graphic.



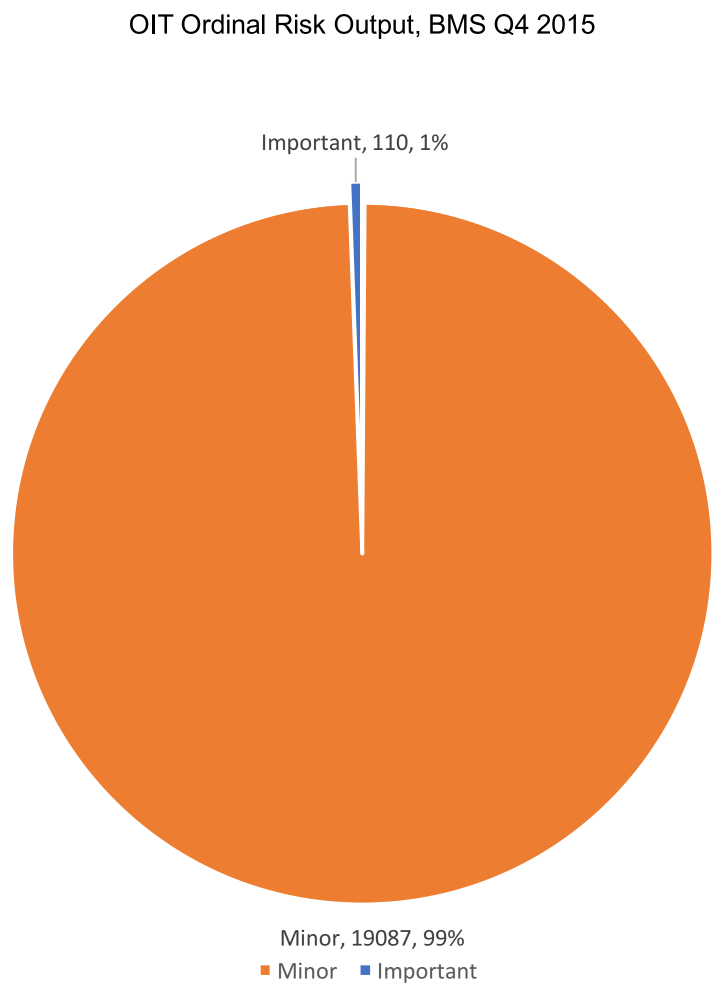
8.7.2.4 Q4 2015

BMS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
21	19087	0	0	110	0

OIT summary graphic.

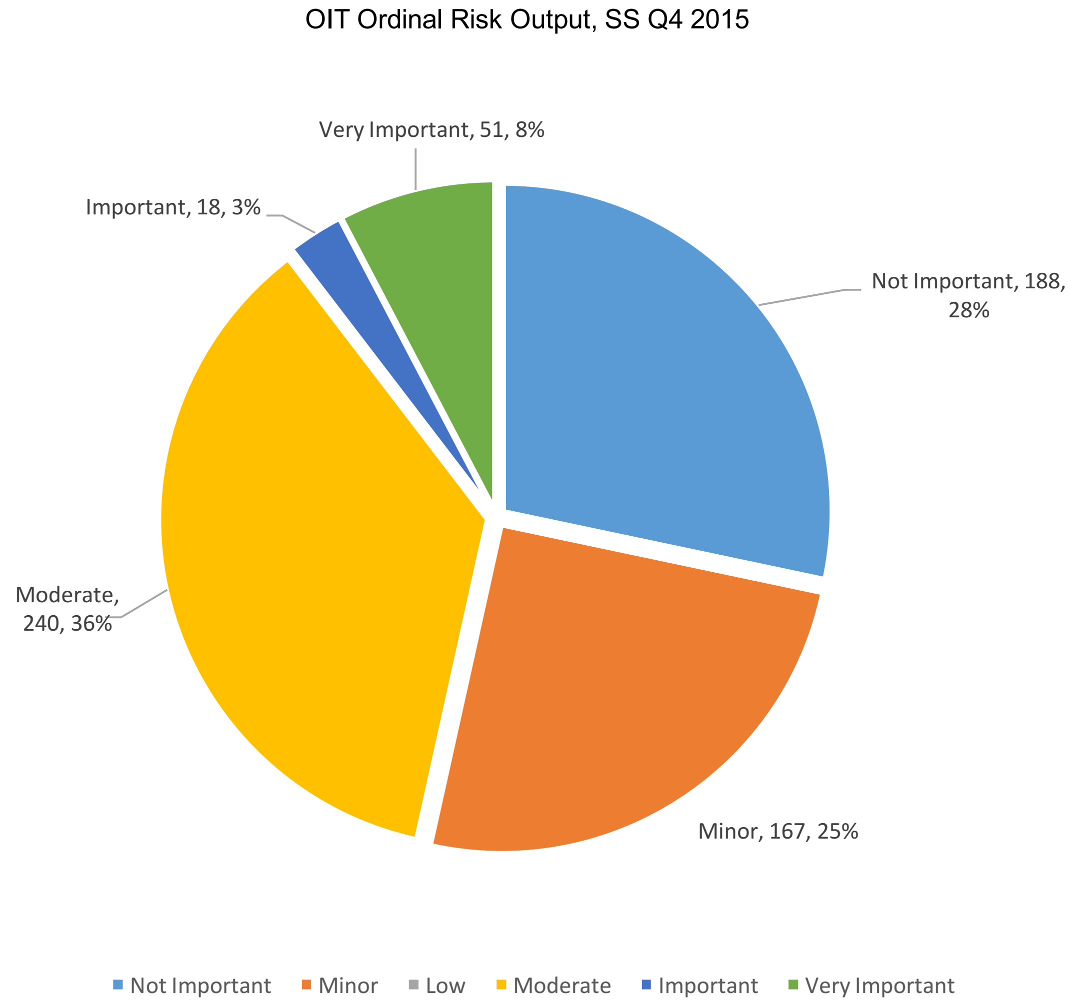


SS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
188	167	0	240	18	51

OIT summary graphic.



8.7.2.5 Q1 2016

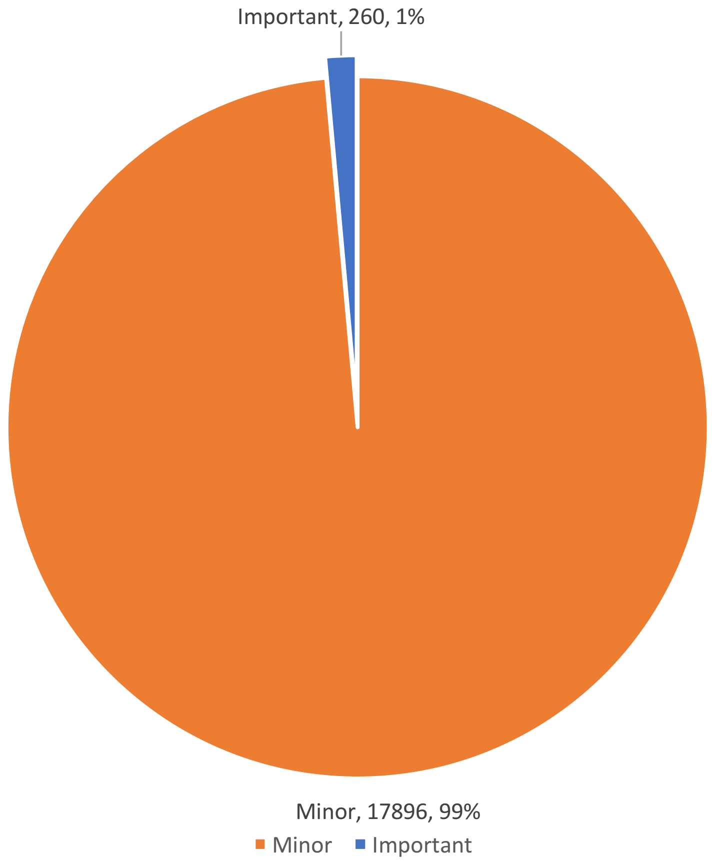
BMS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
0	17896	0	0	260	0

OIT summary graphic.

OIT Ordinal Risk Output, BMS Q1 2016

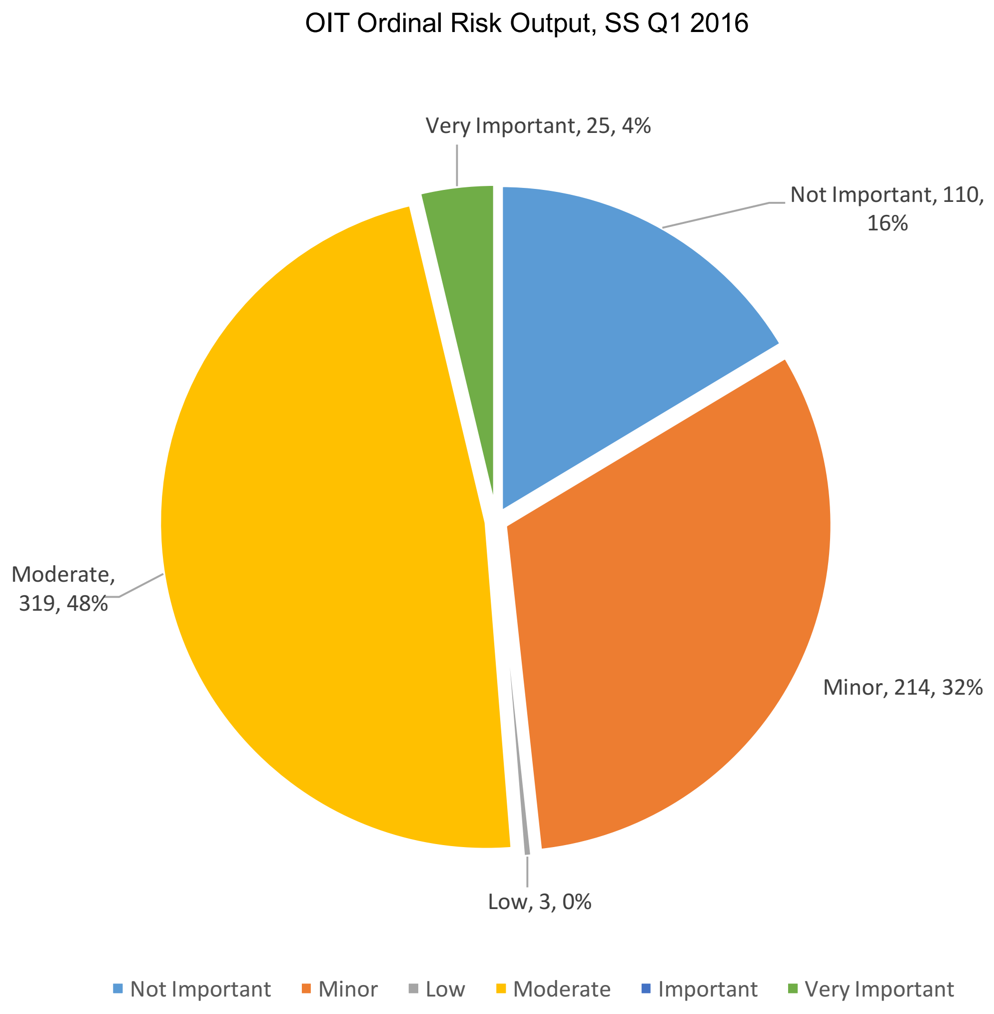


SS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
110	214	3	319	0	25

OIT summary graphic.



8.7.2.6 Q2 2016

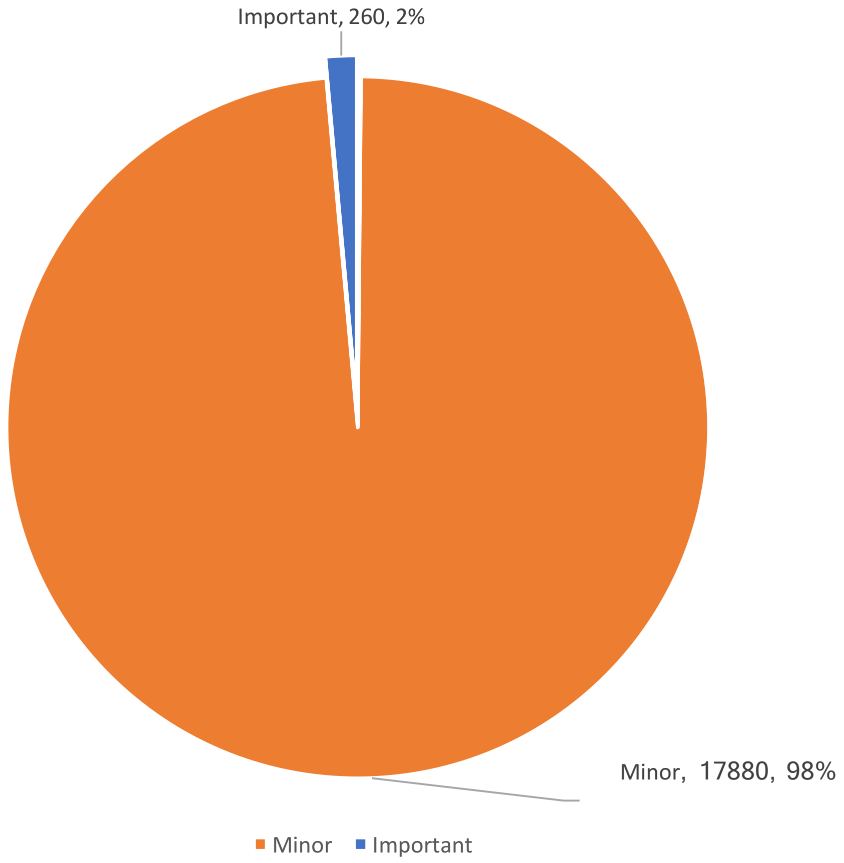
BMS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
27	17880	0	0	260	0

OIT summary graphic.

OIT Ordinal Risk Output, BMS Q2 2016

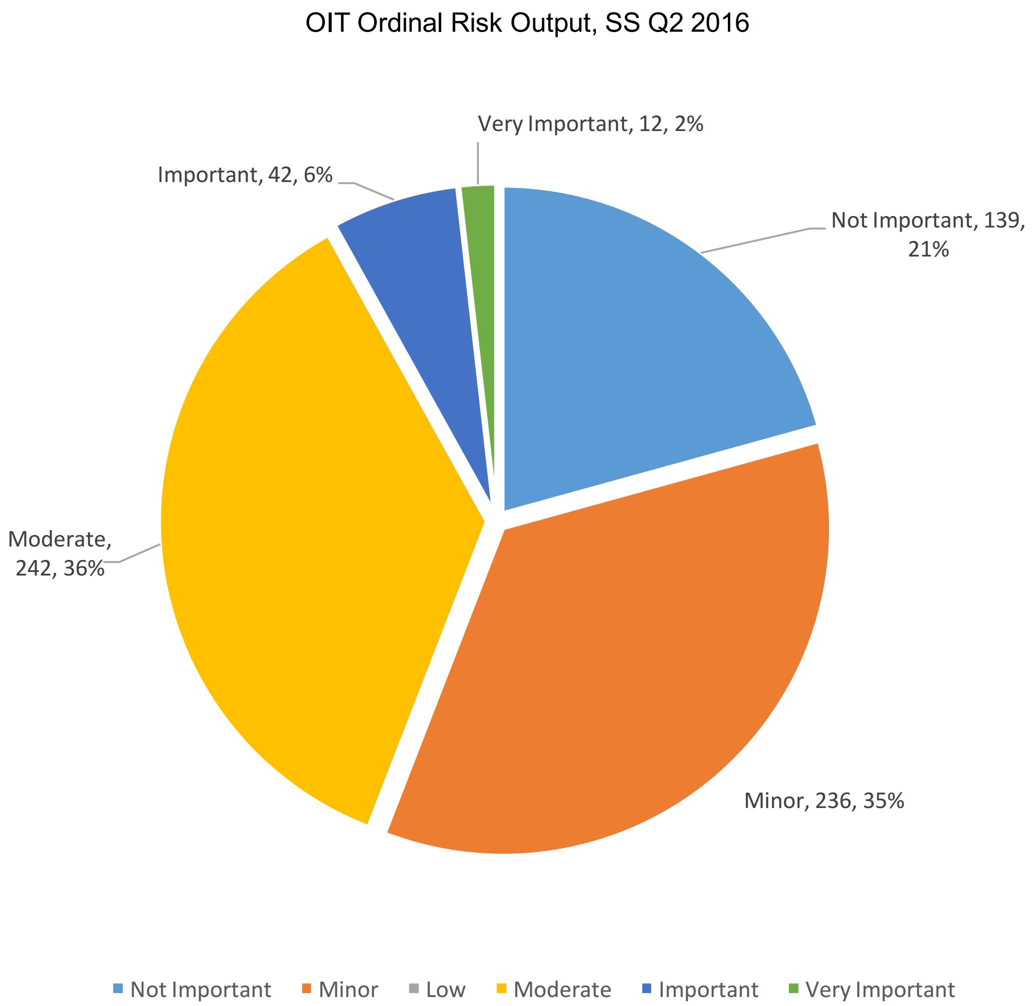


SS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
139	236	0	242	42	12

OIT summary graphic.



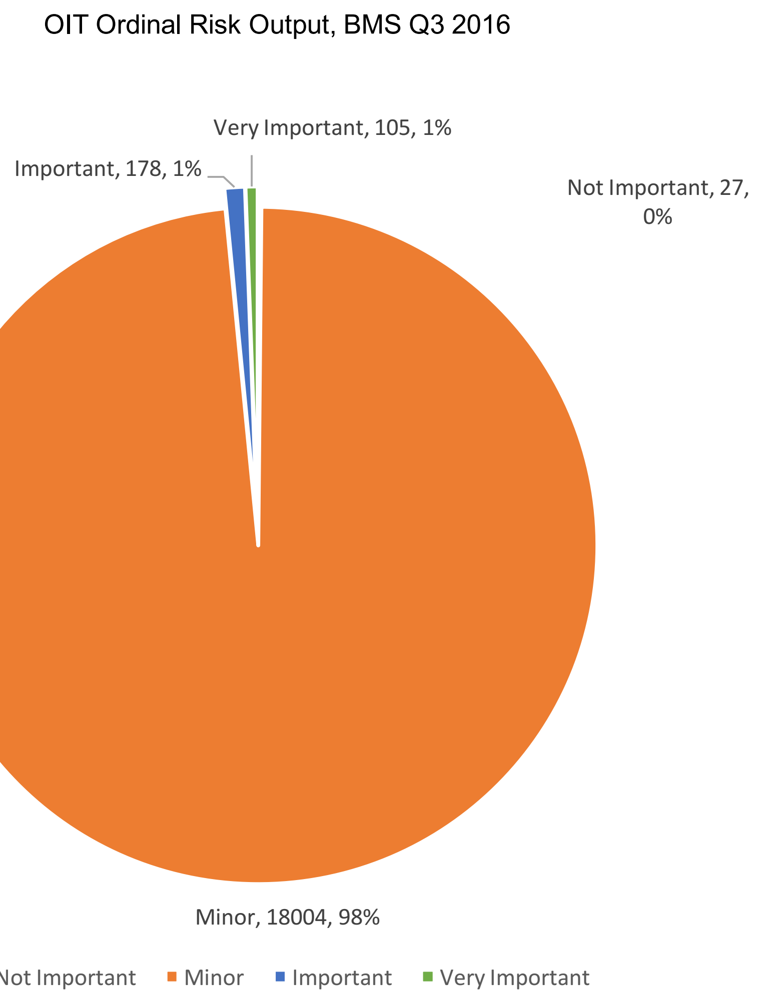
8.7.2.7 Q3 2016

BMS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
27	18004	0	0	178	105

OIT summary graphic.

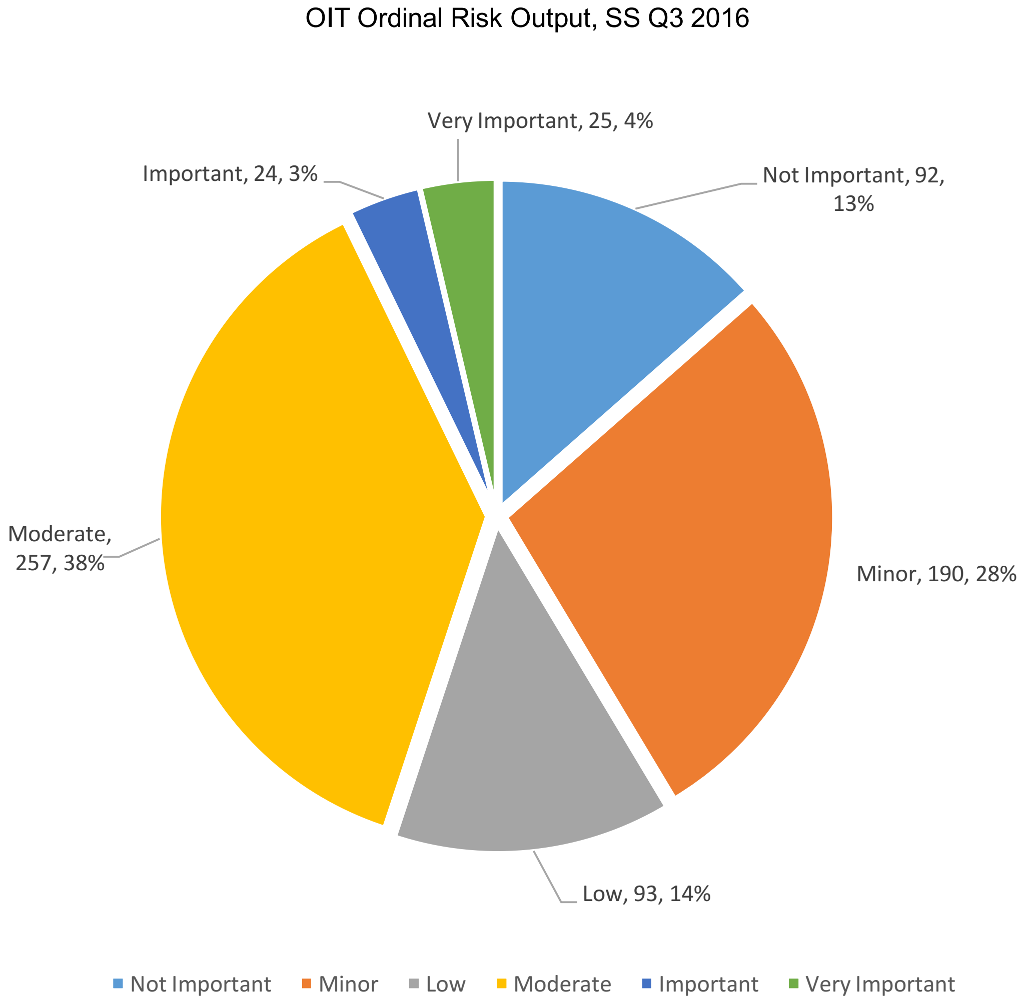


SS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
92	190	93	257	24	25

OIT summary graphic.



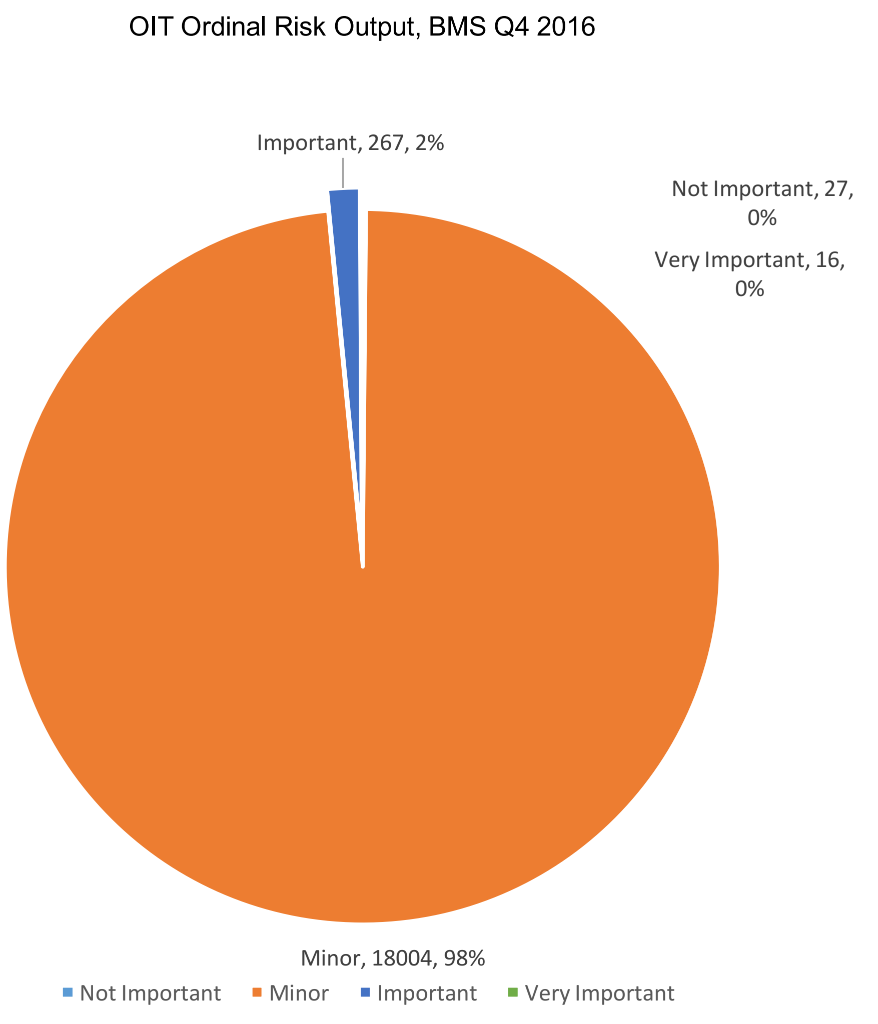
8.7.2.8 Q4 2016

BMS Results.

Data summary table.

Not Important	Minor	Low	Moderate	Important	Very Important
27	18004	0	0	267	16

OIT summary graphic.

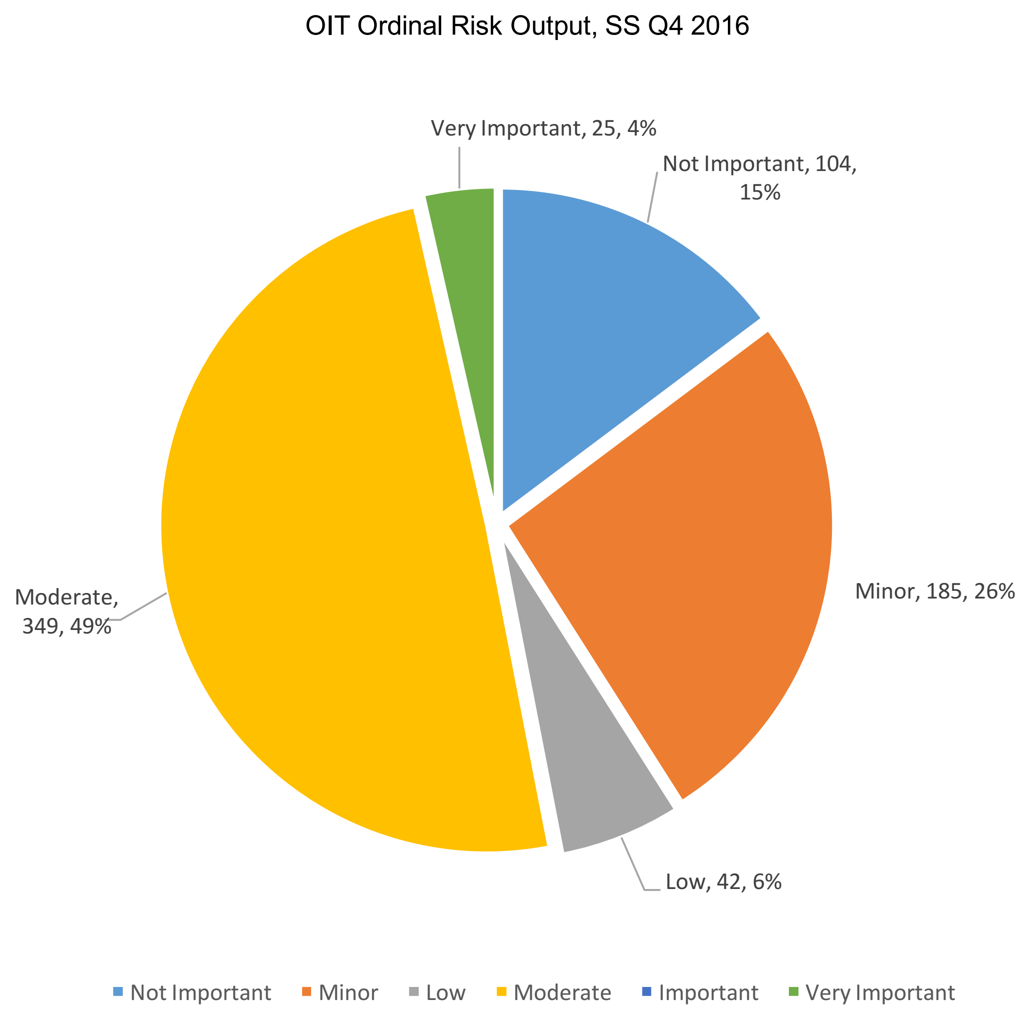


SS Results.

Summary data table.

Not Important	Minor	Low	Moderate	Important	Very Important
104	185	42	349	0	25

OIT summary graphic.



8.8 Case Study Purchase Orders

BMS.

Order Date	***Order No.***	***Asset***	***Details***
27/02/2015	MSL 1536	BMS	Replacement of 4 No Outstations - Cooling Towers
11/03/2015	PFICVO HFM556	BMS	SFS Support to Cooling Tower Outstation Replacement
31/03/2015	MSL1586	BMS	Outstation Replacement on BLN1
19/05/2015	MSL 1561	BMS	VFD Replacement
19/06/2015	MSL 1586	BMS	BMS Replacement of 15 No. outstations on BLN1
20/07/2015	PFICVO HFM 578	BMS	Replace obsolete westermo fibre hubs for BMS network
29/07/2015	MSL 1602	BMS	Replacement of faulty UPS in MCC Panel
07/08/2015	PFICVO HFM 581	BMS	Reset function for tiger trap control Panels
25/08/2015	PFICVO HFM 584	BMS	IT Chiller control panel replacement
07/10/2015	FMVO 402SFM	BMS	TS Fibre
04/11/2015	FMVO 413SFM	BMS	Fibre IT Room
11/11/2015	PFICVO 601HFM	BMS	BMS Fibre Network - Review of Proposal
29/01/2016	FMVO 447HFM	BMS	AS Fibre
29/01/2016	FMVO 448sFM	BMS	AS Fibre
05/02/2016	MSL 1665	BMS	BMS 12-year Defect survey
05/02/2016	MSL 1666	BMS	BMS 12-year Defect survey
10/02/2016	PFICVO 611 HFM	BMS	Installation/Replacement of UPSs for BMS Panels
15/02/2016	MSL 1671	BMS	BMS Asset Trends
24/03/2016	PFICVO HFM 615	BMS	BMS Fibre Backbone
05/07/2016	PFICVO HFM 625	BMS	Door Actuator Replacement
15/07/2016	MSL 1721	BMS	VFD Replacement phase 2
28/07/2016	MSL 1723	BMS	LON Replacement
28/07/2016	MSL 1724	BMS	BMS Outstation Replacement 2016
28/11/2016	MSL 1761	BMS	BMS IT Risk Assessment

SS.

Order Date	***Order No.***	***Asset***	***Details***
23/02/2015	FMVO 324HFM	SS	Simplex Locks on 2nd Floor
23/02/2015	FMVO 327SFM	SS	Room 101 Lock
23/02/2015	FMVO 333SFM	SS	PED Lockers
24/02/2015	FMVO 335HFM	SS	Temporary CCTV Cabling
11/03/2015	PFICVO HFM 557	SS	APC Security Upgrade
18/03/2015	PFICVO HFM561	SS	CCTV AMG Fire Transmission System Replacement
31/03/2015	FMVO 337SFM	SS	Security Cabinets
07/04/2015	PFICVO HFM563	SS	IDS Upgrade Survey & Design

17/04/20 15	PFICVO HFM564	SS	Access Control Ccure 9000 Upgrade
07/05/20 15	FMVO 357HFM	SS	Curtis Green Camera
22/05/20 15	FMVO 363HFM	SS	MDP Additional Simplex Locks
29/06/20 15	FMVO 373HFM	SS	TFL Camera Move
19/08/20 15	PFICVO HFM 583	SS	Fire Alarm Panel / Intruder Detection / Access Control Standby DC Battery Replacement
08/10/20 15	PFICVO HFM593	SS	Fire Escape Door Maglock Replacement
20/10/20 15	PFICVO HFM 596	SS	CCTV Camera 109 repair
02/12/20 15	FMVO 420SFM	SS	Selex Lock
17/12/20 15	PFICVO 604HFM	SS	IDS Replacement
22/02/20 16	FMVO 454HFM	SS	Ccure Back up
25/02/20 16	FMVO 460SFM	SS	Kaba Quattro Plus Locks
10/05/20 16	FMVO 478SFM	SS	Class 3 Kaba Door Lock
12/05/20 16	PFICVO HFM 619	SS	Maglock Replacement
26/07/20 16	MSL 1722	SS	Witness Testing & Review of Intruder Detection
26/08/20 16	FMVO 492 HFM	SS	IT Door lock
07/11/20 16	FMVO 515HFM	SS	CCTV Feed
25/11/20 16	FMVO 525 HFM	SS	CCTV Cameras Proof of Concept

8.9 *Original Equipment Manufacturer Master Sheet*

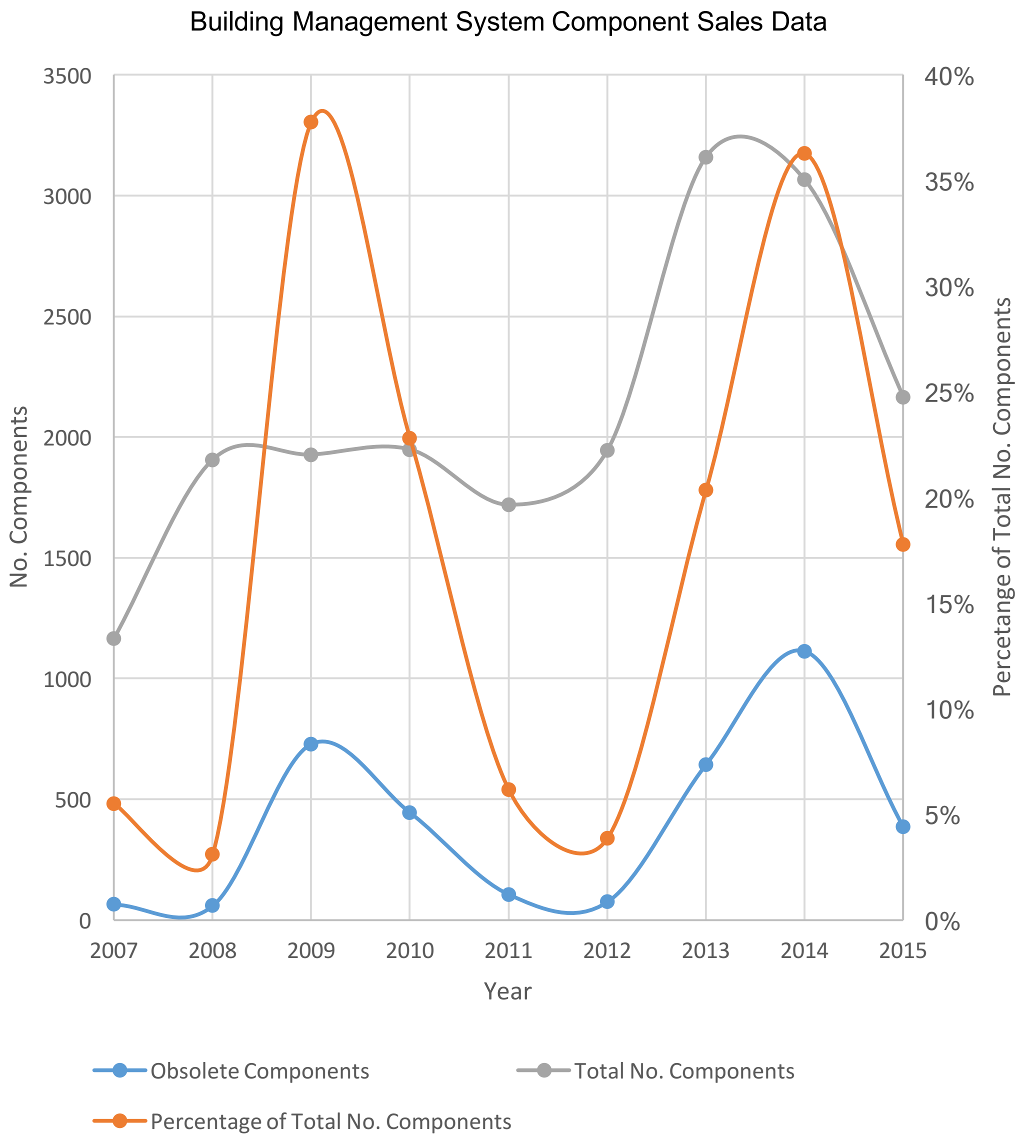
Pivot table used for probability density functions.

Row Labels	Average of Life (years)	Max of Life (years)	Min of Life (years)	StdDev of Life (years)	Count of Part Number
ABB	1	1	1	0.00000	38
Apogee	1.749805144	8	1	0.79913	1283
BACnet Room Controller	1.25	2	1	0.50000	4
Damper actuators	1	1	1	0.00000	3
Desigo	3.355263158	8	1	2.51184	228
Field	4.451219512	8	1	2.13158	164
Gamma	1.691415313	3	1	0.52818	431
Gamma Wave	1	1	1	#DIV/0!	1
Integral AS1000	4.142857143	5	1	1.37728	98
KNX	1.25	2	1	0.46291	8
KNX Wireless	1	1	1	#DIV/0!	1
Meter	1.637931034	4	1	0.66750	58
Pronto	4.653846154	6	1	0.93562	26
Room Control	1.666666667	2	1	0.51640	6
Sensors	2.476190476	6	1	1.54979	42
Sensors - BAS	1	1	1	#DIV/0!	1
Services	1	1	1	#DIV/0!	1
Sigmagyr	3	3	3	0.00000	4
Standard Controls	2.5	3	2	0.70711	2
Synco 200	4	4	4	0.00000	2
Synco 700	1.933333333	2	1	0.25820	15
Synco living	2.375	3	1	0.74402	8
Thermostats	1.25	2	1	0.44426	20
Unigyr	2	7	1	1.59041	35
Valve actuators	1.214285714	2	1	0.42582	14
Valves	1.733333333	2	1	0.44978	30
Valves	4.012658228	6	1	2.36694	79
Visonik	2.300492611	7	1	1.63603	203
VSD	1.75	2	1	0.50000	4

The below table contains the probability functions for the component groups within the dataset.

VSD	0.001745	0.259035	0.704131	0.035057	0.000032	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Visonik	0.090733	0.177790	0.239770	0.222547	0.142165	0.062504	0.018913	0.003939	0.000565	0.000056	0.000004
Valves (2)	0.040053	0.074978	0.117413	0.153807	0.168545	0.154503	0.118479	0.076002	0.040784	0.018308	0.006875
Valves (1)	0.000528	0.234781	0.744017	0.016815	0.000003	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Valve Actuators	0.016063	0.825462	0.170747	0.000142	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Unigyr	0.113764	0.205850	0.250842	0.205850	0.113764	0.042341	0.010613	0.001791	0.000204	0.000016	0.000001
Thermostats	0.017147	0.766493	0.215974	0.000384	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Synco Living	0.003286	0.097207	0.472238	0.376786	0.049374	0.001063	0.000004	0.000000	0.000000	0.000000	0.000000
Synco 700	0.000000	0.002247	1.494443	0.000304	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Synco 200	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!
Standard Controls	0.001089	0.059465	0.439391	0.439391	0.059465	0.001089	0.000003	0.000000	0.000000	0.000000	0.000000
Sensors	0.071829	0.163540	0.245548	0.243126	0.158748	0.068355	0.019410	0.003635	0.000449	0.000037	0.000002
Room Control	0.004226	0.335748	0.627260	0.027560	0.000028	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Pronto	0.000002	0.000208	0.007634	0.089396	0.334012	0.398187	0.151459	0.018382	0.000712	0.000009	0.000000
Meter	0.029441	0.378551	0.515905	0.074522	0.001141	0.000002	0.000000	0.000000	0.000000	0.000000	0.000000
KNX	0.022493	0.744867	0.231954	0.000679	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Integral AS1000	0.003141	0.021437	0.086345	0.205291	0.288105	0.238662	0.116699	0.033682	0.005738	0.000577	0.000034
Gamma	0.004480	0.320642	0.636808	0.035094	0.000054	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Field	0.021149	0.050462	0.096617	0.148442	0.183012	0.181057	0.143738	0.091567	0.046809	0.019201	0.006321
Desigo BACnet	0.065082	0.102329	0.137310	0.157244	0.153678	0.128178	0.091240	0.055427	0.028736	0.012714	0.004801
Room	0.035057	0.704131	0.259035	0.001745	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Apogee	0.045412	0.321458	0.475346	0.146833	0.009475	0.000128	0.000000	0.000000	0.000000	0.000000	0.000000
x	0	1	2	3	4	5	6	7	8	9	10

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015
Obsolete Components	64	59	728	444	106	75	643	1112	385
Total No. Components	1166	1906	1927	1948	1719	1945	3160	3065	2166
Percentage of Total No. Components	5.489%	3.095%	37.779%	22.793%	6.166%	3.856%	20.348%	36.281%	17.775%



8.10 Electronic Material

All Excel and MATLAB files for both models featured within this thesis, along with OME Sales Catalogue Analysis can be found on an attached compact disk. Whilst key tables, summary data and graphics have been extracted and populated within the appendices, the whole datasets and results can be found in electronic form in the essence of saving space.