A Holistic Approach for Selecting Appropriate Manufacturing Shop Floor KPIs

By

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Declaration

This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy. It has been composed by me and has not been submitted in any previous application for any degree.

The work presented (including data generated and data analysis) was carried out by the author.

[redacted] (Signed)

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Abstract

In the era of globalization, manufacturing industries need to monitor their manufacturing operations acutely in order to remain competitive. Manufacturers seek to engineer highly flexible, robust, and efficient manufacturing processes enabling the production of high-quality goods at competitive costs while always addressing and adapting to evolving challenges. As a result, manufacturing industries in the present time have realized the significance of shop floor data analysis. They are implementing performance measurement systems to continually assess and improve the operational state of their manufacturing operations. These systems comprise a set of Key Performance Indicators (KPIs), which can enumerate the effectiveness, competence, efficiency, and proficiency of manufacturing processes. There is a lack of KPI understanding by the manufacturers and no framework or methodology available in the literature to select KPIs systematically, methodically, and/or scientifically for a manufacturing facility. This deficiency typically leads to failures in reporting and monitoring critical performance measures, with resultant losses to achieve key business objectives.

Viewing the current industrial needs and limitations highlighted in the literature, this research presents a holistic approach that enables manufacturers to systematically understand, analyze, and select appropriate KPIs for their shop floor operations assessment. The approach is mainly centered on the premise that KPIs can be chosen based on a set of measures that are theoretically grounded.

First, a manufacturing shop floor exploration model is developed to 1) recognize the key business objectives, 2) identify the bottlenecks in the manufacturing shop floor facility that negatively impacts the throughput, 3) point out the problems and challenges, and 4) list the KPIs used for monitoring shop floor performance. The model uses a set of questionnaires and structured interviews to collect the required data (i.e., data related to manufacturing shop floor performance) along with the real-time data extracted from the manufacturing shop floor.

Second, a novel KPI guideline is developed to systematically guide the manufactures to understand, analyze, and select appropriate KPIs. These guidelines consist of five stages: information stage, discernment stage, scheming stage, the origin of the data stage, and assisting technology to capture the data stage. Every stage consists of a set of measures and their corresponding elements dedicated to providing vital information to help manufacturers better monitor their shop floor operations and improve decision-making capabilities. Last, to streamline the decision-making by prioritizing key business objectives and KPIs, the SMART criteria technique is prudently selected. The practicality of the proposed approach is demonstrated through its application to an automotive seat manufacturing company.

It is sensible to indicate that the complete methodology of selecting appropriate KPIs and reviewing the manufacturing shop floor performance is a continuous process. After suggesting and implementing the KPIs, the manufacturers should evaluate the performance regularly since, in the current complex manufacturing environment, both internal and external business factors change over time. Hence it is necessary to incorporate these changes and provide continuous improvement, evaluating the shop floor performance on a regular basis.

Keywords: KPIs, manufacturing shop floor exploration model, KPI guidelines, SMART criteria, manufacturing industries, Industry 4.0

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To my family

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List of Acronyms

ADOT	Actual Unit Down Time
ADT	Actual unit Delay Time
ANSI	American National Standards Institute
APAT	Actual Personnel Attendance Time
APT	Actual Production Time
APWT	Actual Personnel Work Time
ASTM	American Society for Testing and Materials
AUBT	Actual Unit Busy Time
BI	Business Intelligence
BSC	Balanced Score Card
CPS	Cyber-Physical Systems
EFQM	European Foundation for Quality Management
eKPI	Energy-related Key Performance Indicator
ELECTRE	ELimination Et Choice Translating REality
ERP	Enterprise Resource Planning
FCM	Fuzzy Cognitive Map
FFT	Fast Fourier Transforms
GP	Good Part
GPS	Global Positioning System
GQ	Good Quality
ICT	Information Communication Technology
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
IIoT	Industrial Internet of Things
IoT	Internet of Things
IP	Inspected Part
IPMS	Integrated Performance Measurement System
ISA	Industry Standard Architecture
ISO	International Standards Organization
IT	Information Technology
KPI	Key Performance Indicators
LLC	Limited Liability Company
MCDM	Multi-Criteria Decision Making
MES	Manufacturing Execution System

MOM	Manufacturing Operations Management
MPC	Manufacturing, Planning & Control
MTBF	Mean Time Between Failure
MTTR	Mean Time To Repair
ODPM	Objective-Driven Performance Measurement
PBT	Planned Busy Time
PCA	Principal Component Analysis
PLS	Partial Least Squares
PM	Performance Management
PMS	Performance Measurement System
POQ	Planned Order Quantity
POT	Planned Operation Time
PQ	Produced Quantity
RFID	Radio Frequency Identification Device
ROI	Return On Investment
RQ	Rework Quantity
SoA	Service-oriented Architecture
SoS	Systems of Systems
SMART	Strategic Measurement Analysis and Reporting Technique
SQ	Scrap Quantity
UFSJ	University of São João del-Rei
VBA	Visual Basic for Applications

List of Publications

1. A. R. Khan Mohammed and A. Bilal, "Manufacturing Enhancement through Reduction of Cycle Time using Time-Study Statistical Techniques in Automotive Industry," 2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS), Taipei, Taiwan, 2019, pp. 681-686, doi: 10.1109/ICPHYS.2019.8780198.
2. M. A. R. Khan and A. Bilal, "Literature Survey about Elements of Manufacturing Shop Floor Operation Key Performance Indicators," 2019 5th International Conference on Control, Automation and Robotics (ICCAR), Beijing, China, 2019, pp. 586-592, doi: 10.1109/ICCAR.2019.8813436.
3. A. R. Khan Mohammed, B. Ahmad, and R. Harrison, "A Holistic Approach for Selecting Appropriate Manufacturing Shop Floor KPIs," 2020 IEEE Conference on Industrial Cyber physical Systems (ICPS), Tampere, 2020, pp. 291-296, doi: 10.1109/ICPS48405.2020.9274690.
4. A. R. Khan Mohammed, A. Bilal and R. Harrison, "A Holistic Approach for Understanding, Analyzing and Selecting Appropriate Manufacturing Shop Floor KPIs, "Asian Journal of Control" (Final review).
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CHAPTER 1 INTRODUCTION

1.1 Background

In order to survive in the current competitive environment, manufacturers are pushed to engineer a highly flexible, robust, and efficient manufacturing process to produce high-quality goods at a reduced cost to combat evolving challenges and attain full economic potential (Leachman, Pegels, and Kyoon Shin, 2005). As a result, manufacturing industries in the present time have realized the significance of shop floor data analysis and are implementing performance measurement systems to continually assess and improve the operational state of their manufacturing operations (Collins *et al.*, 2016; Hester *et al.*, 2017). To improve the effectiveness and efficiency of shop floor operations, a set of comprehensive indicators are defined by the International Standards Organization (ISO) to comprehend tactical goals of performance management and improvement often referred to as Key Performance Indicators (KPIs) (Tugnoli *et al.*, 2012; Jain and Samrat, 2015; Badawy *et al.*, 2016).

KPIs are a critical part of an organization's ability to monitor its business performance health, ensuring that organizations' intended goals are achieved. Many researchers and think-tank experts have emphasised the significance of selecting the right KPIs to provide the most effective business performance measures and identify bottlenecks (Meier *et al.*, 2013; Woolliscroft *et al.*, 2013; Amrina and Vilsi, 2015a; Collins *et al.*, 2016). KPIs provide managers, supervisors, operators, and various other decision-makers with a snapshot of the business performance, highlighting the bottlenecks encountered in attaining its set business objectives (Zackrisson *et al.*, 2017). The correct selection and appropriate implementation of KPIs has a significant potential to assist manufacturers in improving business performance.

There is copious literature related to organizational performance measurements. Despite this, 80% of organizations, estimated by the Industrial Review Report (IRR), fail to achieve their business objectives (Latorre, Roberts and Riley, 2010; Radujković, Vukomanović, and Burcar Dunović, 2010; Badawy *et al.*, 2016). Reasons for this failure include a limited understanding of the KPIs used for their business operations, the abundance of KPIs present in the literature for selection purposes, an unnecessarily large number of KPIs used by businesses for performance measurement, and technological issues that hinder their effective implementation (Onyemeh, Lee and Iqbal, 2015; Almeida and Azevedo, 2016; Collins *et al.*, 2016; Hester *et al.*, 2017).

1.2 Problem Statement

Most of the traditional KPI selection methods are consultant-driven and ad-hoc, lacking the scientific foundation essential for realizing a generalizable and repeatable KPI selection approach (Elzahar *et al.*, 2015). The selection of the appropriate KPIs is one of the significant challenges faced by manufacturers in the current era of industrialization (Carlucci, 2010). Often managers select KPIs without an accurate understanding of the shop floor operations. Choosing appropriate KPIs from the literature can be inferred as a complex decision-making process, also termed a Multi-Criteria Decision Making (MCDM) problem. It involves numerous factors and associated interdependencies (Kaganski *et al.*, 2017).

Undeniably, it is observed that a set (finite) of KPIs can be estimated and carefully chosen utilizing predetermined conditions (Kaganski, Majak, and Karjust, 2018). ISO offers a collection of KPIs, ISO 22400 (ISO 22400-2:2014+A1:2017), focusing |on manufacturing operations management, referred to as Manufacturing Execution System (MES). The Manufacturing Operations Management (MOM) is a term used in International Electrotechnical Commission (IEC) 62264 to address a particular level in the manufacturing enterprise functional hierarchy model as shown in figure 1 (ISO British Standards Institution, 2018).

Figure 1 ANSI/ISA-95 functional hierarchy model (ISO British Standards Institution, 2018)

KPIs mentioned in the ISO standard are described through name, description, formulae, unit of measure, production methodology, and other characteristics. This standard attempts to generalise its applicability to all industries, however in some statements, it clearly states that 'the indicators are suitable only for discrete manufacturing' and 'limited to managers as the audience.' These statements are often equivocal and imprecise, and the information provided is, at times, fragmented. Thus, ISO standards may not be a practical guide for KPI selection and deciding its applicability (Zhu *et al.*, 2017; Khan and Bilal, 2019).

Furthermore, essential KPIs required for measuring the manufacturing shop floor performance are ambiguously covered. In this context, the main challenges encountered by the manufacturers in selecting appropriate KPIs and achieving their business objectives include:

1. Excessive number of KPIs selected for monitoring purposes, which weakens the main focus on business objectives.

2. The selected KPIs often fail to establish a connection with the business objectives to be achieved.

3. A lack of understanding of KPIs leads to failure in their implementation and interpretation.

With more than 1,700 KPIs available in the literature, it becomes difficult for any manufacturer to understand, analyze, and implement the right KPIs for monitoring their shop floor operations. Therefore, there is a need to develop a KPI selection guideline using a systematic approach to help manufactures understand, analyze, and implement appropriate KPIs.

1.3 Industry 4.0- the New Beginning of KPIs in Manufacturing Industries

The German administration first put forth the "Industry 4.0" model in November 2011 as a futuristic stratagem for 2020. After mechanization, automation, and computerisation, the new era of industrialization was termed as "Industry 4.0". The word Industry 4.0 was first presented to the public in April 2013, during the Hannover Fair held by the German manufacturing industry in order to strengthen German's manufacturing sector, attended by representatives from various interdisciplinary fields such as academia, business, politics, and research organizations (Zhou, Liu and Zhou, 2016). Internet of Things (IoT), Industrial Internet of Things (IIoT), Service-oriented Architecture (SoA), digitalization, KPIs, Cyber-Physical Systems (CPS), Artificial Intelligence (AI), virtual and augmented reality are few words that emerged and gained popularity from Industry 4.0 (Nagorny *et al.*, 2017).

This new industrial revolution has attracted numerous currently operating industries to reflect on it. It substantially impacts businesses and service models, product lifecycles, productivity, and machine maintenance. With the potential to realise data-driven control and monitoring stratagems, the Industry 4.0

approach can help industries become more competitive by learning smart manufacturing systems (ECSEL PMB, 2016; Schwab, 2016; Nagorny *et al.*, 2017). Figures 2 and 3 summarise the framework and key enabling technologies of Industry 4.0. One of the primary focuses of the current industrial era is integrating the manufacturing shop floor with digital technologies (smart manufacturing systems). These digital technologies enable real-time monitoring of the production process using performance measures, essentially KPIs, for identifying the bottlenecks (Bunse, 2013; Russwurm, 2014; Chen *et al.*, 2017).

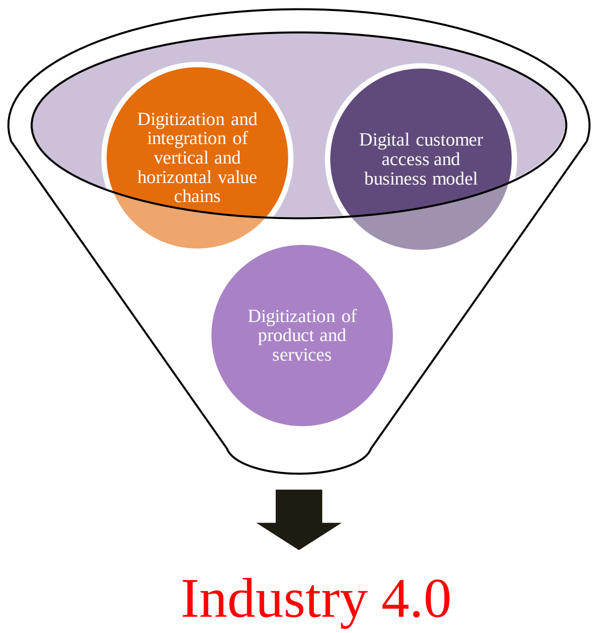


Figure 2 Framework of Industry 4.0

In the modern period, smart manufacturing systems are no longer a hierarchical and physically capsulated system, but loosely coupled, heterarchical, heterogeneous, integrated Cyber-Physical System (CPS) (Schwab, 2016). Such new systems engender new technological opportunities potentially appropriate to today's customer desires, expectations, and demands. The new designs of modern manufacturing systems reflect a shift from on-demand and periodical to the real-time (continuous) monitoring of production flexibility, visibility, and waste efficiency. Alongside with supply chain adaptions, customizable products, ambient conditions, dynamic market trends, and changes in the product life cycle (Candra, Truong and Dustdar, 2016; Aerts, Reniers and Mousavi, 2017).

Figure 3 Key enabling technologies of Industry 4.0

The key features of Industry 4.0 are horizontal integration, vertical integration, through-engineering, and advancement via exponential technologies. Horizontal integration will be attained using globally advanced valued chain networks that offer the highest degree of flexibility and transparency throughout the production of goods or services. Vertical integration is possible with the help of CPS that allows machines to react swiftly to any change in stock levels/demands and the level of faults, decreasing the turnaround time. Through-engineering on all the aspects that cover the complete life cycle of goods and customers, it is based on the information and data obtained at each production step. Advancement via exponential technologies such as artificial intelligence, sensor technology, and advanced robotics (Russwurm, 2014).

Moreover, industry 4.0 can be broadly realised into six steps: *interoperability, virtualization, decentralization, real-time capability, service orientation, and modularity* (Leitao, Colombo, and Karnouskos, 2016), with the key characteristics of industry 4.0 highlighted in figure 4. This realization helps industries achieve additional flexibility, decrease lead times, deliver high-performance services, and make it solely customer-oriented. Industry 4.0 is seen as a network of the internet of things, services, data, and organizations, and its complexity creates new challenges for development, innovation, and research undertakings (Russwurm, 2014). These key features enable to capture almost every information available on the manufacturing shop floor. As KPIs play a critical part in exploiting this information available at various levels of the ANSI/ISA-95 functional hierarchy model to cautiously monitor the vital processes and highlight the bottlenecks (Unver, 2012). In the era of Industry 4.0, manufacturing industries see KPIs are an essential tool to monitor their critical performances and assist them in highlighting the problems and challenges and achieving their key business objectives.

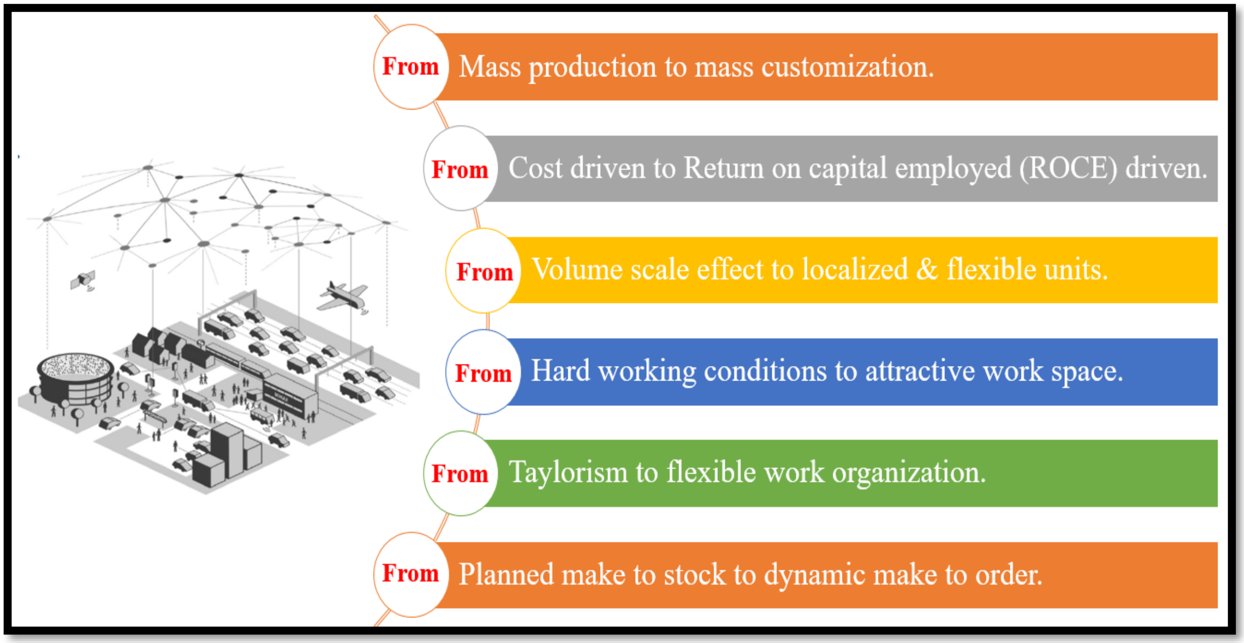


Figure 4 Characteristics of Industry 4.0 (Russwurm, 2014)

1.4 Manufacturing Shop Floor- Heart of Manufacturing

Due to the Industry 4.0 initiative, industrial manufacturing has witnessed histrionic upheaval of technology, but few features remain unchanged. The manufacturing shop floor is still considered as the heart of any manufacturing operation, and it is a place where equipment, processes, and people merge collectively to add value to material and manufacture products for trade (Demchenko, Ngo and Membrey, 2013; *Data Magnum- The Big Data Connection*, 2015). In simple words, the manufacturing shop floor is an area where production is carried out manually by workers, semi-automatic by workers and machines, or automatic by machines. This area includes inventory, warehouse, and equipment. It is common in manufacturing to contemplate the shop floor operations as the least important factor to be addressed by the manufacturers (Demchenko, Ngo and Membrey, 2013; *Data Magnum- The Big Data Connection*, 2015; Russwurm, 2014).

Asymptomatic issues that can be measured using KPIs such as idle equipment, inventory inaccuracies, emergency breakdown, worker inefficiency, or stations/equipment/machine waiting for attention can go unnoticed until a severe customer-affecting event arises. Overlooking shop floor operations is a grave insight (Deloitte, 2015). Problems that may initially appear insignificant, such as unexplained variations in the cycle time for a manufacturing operation, can swiftly escalate and become a significant issue (or result in a substantial setback)—affecting the overall production cycle, customer order fulfillment time, profit, and growth across many internal departments (Chong, Ng, and Goh, 2016).

This research is mainly focused on the manufacturing shop floor KPIs because it reveals the loopholes in production or process that can severely impact manufacturers through efficient monitoring. It can also reduce the occurrence of errors in the output or process by enabling proactive rather than reactive decision-making, finding deviation from standard procedures and processes, and increasing staff productivity by continuously monitoring their performances and enabling the smart scheduling of staff and resources operations. Thus, assisting the manufacturing industries in bringing out usable, tangible, and superior quality products as per the customer specifications from their shop floor seamlessly.

1.4.1 Identifying the Challenges Faced by Manufacturers While Selecting KPIs

According to Kucukaltan *et al.*, in manufacturing industries, performance measurements are based on numerous performance indicators. The information on determining the right performance indicators (i.e., KPIs) and identifying the interrelationships between several performance indicators have been lacking. For manufacturers, selecting and implementing KPIs to remain competitive in the current business environment is severe. These challenges include:

What are the appropriate KPIs?;

How many KPIs are needed?;

How to prioritize the KPIs?;

How can these KPIs help to improve performance?;

Finding relevant KPIs to measure the manufacturing performance is challenging and time-consuming. It considers all current and future business objectives and targets the weak spots in the production that needs attention. There are no KPIs mentioned in the literature that can give manufacturers a complete picture of the shop floor performance. Each KPI presents a partial insight into the performance and hence not sufficient to serve as a source for decision making. For this reason, the selection of a set of KPIs that can capture the complete picture of the shop floor performance is a necessary but challenging task for the manufacturers.

When selecting KPIs and using them efficiently, everyone involved in the manufacturing facility must know:

How the KPIs affect their manufacturing operation (work or responsibilities)?;

Do the KPIs help them to improve their manufacturing operations?;

What kind of changes shall be incorporated from the information received by KPIs?

Moreover, the selection of KPIs must be in-line with the approach and business objectives that the manufacturers are aiming to accomplish. In a complex business environment, where the objectives need to be transformed over-time, the KPIs selected should also be altered. Lack of actionable KPIs can cause delays in identifying weak spots and severely impact performance improvement. In order to improve overall performance, manufacturers should carefully answer the following questions while identifying and selecting KPIs for monitoring their shop floor operations:

Is there a link between KPIs and the business objectives?;

How many KPIs should be used?;

How often should the KPI be monitored? KPI accountability?

To address these challenges, the manufacturers face no framework or methodology to systematically, methodically, and/or scientifically select KPIs for a manufacturing facility. A KPI guidelines approach is developed to guide the manufacturers to analyze and choose appropriate KPIs systematically. Furthermore, prioritizing the KPIs is also discussed within the scope of this research using SMART criteria.

1.4.2 Manufacturing Shop Floor Related Problems

Visibility—from the many tools and techniques that are used as a part of the Industry 4.0 initiative, manufacturers have several options for managing and monitoring their shop floor. Because there may be siloes of data from non-integrated systems, overall operation visibility might be hard to achieve and challenging to organize these fragmented reports together (Kaifei He, 2016). Lacking real-time integration to a single version of manufacturing status, identifying errors or inefficiencies may be impossible (Donald N. Heirman, 2002). Every interruption in production means the waste of resources and failure to fulfill customers' demands on time. Manufactures might have a nebulous sense that the production throughput KPI is not "where it should have been" and disruptions "are hard to control" and "something" needs to be fixed. But what? Maybe machines in a few stations are failing to keep up with the production takt time? Perhaps communication gaps between different areas of the shop floor are delaying orders? Maybe labours are performing inefficiently? Maybe shop floor managers have limited knowledge? Maybe they do not measure the right performance indicators needed to improve the shop floor efficiency.

With the lack of shop floor data visibility, manufacturers are stuck with reactive rather than proactive decision-making. These types of problems in manufacturing can be expected and essential characteristics of complex manufacturing. A shop floor with complete visibility typically will potentially reduce these types of problems.

*Automation—*for any manufacturing industry, it is essential to recruit and retain skilled workforce. However, on the shop floor, spotting idle personnel are expected. Often the production staff is made to wait for the final product confirmation or authorization from the customer on the design amendments (Krumeich *et al.*, 2014). For some manufacturers, understanding labor costs and inadequacies is a complex challenge. Automation stands as the solution to many of these issues but it is crucial to experience which jobs to automate. Most manufacturers lack insights into the shop floor, directly impacting the overall production rate and time invested in fulfilling customers' orders. Automation can also help manufacturers to achieve high product quality and guarantee compliance with corporate obligations. For instance, product quality KPI checks can be controlled and automated using sensor technology superior to human inspection methods (Niggemann *et al.*, 2015). Maintaining high quality helps to improve brand image and increases customer satisfaction.

*Digitalization—*for manufacturers, is seen as the application of Information Communication Technology (ICT) to enhance manufacturing processes' productivity and efficiency. Digitalization can be defined as "embracing or escalating the use of computer technology by an organization or industry" (Merkel *et al.*, 2017). Regrettably, the acceptance of digital technologies in the manufacturing industries is slow-paced, with most manufacturers adopting a 'wait and see' method. Digitalizing industrial processes should be viewed as a continuing process, not just as a one-stop solution, as manufacturers incessantly evaluate 'what is worth digitalizing' (Prades *et al.*, 2013). In the current industrial revolution, digital technologies, such as RFID scanners, telemetry, machine sensors, and GPS tracking, are evolving at a rapid pace. To survive and thrive, manufacturers have to adapt to and utilize these new technologies. Shop floor digitalization can be applied across manufacturing operations such as material handling, scheduling, inventory, planning, logistics, labor, and time tracking (Georgoudakis *et al.*, 2006).

Out-of-date shop floor equipment, poorly combined with inadequate software solutions, cannot offer the much-needed dexterity and visibility required by the shop floor to meet current market demands. The shop floor is where most manufacturing profits are made, and customer satisfaction is retained (Williams, 1994). If the shop floor is functioning poorly, the entire organization suffers. It is the reason why manufacturers should consider shop floor processes as their top priority. Digitalizing shop floor processes certainly makes everyone involved in manufacturing jobs easier. Digitalization makes the complete manufacturing process completely secured, automated, continually monitored, and managed as a global entity. That, in turn, helps achieve reduced downtime, improved efficiencies, increased return on investment, and greater resource utilization (Hankel and Rexroth, 2015).

1.5 Need for KPIs in Manufacturing Shop Floor

The significant reasons for deploying KPIs in manufacturing shop floor are (Bhanot, Rao and Deshmukh, 2015, 2017; Ghazilla *et al.*, 2015; Star *et al.*, 2016; Zackrisson *et al.*, 2017; Zailani *et al.*, 2017):

Monitoring the health: KPIs acts as an essential tool for manufacturing industries to track and monitor their operational and strategic performances. The bottleneck equipment, process, station, or production line can be acutely observed to increase performance by reducing downtime. The major challenge arises when the KPIs selected for monitoring are inappropriate and incomprehensible by the manufacturers leading to further degradation in performances. The number of KPIs used for monitoring and its accountability plays a significant part in sustaining improved industrial health. The selected KPIs should incorporate each department of production, namely: product, process, and resource, making sure that overall improvement in performance is achieved.

Measuring progress over time: KPIs such as cycle time, stop time, machine idle time, etc., needs to be measured in real-time to improve quick decision-making capabilities. Strategic KPIs, for instance, employee performance, production line monthly performance, gross margin, revenues, need to be measured periodically since they are result indicators used to track the industry's progress (weekly, monthly, quarterly, or annually) towards achieving its strategic objectives. With appropriate selection of KPIs that can be measurable in the real-time, periodical, and on-demand can support manufacturers to monitor their performance both in short- and long-term perspectives.

Making modifications and tackling opportunities: to survive in the current complex environment, manufacturing industries make frequent alterations to their operational and strategic objectives. KPIs monitors the performances based on new objectives and support manufacturers to make modifications to the set objectives. These modifications can be achieved by selecting the right set of KPIs, which has a balanced set of leading and lagging indicators. New opportunities, such as increasing the production rate, throughput rate, etc., can be realized if the manufacturers succeed in achieving their objectives. Therefore, manufacturing industries depend on the results generated by KPIs to make modifications and tackle opportunities.

Analyzing patterns in performance over time: manufacturing industries tend to measure a small number of commonly known KPIs frequently over time, such as production ratio, quality, OEE, etc. Measuring KPIs over time (quarterly, annually, or a more extended period) tends to generate a pattern. These patterns tend to support manufacturers in countless ways. For example, patterns can help them be aware of the lowest quarter of production rate and use that time to carry out maintenance activities or other productive initiatives. It can help to know the shifts' performances over a certain period, which shift underperforms or over-performs. Patterns act as a forecaster for manufacturers to understand what can be expected in the next production phase.

1.6 Motivation

The manufacturing industry is composed of several operational areas, for instance, manufacturing, sales, marketing, and many other related functional areas. Based on the operational areas, manufacturing industries can have diverse sets of KPIs. The performance of equipment, process, production line, or the whole manufacturing industry is principally measured in two ways: result indicators and performance indicators (Kang *et al.*, 2016). Result indicators are used to measure the effects of the operational activities but ignoring their causes. In comparison, performance indicators are used to generate the next plan of action based on the results. Therefore, performance measures principally key performance measures are commonly used at levels 0, 1, and 2 of the ANSI/ISA-95 functional hierarchy model to increase quick decision-making capability. According to International Standard ISO 22400-1 and 22400-2 (2014), KPIs plays a vital role in swiftly and effectively providing precise and detailed statistics of the whole manufacturing industry by equating real-time performance alongside with their nominal performance to accomplish set objectives (International Standard ISO 22400-1, 2014; International Standard ISO 22400-2, 2014).

Centered on the operational area, within the manufacturing industries functional hierarchy model: discrete, continuous, or batch control of the manufacturing process is at level 1-2. Whereas manufacturing operations management is at level 3, and business planning and logistics are at level 4. Figure 1.3 illustrates the different levels of the manufacturing industries hierarchy model. As mentioned in IEC 62264-1, manufacturing shop floor operations can be categorized into sub-operations, such as production, maintenance, quality, inventory, and other manufacturing-related operations. KPIs based on each of these sub-operations can be defined independently or depending on combinations of these sub-operations. In this research, level 1-2 of the mentioned hierarchy model, predominantly focusing on manufacturing shop floor operation KPIs, is addressed.

Several manufacturing industries that use KPIs to improve their shop floor operations often detract from their objectives because they measure too many KPIs, which leads to a loss of clarity of their primary goals (Zhu *et al.*, 2017). Also, various manufacturers have a limited understanding of the appropriate KPIs that can help them to enhance their manufacturing operations (Leachman, Pegels, and Kyoon Shin, 2005; Woolliscroft *et al.*, 2013). Equally, some of the KPIs have no links related to the manufacturers' objectives. In other cases, they monitor one part of the process, not targeting other more imperative parts of the process. Many manufacturers are still struggling to find the required guiding KPI approaches, techniques, or rules to enable the effective design, measurement, and improvement of their shop floor performance (Collins *et al.*, 2016). In order to effectively address the difficulties faced by the manufacturing industries, a holistic approach for selecting appropriate manufacturing shop floor KPIs is required.

1.7 Research Objectives

1. Develop a manufacturing shop floor exploration model to identify the critical business objectives, problems, challenges, crucial performance details, bottlenecks, and a list of KPIs within the given manufacturing shop floor facility by using questionnaires and structured interviews with shop floor production data.

2. Develop KPI guidelines by extracting every essential guiding performance measures needed for the manufacturer to understand, analyze, select, and implement appropriate KPIs. The KPI guidelines consist

of five stages, namely: information stage, discernment stage, scheming stage, the origin of the data stage, and assisting technology stage. Each stage consists of measures dedicated to providing vital information to help manufacturers better monitor their shop floor operations and improve decision-making capabilities.

3. Conduct a case study on a tier 1 automotive manufacturing suppliers' shop floor facility to evaluate the proposed manufacturing shop floor exploration model's effectiveness and practicality combined with the KPI guidelines. The case study will mainly concentrate on analyzing the usefulness of the existing KPIs generated from the manufacturing shop floor exploration model in monitoring the critical business objectives using KPI guidelines.

4. From the data collected through the manufacturing shop floor exploration model and coalescing it with the focused literature review on KPIs, opinions from industrial and academic experts, and evaluating it using KPI guidelines, a set of KPIs are proposed. An explanation of implementing the proposed KPIs in the manufacturing shop floor facility is discussed.

5. Prioritising key business objectives and the proposed KPIs using SMART criteria.

1.8 Thesis Outline

The rest of the thesis is outlined as follows: Chapter 2 describes the current manufacturer's problems and needs and critically reviews the industrial practices and relevant research for improving their shop floor operation assessments. It discusses the literature review around the key topics such as performance measurements- frameworks and models, categorization of KPIs- KPI measures and corresponding elements, identify the limitations of current industry practices, and highlights the research gaps. Moreover, various manufacturing industries' prioritizing techniques to streamline decision-making are explained at the end of chapter 2 (section 2.5).

To address the industrial need and research gap mentioned in the literature review that there is no framework or methodology to select KPIs systematically, methodically, and/or scientifically for a manufacturing facility. A KPI guidelines approach is developed to systematically guide the manufactures to understand, analyze, and select appropriate KPIs in chapter 3 (section 3.3). Chapter 3 also illustrates how the proposed KPI guidelines are combined with the manufacturing shop floor exploration model. The aim of developing this model is to distinguish the key business objectives; identify the bottlenecks in the manufacturing shop floor facility that negatively impacts the throughput; point out the problems and challenges, and list the KPIs used for monitoring shop floor performance (section 3.2).

For proof of concept and evaluation, chapter 4 demonstrates the procedure of applying the proposed approach as described in chapter 3 for understanding, analyzing, and implementing appropriate KPIs within company X. Company X is an automotive seat manufacturer. The case study is conducted on the L494 assembly line within this facility. Firstly, by employing the manufacturing shop floor exploration model, company X's key business objectives, list of KPIs, bottleneck, problems, and challenges are identified. Secondly, company X's list of KPIs is evaluated using KPI guidelines to realize the existing KPIs' applicability and effectiveness. Thirdly, a set of appropriate KPIs that can enable the company X to monitor the key performances and achieve its business objectives are determined using the proposed approach. Lastly, the prioritization of key business objectives and appropriate KPIs is offered using SMART criteria.

To conclude, chapter 5 summarises the research objectives' achievements, highlights the research benefits, and mentions the research's novelty followed with future directions.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter aims to find and critically assess the techniques, frameworks, models, approaches, and procedures available in the literature relevant to this research topic. A meticulous exploration of the literature linked to manufacturing industries' shop floor KPIs was conducted. This literature review covers material from the last three decades (1990-2020). During the initial literature search on manufacturing industries' shop floor KPIs via google scholar and ResearchGate, it was observed that this term arose. It gained popularity after the year 1987, with only seven publications registered during that year, followed by 10, 11, and 13 publications in the upcoming years 1988, 1989, and 1990 respectively.

The literature was examined by means of the following electronic databases: ABI/INFORM Global, ACM Digital Library, EBSCO host, British Standards Online, ProQuest Science, Engineering Village, IEEE Xplore Digital Library, Science Direct, Emerald Full-text, and Scopus. Moreover, the University of Warwick library search was also conducted to consider all related books and dissertations. Several keywords used to search online literature for this research were: KPI frameworks and models, KPIs in manufacturing industries, KPI selection process, KPI guidelines, KPI as performance assessments in manufacturing industries, and list of KPI measures in manufacturing industries. The initial evaluation of the literature was found to cover several research disciplines, for instance, operational and strategic management of KPIs, accounting and finance KPIs, manufacturing logistics, etc. The coverage of journals was diverse, illustrated in table 1.

Only the abstract and introduction of the journals were studied to ascertain whether it discusses the given research topic. Many journals discussing KPIs related to industries other than manufacturing were overlooked because this research focuses on manufacturing industries. Mostly, the literature review related to KPI guidelines, performance measurement models and frameworks, and prioritization techniques for manufacturing industries were included in the study's scope. The list of articles reviewed from various publications is illustrated in table 1, starting from 1998-2020.

Table 1 List of articles reviewed from various publications (1998-2020)

Articles (1998-2020)	98	99	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	Total
AASRI Procedia															1					1				**2**
ACM Computing Surveys (CSUR)			3			3										3		3	3	1	1	2		**19**
ACM Journal on Emerging Technologies in Computing Systems (JETC)								1	6		3	3			1	4	2	2	1		1			**24**
ACM Transactions on Accessible Computing (TACCESS)													1											**1**
ACM Transactions on Algorithms (TALG)										1		1				1								**3**
ACM Transactions on Computing Education (TOCE)																1								**1**
ACM Transactions on Computer Systems (TOCS)																				1				**1**
ACM Transactions on Cyber-Physical Systems (TCPS)																			1	2				**3**
ACM Transactions on Database Systems (TODS)									1															**1**
ACM Transactions on Design Automation of Electronic Systems (TODAES)	1	1			1	3			1		1	2	2			5	7	4	7	5	3		1	**43**
ACM Transactions on Graphics (TOG)								1	1	1	2	5	6	4	10	7	9	12	13	10	5	7	3	**96**
ACM Transactions on Information Systems (TOIS)											1													**1**
ACM Transactions on Intelligent Systems and Technology (TIST)													1		2	1	1							**5**
ACM Transactions on Internet Technology (TOIT)																1			1			2		**2**
ACM Transactions on Knowledge Discovery from Data (TKDD)																								
ACM Transactions on Management Information Systems (TMIS)												1	1					2			1			**5**
ACM Transactions on Modeling and Computer Simulation (TOMACS)	1							1			1	2	2	2	7	1	7							**24**
ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)																		1						**1**
ACM Transactions on Privacy and Security (TOPS)																			1	1	1	2		**5**
ACM Transactions on Reconfigurable Technology and Systems (TRETS)											1	2	1	1	1	2	2	1			1			**12**
ACM Transactions on Sensor Networks (TOSN)																	1							**1**
ACM Transactions on Software Engineering and Methodology (TOSEM)			1								1													**2**
ACM Transactions on Storage (TOS)										1											1			**2**
ACM Transactions on the Web (TWEB)																		1	1					**2**
Acta Astronautica												1												**1**

Additive Manufacturing																	1							**1**
Advances in Management and Applied Economics																1				1	1			**2**
Advanced Cement Based Materials																1			1					**2**
Ain Shams Engineering Journal																			1					**1**
Annual Reviews in Control																	1							**1**
Applied Energy															1		2	5	2	2	3	2		**17**
Applied Ergonomics																1	1							**2**
Applied Mathematical Modelling																1								**1**
Automation in Construction									2						1	4	1	1	1	3	1	1		**15**
Automotive User Interfaces and Interactive Vehicular Applications													2	2	4	3	2	1						**14**
Benchmarking	1			1	1		1			3	3	1	2	1	1	2	5	3	4	1	3	5		**38**
Business Process Management Journal		1			2		1			1		1	1		4	2	2	3	3	4	2	3		**30**
Chinese Journal of Electronics																		1						**1**
CIRP Annals																		8	5	2				**15**
CIRP Journal of Manufacturing Science and Technology																		1	2	3	4			**10**
Computers & Electrical Engineering																			1	1				**2**
Computers & Industrial Engineering		1	1	1	1								2	1	1	1	1	5	1	3	8	5		**32**
Computers in Industry							1	1		3	1	1	4	2	4	6	6	5	5	2				**41**
Conference on Information and Knowledge Management				1		1			1		1			2	2	1	1	1	2					**13**
Control Engineering Practice														1				1	3		1			**6**
Data & Knowledge Engineering																		3	1					**4**
Digital Communications and Networks																				1				**1**
Electronic Journal of Information Systems Evaluation														1	1			1						**3**
Energy Conversion and Management																	1							**1**
Engineering Applications of Artificial Intelligence									1						1									**2**
Engineering Management Journal																	1							**1**
Engineering Science and Technology, an International Journal																				1	1			**1**
Expert Systems with Applications						1					2	2	1	1	3	2	3		2	1	2	1		**21**
Fusion Engineering and Design																				2				**2**
High Performance Distributed Computing (HPDC)																		1	1					**2**
IEEE Conferences				1	1		1		3	5	2		4	4	4	7	7	10	3	4	1	15	7	**79**
IEEE Robotics and Automation Letters																				1				**1**
IFAC-PapersOnLine																	21	32	23	1				**77**
IFAC Proceedings Volumes			1	2	3	1		1	5	3	3	9	8	2	16	18	7							**79**
Informatica Economica															1		1	1						**3**
Information Sciences																			1	1				**2**

Industrial Management & Data Systems									2		1	2	1	2			1		1	2				**12**
International Conference on Autonomous Agents and Multiagent Systems	2		1	2	3	2	4	10	4	2			4	1	6	1	4	2						**48**
International Conference on Software Engineering	2	3	1	5	3	6	5	7	9	3	5		1	6	6	2	4	5	4	1		12	4	**94**
International Journal of Electrical Power & Energy Systems																			1					**1**
International Journal of Emerging Markets										1				1										**2**
International Journal of Human-Computer Studies																			1					**1**
International Journal of Lean Six Sigma													2	1		2			3	4				**12**
International Journal of Production Economics			1		1		1	1	1	1	7	5	6	7	9	4	8	13	5	14	4	1		**89**
International Journal of Productivity and Performance Management							1		2	4		3	1	3	2	4	8	8	5		2			**43**
International Journal of Project Management										2		1		4	1	1	2	2	3	1	2	1		**20**
ISA Transactions																	1			1				**2**
Journal of Advanced Research																	1							**1**
Journal of Applied Research and Technology																1				1				**2**
Journal of Building Engineering																					2	5		**2**
Journal of Data and Information Quality (JDIQ)																1			1					**2**
Journal of Experimental Algorithmics (JEA)		1	1							1						1								**4**
Journal of Innovation Management																1			2					**3**
Journal of Intelligent Manufacturing									1					2	4	1	1	1	4	2	2	1		**19**
Journal of Loss Prevention in the Process Industries															2	1				1	1			**5**
Journal of Knowledge Management						1						1				1			1	2				**6**
Journal of Manufacturing Processes																			1					**1**
Journal of Manufacturing Systems																		1	1	5	4			**11**
Journal of Manufacturing Technology Management							1			2	2	3	1		3		2	3	2	1	5	2		**27**
Journal of Materials Processing Technology						1				1	1													**3**
Journal of Mathematics in Industry																				1				**1**
Journal of Operations Management					1			1		2				2	1	2		2	1					**12**
Journal of Process Control														1						1	1			**3**
Journal of Rail Transport Planning & Management																		1						**1**
Journal of Remanufacturing															1	1		1						**3**
Journal of Systems Architecture																					1		5	**1**
Journal of the ACM (JACM)			1															1						**2**
Journal of the Franklin Institute																	1	2						**3**

Journal of Quality in Maintenance Engineering								1	1	1	1		2	2	6		2		1				**17**
Journal on Computing and Cultural Heritage (JOCCH)																1	1						**2**
Knowledge-Based Systems												1						1					**2**
Logistics Research													2	2		1	1	2					**8**
Malaysian Journal of Economic Studies																	1						**1**
Management Research Review											1	1				1	1						**4**
Manufacturing Letters																1				1			**2**
Manufacturing Engineer				1																			**1**
Mathematics and Computers in Simulation	1																						**1**
Mathematical and Computer Modelling	1																						**1**
Measuring Business Excellence				1		3	1	1	2		1					1	1		3				**14**
Mechatronics																	1	1					**2**
Nuclear Engineering and Design													1										**1**
Pattern Recognition													1										**1**
Procedia CIRP														8	20	33	33	89	103	24	15		**325**
Procedia Engineering													1	1	5	4	10	2	7	2	5		**37**
Procedia Manufacturing																	15		43	18	12		**88**
Procedia Technology														2	4	4		1					**11**
Pump Industry Analyst											1					1							**2**
Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT)																			1	2			**3**
Reliability Engineering & System Safety										1	1				2		1		1				**6**
Renewable Energy																2	1		1	1			**5**
Review of International Business and Strategy														1				1					**2**
Robotics and Autonomous Systems	1																						**1**
Robotics and Computer-Integrated Manufacturing				1					1	3	1	2	1	2			3	2	2	3	4		**25**
Safety Science									1		2	1	2	1	1	4	2		1	3	1		**19**
Sensors and Actuators A: Physical						4	1	1	1	1									1				**9**
She Ji: The Journal of Design, Economics, and Innovation																		1					**1**
Simulation Modelling Practice and Theory												1			1	1			2	1	1		**7**
Sustainable Production and Consumption																			1				**1**
The Electricity Journal																			1				**1**
Theoretical and Applied Mechanics Letters																1							**1**
Transportation Research Part C: Emerging Technologies																			1				**1**

TQM Journal						1					1	2	2			1	3	4		3		1		**18**
Vehicular Communications																				1				**1**
Total articles reviewed	**7**	**10**	**11**	**13**	**20**	**20**	**23**	**26**	**46**	**43**	**43**	**45**	**56**	**62**	**64**	**118**	**138**	**159**	**205**	**240**	**287**	**127**	**113**	**1830**

2.2 What are Performance Measurements?

It is the process of assembling, studying, monitoring, and/or reporting statistics (facts and figures) regarding the performance of a component, individual, group, system, or organization. The origin of performance measurements can be traced back to the 19th century and can be broadly differentiated into three significant generations, namely: measurement 1.0, 2.0, and 3.0 (Salloum, 2011). The history of performance measures can be observed in figure 5.

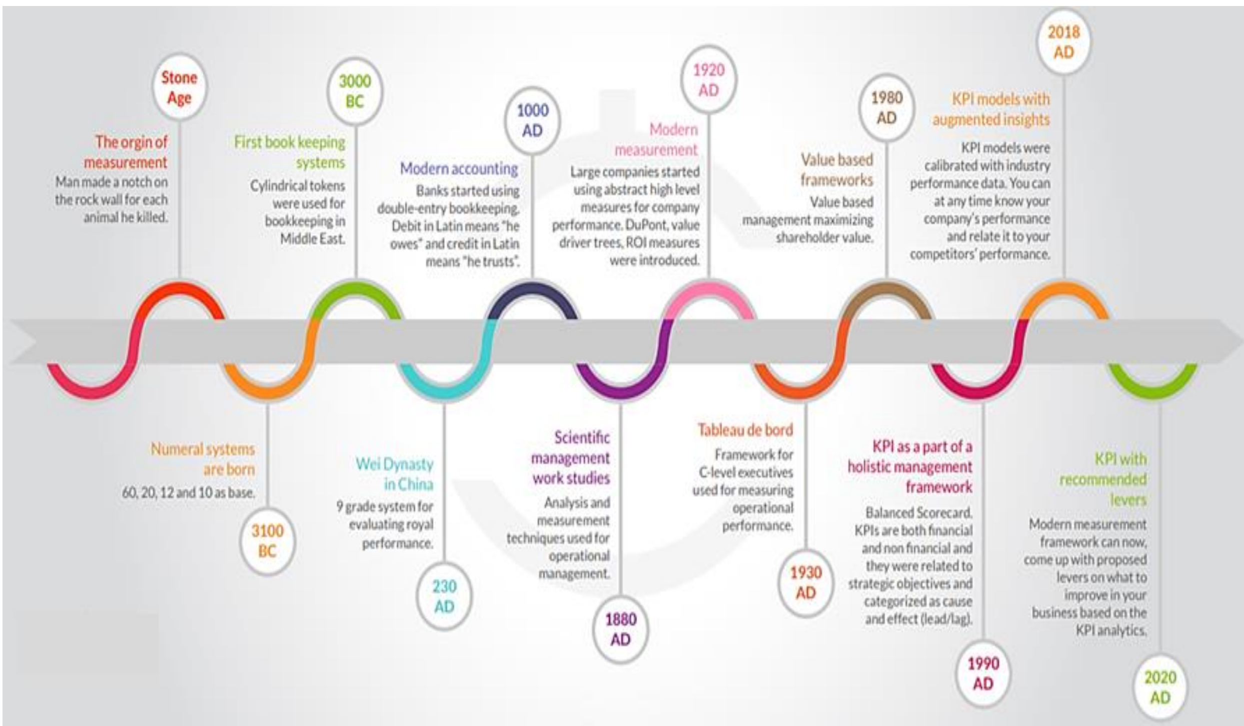


Figure 5 History of performance measurements (Salloum, 2011)

2.2.1 Measurement 1.0

This was an early stage of analysis characterized by accounting and finance measures because that was the only meaningful information available during that period. These measures were considered complementary to accounting and financial results, and also, the data required for measurement purposes was available after the end of an accounting period (David and Jenson, 2014). Thus, these measures provided limited value due to their lagging nature (i.e., results indicators), for which administrations had no direct control. One main weakness in measurement 1.0 was what researchers denote to as the approach to the implementation gap. The implementation gap approach is the philosophy in which organizations spend innumerable funds on designing and developing sophisticated approaches. Those approaches are pointless without an exact linking procedure to implement them (Nudurupati et al., 2011). Thus, in measurement 1.0, performance measures, i.e., results indicators, were merely used to present the financial results.

2.2.2 Measurement 2.0

A major influx of data marked it. This generation was data and technology focussed. Organizations started asking themselves a question about what to do with the data? The Information Technology (IT) cell of the various organizations accepted that the traditional Business Intelligence (BI) tools were the only solution to insufficient information and rich data dilemma (Striteska and Spickova, 2012). Internal IT cells within the organizations were solely responsible for implementing solutions that typically lacked the critical understanding of the business performances to deliver what is required to drive informed decision making (Klovienė and Speziale, 2015). The requirement analysis was also under IT control, typically taking months for designing and years to implement and deliver value. This delay in delivering values repeatedly created a stiff environment that could not handle the rapidly changing business demands (Heinicke, 2018).

Few organizations addressed these inherent delays in developing solutions by marketing KPI catalogs with the assurance of delivering hundreds and thousands of common measurements to their valuable customers (Ambalangodage, Yong, and Fie, 2016). Forlornly, these solutions incorrectly assumed that the measurement requirements for all organizations were identical. Every organization is distinctive, facing unique challenges and using varied strategies to overcome them. Data collected to address various organizations' key business objectives is certainly uneven, making one-size-fits-all solutions inappropriate (Ossovski, Lima, and Costa, 2013). This generation also witnessed the rise of bloated Business Intelligence (BI) support establishments to maintain their cumbrous tools. These establishments placed the burden of extracting the data from BI systems on the organization that demands it.

Organization's overburdened IT support lacking the technical knowledge of interacting with these complex BI systems prevented them from fully embracing BI tools (Kulatunga, Amaratunga, and Haigh, 2015). Inconsistent, unreliable, and untrusted data was also one of the reasons for low BI adoption rates. Organizations started blaming the BI support establishments for not providing usable performance measurements, while those establishments argued that they did not provide functional data. The difference between the performance indicators used in measurement 1.0 to the performance indicators used in measurement 2.0 are mentioned in table 2 (Hasan, 2018).

Table 2 Difference between KPIs and KRIs (Hasan, 2018)

Criteria	KPIs	KRIs
Measurement type	Non-financial	Financial and non-financial
Measurement frequency	Frequently	Monthly, quarterly, or annually
Reporting	Supervisor, manager, and CEO	Board of directors
Problem fixing	Highlights the bottleneck that needs attention	Does not mention what needs to be fixed
Focus	Specific operation	Results of many operations
Indicator form	Leading and lagging	Always lagging

2.2.3 Measurement 3.0

It is the present generation of performance measurements. It concentrates on Objective-Driven Performance Measurement (ODPM), based on operational excellence (Kulatunga, Amaratunga and Haigh, 2005). It uses approaches that align the critical processes' execution to strategic business objectives by assessing and monitoring an organization's bottlenecks. Performance measurements are evidence of an organization to ensure that they progress in the right direction to achieve its business objectives. In a practical scenario, not many organizations can do so; they instead use the performance measures for which the data is easily obtainable (Parida *et al.*, 2015). The configuration and ownership of these measurements in the present generation (i.e., measurement 3.0) are directly under organizations' control because they have rich knowledge about processes and strategies being measured. Such a distributed model is essential to constantly changing customers' demands by eliminating the constraints traditionally imposed by internal IT teams and BI support establishments. Flexibility and agility are the characteristic tenets of measurement 3.0 (Taticchi, Tonelli, and Cagnazzo, 2010).

The OPDM also includes clear performance goals so that every organization upholds a consistent definition of acceptable and objectionable performance. These performance goals are typically linked with predefined response strategies (Goshu and Kitaw, 2017). For example, if the organizations know all the data variables used to generate the measurement and if they understand how these variables affect the measurement direction, then organizations should have a realistic notion of the actions that need to be taken if the performance effects fall outside the tolerable limits (Sinclair and Zairi, 2000). Response plans illuminate culpability and establish a straight action structure when performance goals are overlooked.

Measurement 3.0 further clarifies that one-size-fits-all temperament is unrealizable because performance measures that work for one organization will not ineludibly work for others. Figure 6 highlights the different generations of performance measurements. Measurement 3.0 gave rise to thousands of KPIs depending on the type of industry, nature of production, and audience category. It failed to mention the mechanism/ techniques/ methods/ approaches wherein the organization can identify their relevant KPIs (Mirela-oana, 2005).

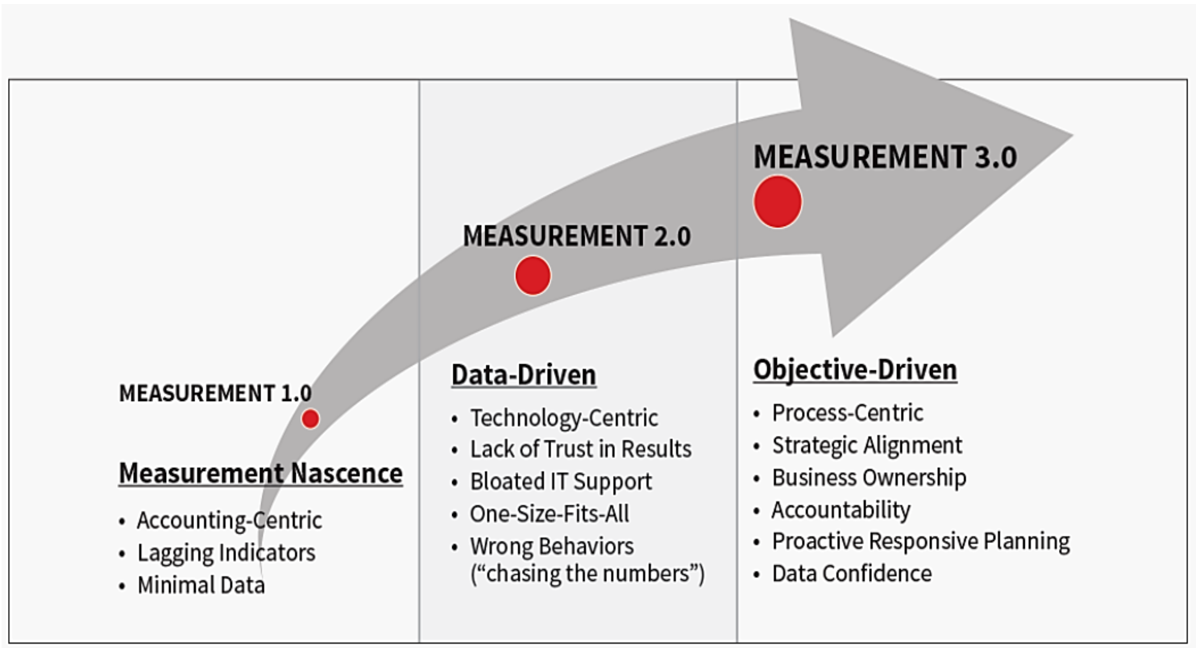


Figure 6 Generations of performance measurement (Mirela-oana, 2005)

2.3 Performance Measurements–Frameworks and Models

In measurement 1.0, it was apparent that traditional accounting and cost management-based performance measures were solely used. Those accounting and cost performance measures were soon proved misleading and inadequate because they could not trace the cost of product, process, and resource; instead, they concentrated on the governing processes in separation. Throughout these generations, various models and frameworks emerged (Beleska-Spasova, 2014). They were mainly developed to tackle the increasing complexity both inside and outside of the organization. The frequently cited models and framework are mentioned below in chronological order, which comprises of (Van Looy and Shafagatova, 2016):

1984 Du Pony Model
1987 Malcolm Baldrige Model
1989 Performance Measurement Matrix

1990 Performance Questionnaire

1991 Results and Determinants Framework

1992 Strategic Measurement Analysis and Reporting Technique (SMART)

1993 Balanced Scorecard

1995 Pyramid of Organizational Development

1996 Cambridge Performance Measurement Design Process

1997 Integrated Performance Measurement System Reference Model

1999 Business Excellence Model of the European Foundation for Quality Management

2000 Performance Prism

2003 Integral Framework for Performance Measurement

2004 Performance Planning Value Chain

2005 Total Performance Scorecard

2006 Holistic Performance Management Framework

2010 Flexible Strategy Game-card

2011 System Dynamics Based Balance Scorecard

Du Pont Corporation developed the earliest performance measurement model in the 1920s to present the Return On Investment (ROI) financial ratios. The Du Pont model is still widely used by organizations as a problem-solving tool for indicating their financial health. Steadily organizations' directors recognized that financial accounting measure ROI presented disingenuous indications to innovation and continuous enhancement activities needed in the current competitive environment (Colbran *et al.*, 2019). Tableau de bord model developed by French engineers by combining financial and non-financial performance measures helped the organizations focus more on daily operations rather than fixing whole time on strategic issues.

Post-1985, quality-related performance measures were accounted for as one of the key aspects of determining its dependability and quality. Malcolm Baldrige model and the European Foundation for Quality Management (EFQM) framework worked towards including quality and management and financial performance measures. Kaplan and Norton brought a revolution in performance measurement by introducing Balanced Score-Card (BSC). BSC joined strategic and operational performance measures to complement financial measures. While many research pieces already thought beyond financial measures, Kaplan and Norton were the first to identify financial performance measures as lagging indicators depending on leading causes such as quality, improvement activities, customer satisfaction, and innovation (Kaplan and Norton, 1992).

The BSC framework suggested that an organization have a balanced set of financial and non-financial performance measures to improve profitability and operational efficiency. Even though BSC gained popularity, the researchers stressed many shortcomings of this framework: its static nature, clustering of performance measures, lack of shareholder focused, etc. This integration of traditional financial measures with non-financial measures brought in the integrative perspective of performance measures marking it as a significant development phase in performance measurement models and frameworks. During the initial stages of development of models and frameworks for performance, measurement went through three transition stages: the accounting management stage, the financial and integrative stages (Closs and Tierney, 1993).

From the 1990s, the focus from *"what gets measured get done"* got shifted to *"how to manage what is measured."* The primary purpose of any measurement model or framework was to encourage proactive management. The necessity for balanced, integrated, strategic, relevant performance improvement orientation has been recognized in several publications. Integrating non-financial measures with financial measures was the main topic of interest during the 1990s. The results and development framework was established to incorporate lagging and leading performance indicators (Parhami, 1990). This framework was grounded on the assumption that every organization's performance can be measured through– results (lagging indicators) and determinants of results (leading indicators) and financial measures. To validate a strong connection amongst performance measures at the different hierarchical and functional levels of an organization, Lynch and Cross proposed a performance pyramid, i.e., a SMART system. Key performance and operational measures were used to bridge the gap between operational and management levels. Nonetheless, according to several researchers, the SMART system failed to provide a mechanism to identify KPIs (Lynch and Cross, 1993).

Since 1996, inspiring research has been conducted by various researchers and think-tank experts to provide dynamic, integrated, and consistent Performance Management Systems (PMS) for organizations. PMS claimed to include all the key performance measures applicable to an organization. The major improvements associated with PMS were mainly associated with the manufacturing company's perspective. Integrated Performance Measurement System (IPMS) was proposed by Ghalayini *et al*. to relate strategical success areas with an organization's performance. However, the dynamic aspect of PMS was poorly incorporated in this system (Ghalayini *et al*., 1996). To include dynamic PMS within IPMS, Bititci *et al*. suggested including internal and external monitoring, review and deployment system, and

PMS. One of the PMS framework's chief shortcomings was failing to integrate competitive and dynamic dimensions. Also, several organizations have seen PMS as proactive rather than reactive (Bititci *et al.*, 1996).

It can be specified that the period from 1992-2000 has witnessed several transformations and developments in performance measurements model and frameworks. These developments were mostly related to manufacturing organizations because operational measures that gained high popularity were crucial. The dimensions of measures focused during this period were financial, customer satisfaction, quality, competitiveness, etc. This shift from exclusively measuring financial performance measures in the early 19th century marked it significantly. Nevertheless, the process of selecting the KPIs to achieve organizations' strategic and operational objectives to enable efficient decision making was failed to be incorporated in the development of models and frameworks. Merely, a list of KPIs based on different dimensions of measures was populated and used by organizations without understanding its purpose of use in attaining their objectives. The transition of performance measurements since the early 19th century is pointed out in figure 7 (Sheykholeslam and Sachin, 2015).

In the era post-2000, the researchers predominantly started working on finding the solutions for the shortcoming of a few well-established models and frameworks of the previous era, such as BSC, SMART system, and PMS. For instance, Kanji *et al*. restructured the BSC framework to Kanji's business scorecard for providing consistent Total Quality Management (TQM) and business excellence to organizations. This was achieved by providing organizations with four key factors for consideration– cultivating organizational learning, attaining process excellence, appreciating, and exploiting shareholder value (Chae, 2009). This era also witnessed the emergence of international standards dedicated to performance measurement, for example, *Automation systems and integration — Key performance indicators (KPIs) for manufacturing operations management*. This standard listed 34 KPIs for monitoring level-3 of the ISA-95 hierarchy model with a few basic KPI selection guidelines for an organization's managers (Zhu *et al.*, 2017). Table 3 provides the significant models and frameworks developed since the 19th century by highlighting key issues, dimensions of performance measures, contributions, and limitations.

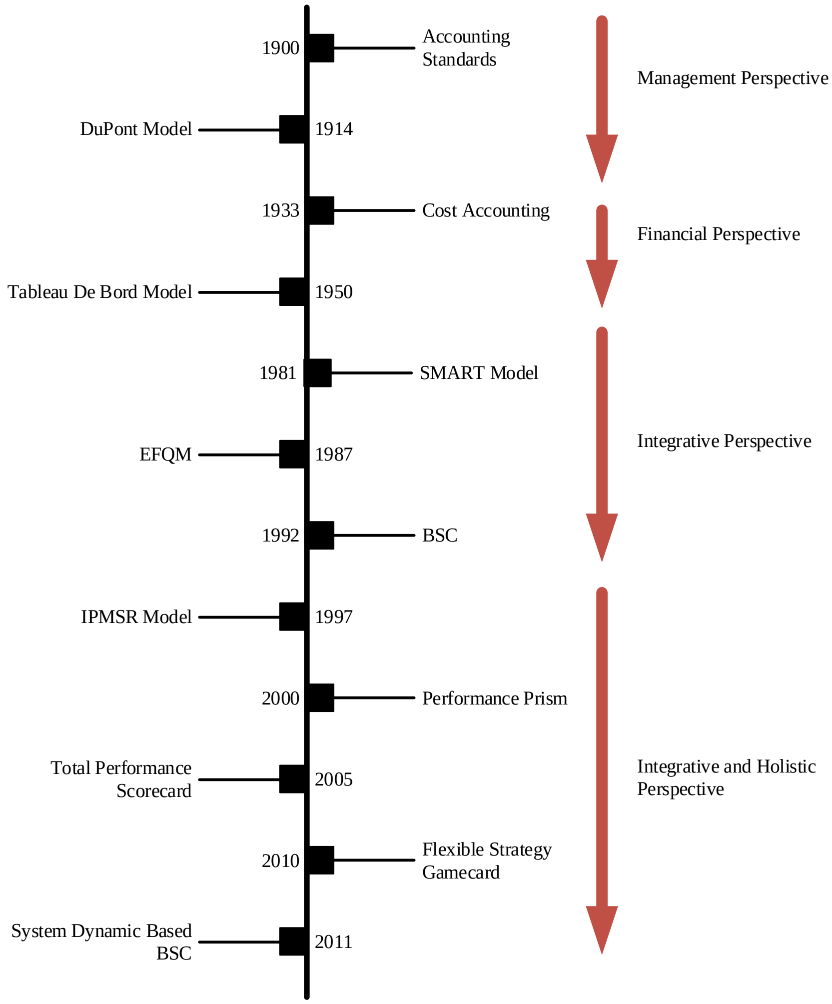


Figure 7 Transitions of performance measurement (Sheykholeslam and Sachin, 2015)

Table 3 Summary of significant performance measurement models and frameworks

Name of the performance measurement framework and models (Author and year)	**Dimensions of measures**	**Issues addressed**	**Strengths**	**Limitations**
Results and determinant framework (Fitzergald *et al*., 1991)	Financial performance, competitiveness, quality, flexibility, resource utilization, innovation	Identification of leading and lagging factors	It highlights that results are lagging indicators and determinants are leading indicators	Considerations of non-financial measures, stakeholders, and their behavioral aspects related to performance have been neglected
Performance pyramid (Lynch and Cross, 1991)	Market, financial, customer satisfaction, flexibility,	Identification of performance measures for	It ties together the hierarchical view of business performance	It does not provide any mechanism to identify KPIs and

	productivity, quality, delivery, cycle time, waste	organizational hierarchy	measurement with the business process view	does not explicitly integrate the concept of continuous improvements
EFQM- excellence model (European Foundation, 1991)	Leadership, people, policy and strategy, partnership and resources, processes, key performance results	Organizational improvement through self-assessment	It is a non-prescriptive framework based on nine criteria related to enablers and results for self-assessment to improve performance	It does not consider the dynamics of changing external environment
Balance scorecard (Kaplan and Norton, 1992)	Financial, customer, internal processes, learning and growth perspectives	Complements financial measures with non-financial performance measures	Most dominating and highly used performance measurement framework which highlights to consider non-financial measures complement to financial performance measures	The problems to identify cause and effect relationships between linkages of different perspectives, static nature of performance measurement, and major stakeholders related to performance are not adequately addressed
Consistent performance measurement system (Flapper *et al*., 1996)	Specific dimensions of performance are not defined	Designing of PMS covering all aspects of performance relevant for the organization	It describes the steps to develop consistent PMS by defining PI, relations between PI's and set target values for PI's	The framework needs to be examined for general use
Dynamic performance measurement system (Bititci *et al*., 2000)	Specific dimensions of performance are not defined	To bring in dynamics to performance measurement systems	It highlights the integration of IT for review mechanism, feedback loops, and integrating changes in the internal and external environment	The wicker application of this framework is not highlighted in the literature
Integrated performance measurement framework (Medori and Steeple, 2000)	Quality, cost, flexibility, time, delivery, future growth	Auditing and enhancing performance measurement systems	This is an integrated framework to audit and control the performance measurement system	For designing the PMS, very few competitive dimensions are considered
Performance prism (Neely *et al*., 2001)	Stakeholder satisfaction, stakeholder contribution, strategies, processes, capacities	The stakeholder orientation	It highlights a comprehensive view of different stakeholders related to the performance of any enterprise, and new stakeholders are also considered	It gives little away about how performance measures are being realized, and hardly any consideration is given related to the use of the framework for existing PMS
Kanji's business scorecard (Kanji and Sa, 2002)	Stakeholder values, process excellence, organizational learning, delighting stakeholders	Overcoming the weakness of BSC	It looks for process excellence, organizational values, and learning and	This scorecard focuses mainly on the external stakeholders

			delighting stakeholders	
Total performance scorecard (Rampersad, 2005)	Financial, customer, internal, knowledge and learning perspectives, process improvement, personal improvement	Integrating personal and organizational performance	It integrates personal and organizational scorecard with PDCA cycle, talent development cycle, and Kolb's learning cycle	The insights are built from experience; no empirical validation is presented
Flexible strategy game card (Sushil, 2010)	Situation, actors, process, performance, the value in offering and relationships	The dual perspective of performance	This is an attempt to provide a holistic, integrated, and dynamic view of performance management which highlights the importance of the dual perspective of performance, i.e., enterprise and customer perspective	A recent development needs empirical validation
Proactive balance scorecard (Chytas *et al*., 2011)	Specific dimensions of performance are not defined	Using fuzzy cognitive map (FCM) and simulations	It addresses the problems of BSC and overcoming them by generating dynamic networks, simulating KPIs	It needs empirical validation
Sustainability performance measurement system (Searcy, 2011)	Specific dimensions of performance are not defined	Reviewing and updating of corporate sustainable PMS	It provides a conceptual framework to structure the process of updating a corporate sustainability performance measurement system	The conceptual framework needs an empirical validation
Link and effect model (Stenstrom, 2012)	Technical indicators, like; availability, capacity utilization, etc.	Using fuzzy cognitive map (FCM) and simulations	Technical indicators at the operational the level is linked to the strategic level through the tactical level and vice versa	A recent development needs empirical validation

Nearly every single performance measurement framework and model mentioned in this section was concerned with *what needs to be measured, how to organize and report those measures*. This included generating a set of performance measures to reveal the strategy and purpose of an organization; constructing a composed set of measures (for example, lagging vs. leading, external vs. internal, operational vs. financial); deploying the composed measures to evaluate objective organizational alignment; knowing the causative relationships between measures and reporting the measures. The primary purpose of these frameworks and models was to implement a composed and integrated set of measures to improve and manage an organization's performance (Sarode, Sunnapwar, and Khodke, 2008). The success of these initiatives was calculated by three conditions–is the PMS designed and deployed? Is the PMS envisioned to accomplish the performance? Did the organization performance improve? The second and third conditions were not completely achieved through these frameworks and models due to limited understanding of the indicators deployed within the PMS by the organizations (mainly manufacturing sector). Scores of KPIs selected during model development failed to mention the motives behind selecting those set of indicators (Haponava and Al-Jibouri, 2009).

From the organizations' perspective, developing highly sophisticated frameworks and models for performance measurements was not rewarding. These organizations needed a method/ tool/ technique/ approach that can seamlessly guide them to link their strategic and operational objectives with performance measures. Populating a set of measures based on dimensions of measures and organization type was simply not sufficient for organizations to improve their performances (Yadav, Sushil, and Sagar, 2013). To address this research gap, researchers started considering different dimensions to the selection of KPIs. The problem of thoroughly understanding KPIs, developing a holistic approach for guiding, selecting, and implementing appropriate KPIs remained a significant challenge for organizations. In order to address this problem, the author developed a holistic approach for guiding the manufacturers to analyze, select, and implement appropriate KPIs. The significance of this approach will be discussed in Chapter 3.

2.4 Categorization of KPIs Based on Various Research Publications

Kang *et al*. understanding the complexity of selecting the right KPIs for improving manufacturing system operations, suggested categorizing the KPIs, mainly into primary and comprehensive KPIs; and supporting metrics. Basic KPIs were used to represent a single aspect of system performance, and comprehensive KPI was used to describe the overall performance. The supporting metrics were directly monitored elements. The categorization was based on a hierarchical structure with several categories at several levels, as shown in figure 8. The supporting elements level included time and quantity related to production, maintenance, and quality-related to the machine, order, and worker. These supporting elements help compute basic KPIs and desired mathematical operations over primary KPIs to raise comprehensive KPIs. Kang *et al*. failed to discuss critical parameters: the audience, timing, and production methodology essential for KPI selection (Kang *et al.*, 2015).

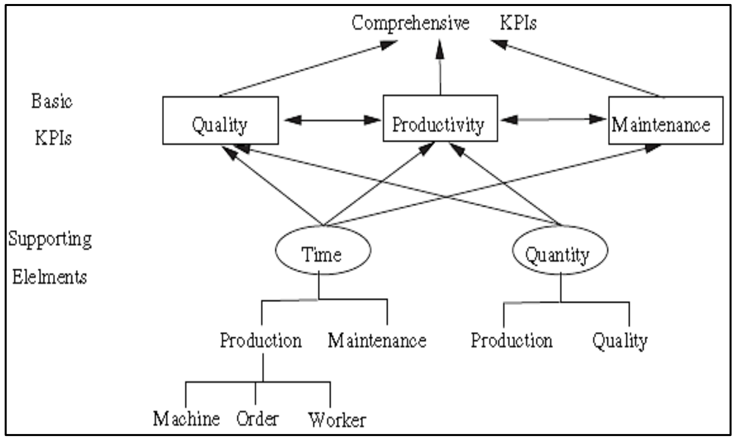


Figure 8 KPI classification (Kang et al., 2015)

Li *et al*. worked on one of the limitations of the ISO 22400 standard (i.e., standard applicability). The KPIs mentioned in ISO 22400 standard are applicable for discrete production, making them technically unsuitable for the process industry. Li *et al*. proposed a framework for classifying KPIs in the process industry. The framework follows a similar hierarchy mentioned in ISO 22400 and can be evaluated in three levels: equipment KPIs, measurement elements, and process KPIs. Measurement elements, the middle level of the framework contains the data that can be directly collected and monitored throughout the production process, as shown in figure 9. Equipment and process KPIs are calculated based on the measurement elements. This framework provides useful ideas for decision-makers and manufacturing engineers to describe and measure appropriate KPIs for process industry process assessment. Li *et al*. also provided the description and formula for the KPIs but failed to discuss few parameters: the audience, timing, and production methodology essential for KPI selection (Li *et al*., 2009).

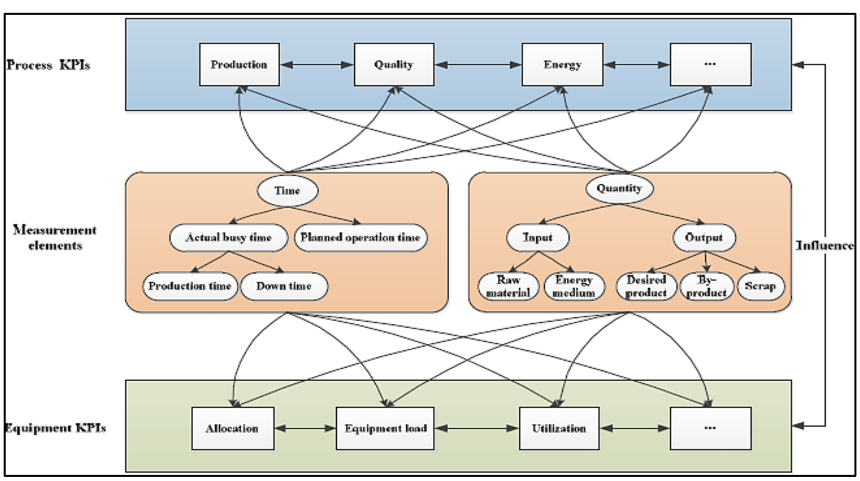


Figure 9 Process industry: a framework for organizing KPIs (Li et al., 2009)

Hester *et al*. proposed a method for KPI assessment in manufacturing organizations. The proposed method is profoundly dependent on the stakeholder contribution at varying levels during the complete course of the KPI assessment process. The aim is to improve KPI assessment methods by introducing a mathematical foundation centered on value-focused thinking. The steps involved in the assessment are shown in figure 10, divided into three main activities: preparatory manufacturing activity, stakeholder values, and preference elicitation activity, and manufacturing company KPI characterization and analysis activity. Ranking criteria used for assessment are based on KPI characterization.

The parameters which are considered for KPI characterization are: verified, standardized, relevant, predictive, quantifiable, inexpensive, actionable, inexpensive, accurate, documented, independent, traceable, understandable, and timely. This proposed method lets the stakeholders assess the organization's KPIs to determine its performance compared to predetermined KPI thresholds. A case study was conducted within a chemical manufacturing company to test its validity. With stakeholders playing a pivotal role in the KPI assessment method, any failure in understanding the manufacturing process and KPIs can result in the incompetence of the developed method (Hester *et al.*, 2017).

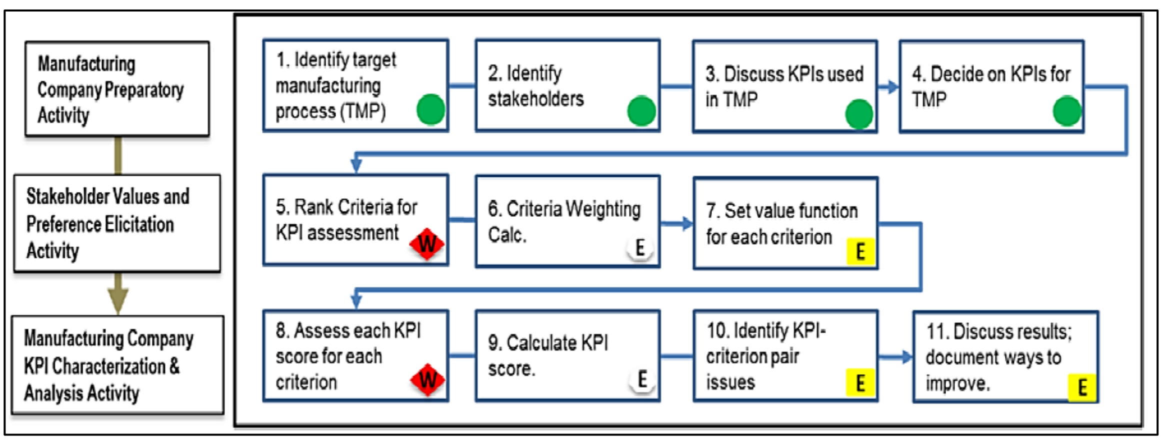


Figure 10 KPI assessment methodology (Hester et al., 2017)

Carlucci *et al*. addressed one of the significant challenges faced by manufacturing industries, i.e., selecting the most meaningful KPIs for monitoring manufacturing operations. The KPI selection was described as an MCDM problem involving several factors and associated interdependencies. Using the ANP method, a decision-based model was proposed to help manufacturers in KPI selection. This model was based on the contemplation that KPIs can be selected and evaluated based on a set of criteria. These set of criteria are relevance, reliability, understand-ability, representational quality, comparability, and consistency. A set of relevant questions is prepared for the decision-makers founded on criteria to assess the manufacturing company's performance. While selecting KPIs, it was mentioned that decision-makers do not rigorously consider the dependency of criteria and interdependencies among the chosen indicators, compromising the indicators' quality.

The developed model provides a more viable approach to deal with this problem consisting of two clusters, namely criteria and performance indicators, as shown in figure 11. Carlucci *et al*. proposed a model to help decision-makers select KPIs' best set for their manufacturing operations. For this model to work competently, decision-makers must know the manufacturing process and all the relevant KPIs available in the literature to monitor the performance. It is because the proposed model only provides that KPIs selected by decision-makers are appropriate or vice-versa. Decision-makers do not always have to compete for knowledge of the KPIs available in the literature, so this does not seem to work efficiently (Carlucci, 2010).

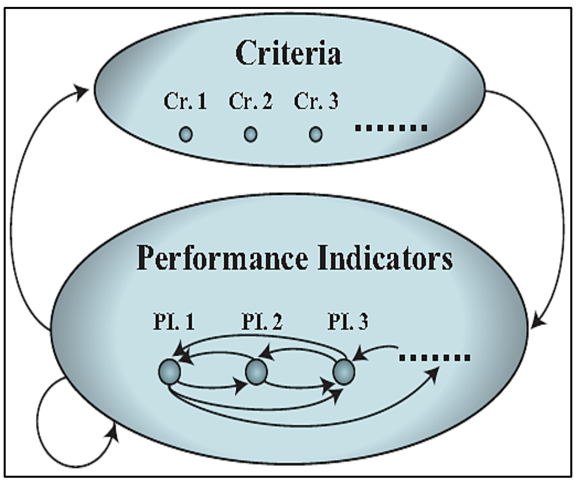


Figure 11 ANP model for selecting KPIs (Carlucci, 2010)

Lindberg *et al*. state that benchmarking KPIs against other KPIs from comparable equipment, process, and industry can identify and select appropriate KPIs to monitor industrial performance. A case study was carried out on a heat and power plant; a set of KPIs was suggested to the managers after benchmarking them with the literature on similar industries. The list of suggested KPIs was divided into energy, raw-material, equipment, operation, control performance, maintenance, planning, inventory, and buffer utilization KPIs. It was seen that the boiler efficiency was considerably improved by deploying benchmarked KPIs in their heat and power plant. With the surge in the literature related to KPIs, using the benchmarking method for KPI selection would result in using outdated KPIs that have been replaced with more efficient ones or new KPIs that have been generated recently. Also, for KPI selection, the manufacturers need to know its description, audience, timing, production methodology, etc. Without a complete understanding of the KPI, it would merely remain a number (Lindberg *et al.*, 2015).

kibira *et al*. present a procedure for evaluating, monitoring, and improving KPIs for sustainable manufacturing industries. The purpose of this procedure was to address KPIs' inconsistent meanings, lack of compelling selection, and evaluation methods for environmental KPIs in manufacturing processes. The procedure was developed based on ASTM International standard guidelines. The development stages include identifying appropriate KPIs from existing literature, defining new KPIs if needed, selecting KPIs based on set criteria, and assigning weights. The weights are used to reduce deteriorating effects that result from emphasizing similar or interrelationship KPIs.

By analyzing the relations between the number of KPIs and their supporting matrices, it can be probable to compute a similarity score to select appropriate KPIs. For instance, if several KPIs are calculated using the same supporting matrices, it can be possible to compute a similarity score to help in effective KPI selection. Using repositories that store all the relevant manufacturing processes, KPIs were used to provide pre-defined KPIs for initial selection. The procedure is based on both quantitative methods and human judgment. Humans are the think tank experts aware of all the key activities critical for successful business performance. Figure 12 highlights the keys steps involved in the designed procedure (Kibira *et al.*, 2018).

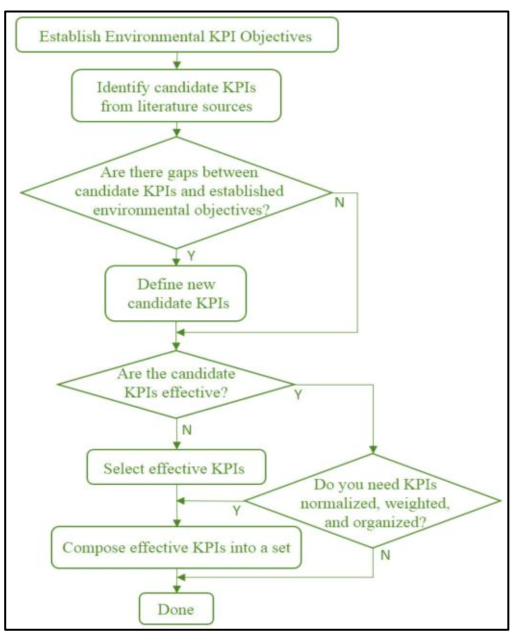


Figure 12 KPI identification and selection procedure (Kibira et al., 2018)

Ding *et al.* develop a data-driven scheme to predict and diagnose KPIs for static and dynamic processes. It aims to apply this scheme to solve the KPI prediction and diagnosis problems faced in the steel manufacturing industry's hot strip mill process. This paper discusses the two most popular data-driven methods to achieve fault diagnosis tasks, i.e., Partial Least Squares (PLS) and Principal Component Analysis (PCA) for complex industrial processes. Despite having wide applications in the industry, these schemes have been reported to have certain limitations. Hence, the paper builds upon these schemes to give two algorithms for KPI computation and prediction for static and dynamic processes. To implement KPI prediction in the hot strip mill process, a four-step procedure is defined in the paper, which includes defining the KPI, variable selection, off-line training, and finally, on-line prediction and diagnosis.

KPI is to be defined according to specific process characteristics, quality requirements, and economic benefits. Variables that are responsible for the given KPIs are selected. This implementation shows that the dynamic approach's prediction performance is better than that of the static approach. There is a smooth variation between the actual and predicted values of the process variable. The dynamic process also gives more useful results for fault-detection. However, Ding *et al*. suggest that selecting a static or dynamic method should depend on the underlying process's nature, memory cost, computational cost, design complexity, and the required robustness. This paper provides an insight into which methods should be utilized for KPI prediction and diagnosis in complex processes where a sophisticated modeling procedure is not realizable. Therefore, model-based techniques cannot be utilized.

Tatsiana *et al*. identify process-based KPIs that can control the pre-processing stage in a construction project. This is done by conducting a pilot-study and validating its results through interviews of experts in this industry. It is first identified that even though the pre-project stage is vital to a project’s success, it does not always perform well in the construction industry leading to time delays and budget overruns. Therefore, the project performance must be governable in the early stages of the construction process. An extensive literature review conducted by the authors highlights that most of the KPIs in the construction industry focus on end-products rather than providing measures to control the process while it is in progress, meaning there is a lack of process-oriented KPIs, which their paper aims to develop.

A pilot study was conducted in which experts were asked to review a list of main sub-processes in the pre-project stage, and as a result, eight process-based KPIs were developed. These were again validated by experts mainly from large construction organizations as they experienced dealing with large projects' early stages. This method is advantageous because large projects can be challenging to control, involve many stakeholders with differing interests that are tough to align. Bad decisions taken in the early stages of the process can have massive consequences for the later stages. After considering the suggestions and comments of these experts, the KPIs were reduced from eight to five.

These are initial problem definition, management of client requirements, and alignment of stakeholders' requirements, design solution, and stakeholder involvement. The experts pointed out that it is necessary to align clients' needs on different levels before defining and managing client requirements. Additionally, the alignment of interests of different stakeholders involved by defining their objectives and influence on the project was also deemed essential. Keeping the stakeholders involved continuously in the project regarding the decisions that are to be made is also one of the critical indicators of performance.

Gonzalez *et al*. aim to establish a useful set of KPIs to measure maintenance services' performance using an MCDM methodology. After a comprehensive literature review of different MCDM methods, the authors propose a methodology based on the original ELECTRE I method, which uses a preference model that uses the concept of concordance and discordance to carry out paired comparisons between the alternatives. This method has evolved to allow the ranking of alternatives from best to worst with complementary analyses. This ranking method is deemed suitable for selecting KPIs in the maintenance framework as it has been successfully applied to other ranking problems. Moreover, it is easy to use, and the logic behind it is rational, and the computation process systematic and well-organized. It is also the most used method for ranking alternatives. The first step in the proposed methodology is defining the maintenance management objectives. Then a set of criteria to evaluate the KPIs are specified to which appropriate weights are assigned. Based on the defined objectives, KPIs are pre-selected to be assessed as competing alternatives. Then those alternatives are evaluated against the selected criteria by the decision-makers. The higher the response level on the Likert scale, the more critical it is for KPI (Gonzalez *et al.*, 2017).

Effendi *et al*. emphases on the problems of KPI development in an aerospace manufacturing enterprise. The KPIs were targeted to provide the enterprise with the best PM tools to remain cost-competitive and effectively implement lean manufacturing. Through techniques such as internal benchmarking, intensive literature review, and best industrial practices, a set of KPIs was developed and measured both subjectively and objectively. To analyze and investigate the communication issues between different manufacturing levels (ISA-95 architecture), focus group discussions and semi-structured interviews were used. To overcome these issues, a standard report was generated. The enterprise was suggested to recruit personnel at every manufacturing level to report and review their manufacturing process to their subordinates' regularly. This paper highlighted several problems related to KPI developments, such as lack of ownership of responsibility, misinterpretation of company objectives, no normalization of reporting, and difficulty measuring employee performance in the given aerospace manufacturing enterprise. Nevertheless, the paper could not resolve these problems apart from lack of ownership of responsibility (Effendi *et al.*, 2008).

Rødseth *et al*. focused on the challenges faced by silo departments working independently in a number of disciplines within manufacturing industries resulting in a sub-optimized effect on production. It is due to poor communication between different departments and disciplines working together. The disciplines focussed were maintenance management and Manufacturing, Planning & Control (MPC). The purpose of this paper was to identify the relevant KPIs through a literature review for these disciplines. Accordingly, throughput time was marked as an essential KPI for MPC; OEE for maintenance management and MPC disciplines used integrated planning concepts. This paper also highlights the relationship between several leading and lagging indicators. However, identifying two indicators to optimize production performance by improving communication between two disciplines was not realistic since manufacturing industries are placed where many disciplines have to work simultaneously to achieve organizational objectives. Moreover, two KPIs are insufficient to solve the silo problem in manufacturing industries (Rødseth, Strandhagen, and Schjølberg, 2015).

May *et al*. addressed the challenges faced by current manufacturing industries in supporting the development of energy-related KPIs (e-KPIs). The challenges included a lack of applicable KPIs to compare energy-use profiles of equipment, processes and benchmarking them alongside competitors' energy performance measures. Aiming to address these challenges, this paper's key motive was to outline a method to assist manufacturing industries in e-KPIs development. The paper presents an e-KPIs development method containing the following sequential steps: definition of the reference manufacturing system; identification of manufacturing resource power requirement; investigation of the causes related to energy inefficiencies through exploring manufacturing states of the given resource; connecting energy requirements with appropriate time drivers; constructing a hierarchical structure of power resource energy consumption; e-KPIs development, design, and management.

The developed e-KPIs allows the manufacturers to interpret cause-effect relationships and help them in making enhanced operative decisions. This method also identifies strong and weak areas for energy efficiency enhancements related to MPC. The granularity of the accessible data is one of the drawbacks of the developed method. In the current industrial practices, the energy monitoring is done at level-2, a finer granularity at level-0, and 1 of the ISA-95 functional hierarchy model is needed (May *et al.*, 2015).

Gonçalves *et al*. stated that several KPIs present in the literature could be applicable for measuring maintenance performance. Still, manufacturers must choose an appropriate set of KPIs that impact their maintenance-related activities. Creating a suitable set of maintenance KPIs is subjected to manufacturers' maintenance objectives and is considerably associated with definite business processes, systems, strategies, and contexts. The maintenance team was responsible for selecting the KPIs, which can help them realize their business goals. Cesar *et al*. offered a new method to choose necessary maintenance KPIs using a methodology based on the ELECTRE II (ELimination Et Choice Translating REality), an MCDM method. The proposed ELECTRE I established methodology supports manufacturers' resolve their ranking issues by assessing numerous conflicting options through MCDM. Since the manufacturers are generally inexperienced with the mathematical formulation required for MCDM methods, a software tool was designed utilizing Visual Basic for Applications (VBA).

All the needed mathematical formulation was encoded using VBA to offer computational analysis for decision making. A case study was carried out with two maintenance experts in service quality at the airports to validate the methodology. Using the methodology, the experts ranked the alternatives from good to bad and steadily selected KPIs with higher interest to airport quality service teams. The case study outcome proved that the methodology is an efficient tool to assist maintenance teams in relevant KPI selection based on maintenance strategies and objectives (Gonçalves, Dias, and Machado, 2015).

Alsyouf states that the "fix when it breaks"-concept, which describes the corrective maintenance method, mostly moved towards the preventative maintenance concept after the end of the second world war due to advancements in industrial production systems with planned maintenance actions aiming to prevent machine breakdown from occurring (Alsyouf, 2007). Nevertheless, with the globalization of industries and more generous than before worldwide competition, planned maintenance methods used for replacement or repair of machine parts did not stand out to be the best solution to solve the given problem.

Therefore, in order to make the most of industrial assets and curtail unwanted stops for running preventative maintenance procedures, the condition-based maintenance method alongside maintenance-related KPIs was established (i.e., Mean Time To Repair (MTTR) and Mean Time Between Failure

(MTBF)). The maintenance-related KPIs were used to closely monitor machine behavior using simple visual check-ups to evaluate real-time data using computer-aided technology continuously. The critical parameters were carefully observed, and with any small variation in their values compared to a set of predetermined values, condition-based maintenance actions were initiated.

Pereira *et al.* used a predictive maintenance fuzzy logic technique for on-line monitoring of induction motors using related KPIs (Pereira and Augusto, 2016). The authors' main concern was using maintenance-related KPIs to analyze the induction motor's vibration spectrum resulting from a mechanical failure such as misalignment, unbalanced disk, bearing faults, and mechanical clearance during motor operation. This vibration spectrum was investigated using the fuzzy logic technique. In this technique, the motor operating conditions are defined in fuzzy linguistic variables; these variables are then exploited to present the result using monitoring programs such as Fast Fourier Transforms (FFT). To prove the proposed control method's effectiveness, an experimental test was performed at Dynamic Systems Laboratory in the Federal University of São João del-Rei (UFSJ). They were able to identify and diagnose faults in the motor casing using maintenance-related KPIs (i.e., MTTR and MTBF).

Bastos *et al.* present an architecture aimed to collect the data produced during the industrial maintenance schedules and predict future fiascos based on data exploration. Rapid Miner, a product of software innovation lab Limited Liability Company (LLC), is used to analyze maintenance data, apply various prediction algorithms to gather data, and then compare their accurateness in the detection of predictions and patterns using applicable maintenance KPIs. Rapid Miner is incorporated with a real-time system that gathers data utilizing automatic agents. These data results are presented in KPIs to the maintenance team for decision-making (Bastos, Lopes, and Pires, 2014).

Goundar *et al*. work is centered on the real-time monitoring of three-phase AC industrial induction motors using KPIs (Goundar et al., 2015). The KPIs monitored here are the vibration and temperature of induction motors. Any failure resulting from lubrication, motor ventilation, motor load, electrical consideration, and alignments directly impacts motor temperature and vibrations. The data set collected while monitoring these motors predicts the motor's bearing breakdown by comparing the healthy and faulty motor working operations' variances. To measure vibration and temperature KPIs, necessary sensors such as accelerometer and thermistor are incorporated.

Furthermore, to obtain the sensor data, communicate with various other devices, and store the sensor data, the author uses Waspmote IDE pro v1.2 board. The data collected from the sensors is further scrutinized and converted from the time domain to the frequency domain so that FFT techniques can be applied to solve the motor bearing problem. This technique transforms the data into frequency plots that can distinguish the frequency spectrum from a faulty to a new bearing.

Susto *et al.* explain how flexible, adaptive predictive maintenance based planning decision support system employing regularized regression and machine learning approaches are used to reduce maintenance linked cost and downtime KPIs in a semiconductor manufacturing plant for Ion Beam etching process (Susto et al., 2014). To reduce the maintenance cost and downtime, Susto *et al*. made use of the newly processed data accessible from the semiconductor process equipment is to enhance remaining valuable life estimates, thus decreasing unpredicted breaks and entire equipment lifetime. The above predictive maintenance-based system was validated on a real industrial dataset associated with semiconductor manufacturing plant experimentally out-performing preventative maintenance and run-to-failure maintenance.

Munir *et al*. emphasized the importance of improving the existing KPIs assessment methodology. The main objective was to develop a better assessment methodology for KPIs to improve the manufacturing plant process. By combining qualitative methods such as questionnaires and assessment matrices adapted from EFQM, this methodology was developed. By using these qualitative methods, it was seen that KPIs to be considered as an essential element for planning manufacturing strategies were quality, cost, delivery, inventory and flexibility; and the top five KPIs to be used where the return on investment, conformance to specifications, profitability, overhead cost, and customer satisfaction. Based on the importance of specific processes, it was possible to prioritize the KPIs linked to those processes using the developed methodology. However, the applicability of using the resultant five KPIs was limited because the nature of operations within different manufacturing industries tends to alter, and the tactical and operational goals. Merely suggesting the top five KPIs will not improve the process utilization for every manufacturing industry. There is still a need for a generalized KPI assessment methodology that can apply to all manufacturing industries.

Stricker *et al*. understanding the problems arising due to increasingly distributed production, growing variant diversity, and disruptions due to shorter product life cycles on the production performance and quality of the manufacturing industries, recommended an approach for selecting KPIs. Since KPIs are commonly used tools for detecting any changes in production system performance to organize suitable countermeasures. It underlined that the need for choosing an appropriate number of KPIs is significant. The manufacturers should not be overburdened or given insufficient KPIs to monitor the production performance overstraining decision-makers' cognitive capabilities. By knowing the critical areas of performance improvement, a set of KPIs were selected based on employing a mathematical linear programming approach (based on integer linear programming). This approach focused on bridging the gap between information content and simplicity. The appropriate KPIs needed for this selection approach are assumed to be linked to the manufacturers' business objectives. Nevertheless, from a manufacturer's perspective, they require an approach that can make them understand, analyze, and link the KPIs to the business objectives before moving towards the selection procedure.

Bongsug *et al*. recognized that developing KPIs for monitoring critical business performance is challenging, and the set of practical guidelines available in the literature are limited. A list of essential KPIs and a practical approach to performance measurement are presented in this paper to address this challenge. The list of essential KPIs was developed based on incorporating a rich industrial experience and Supply Chain Operations Reference (SCOR) model and hierarchically clustered (i.e., primary and secondary). Furthermore, these KPIs were grouped into five categories: planning, sourcing, production, and delivering, as shown in figure 13, to cover the whole supply chain management structure. As a limitation, the KPIs presented were lagging in nature and specific to managers.

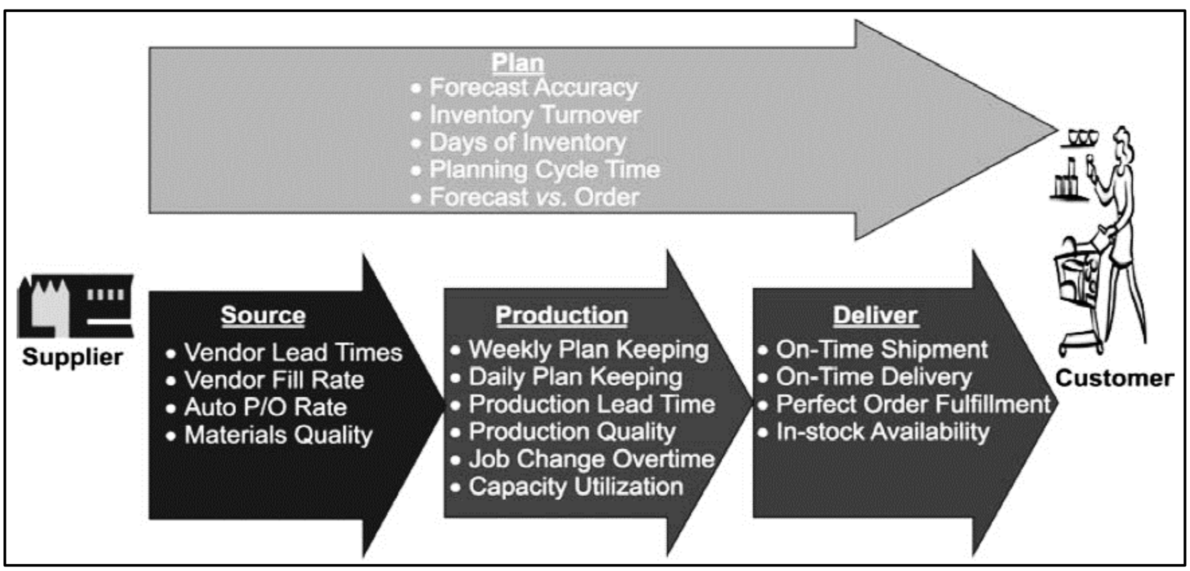


Figure 13 List of essential KPIs based on the SCOR model

Table 4 summarizes various other research publications by outlining their objectives and categorizing KPIs (KPI measure and corresponding elements). These publications are within the research objectives domain and target how the manufacturers and/or decision-makers understand, analyze, select, and implement KPIs within their production facility. Also, the KPI measures with their respective elements identified in this section will play a vital role in the development of KPI guidelines in chapter 3.

Table 4 Categorization of KPIs from the existing literature

Author and year	Objectives	KPI measures (element)
(Amrina and Yusof, 2011)	Evaluate sustainable manufacturing performance in the automotive industry. It proposes a set of sustainable manufacturing KPIs believed to be appropriate for the automotive industry	Production methodology (discrete), type (product), dimension (sustainability)
(Wang, Zhang, and Wang, 2018)	Reducing the cycle time in semiconductor wafer fabrication system by identifying the root causes within the manufacturing process	Production methodology (batch), equation variables (WIP, utilization time, waiting time), dimension (time), formulae
(Jain and Samrat, 2015)	Determine the state of the art of quality practices of manufacturing industries in Gujrat through interviews	Production methodology (discrete), dimension (quality), type (product)
(Rodrigues *et al.*, 2010)	To study the influence of production cycle time in manufacturing supply chain management	Production methodology (discrete), dimension (time), equation variables (WIP, production rate, distribution inventory, distribution rate, and waste rate), formulae
(Sonar, Shinde and Teh, 2013)	Improving the automated diffusion furnace operation using cycle-time	Production methodology (batch), dimension (time), timing (real-time), formulae
(Chien, Hsu, and Hsiao, 2012)	Reducing the cycle time in the semiconductor fabrication process by identifying the root causes	Production methodology (batch), dimension (time), equation variables (WIP, production rate) , timing (real-time), formulae
(Kibira *et al.*, 2017)	Exploring KPI relationships for manufacturing production systems	Dimension (time, quality, cost), equation variables, equation, ER model

(Borsos, Iacob and Calefariu, 2016)	Using KPIs to determine the waste in the production process	Formulae, equation, equation variables, type (resource)
(Badawy *et al.*, 2016)	A survey on exploring key performance indicators	Form (leading, lagging), production methodology (discrete, batch, continuous), nature (fundamental, derived)
(Andrej Rakar, Sebastjan Zorzut, 2004)	Production performance assessment through KPIs	Dimension (time, cost, quality, environmental, sustainability), formulae, equation, equation variables
(Rahman, 2015)	Implementation of total productive maintenance assessment in a semi-automated manufacturing company through downtime and mean downtime analysis	Production methodology (discrete), type (process), dimension (time, quality), equation, equation variables
(Bhutani, 2015)	Performance assessment and benefit estimation in paper machines using KPIs	Production methodology (discrete), dimension (time)
(Lingam, Ganesh and Ganesh, 2015)	Reducing the cycle time of the T-shirt production in the textile industry	Production methodology (discrete), dimension (time), equation variables (standard time, basic time, machine allowance time, contingency allowance time), timing (real-time)
(Meidan *et al.*, 2011)	Employing cycle time identifying key factors for production loss in semiconductor manufacturing	Production methodology (batch), dimension (time), formulae, equation, equation variables, timing (real-time)
(Radujković, Vukomanović and Burcar Dunović, 2010)	Exploring KPIs in southeastern European construction industries	Production methodology (discrete), dimension (time, cost, quality), formulae, equation, equation variables, the audience (manager)
(Sowmya K and Chetan N, 2016)	Review on effective utilization of resources using OEE KPI in manufacturing industries	Production methodology (discrete), dimension (time, quality), type (resource), formulae, equation, equation variables, nature (derived)

(Venkataraman *et al.*, 2014)	Reducing cycle time in manufacturing machining process by application of value stream mapping	Production methodology (discrete), dimension (time, quality, cost, environmental, sustainability), type (product), formulae, equation, equation variables
(Sriratana, 2018)	Improving the efficiency of door frame manufacturing process in the wood manufacturing industry using takt-time KPI	Production methodology (discrete), dimension (time), type (product), formulae, equation, equation variables, audience (operator)
(Nallusamy and Majumdar, 2017)	Enhancement of OEE using TPM in the manufacturing industry	Production methodology (discrete), dimension (time, quality), type (product), formulae, equation, equation variables
(Chien *et al.*, 2005)	Defining time goals in a semiconductor foundry industry using cycle time KPI	Production methodology (batch), dimension (time)
(Amrina and Yusof, 2011)	KPIs for sustainable manufacturing evaluation in the automobile industry	Production methodology (discrete), type (product), dimension (time, quality, cost, environmental, social), form (lagging, leading)
(Marr, 2009)	Designing performance indicators	Type (product, process, resource), dimension (time, cost, quality)
(Latorre, Roberts and Riley, 2010)	Development of a systems dynamics framework for KPIs to assist project managers' decision-making processes in the construction industry	ER model
(Friedrichs, 2013)	Assessment of meaningful KPIs for the use of energy in European companies	Timing (real-time, perioral), production methodology (discrete), type (process, resource), dimension (time, cost, quality)
(Taylor, 2016)	KPI selection support for global product development	Type (product), dimension (quality)
(Kaganski *et al.*, 2017)	Implementation of the KPI selection model as part of the Enterprise Analysis Model (EAM)	Timing (real-time, periodical, on-demand), the audience (operator, supervisor, manager), dimension (time, cost, quality)

(Giegling *et al.*, 1997)	Implementation of OEE KPI in the semiconductor manufacturing facility	Production methodology (batch), ER model
(Lindberg *et al.*, 2015)	KPIs to improve industrial performance	Production methodology (discrete), type (product, process, resource), dimension (time, quality), formulae, equation, equation variables
(Schmidt *et al.*, 2016)	Implementing KPIs for energy efficiency in a pharmaceutical manufacturing company in Australia	Production methodology (batch), ER model, type (process)
(Chan *et al.*, 2006)	Managing uptime, cycle time, and downtime KPI using integrated production control system in foundry wafer fabrication industry	Production methodology (batch), dimension (time), formulae, equation, equation variables
(Lepratti *et al.*, 2013)	Introducing flexible manufacturing control in manufacturing shop floors using dynamic cycle time KPI	Production methodology (discrete), timing (real-time, periodical), ER model, dimension (time), formulae, equation
(Janakiram, 1996)	Fabrication cycle time reduction at Motorola's advanced custom technologies center	Production methodology (batch), dimension (time), equation variables
(Zhu *et al.*, 2017)	KPIs for manufacturing operation management in the process industry	Timing (real-time, periodical, on-demand), production methodology (batch), ER model, type (process), dimension (time, quality), formulae, equation, equation variables
(Meier *et al.*, 2013)	Assessing the planning and delivery of industrial services using KPIs	Production methodology (discrete, batch, continuous), type (product, process, resource), ER model
(Gonzalez *et al.*, 2017)	KPIs for wind farm operation and maintenance	Production methodology (discrete), dimension (time, quality)
(Kumagai *et al.*, 2017)	Using ISO 22400 standard for KPI element information modeling	Production methodology (discrete, batch, continuous), type (product, process, resource), ER model, dimension (time,

		cost, quality), formulae, equation, equation variables
(Lanza and Mourtzis, 2015)	Operational KPI evaluation framework within manufacturing industries	Production methodology (discrete), type (product, process, resource), dimension (time, quality), formulae, equation, equation variables
(Amrina and Vilsi, 2015b)	KPIs for sustainable manufacturing evaluation in the cement industry	Production methodology (discrete), type (product), dimension (time, quality, cost, environmental, social), form (lagging, leading)
(Mohammed and Bilal, 2019)	Manufacturing enhancement through reduction of cycle time using time-study statistical techniques in the automotive industry	Timing (real-time, periodical, on-demand), production methodology (discrete), audience (operator, manager), type (process), form (leading), dimension (time)
(Rohana, Effendi and Mohd. Razali, 2008)	Using KPIs as a performance measurement tool in an aerospace manufacturing facility	Production methodology (discrete), ER model, type (product, process, resource)
(Kolte, 2017)	Implementing effective preventive maintenance strategies to improve machine operational availability	Production methodology (discrete), dimension (time, quality), formulae, equation, equation variables
(Roberts and Latorre, 2009)	KPIs in the UK's construction industry	Production methodology (discrete), dimension (time, cost, quality), type (product, process, resource), form (lagging)
(Khan and Bilal, 2019)	Literature survey about elements of manufacturing shop floor operation KPIs	Timing (real-time, periodical, on-demand), production methodology (discrete, batch, continuous), audience (operator, supervisor, manager), type (product, process, resource), form (lagging, leading), dimension (time, cost, quality), nature (fundamental, derived)
(Raj *et al.*, 2016)	Optimization of cycle time KPI to solve assembly line balancing problem	Production methodology (discrete), timing (real-time, periodical, on-demand),

		dimension (time), ER model, formulae, equation, equation variables
(Relkar and Nandurkar, 2012)	Optimizing and analyzing OEE KPI in an automobile company through the design of experiments	Production methodology (discrete), dimension (time, quality), formulae, type (product, process), equation, equation variables
(Kibira *et al.*, 2017)	Procedure for selecting KPIs for sustainable manufacturing	Production methodology (discrete), dimension (sustainability), type (product, process, resource)
(Jovan, Zorzut and Znidarsic, 2006)	Utilization of KPIs in production control	Production methodology (discrete), type (product, process), ER model, dimension (time, cost, quality), formulae
(Tugnoli *et al.*, 2012)	Supporting the selection of process and plant design options by inherent safety KPIs	Timing (on-demand), audience (manager), type (product, process), ER model, dimension (time, cost, quality), formulae, equation, equation variables

2.5 Manufacturing Industries Prioritizing Techniques

To sustain in the highly complex business environment, decision-makers have to modify and/or change their priorities frequently. These adjustments in the priorities help them to remain competitive and ensure business continuity. Prioritization becomes critical when everything seems imperative. Typically, any organization or business sets out a list of the task, also termed as requirements to achieve set goals. These requirements consist of measures that enable the organization to ensure business continuity and remain competitive in the current complex market environment. One of the advantages of prioritizing key business objectives and associated KPIs (also perceived as essential requirements) for a manufacturing industry is to help manufacturers streamline the decision-making process. Several techniques/ procedures/ approaches to prioritizing these requirements have been developed in the literature.

Some of these techniques/ procedures/ approaches work most OK on a lesser number of requirements. In contrast, others are suitable for a more significant number of requirements involving complex decision-making. This section mentions assessments of various requirement prioritization techniques/ methods/ approach, such as simple ranking, grouping, five Whys, MoSCoW, bubble sort, value vs. complexity matrix, hundred dollar, SMART, and AHP based on previous literature. Research papers in manufacturing industries are critically studied to select the best prioritization techniques/ methods/ approach. The literature study shows that SMART is the best requirement prioritization technique amongst all the requirement prioritization techniques. An overview of some of these methods applicable to manufacturing industries is mentioned below.

Numerical assignment: is the most commonly used traditional way of prioritizing the requirements. It is grounded on assigning numerical values to the requirements using an ordinary scale. The numeric values are based on the significance of the requirements. For instance, number 1 means that the requirement is significant, and the number *n* means that the requirement is least significant, wherein n denotes the total number of requirements. This method works best for the industries having fixed customers' demands and unvarying manufacturing processes involving simple decision-making capabilities. In this method, it is assumed that the personnel, typical managers, has complete information about the requirements before ranking them with some requirements that are ranked higher on this scale being generic, complex to achieve timely stops the managers from focusing on other less significant requirements that are specific (goal-oriented) and can achieve on-time. Therefore, the prioritization of requirements using a numerical assignment method is rewarding when the requirements are specific and swiftly achievable.

Grouping: this method categorizes the requirements into different priority groups such as high priority, moderate priority, and low priority. For instance, the requirements that significantly impact the overall business performance are placed in a high priority group compared to the least significant ones. The method is analogous to the ranking, wherein different groups replace the ordinary scale. This method assumes that managers have complete information about the requirements and subsequently chosen for grouping. Like the ranking method, if the requirements are not specific and achievable timely, the results generated by using this method will not be productive. Also, if every requirement falls under one group, then this method will not be applicable.

Five Whys: it the simplest method of prioritizing the requirements. It depends on asking the decision-makers repeatedly (at least five times) whether the given requirement is essential for the business continuity or negated/ deferred once the priority is determined. The process of questioning the decision-makers continues until every requirement is ranked according to its significance. The massive dependence on decision-makers makes this method an individual affair, and the outcome generated becomes questionable. It also adds pressure on the decision-makers by repeatedly answering the same question (up to five times). This method applies to a fewer set of requirements employing simple decision-making competencies.

MoSCoW (Museum of Soviet Calculators on the Web): this technique prioritizes the requirements based on the MoSCoW framework, which stands for Must, Should, Could and Would, and treated as a group. The requirements must be monitored/ satisfied/ measured to improve business performance and ensure business continuity are placed in the Must group. The requirements in the Must group are considered as time-critical and are given the highest priority. The requirement which is equally important to keep up with business performance is placed in the Should group. The nice-to-have or desirable requirements that are not time-critical and placed in the Could group, and rest all the requirements currently least significant for the business are grouped in the Would group. Like the ranking and grouping method, if the requirements are not specific but achievable timely, the results generated using this technique will not be creditable. Besides, if every requirement falls under one group, then this technique will not be relevant. Also, this method does not introduce sequencing of requirements and lacks planning.

Bubble sort: this is one of the easiest methods for prioritization of the requirements. In this method, two requirements are compared, and the decision-makers decide the criteria for comparison. This comparison is carried out until the decision-makers find out that one requirement should have a high priority over others. The procedure of comparison is continued until the last requirement is appropriately sorted. The outcome of using this method is the list of requirements that are ranked. Bubble sort is a time-consuming method and is often used when the number of requirements is fewer. With no standard rules set based on the comparison, it remains a challenge for all the decision-makers to come to a mutual agreement while comparing and prioritizing the requirements.

Value vs. complexity matrix: this technique involves a balanced approach to business and technology facets of development. The value vs. complexity matrix technique is established, taking into account the Eisenhower matrix. The requirements are distributed into two dimensions: value and complexity, with four quadrants, as shown in figure 14, and are widely used by the project managers to evaluate the requirements of a product roadmap. Requirements that are least problematic but have high value are prioritized. This technique works better than ranking, grouping, and bubble sort as the requirements' complexity is considered while ranking. If all the requirements fall under one quadrant, this technique fails to generate useful results.

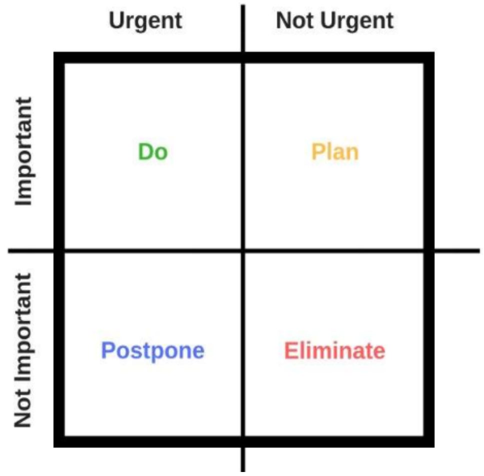


Figure 14 Eisenhower matrix

Hundred dollar: in this method, as the name suggests, every person involved in decision-making are given a conceptual 100 dollars, which they are supposed to be distributed between the requirements. For example, the decision-makers can choose to allocate all 100 dollars to a single requirement or allocate evenly between them. The priority of the requirement is decided based on the number of dollars allocated. Finally, the total dollars allocated by all the decision-makers are accumulated and counted, and the requirements are ranked based on the highest dollars allocated. As this method is time-consuming, it is used when the number of requirements is fewer. Also, the difficulties in keeping track of how much amount has been assigned and unassigned, this method's results are questionable.

Analytic Hierarchy Process (AHP): developed by Thomas L.Saaty, this method defines a complete framework for making accurate decisions in healthcare, manufacturing, business, etc. It is an effective tool for solving MCDM problems and supports the decision-makers to make the best decision by setting priorities. In this method, the requirements are decomposed into smaller sub-problems, which can certainly be analyzed in a hierarchy. Decomposing the requirements helps to capture both objective and subjective features of a decision. As soon as the hierarchy is put together, decision-makers calculate the elements by comparing pairs (sub-problems). With AHP, the total number of suggested comparisons is $n*(n-1)/2$, where n stands for the number of requirements at every hierarchy level. The significance of each element placed in the different hierarchy is decided through pairwise evaluations by the decision-makers and assigned a numeric value (weight). The higher the weight, the significant the element. The pairwise comparison is unreliable from the literature due to the excessive amount of repetition in the correlations.

To decrease the bias in the decision-making process, the AHP method incorporates checking the consistency of the decision maker's assessments. Implementation of AHP can be carried out in three simple steps: calculating the vector of pairwise comparison of weights, calculating the matrix of option scores, ranking the options. Other methods such as Analytic Network Process (ANP) and Analytic Web Process (AWP) are also based on the AHP concepts. Furthermore, many researchers and think tank experts have proved that the results generated using this method are defective and considered as an individual's affair.

SMART (Specific, Measurable, Attainable, Realistic, and Time-sensitive): this technique categorizes the requirements based on SMART criteria. Unlike various other prioritizing techniques, the SMART technique distinguishes the requirements into specific, measurable, attainable, realistic, and time-sensitive; and prioritizes them accordingly. Each element in these criteria works together to generate a sensibly planned, transparent, and trackable goal. Peter Drucker and G.T. Doran were the first to design and implement the SMART technique in the manufacturing industry. A detailed explanation of the SMART technique will be illustrated in section 3.4.

Prioritization requirements for any manufacturing industry can be broadly categorized into three major groups' business aspects, technical aspects, and customer aspects. It has been witnessed from the existing literature that most of the existing techniques, approaches, and methods are incapable of supporting these aspects, which affects the manufacturers' quality of decision-making in the process of prioritizing requirements. When prioritizing the requirements, different factors are related to business, and the customer needs to consider them. These factors include risk, complexity, cost, sensitivity against errors, effort, easy-use, approach type, dependencies, support for consistency index, accuracy, customer importance, type of technique, robustness, result type, time constraint, resources, value, effort, time-complexity, number of comparisons, scalability, expert biases, granularity and size of requirements. Out of all the factors mentioned, the once critical manufacturing industry is scalability, easy-use, time-complexity, accuracy, robustness, and customer satisfaction. Table 5 highlights different techniques and their performance towards the manufacturing-specific factors.

Table 5 Requirements prioritization techniques

Techniques	A	C	E	R	S	T
Analytic Hierarchy Process (AHP)	●	●		●	●	
Attribute Goal-Oriented Requirement Analysis (AGORA)	●	●	●			
Binary Priority List (BPL)			●			●
Bubble sort			●	●		●
Correlation-Based Assessment framework (CBA)	●		●	●		
Cumulative Voting (CV)		●	●	●		
Eclipse Process Framework (EPF)	●		●			
Fuzzy AHP	●	●		●	●	
Hierarchical Cumulative Voting (HCV)	●		●			
Kano analysis		●	●			●
Mathematical programming techniques	●				●	
Minimal spanning tree			●			●
MoSCoW method			●			●
Multi-Criteria Preference Analysis Requirement Negotiation (MPARN)	●		●		●	
Multi-Attribute Utility Theory (MAUT)	●	●			●	
Multi-objective next release problem		●	●			●
Multi-voting system		●	●			●
Numeral Assignment of Numerical Assignment Technique (NANAT)			●		●	●
Pair-wise analysis			●		●	
Planning game combined with AHP	●	●		●	●	
Priority groups			●	●	●	
Purpose Alignment Model (PAM)	●		●			
Ranking		●	●	●		●
Ranking based on product definition		●	●			●
Relative weighting		●	●	●		●
Simple Additive Weighting			●	●		●
SMART	●	●	●	●	●	●
Theme Screening/Scoring			●			●
Top ten requirements		●	●	●		●
Value-Oriented Prioritization (VOP)	●		●		●	
Weighted criteria analysis			●	●		●

S=Scalability, E=Easy-use, T=Time-complexity, A=Accuracy, R=Robust, C=Customer satisfaction

Table 5 shows that existing prioritization techniques are not appropriate for many requirements (scalability issue), making the prioritization process complex. In most cases, the solution obtained from these techniques is not robust. Likewise, complexity is another technical factor that must be considered for the prioritization process, and many of the existing techniques are incapable of addressing it. Also, these techniques have problems such as automation support and inclination to error.

CHAPTER 3 RESEARCH METHODOLOGY

3.1 Introduction

The development of methodologies that explicitly aim to support manufacturers in improving their decision-making capabilities is impacted by the mutual relationship of practical and academic stringencies: *Research stringency:* arises while implementing approaches scientifically not underpinned but applicable in practice (C.R.Kothari, 2004). *Practice stringency:* arises while implementing scientifically rigid approaches but challenging to be practically functional (Goundar, 2000). By combining an extensive literature review on KPI selection techniques, procedures, methods, and practices with an empirical set of questionnaires and structured interviews, this research sets up an effective mechanism to deal with the research and practice stringency and support the rationality of the proposed approach.

This research employs a pragmatic research philosophy that includes both axiomatic and empirical methods. The axiomatic methods incorporate all the traditional and modern KPI selection techniques, procedures, methods, and practices that support the given research. The empirical methods comprise a set of questionnaires and structured interviews, and real-time shop floor data to highlight the key business objectives, challenges, and bottlenecks that need to be monitored to attain the required business performance. These methods are also useful for receiving continual feedback about research advancement (Kapur, 2018).

The overall process which aims to propose a holistic approach for understanding, analyzing, selecting, and implementing appropriate KPIs within the manufacturing shop floor facility is outlined below:

1. Develop a manufacturing shop floor exploration model to identify the key business objectives, problems and challenges, crucial performance details, bottlenecks, and a list of KPIs within the given manufacturing shop floor facility.
2. Develop KPI guidelines by extracting every essential guiding performance measure needed for the manufacturer to understand, analyze, select, and implement appropriate KPIs.
3. Compare the results generated from the manufacturing shop floor exploration model with KPI guidelines to demonstrate the proposed KPI holistic approach's effectiveness.

4. Suggest appropriate KPIs based on data collected from the manufacturing shop floor exploration model combined with KPI guidelines and prioritize the key business objectives and KPIs using SMART criteria.
5. Implement appropriate KPIs in the manufacturing shop floor facility.

It is sensible to indicate that the complete methodology of selecting appropriate KPIs and reviewing the manufacturing shop floor performance is a continuous process. After suggesting and implementing the KPIs, the manufacturers should evaluate the performance regularly. Since, in the current complex manufacturing environment, both internal and external business factors change over time, incorporate those changes, and provide continuous improvement, evaluating the shop floor performance on a regular basis is needed.

The proposed approach is illustrated in figure 15.

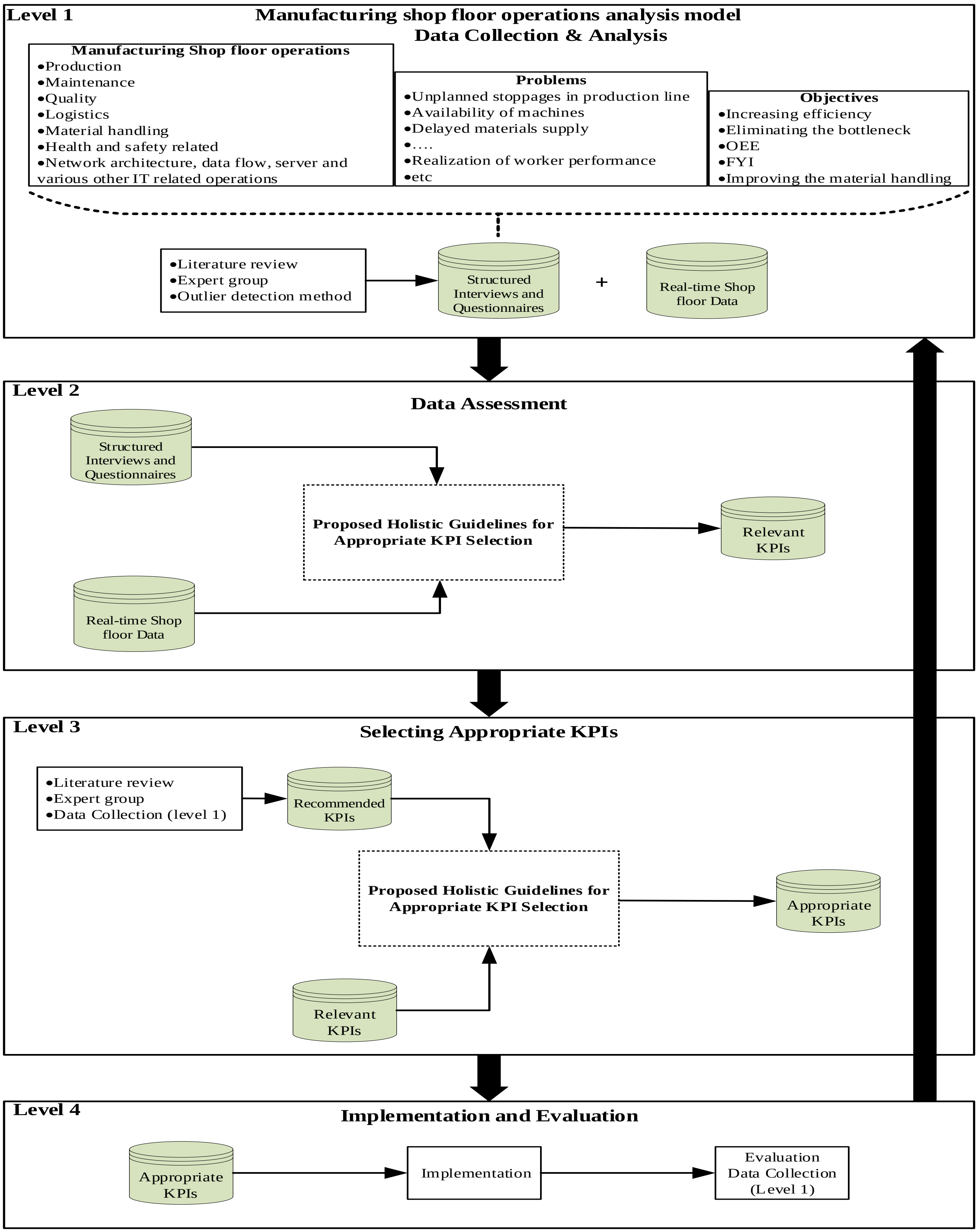


Figure 15 Proposed systematic and holistic approach

3.2 Development of the Manufacturing Shop Floor Exploration Model

Developing a manufacturing shop floor exploration model recognizes the key business objectives; identify the bottlenecks in the manufacturing shop floor facility that negatively impacts the throughput; point out the problems and challenges, and list the KPIs used for monitoring shop floor performance. The proposed model uses questionnaires and structured interviews to collect the required data (i.e., data related to manufacturing shop floor performance) along with the real-time data needed from the manufacturing shop floor. The developed model is shown in figure 16. Furthermore, a procedure for analyzing the raw data by applying weights, sorting, grouping, and feeding in expert group opinions to obtain accurate data for further research is designed in this section.

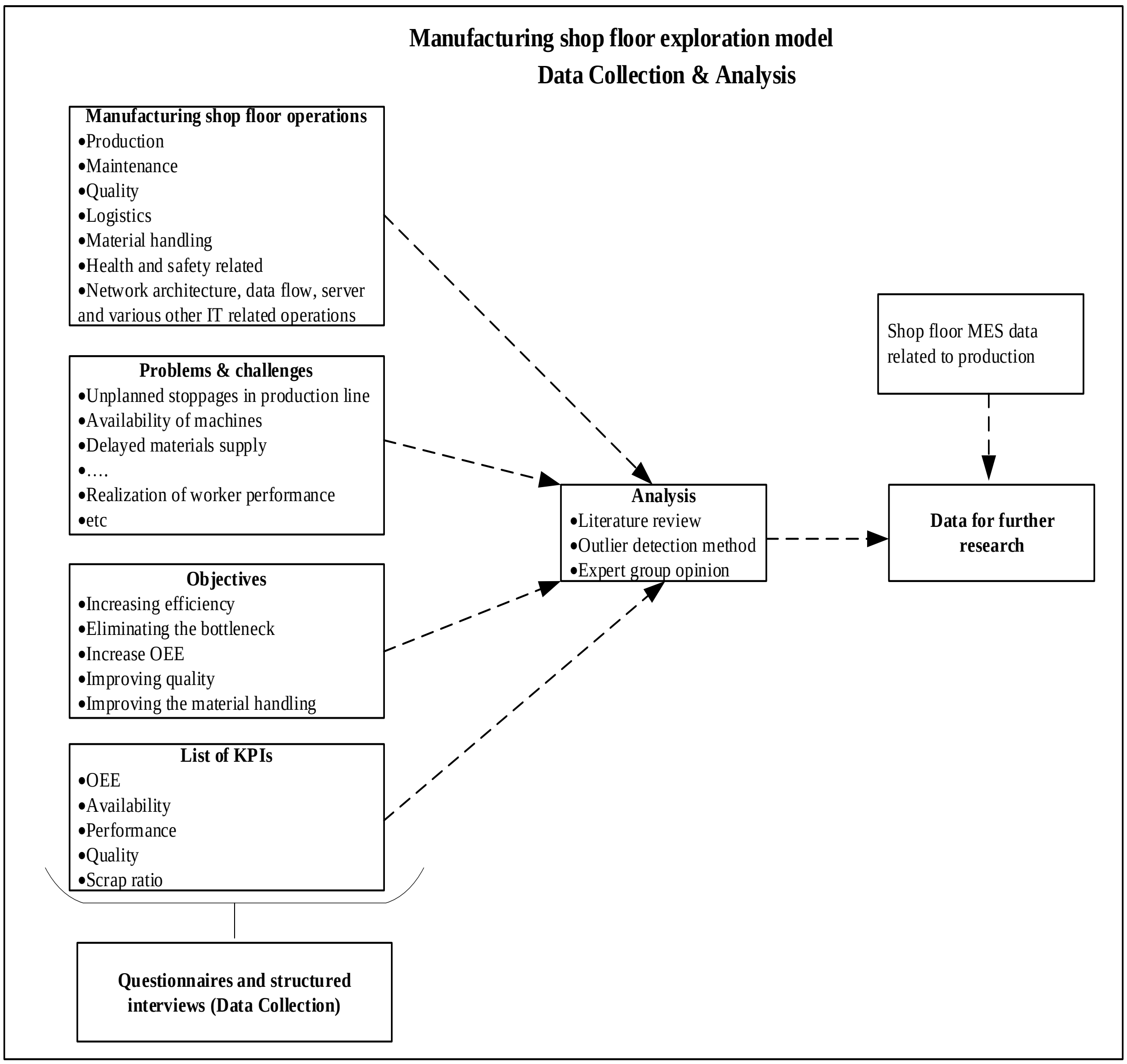


Figure 16 Proposed manufacturing shop floor exploration model

The core of this model is acquiring data through questionnaires and structured interviews. The questionnaires and interviews are designed based on examining over 170 research publications covering KPIs in manufacturing, KPI challenges to improve efficiency, KPI manufacturing effectiveness, performance measurement in the production facility, etc. The complete list of questions (presented through questionnaires and structured interviews) are distributed into several categories, as shown in table 6. In total, 11 categories with 210 questions are designed (helping the manufacturer and the researcher) to acquire the information required about the shop floor. The frequency of questions based on the category is also mentioned in table 6. These questions are designed based on the job roles of the participants. The participants are supplied with those questions that he/she has knowledge, competence, and experience. Developing the questions based on job roles is undertaken to record meaningful information without overwhelming the participants with scores of questions to answer outside their area of expertise and capture detailed insights into the problems encountered while performing their respective jobs (Macdonald and Headlam, 2008). For this proposed research, four job roles were considered: research and development, production manager, production supervisor, and operator.

Table 6 Categories of the proposed questions

Category	Questions
Enterprise name	1
General information	25
Respondent information	3
Mission and goals	27
Production	21
Performance assessment	23
KPIs	35
KPI monitoring	32
Quality management	5
PMS implementation	23
Human resource	15
Summary	**210**

To simplify working with a large set of questions (210 in total), this research employs a simple coding technique (Haradhan, 2017) to assign unique codes to each question. Figure 17 explains the coding style consisting of a string of seven variables. The first three variables are used to highlight the category to which the question belongs; for instance, ENT is used for the category enterprise name (essentially the first three letters in most cases). The next two variables refer to the sequence number of the question in a particular category. The last two variables are used to identify the question's uniqueness, which is either 00 if the question is unique or 01 if it is a clone. The questions were framed so that they can support in achieving the objectives of the given research. Clone questions help to make sure the data collected from the participants are consistent and reliable.

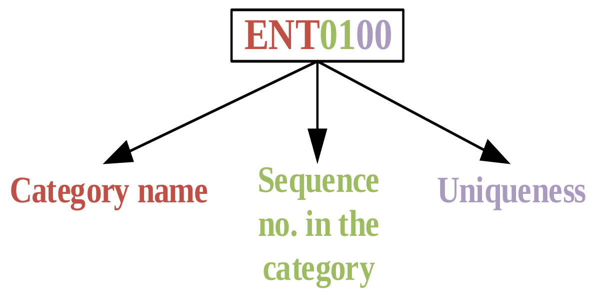


Figure 17 Coding used for designed questions

The questionnaires are grouped into two types: facts-based questions; and situational based questions. Fact-based questions are later used to compare the answers directly with the extensive literature review containing similar reported trends/ surveys/ opinions and analyze them. The answers to these questions are multiple choices; for example, one of the questions modeled for the research and development team is:

What were the main challenges faced in implementing the current KPIs for measuring the performance of the manufacturing shop floor?

Tick all relevant

- Lack of available data
- Fragmentation and incompatibility of data
- Lack of finance/funding
- Lack of staff resources
- Lack of knowledge/skills
- Lack of guidance / best practice
- Lack of co-operation with interested parties
- None
- Other (please specify____)

Whereas the situational based question is focused on recording the problems appearing inside the manufacturing shop floor facility and the manufacturers' actions to resolve them. The situational based question will help the manufacturers and the personnel involved in conducting the survey (i.e., interested in selecting and implementing KPIs) to understand the specific problems or issues within the shop floor and the ways employed to overcome them. The questionnaires' response is collected manually or based on the participants' preference. Still, when the whole survey is concluded, all the data collected is transferred to a university secured web server. The online data available is much easier to analyze, manipulate, and access than the data available on paper. Also, data available in the database will increase the possibility of making quick decisions in less time.

Moving forward from questionnaires, structured interviews were conducted to scrutinize further the data collected through questionnaires, emphasize the problems faced specific to the job roles while delivering their task, understand the existing performance measures, and link to achieving business objectives. An example question modeled for a production supervisor working within the manufacturing facility is: *Are the existing KPIs helpful in monitoring the current production performance to achieve the production target?* This question aimed to know from the supervisors' perspective on the effectiveness of the existing KPIs in achieving business objectives. Questions for the structured interviews are focused and targeted for a few participants from each job role.

The structured interviews are categorized into three main themes set out by Gabriele Beissel-Durrant, with each theme containing a set of structured questions (Gabriele Beissel-Durrant, 2015). The first theme covers the business context, helping to ascertain the manufacturing company's key business objectives and aligning them with the data acquired through the questionnaires needed for validation purposes. It also enables the personnel surveying to ensure the accuracy and quality of the information collected through questionnaires. The second theme is about manufacturing shop floor exploration, assisting the person in realizing the state of the art of current shop floor operations, various KPIs employed for performance measurements, and underlying weak spots that need attention. The emphases of the third theme are KPI selection, design, and implementation. This theme will investigate relevant approaches, methods, techniques, and models. The results generated from the structured interviews benefit this research in comprehending the main underlying problems within the manufacturing facility, investigating the usefulness of the existing KPIs and challenges faced by manufacturers in analyzing and implementing various performance measures.

The questions are designed to cover most of the shop floor's critical areas such as inventory, workforce, energy consumption, performance monitoring, environmental, and sustainability, distributed into various categories (refer to table 6). However, it does not cover financial, health and safety, which is well thought-out as future work (or limitation) for this research. To summarize, the questionnaires are intended to highlight key business objectives, identify the weak spots, problems, and challenges the manufacturers to face, and list the KPIs employed to monitor the performance. In comparison, structured interviews are used to capture a detailed understanding of the manufacturing shop floor performance assessments and link the existing KPIs with the current business objectives to monitor the shop floor performance better.

Besides, real-time data related to production collected directly from the shop floor MES helps highlight the weak spots within the shop floor facility and check the validity of the data collected through questionnaires and structured interviews. The real-time data includes production time, cycle time, production capacity, OEE, etc., mainly depending upon the business objectives. The real-time data can help validate the data collected through questionnaires and interviews, as mentioned in the case study mentioned in chapter 4, section 4.4.5. To provide additional effectiveness to the given research and eliminate any misinterpretations, right from designing the questions to analyzing the data, the study is carried out under the guidance of an expert group comprising professionals from academia and industry. The group consists of five experts from academia and five from the industry; the information is mentioned in table 7.

Table 7 Expert group information

Expert	Experience	Role
1	33	Professor at University of Warwick
2	25	Associate Professor at University of Warwick
3	21	Associate Professor at University of Warwick
4	19	Researcher at the University of Warwick
5	11	Specialist in the field of production, design, and implementation
6	33	Specialist in the field of production, design, and process development
7	27	Specialist in the field of production optimization
8	17	Specialist in the field of production development
9	15	Research and development officer for production design and implementation
10	13	Production manager

Once the raw data is collected through questionnaires and structured interviews, the procedure for analyzing the answers is outlined below:

1. Acquiring the data (answers) from the university webserver
2. Applying weight to the answers based on their significance
3. Sorting the data
4. Modifying the weight by multiplying it with the reliability index
5. Forming new groups and using Cronbach Alpha to test the consistency

Outliers in the data arise due to inconsistencies in responses, for example, inconsistencies in answers to unique and clone questions. These outliers can also occur due to incorrect responses filled in by the participants. These outliers can have a critical impact on research outcome, therefore using the procedure mentioned above for analyzing the raw data, these outliers are removed. The first step in analyzing the raw data is by applying weights to the responses based on their significance to the study by the person conducting the survey. To determine each response's effect on the situation defined in the question, the index of significance using a 1-5-point scale is applied. In the 1-5-point scale, 1 represents highly insignificant, and 5 donates highly significant (Emerson, 2017). In simple words, the questions with the highest average significance value should be analyzed first. The full scale is publicized in table 8. The significance of the questions varies from one study to another and depends on conducting the survey. For instance, if the study's definition does not deal with shop floor inventory-related issues, then the questions related to it are considered insignificant and vice-versa.

Table 8 Point scale

1	Highly insignificant
2	Slightly insignificant
3	Neutral
4	Slightly significant
5	Highly significant

In the next step, sorting the data based on clone questions is carried out. If the clone and original question's response differs, then those questions' data are not considered. One of the central notions behind setting-up clone questions is to check if the participants fully understand the concepts described in the questions. Since clone questions are the reworded question, if the participants fail to answer both the original and clone questions, all the participants' responses will be unreliable and deleted from further data analysis. The data related to any incomplete questionnaires is also deleted in this step.

After sorting, the next step is to introduce a reliability index. Depending on the participant's position within the manufacturing facility and his/her experience and influence on the decision-making, the reliability index is introduced. In this research, the reliability index is used to define the trustworthiness of the answers and is calculated as:

$$Reliability\ index = \frac{P_{ECP} * P_{YEC} * P_{TGA}}{100}$$

Where, P_{ECP} −participant's experience in the current position; P_{YEC} −participant's years of experience in the current manufacturing facility; P_{TGA} −Participants' total experience in the given area, respectively. The reliability index is multiplied with weights to get the modified weights for each answer. The next step in analyzing the raw data is grouping the data after applying modified weights to perform the consistency test. The data is grouped into four groups, with an equal number of respondents. These groups were asked similar questions but structured differently, for instance, 'production did stop due to downtime,' 'downtime did cause production delays,' and 'production delays are caused due to downtime.' A similar answer is expected to these questions; a consistency test is carried out to check the collected data's evenness based on the groups. Cronbach Alpha is calculated to confirm the data's reliability and consistency; if Cronbach Alpha's coefficient is above 0.7, then the responses are acceptable. The group with a Cronbach Alpha value coefficient of less than 0.7 is not selected for further data analysis (Taber, 2018).

Since the manufacturing shop, floor exploration model supports acquiring all the essential information about the manufacturing facility, the results generated through this model identify: key business objectives, problems, and challenges that negatively impact the throughput and a list of KPIs used for monitoring the performances. The model should be seen as a vital tool that can help the manufacturers reduce their time required to conduct similar shop floor analyses and moderating the research group's size. Combining this model with the proposed KPI guidelines (section 3.3) can help the manufacturers make accurate decisions. Simultaneously, select appropriate KPIs for their shop floor operations, link their business objectives with the KPIs, improve their manufacturing performance, and effectively monitor weak spots.

3.3 Developing KPI Guidelines

To address the research gap mentioned in the literature review that there is no framework or methodology to systematically, methodically, and/or scientifically select KPIs for a manufacturing facility, a KPI guidelines approach is developed to guide the manufacturers, analyze and select appropriate KPIs systematically. Table 9 lists the current problems and industrial needs addressed through this research (Woolliscroft et al., 2013; Almeida and Azevedo, 2016; Collins et al., 2016; Kibira et al., 2018; Khan and Bilal, 2019). The guidelines are developed by considering every possible KPI measure and their corresponding elements from the extensive literature conducted in Chapter 2. These KPI measures and elements are already discussed in Chapter 2. To avoid repetition, only the importance of using those measures and their elements is provided in this section. Elements are the relevant measurements used for categorizing KPIs.

Table 9 Problems and industrial need addressed through this research

Problems related to KPIs	Industry need	Gaps addressed through the research
1. *Lack of KPI understanding*, which leads to failure in reporting and monitoring critical performance measures 2. Selected *KPIs fails to establish a connection* with the business objectives 3. *Excessive KPIs* selected for monitoring purposes, further weakening the main focus on business objectives	Need a methodology that can guide them to select appropriate KPIs for their shop floor operations assessment systematically	Development of a holistic KPI selection approach that can systematically guide the manufactures and decision-makers to understand, analyze, and select appropriate KPIs

The proposed KPI guidelines are presented as a step-by-step guide consisting of five stages, namely: information stage, discernment stage, scheming stage, the origin of the data stage, and assisting technology stage. Every stage consists of different measures and corresponding elements which provide indicative information about the KPIs. The proposed KPI guidelines are illustrated in figure 18. The idea behind choosing a step-by-step approach is to lay a strong foundation of KPI understanding without overwhelming the manufacturers with all the guiding information simultaneously. Moreover, to effectively address the current industrial needs, it is deemed necessary for the manufacturers to acquire a basic (general) understanding of the KPIs before sequentially obtaining detailed aspects (i.e., by following different stages). The approach will help impart KPIs' knowledge, starting from providing essential to precise details as needed by the manufacturers.

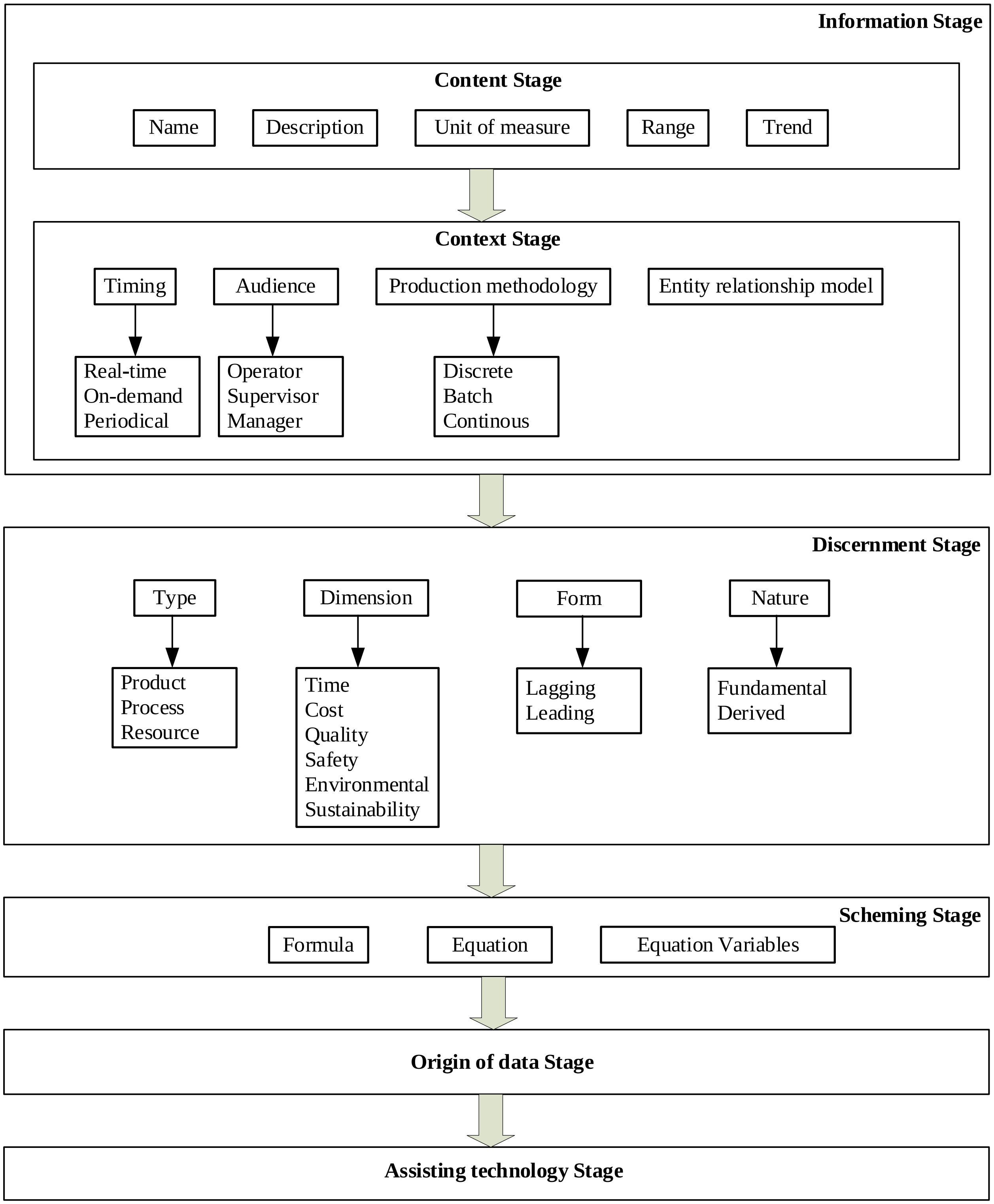


Figure 18 KPI guidelines

3.3.1 Information Stage

The purpose of this stage is to enable manufacturers to acquire necessary information, which is also regarded as fundamentals of KPIs from the relevant international standards and literature review (chapter 2). This stage is further divided into two sub-stages: content and context stage, as shown in table 10 and table 11. The reason for dividing the information stage into two sub-stages is to support the manufacturers by first guiding them in knowing what a KPI encompasses (contain stage). Its explanation comprises a list of measures, such as name, description, unit of measure, range, and trend. The detailed explanation of each of these measures is provided in table 10 and then proceeds by providing an accurate understanding of various applicable situations for KPIs contemplation. These contemplations are the KPI measures listed in the context stage, such as timing, audience, production methodology, and an Entity-Relationship (ER) model. The measures consist of corresponding elements that are explained in table 11. The purpose of selecting these measures for the information stage is mentioned in chapter 2.

Table 10 Information-content stage

Content Stage	
Measure	**Detail**
Name	Name of the KPI
Description	A brief description of the KPI
Unit of measure	The basic unit or dimension in which the KPI is stated (Kg, Nm, sec, %, etc.)
Range	Specifies logical limits (upper and lower) of the KPI
Trend	Is the statistics about the improvement direction, for instance, higher is better or lower is better

According to ISO 22400-2 guidelines, in the beginning stage of understanding a KPI, manufacturers must comprehend the fundamental concepts about KPI of their interest (International Standard ISO 22400-2, 2014; ISO British Standards Institution, 2018). From the literature, it is witnessed that more than 80 percent of the manufacturers fail to improve their shop floor performance due to failure in understanding the necessary concepts of KPIs or fail to realize their business objectives (Iuga, Kifor, and Rosca, 2015; Almeida and Azevedo, 2016; Badawy *et al.*, 2016; Kang *et al.*, 2016; Stricker, Echsler Minguillon and Lanza, 2017). Having fundamental knowledge through this stage will help the manufacturers familiarise themselves with relevant KPIs before further consideration.

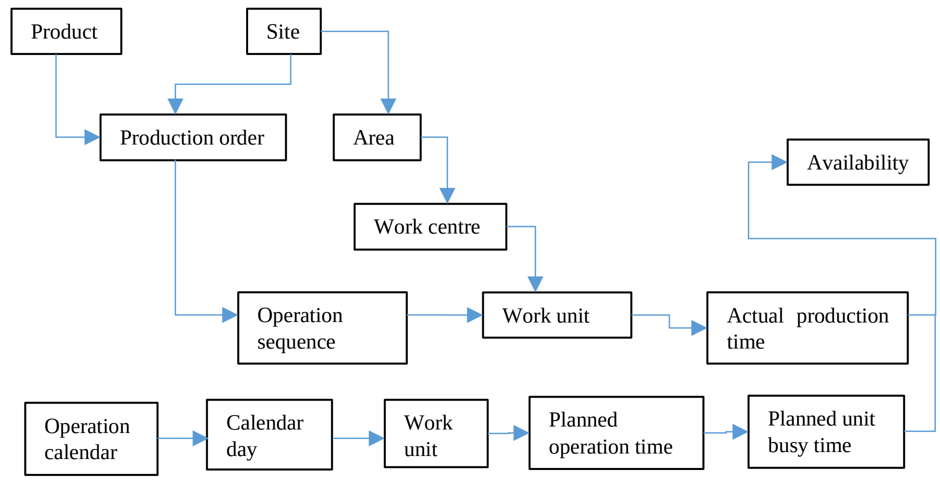
Table 11 Information-context stage

Context Stage	
Measure	**Detail**
Timing	A KPI can be calculated either in *Real-time*- after each new data acquisition event *On-demand*- after a specific data selection request *Periodical*- done at a specific interval, e.g., once per day
Audience	The audience is the user group typically using this KPI. Typically, the audience is: *Operators*- personnel responsible for the direct operation of the equipment *Supervisors*- personnel responsible for directing the activities of the operators *Manager*- personnel responsible for the overall execution of production
Production methodology	Specifies the production methodology that the KPI is generally applicable for: *discrete, batch, and/or continuous*
ER model	The effect model diagram is a graphical representation of the dependencies of the KPI elements that can be used to drill down and understand the source of the element values

For illustration, an example of one of the most used KPI 'availability' is provided in table 12. The information stage, as mentioned in table 12 about availability KPI delivers the fundamental knowledge needed by a manufacturer to know before moving to the next stage.

Table 12 Availability KPI-information stage study

Information Stage	
Content stage	
Name	Availability
Description	It is the ratio between Actual Production Time (APT) to the Planned Busy Time (PBT)
Unit of Measure	%
Range	Min: 0% Max: 100%
Trend	The higher, the better
Context stage	
Timing	Periodical, on-demand
Audience	Supervisor, management
Production Methodology	Discrete, batch, continuous
Effect Model Diagram	



3.3.2 Discernment Stage

The discernment stage covers process specific aspects of KPIs. This stage encourages manufacturers to critically comprehend new or existing KPI's applicability to achieve their desired business objectives. Every critical measure and its corresponding elements covered in this stage provides a high-level mapping of KPIs to set business objectives. The list of measures covered by this stage is type, dimension, form, and nature. Description of each measure is mentioned in table 13 and covered at a stretch in chapter 2. This stage facilitates them to think and question the KPIs cogency in achieving astounding performance by providing their detailed aspects. This stage further aids the manufacturers to know (specifically) which type of measure, for instance, product, process, and/or resource of the manufacturing shop floor, can be improved using specific KPIs. The literature has observed that most managers are unaware of the KPI relevance, resulting in poor KPI selection (Andrej Rakar, Sebastjan Zorzut, 2004; Borsos, Iacob Calefariu, 2016; Taylor, 2016; ISO British Standards Institution, 2017). This stage will help address the KPI relevance issues by providing detailed process-specific insights into the KPIs as underlined in table 13.

Table 13 Discernment stage

Discernment Stage	
Measure	**Detail**
Type	Identification of the element that the KPI is relevant for- *Product, process, and/or resource*
Dimension	Identification of the element that the KPI is relevant for- *Time, cost, quality, quantity, environmental, sustainability, and other*
Form	Specifies the form of KPI-

	Lagging- are typical "output" oriented, easy to measure but hard to improve *Leading*- typically input-oriented, hard to measure, and easy to influence
Nature	Specifies the nature of the KPI- *Fundamental or derived*

Identifying the elements present in each measure to which the KPI is pertinent to an appropriate dimension, form, and nature can benefit manufacturers precisely map their business objectives with the selected (or candidate) KPIs. Additionally, it will allow the manufacturer to focus on an element that can enable them to make quick and informed decisions. For example, suppose the key business objective is improving the quality of the production process. In that case, only the KPIs that have the quality element in dimension measure and process element in type measure can be mapped to achieve the key business objectives. Therefore, this stage gives the high-level mapping of the KPIs with the business objectives. A worked-out availability KPI example for the discernment stage is mentioned in table 14.

Table 14 Availability KPI-discernment stage study

Discernment Stage	
Type	Process
Dimension	Time
Form	Lagging
Nature	Derived

3.3.3 Scheming Stage

After acquiring a vital and thorough knowledge of fundamental, detailed, and process specific aspects of the KPIs using the information and discernment stage, the scheming stage provides additional measures such as equation and equation variable (usually known as data) obtained from the formulae used for KPI calculation, as shown in table 15. This stage will guide manufacturers to understand the data (also known as equation variable) required to calculate the necessary KPIs. For example, the equation variables needed to calculate availability KPI are operating time and the loading time. The stage is essentially seen as exploring the data stage for what type of data needs to be collected to measure a KPI. This stage provides answers to some of the commonly asked and critical questions related to the manufacturing facility's data to calculate a KPI. Responses to 'what type of data would be required to measure a certain KPI' and 'what type of data needs to be collected to measure a KPI' can be answered through this stage.

Table 15 Scheming stage

Scheming Stage	
Measure	**Detail**
Formula	The mathematical formula required to calculate a KPI
Equation	It resembles the formulae used for KPI calculation
Equation variable	The variables present in the equation are termed equation variables

For example, figure 19 elucidates that in order to calculate availability KPI, manufacturers need to know the equation variables such as reference time, loading time, operating time, net operating time, and downtime. Knowing these equation(s) and equation variable(s) will guide the manufacturers to identify if these variables' data exists within their shop floor data model. This stage helps the manufacturers to link their data model(s) with the KPIs of interest, which is, in turn, connected with their business objectives. A worked-out availability KPI example for the scheming stage is mentioned in table 16.

Table 16 Availability KPI- scheming stage study

Scheming Stage	
Formula	Availability = APT / PBT
Equation	APT, PBT
Equation Variable	AUBT, ADOT, AUPT, ADET, AUST

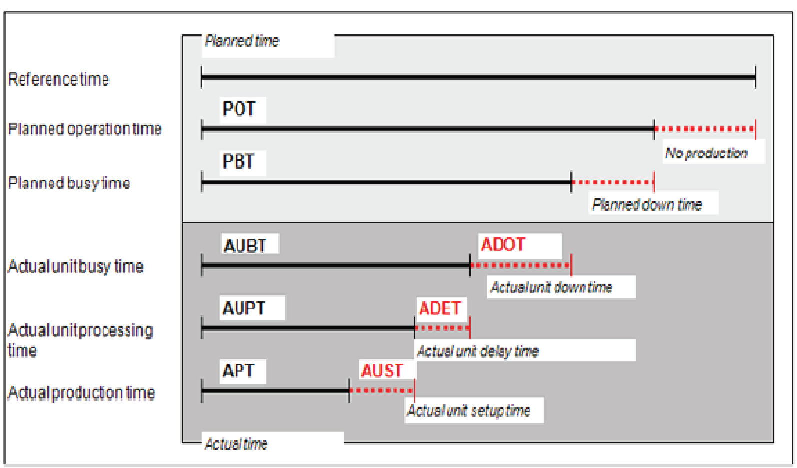


Figure 19 Equation variables for calculating availability KPI

3.3.4 Origin of Data Stage

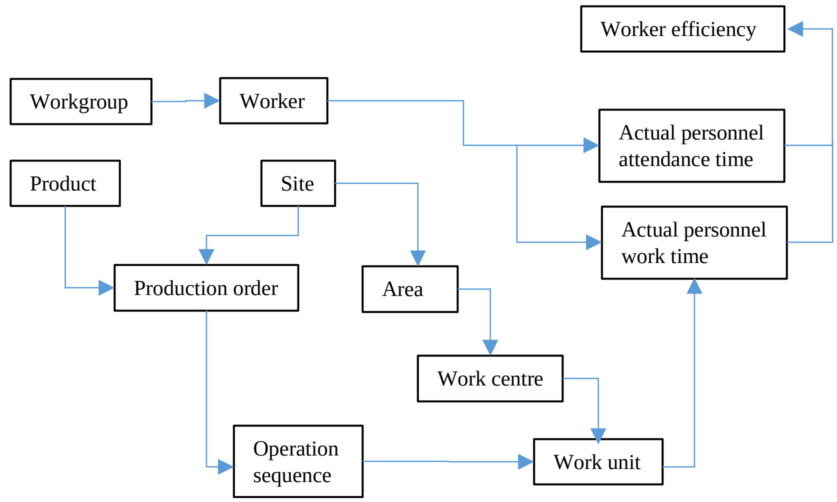
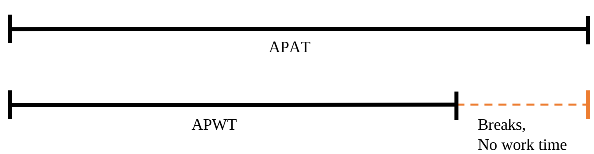
The origin of the data stage helps manufacturers identify the point of origin data within their shop floor. For example, the point of origin can be a Programmable Logic Controller (PLC) used for collecting the data from a station or an energy monitor installed for recording readings of a particular robot. Manufacturers need to identify the origin of the data because it is difficult for data extraction under unexpected circumstances, such as legacy systems. Collecting data from legacy systems remains a challenge. However, with numerous KPIs available, manufacturers may switch to alternative KPIs with different equation variables that do not require data to be extracted from the legacy system (Iuga, Kifor and Rosca, 2015; Rødseth, Strandhagen, and Schjølberg, 2015; Badawy *et al.*, 2016; Kaganski, Majak, and Karjust, 2018). By knowing the origin of the data, manufacturers can decide whether to proceed with data extraction of an individual KPI or look for an alternative.

3.3.5 Assisting Technology Stage

This stage helps manufacturers know the assisting technology applicable for data capturing to collect data swiftly and efficiently. Since cost is a critical factor while deploying technology into the shop floor, this stage aids the manufacturers to decide and then select an appropriate KPI with a reasonable investment in supporting technology (Haponava and Al-Jibouri, 2009; International Standard ISO 22400-2, 2014). For example, to calculate worker efficiency KPI, capturing the worker's operating and idle time is necessary. The worker presence can be captured using various assisting technologies such as RFID readers, camera systems, and motion detectors. Manufactures' can choose a technology that can be quickly and economically deployed and integrated. A worked-out example for worker efficiency using the proposed approach is mentioned in table 17.

Table 17 Worked out an example for worker efficiency KPI using the proposed approach

Information Stage	
Content stage	
Name	Worker Efficiency
Description	The worker efficiency considers the relationship between the actual personnel work time (APWT) related to production orders and the actual personnel attendance time (APAT).
Unit of Measure	%
Range	Min: 0% Max: 100%
Trend	The higher, the better
Context stage	
Timing	Periodical
Audience	Supervisor, management
Production Methodology	Discrete, batch, continuous

Effect Model Diagram	
Discernment Stage	
Type	Resource
Dimension	Time
Form	Lagging
Nature	Derived
Scheming Stage	
Formula	Worker efficiency = APWT / APAT
Equation	APAT, APWT
Equation Variable	APAT, APWT, Break time, and no work time 
Origin of Data Stage	
Manufacturing Execution System (MES)	
Assisting Technology Stage	
RFID reader, camera system, barcode scanners	

After developing the KPI guidelines, the next step is comparing the set of KPIs, as highlighted in the manufacturing shop floor exploration model, with KPI guidelines. It is a simple type of comparison and is conducted in three phases. In phase one, the set of existing KPIs (as known from the manufacturing shop floor exploration model) used for monitoring the manufacturing shop floor facility are studied in the light of the proposed KPI guidelines. Studied means the existing KPIs are elucidated using the five different stages presented in KPI guidelines. In phase two, phase one's study results are equated with the manufacturers' operational and strategic objectives. In phase three, the effectiveness of the existing KPIs towards monitoring the critical manufacturing performance is highlighted. The outcome of the comparison is to obtain a set of relevant KPIs from existing ones. The relevant KPIs are those KPIs which, when studied in the light of KPI guidelines, each measure contained within the guidelines when equated should help to achieve set business objectives. Underline the effectiveness of existing KPIs in monitoring the weak spots and addressing the problems that have a negative effect on throughput.

Once relevant KPIs that essentially helps the manufacturers are figure-out from the previous comparison step. The researcher taking advantage of the immense information available in the literature related to KPIs and the data analyzed from the manufacturing shop floor exploration model, recommends a set of KPIs that can effectively monitor the shop floor performance accounting for the current challenges of the manufacturers. The recommended KPIs are studied using the KPI guidelines making sure that they are indeed helpful to address current business objectives. The recommended set of KPIs along with relevant KPIs forms the appropriate KPIs. The appropriate KPIs are exclusively developed based on a given manufacturing facility, making it more specific and manufacturer centric. The appropriate KPIs are selected in such a way that it helps to monitor all the challenges, problems and future goals addressed by the manufacturers. Also, all those inherent challenges and problems that are gone unnoticed and need attention. SMART criteria are employed to prioritize the appropriate KPIs based on their significance in manufacturing shop floor performance (Mittal *et al.*, 2019).

3.4 Prioritization of Objectives and KPIs using SMART Criteria

Within the complex manufacturing environment, the manufacturers can continue to remain competitive by improving their shop floor performances. The best tactic for enhancement is establishing significant objectives that can foster responsibility and ownership—in basic terms, establishing significant objectives that closely emphasize realizing the desired outcome (Yang, Chang and Choi, 2018). To be substantial and meaningful, this outcome should ideally include five characteristics, namely, SMART, which stands for: Specific, Measurable, Attainable, Relevant, and Time-based (Ezell, 2018). With a holistic approach for selecting appropriate KPIs for the manufacturing shop floor facility, this research also prioritizes those appropriate KPIs based on SMART criteria. The reason for prioritizing is to simplify the efforts of deciding which KPIs should be followed in the first place, to reach the desired shop floor performance effortlessly.

SMART criteria are the best way to keep track of KPIs' planning and implementation phases in the manufacturing facility. It helps in objective setting, i.e., differentiating between realistic and unrealistic business objectives (Sanders, Elangeswaran and Wulfsberg, 2016). The KPIs involved in monitoring realistic business objectives are given higher preference than unrealistic or too difficult to achieve. The goal is to guide the manufacturers to understand, analyze, and implement appropriate KPIs and rank these objectives and KPIs to improve current shop floor performance.

SMART criteria comprise of five steps:

Specific: the objective should be clear, detailed, and as precise as possible. No vague descriptors, uncertain or unclear objectives are not desirable. When these objectives are specified, it becomes convenient for the manufacturers to make informed decisions and perform necessary actions to accomplish desired targets (Kibira, Morris, and Kumaraguru, 2016). A number should be provided, if possible, to specify the objectives. For instance, the example provided in table 18 below provides the best clarity on levels of objective specificity. Example 3 reflects the best way of specifying an objective as it clarifies the production lines and the percentage of improvement needed.

Table 18 Level of specificity examples

Example 1	**Example 2**	**Example 3**
Increase manufacturing facility output	Increase manufacturing facility: production lines 1, 2 & 3 output	Increase manufacturing facility: production lines 1, 2 & 3 output by 5%
Unclear	Better	Best

Measurable: the objectives, targets, or KPIs should be measurable. It offers a means of providing comparative data analysis over a given period. The measure can be qualitative or quantitative, enabling the manufacturers to track their progress in achieving their objectives. Measures should be easily obtainable and accurately reflect present performance. In perspective to measurable KPIs, both leading and lagging indicators should be used to monitor business performance because it will help the manufacturers evaluate the current and future measures to be incorporated in achieving the given objectives (U.S. Department of Health and Human Services, 2018).

Attainable: This is an action-oriented step. It involves creating an action list that reflects all the steps needed to progress from the present state to the desired result. These steps need to be realistic and more straightforward in implementation (MacDonald, 2012). If these steps do not support accomplishing the desired objective, it needs to be re-evaluated and made attainable. For instance, if the manufacturer wants to improve the manufacturing line performance by ultimately reducing the downtime within a week. This will be far too ambitious for the specified time frame, even if the manufacturers establish a Vendor Managed Inventory (VMI) program (Initiative, 2020). To make it attainable, reducing the downtime by 50% or increasing the time frame can help realize this objective. Once this objective has been achieved, and the manufacturers can further reduce the downtime as a part of the continuous improvement effort.

Relevant: the objective should be appropriate, suitable, and useful in improving manufacturing shop floor operations. For example, providing training to all the operators to run every machine installed on the shop floor increases resource availability. Irrelevant objectives are unlikely to be accepted and are considered a waste of effort and time. Evaluating the run-time of a rarely used machine can be viewed as an example of an irrelevant objective (Eleganttheme, 2020). Moreover, every person working within the manufacturing unit should compare and understand how the objectives are relevant to their job roles in improving the shop floor performance. Manufacturers should use relevant KPIs for measuring performance.

Time-specific: objectives defined without time frames makes it unlikely to be achievable. The objectives with a defined time scale provide a possibility for manufacturers to analyze and monitor the progress. It ensures that every person working knows the time scale in which the objective is planned to be measured and realized to develop an appropriate plan (Karl, Roman and Agnes, 2010).

The procedure for prioritizing the key business objectives and KPIs based on SMART criteria:

1. List out all the key business objectives highlighted in the manufacturing shop floor exploration model
2. Implement the SMART criteria and assign weights based on expert group advice and rank the objectives in descending order of their total effective weights
3. Separate the KPIs based on their significance to monitoring the key business objectives
4. Implement the SMART criteria separately to each set of KPIs divided based on their significance to monitoring the key business objectives

The procedure is based on giving preference to the KPIs of key objectives that are realistically achievable in a specified time frame, followed by those that might be unattainable in a given time frame. This procedure's first step is listing all the key business objectives highlighted in the manufacturing analysis model. The next step is implementing the SMART criteria mentioned in section 3.4.1 and assigning weights to each objective, respectively. The weights are assigned using a five-point weight factor, as mentioned in table 19. For instance, a given objective fulfills all the five SMART criteria, the weight assigned to it is the highest. The objective fulfillment using SMART criteria is based on the way they are defined. It is witnessed that sometimes the manufacturers' objectives can be too ambitious and practically unrealistic to differentiate them and give preference to the once achievable weights to each objective.

Table 19 SMART weighing scale

Objectives	**SMART Criteria**					**Applied weights**
	S	M	A	R	T	
1	✓	✓	✓	✓	✓	5 (if the objective fulfills all the five criteria)
2	✓	✓	✓	✓		4 (if the objective fulfills any four criteria)
3	✓	✓	✓			3 (if the objective fulfills any three criteria)
4	✓	✓				2 (if the objective fulfills any two criteria)
5	✓					1 (if the objective fulfills any one criteria)
6						0 (if the objective cannot fulfill any of the five criteria)

After assigning weights, experts are asked to fill in the SMART criteria form (as shown in table 20) for the given objectives. Once the experts fill in the effective weights for each objective, the total effective weight is calculated. Based on the effective weight's decreasing order, the objectives are ranked, meaning the objective with the highest total effective weight is ranked, followed by the next with the second highest weight.

Table 20 SMART criteria weight calculation

Objectives	Effective Weight										Total eff. Weight	Rank
	Ex-1	Ex -2	Ex -3	Ex -4	Ex -5	Ex -6	Ex -7	Ex -8	Ex -9	Ex -10		
1	3	3	3	3	3	3	3	3	3	3	30	1
2	2	2	2	2	2	2	2	2	2	2	20	2
3	1	1	1	1	1	1	1	1	1	1	10	3

In the implementation step, the appropriate KPIs are made available to the manufacturers for their deployment in the manufacturing shop floor facility. All of the above steps are repeated to test the effectiveness of the proposed approach. This approach is cyclic. After implementing the KPIs into the manufacturing shop floor facility, the complete procedure should be frequently repeated. It is to understand the impact of changes in internal and external business factors (due to ever-changing business situations) on the proposed approach's effectiveness. There is a possibility of adjustments in operational and strategic objectives due to a change in the business environment. The appropriate KPIs used to monitor the business performance should also be altered based on the changing business scenario. Therefore, the proposed systematic and holistic approach provides an opportunity for manufacturers to be adaptive and flexible during business situations.

CHAPTER 4 CASE STUDY: IMPLEMENTATION AND EVALUATION

4.1 Introduction

This chapter demonstrates the procedure of applying the proposed approach as described in chapter 3 for understanding, analyzing, and implementing appropriate KPIs within company X. Company X is an automotive seat manufacturer. The case study is conducted on the L494 assembly line within this facility. Firstly, by employing the manufacturing shop floor exploration model, the company X's key business objectives, list of KPIs, bottlenecks, problems, and challenges are acknowledged. Secondly, company X's list of KPIs is evaluated using KPI guidelines to realize the existing KPI's applicability and effectiveness. Thirdly, a set of appropriate KPIs that can enable the company X to effectively monitoring their key performances and achieving business objectives are proposed and evaluated using KPI guidelines. Lastly, the prioritization of key business objectives and appropriate KPIs is offered using SMART criteria.

4.2 Background of Company X

Company X global was founded in 1917 as a manufacturer of welded, tabular, and stamped assemblies for the aircraft and automotive industries. It has grown into a large multinational company providing electrical systems and complete seating worldwide, with an annual turnover of $35.9 billion, company X global ranks among the top 150 in the fortune 500. Company X UK is leading the smart manufacturing initiative for the company globally, focusing on car seats. Company X manufactures approximately 200 support staff and 2000 workers across three UK plants in the UK. This company's success is due to its strong commitment to providing outstanding services to the world's automakers and customers. It manufactures seats for various car brands, with its primary customer being Jaguar Land Rover (JLR) in the UK. In company X, every component required to produce a seat is pre-assembled in sub-assembly lines. The final seat is primed and assembled on the assembly line within their manufacturing facilities.

Figure 20 presents a block diagram representation of an assembly line with a list of inputs and output. The assembly line inputs are fetched from the sub-assembly lines, and inputs to this sub-assembly line are the raw materials that are initially assembled based on the seat requirements before their final assembly.

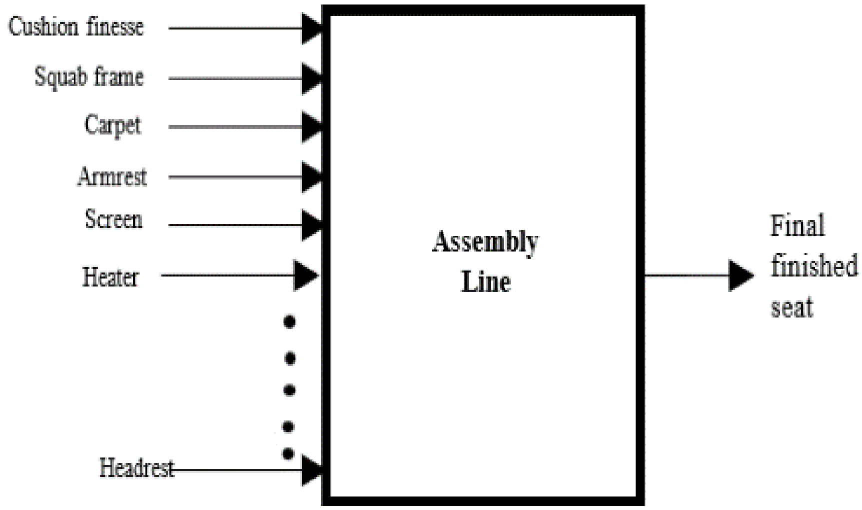


Figure 20 Snapshot of an assembly line with a list of inputs and output

Every seat that is manufactured in these assembly lines includes various seat features and identifiers, such as model number, drive type, model year, country name, the carpet type, rear frame type, heater type, articulation type, screen type, speakers type, armrest type, lumbar type, headrest type, and foot-well lamp type. These seat features are based on the customers' requirements. The detailed product process flow is mentioned in section 4.3. The master layout of company X consists of sub-assemblies, assembly, test and inspection, and rework lines, as illustrated in figure 21. Where ***A*** denotes sub-assembly lines, ***B*** denotes final assembly lines, ***C*** denotes test and inspection line, and ***D*** denotes rework line. Sub-assembly lines are responsible for manufacturing the parts passed to the final assembly lines to produce the finished seat.

Each finished seat is transferred to test and inspection stations, where various electrical and resistance tests are conducted to certify that the seat meets the necessary quality and safety standards. Seats that are not able to pass these tests are moved to the rework line for rectification. The case study is conducted on one of the final assembly lines (B), the L494 assembly line. This line assembles seats for Jaguar and Land Rover models such as the Land Rover Discovery, Range Rover Evoque, Range Rover Sport, Jaguar XE, XJ I-Pace.

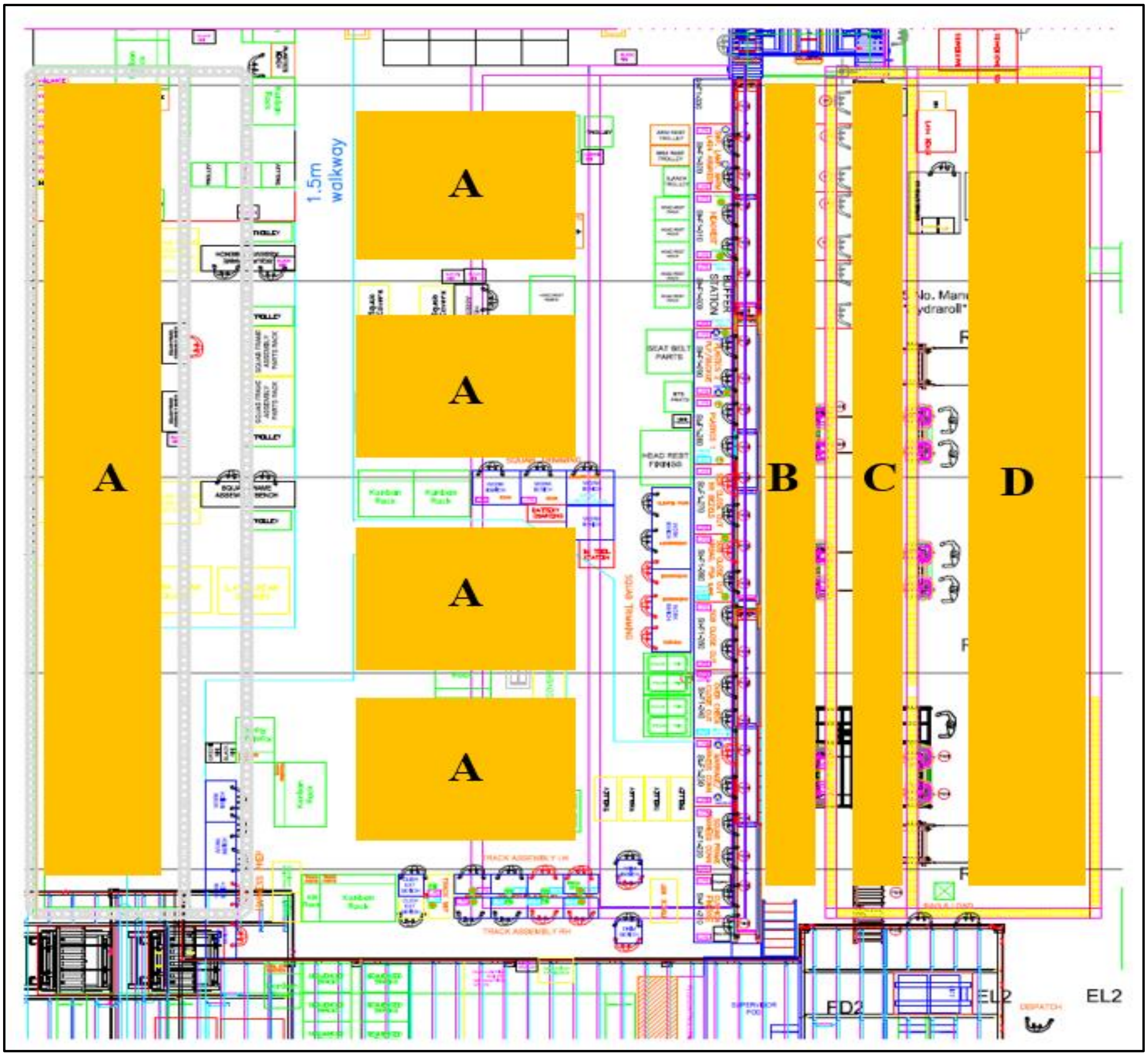


Figure 21 Company X production line layout

4.3 L494 Assembly Line Process Flow

The L494 assembly line consists of 13 stations, with each station having a specific task to be undertaken in assembling the final seat. These stations involve manual processes, machines for material-handling, conveyors for continuous movement of pallets and components, and buffers conveyors to link stations. This assembly line is a typical example of a sequential and intermittent line that does not produce identical products due to the highly customized nature and a wide variety of seat options. Intermittent assembly lines are primarily known for facilitating quick assembly of equal parts while leaving room for customization. Every station in this assembly line has a process to undertake based on its requirement. Due to the high level of complexity involved in seat manufacture, the operations carried out at the stations are mostly manual and vary with seat specifications. The purpose of each station, with quick process steps, is mentioned in table 21.

Table 21 Process flow of L494 assembly line stations

Stations	Purpose	Process steps
STN1	Cushion finesse	1. Lift sequenced track from the input buffer and transfer to mainline. Carefully place the track in a pallet (RH seats on LHS and LH seats on RHS) 2. Lock track into place using locking mechanism of build pallet 3. Remove build ticket and aside to center of the pallet 4. Steam finesse cushion 5. Wipe dry cushion cover 6. Finesse cushion cover fit
STN2	Squab frame	1. Get next sequence squab frame from WIP 2. Present the SQB frame to the LH seat track, align the tabs on either side to the locators on the track and drop the frame into position 3. Scan squab frame sub ticket and then squab frame 4. Position and hand-tighten rear outboard marriage bolt with five wrist turns 5. Grab the squab harness, run and untangle the recline motor lead; connect to the recline motor
STN3	Marriage	1. Secure the fir tree clip on the squab recline lead onto the gutter pressing, above the first one 2. On the airbag lead, secure the center fir tree clip (with tab) to the back of the gutter pressing 3. Secure the third fir tree clip to the lower outboard side of the gutter pressing 4. Get the DC angle tool and fasten the front outboard marriage bolt to 50.0±2.5N.m; confirm tool status for OK fixing
STN4	Squab trim	1. When the four marriage bolts are completed in LPS using the DC Angle tool, there is an over the check of these bolts using a clicker wrench. 2. Grab 50 Nm clicker wrench and over-check front outboard marriage bolt; mark with chinagraph pen 3. With 50 Nm clicker wrench over-check rear outboard marriage bolt; mark with chinagraph pen

		4. With the right hand, grab and hold the airbag chute, and with the left hand, grab the outer side of the foam; lift squab trim above the frame and partially slide it down 5. Guide the top end of the squab foam over the top of the frame, pushing down on the top of the squab 6. Guide the outboard side of the foam over the frame together with the airbag and continue arranging the foam over the frame. Ensure the outboard pull chord is clear and drops in front of the suspension mat 7. Grab the top end of the inboard pull chord, pull it upwards, and feed hook end through inside the hole on the squab frame
STN5	Heater/ connections	1. Grab the heater mat connector on the squab and manually attach it to the heater connector 2. Guide the connection down the gutter, pressing and clip the anti-rotation fir tree clips into place on the inside of the gutter pressing 3. Grab the fir tree clip adjacent to the heater mat connection and secure it to the inside of the gutter pressing 4. Locate bellows in foam sub-assembly through the squab suspension mat, connecting it to the upper and lower wires as shown 5. Guide the massage connector down the gutter and into the location for connection 6. Push the webbing through the bite line and feed it through; pull the bottom J out through the back of the seat
STN6	Airbag	1. Grab the DC tool and place the bit onto the upper airbag nut. Fasten the upper nut to 7.0 ± 1.0Nm and confirm tool status for OK fixing 2. Position the DC tool bit onto the lower airbag nut. Fasten the lower nut to 7.0±1.0N.m and confirm tool status for OK fixing; place the tool back in the holder 3. Grab metal trimming hook and pass it through the eyelet on the outboard pull chord (bottom end) - leave hanging 4. Release the metal trimming hook and fit it to the bottom end of the inboard pull chord; leave hanging
STN7	Valance fit	1. Release the fixture rotation lock and rotate the seat 90 deg (the inboard side facing towards you) 2. Pick the next sequenced pair of inner valances, valance carrier (with wire), and BTS cover. Temporarily place the valance carrier on the seat 3. Fit the inner valance to the seat and ensure the inner hook fits over the squab recline mechanism

		4. Ensure excess leather or nylon is not exposed over the seat recliner wheel 5. Get 4 off screws and valance carrier
STN8	Valance fixings	1. Release the fixture rotation lock and rotate the seat 90 deg (the inboard side facing towards you) 2. Remove T30 bit from tool and place on the bit holding plate 3. Grab the T25 bit and fit it to the DC tool 4. Grab the buckle lead, remove the clip holding the cable, dispose of it in the bin and extend the lead 5. Grab the T30 bit and fit it to the pistol type DC tool
STN9	Headrest/PLP connect/backboard	1. Finesse the squab/cushion cover as required 2. Release the fixture rotation lock and rotate the seat 90 deg (seat facing away from you) 3. With 2 fingers, grab the RH headrest bezel and perform a light pull check to confirm it's firmly engaged 4. Check the visual aid on the monitor to confirm the headrest specification; tap the monitor to acknowledge
STN10	Switch pack/ footwell lamp	1. Using DC tool fit wire to track to 8.5Nm -0.5 +1Nm 2. Using DC tool complete armrest fixing 25.0Nm ± 1.0Nm 3. Grab both track locks and pull them forward to release the seat 4. Grab the seat by the front of the cushion, move it forward slightly and tilt it back, so it rests on the 'T' bar 5. Clip the cover into position by lining upfront and then rotating into place, ensuring clips locate correctly into recess
STN11	Finesse2	1. The blow-down ball valve must be locked with the safety bow after blow-down 2. Never point the steam jet at anybody. The danger of inflicting scalding 3. Do not touch the steam valve at the front of the machine. The danger of inflicting burns
STN12	Backboard fit	1. With 40+/-0.6Nm clicker wrench over-check buckle bolt, mark with chinagraph pen 2. Check that the orange tab is fully in using the "Push-Click-Push" check method 3. With both hands located on the lower portion of the backboard behind the retaining clips, firmly push the backboard to engage the clips 4. Repeat the process for RH backboard
STN13	Finesse1	1. The blow-down ball valve must be locked with the safety bow after blow-down

	2. Never point the steam jet at anybody. The danger of inflicting scalding 3. Do not touch the steam valve at the front of the machine. The danger of inflicting burns

4.4 Applying Manufacturing Shop Floor Exploration Model to Collect Complete Information about L494 Assembly Line

Using the set of questionnaires and structured interviews and L494 assembly line production data, the manufacturing shop floor exploration model is used to conduct the survey and collect the complete information of the L494 assembly line, including crucial performance details and key business objectives challenges, problems, bottlenecks, and KPIs. To ensure quick and easy handling of the data, the questions are stored and analyzed on a webserver. The survey consists of 210 questions, as mentioned in section 3.2. Details of the number of participants taking part in the survey are mentioned in table 22.

Table 22 Participant statistics

Participant statistics	Number
No. of participants contacted to take part in the survey	50
No. of participants took part in the survey	45
No. of participants that completed the whole survey	40 (2-manager, 8- research and development team, 4- line supervisors, 26- operators)

The procedure of analyzing the raw data collected for the L494 assembly line is outlined below (please refer section 3.2 for complete details):

1. Data acquisition from the webserver
2. Weight calculation (section 3.2)
   2.1. Apply weight to the responses depending on their significance
   2.2. Adjust the weight by multiplying with a reliability index
   2.3. Sort the responses for the unique and clone questions
3. Create groups for the consistency test
4. Compute Cronbach Alpha to test the consistency
5. Analyze the L494 assembly line production data (MES)
6. Generate of L494 assembly line detailed information

Table 23 represents a final sample matrix of the first 50 responses from the 40 respondents, their reliability index, and applied weights for further data analysis. Implementation of the sorting process on the final matrix's responses is the next step in analyzing the data collected to confirm its accuracy. The collected data's accuracy is higher if the response to the same questions (unique and clone questions) is comparable. These clone questions are also highlighted in table 23.

Table 23 Final matrix for further data analysis

ID	1	6	3	4	3	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
Reliability index	0.48	21.8	1.28	9.6	3.86	14.4	0.64	0.8	3.6	3.24	2.1	0.96	1.2	6.3	7.8	9.2	6.3	11.2	12.6	12.8	12.3	0.21	0.36	12.3	21.2	0.24	0.69	1.36	3.36	9.65	7.85	3.6	3.24	2.1	0.96	1.2	6.3	11.2	2.3	0.02
Questions	Weights																																							
ENT0100	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7
GEN0100	5	4	5	6	2	5	4	5	7	5	7	6	5	7	2	3	6	5	4	3	6	7	7	3	7	7	6	7	4	3	7	6	7	4	7	6	7	3	6	4
GEN0200	7	7	3	7	7	6	7	4	3	7	6	7	4	7	6	7	3	6	4	5	4	5	6	2	5	4	5	7	5	7	6	5	7	2	3	6	5	4	3	6
GEN0300	7	4	3	7	6	7	4	7	6	7	3	6	4	5	4	5	6	2	5	4	5	7	5	7	6	5	7	2	3	7	6	5	7	2	3	6	5	4	3	6
PAS0100										7			5	6	2	5	4																			5	4			
PAS0200		7								2			3	7	7	6	7										7	7	7							6	7			
PAS0300		2								6																	7	4	7											7
PAS0400		6			7	7	7			4		7	7	7		3	6	7									7	2	3			7								2
PAS0500		4			7	4	7			2		7	4	7		7	3	5									7	2	3			2				3				6
PAS0601		2			7	2	3			7		7	7	3		7																6				3			2	3
KPI0100		7			7	2	3					7	2	2	6	2											1					4				2	3	6		
KPI0200	7									7			3	7	4	6											4					2				6	7	3		
KPI0300	7			1						2						4	5	6									2		7			7								
KPI0400	7			4						2	3		1			2	3	7									3		2		7	6								
KPI0500	5			2	5	6	2	5	4	2	3		4		1	7															2	7				2	6			
KPI0601			1	3	3	7	7	6	7				2		4															7	6					7	4			
KPI0700			4	6			2	3					3		2											2	5	4		2	4									
KPI0801	7		2				2	3				7	7		3											7	6	7		6	2									
KPI0900	2		3						1			2	2		6		7	7												4	7						5	6	2	5
KPI1000	6		6						4			6	6				7	4								7	2	3		2		1					3	7	7	6
KPI1100	4		5			1			2			4	4				7	2								7	2	3		7		4								
KPI1200	2		4			4			3			2	2				7	2														2								
KPI1300	7		7			2			6		7	7	7																			3								
KPI1401	5	6	2	5	4	2	3			7	2	5	6	2	5	4										2	5	4				6								
KPI1500	3	7	7	6	7	2	3	7		5	6	3	7	7	6	7										7	6	7												
KPI1600								2	1	4	4																													
KPI1701					2	2	6	6	4	4	2																									7	2	3	6	
PMS0100					3	7	4	4	2		7		1			7		7												7		7				7	6	7	3	7
PMS0200	7							2	3				4			4		2												3		5								2
HRM0100	2							7	6		7		2			7		6						3	6	7				7		6								6
PMS0300	6										2		3			4		4						7	3	5			1	5		2							2	3
KPM0100	4		5	7	2	3	6	7			2	3	6					2											4		2	2							2	3
KPM0200	2		4	7	6	7	3	5			2	3						7											2		3	7								7
KPM0300	7							7			2							7									2	3	3	1										
KPM0401								7			7	7	7	7												7	2	3	6	4						5	4			
KPM0500	5	6	2	5	4							7	4	7		7										4	7		7	2		7				6	7			
KPM0600	3	7	7	6	7				7			7	2	3		2										2	3		2	3		2								
KPM0701						7			2			2	3	3		6										2	3		6	6		7						7		
KPM0800			1			7			6			2	3			4													4			2						2		
KPM0900			4			3			4					1		2		3	6	7									2		2	3						6	7	1
KPM1000			2			6		7	2	2	6			4		7		7	3	5									7		2	3						4	4	4
KPM1101			3					7	3	7	4			2		6									3	6	7	7	4	7		2				6		2	7	2
KPM1200			6					7	2	3				3											7	3	5	7	2	7		7				3		7	4	3
KPM1300								7	2	3				6				5										7	7	3										6
KPM1400		5	6	2	5	4						4	2	6	1			3										7	2	3						2				
KPM1501		3	7	7	6	7						3	7	4	6											6	2	5	4							6				
PRO0100	4						2	3		1			2	3	7	4	7		7	4	7		7	2		7				6	7			7	2			2	3	6
PRO0200	2	5	6	2	5	4	2	3		4		1	7		7	2	3		2	2	3		2	3		2								7	2			6	7	3

The sorting process was 95.63% accurate, meaning that almost all the respondents recorded similar responses to unique and clone questions. The 3.37% inaccurate data is removed from the final matrix for further data analysis. The data collected in the final matrix is distributed into four groups, with ten respondents in each group. The respondents within each group are evenly divided based on their job role to check the consistency of the data collected by calculating the Cronbach Alpha, as illustrated in table

24. According to Cronbach Alpha's theory, the data is consistent and reliable if Cronbach Alpha's coefficient is 0.7 and above.

Table 24 Cronbach Alpha coefficients for each group

Group No.	Questions asked	Number of respondents	Cronbach Alpha
Group 1	65	10	0.897
Group 2	65	10	0.866
Group 3	67	10	0.877
Group 4	63	10	0.929

Table 24 shows that the results of groups 1, 2, 3, and 4 are consistent as Cronbach Alpha's coefficient is above 0.7. As a result, the responses recorded by all the participants are consistent and reliable. The results of the survey conducted are presented in sections 4.4.1-4.4.4.

4.4.1 Crucial L494 Assembly Line Performance Details

The current production rate of L494 is 230-245 seats per shift. This production rate is flexible for up to 5 extra seats per production shift to accommodate unpredictability in production orders. The production rate is calculated theoretically based on the sequence of the operations that need to be undertaken to complete a given order. Since this assembly line is sequential, the takt-time is set to about 98.5 seconds. The duration of takt-time is based on the longest cycle time recorded by any station amongst a total of 13. Due to the assembly line's intermittent nature, the total number of operators required is 26, i.e., two operators per station: a line supervisor and a manager per shift. The line is operational 15 hours per day and comprises 2 shifts per day, with each shift works for 7.5 hours. From the total finished seats manufactured per production shift, 1-2 seats were expected as a variance for further rework for failing the standard safety tests. Currently, 17-23 seats are ending up in the rework station. This highlights the number of problems occurring at sub-assemblies and assembly lines, severely impacting the production order fulfillment window.

The assembly line can make up to 57 different seats based on the customers' demands, and the cost incurred in manufacturing single-seat ranges from £450-£750. The total time taken for manufacturing a seat is about 6.5 hours, measured from the sub-assemblies to clearing the test and inspection station. The fulfillment of a production order takes about 8 hours, starting from when the production order reaches the manufacturing facility, making it exceptionally challenging for the company to deal with any production delays. To avoid production delays, the managers are presently employing additional operators to keep up with the takt-time and increase the rework station's capacity. In summary, the current L494 assembly line fails to cope with the daily production rate and maintain the seats manufactured. The production data collected for this study is for six months (1/09/2019 – 01/03/2020). The reason for selecting this period is to gather enough data to conduct considerable data analysis.

4.4.2 Key Business Objectives

The questions related to company X's key business objectives concerning the L494 assembly line were posed only to the managers, supervisors, and the research and development team. From the data collected, the key business objectives are stated as follows:

Objective 1: Improve the current production rate to 98% to fulfill production orders on time without involving additional workers

At present, the assembly line production rate (83.5%) is much lower than the set production rate (98%), affecting the fulfillment of production orders on time. The set production rate is about 230-245 seats per shift, but the L494 assembly line produces 205-223 seats per shift, 14.5% below target. The research and development team employs line balancing and optimization techniques to calculate the set production rate for order fulfillment based on the production capacity. To maintain the production rate and promptly fulfill the production order, supervisors are often forced to request managers to employ additional operators to finish the orders due to several bottlenecks in achieving the target production rate.

Since the improvement of production rate is critical, line supervisors are continually looking for the causes behind the decrement of the production rate by constantly monitoring several reoccurring problems such as the station(s) unable to complete the process within the set takt-time due to waiting for the seat parts, the operator(s) unavailable, machine breakdown or missing seat parts/tools, etc. With the existing performance indicators, the managers still find it challenging to maintain the production rate and highlight the potential root causes. Therefore, company X requires an appropriate set of KPIs to effectively monitor the production rate and highlight the possible root causes, convincingly helping them achieve their key business objective.

Objective 2: Improvement in seat quality

The quality decides the customer's faith in purchasing the seat. If company X fails to maintain the highest standards of quality, it will lose valuable customers. As a result, company X must maintain the seat's high quality and retain the customer's gratification. In numbers, the L494 assembly line is producing 17-23 bad quality seats against 1-2 seats per production shift, incurring a total loss of £11,250-£13,650 per production shift. The managers and line supervisors want to link a seat's problems failing the quality inspection to specific assembly line station(s) in the assembly line. Swift decisions can be taken to carefully monitor those station(s) to improve seat quality. These problems are listed in section 4.4.4. The current solution employed to enhance the quality of the seat is a reactive, offline measure. Company X waits for the inspection test reports after the production order is complete. It then starts to link the causes of bad quality seats to the station(s) and focuses on improving the next production order but fails to see considerable improvement.

Objective 3: Real-time monitoring of the stations to increase visibility and quick decision-making capability

The L494 assembly line is a sequential intermittent line consisting of 13 stations, with most station-based operations undertaken manually. Real-time monitoring of the stations is considered necessary because any delay(s) caused by the station(s) can make the whole assembly line stop, affecting the production rate and overall line performance. Currently, company X does not have complete visibility of their assembly line. Real-time monitoring can help the company make quick decisions without causing substantial interruptions in production. Deploying appropriate shop floor technology can benefit the company X in the real-time monitoring of the stations to increase visibility, focus on critical areas that need attention, and make quick decisions.

Objective 4: Identifying the bottleneck process within the stations (visibility)

Seeing it as a tactical objective, the line supervisors want to find the bottleneck process within a station, which can then be precisely monitored. In the given L494 assembly line, every station has a series of operations (process or tasks) that must be accomplished within the set takt-time. If a delay arises due to a station, it will be useful to know the process that caused it. Using an appropriate set of KPIs to monitor station-level performance closely will help the manufacturer identify bottleneck processes. More attention can be given to these bottleneck processes arising within any stations and address any potential delays in time. Identifying the bottlenecks is achievable with increased L494 assembly line visibility using industry 4.0, enabling technologies, and an appropriate set of station-level KPIs.

Objective 5 (additional): Workforce wellbeing

With most of the operations performed in this assembly line being manual, it becomes essential for company X to pay attention to workforce wellbeing. Operators who feel engaged and satisfied in their work tend to be more efficient and productive at work. Real-time monitoring of the employee performance, providing training facilitates, and introducing a robust employee development plan to improve the overall performance is one of the long-term objectives set out by company X. Currently, company X has not taken any initiative to address workforce wellbeing. Therefore, this objective is marked as additional.

4.4.3 Challenges

The challenges faced by company X are listed below:

1. *Labour intensive/ shortage of skilled workforce*

L494 line is a typical example of a semi-automatic intermittent assembly line wherein many seat variants are assembled at any given production order/ shift. Presently, this line needs 26 operators to assemble a single finished seat, making it labor-intensive. Managers realize a need for implementing automation and robotics technology solutions that can fill the labor gap. The research and development team finds it challenging to select a particular technological solution due to the nature of the work undertaken within the line. Moreover, the nature of work undertaken to produce a seat won't be easily replaced by machines. An alternative solution is deploying the right performance indicators to monitor and measure workforce performance, and effective workforce management can be attained.

2. *Improving productivity*

Depending upon this assembly line's nature, managers are bound to function under reduced productivity due to consistent problems arising from workforce engagement, failing to keep up with the set takt-time, etc. At present, the productivity of the line is around 73% causing substantial financial losses. The L494 assembly line produces 205-235 seats per shift against 230-245 seats per shift in terms of seats. One of the evident reasons for the reduced productivity, as mentioned by the managers, is that some stations fail to complete their task within the given takt time, affecting the overall takt-time. The challenge is monitoring real-time productivity using existing KPIs that are incapable of immediately highlighting productivity loss.

3. *Maintaining the right inventory level*

The stock required to assemble seats at the L494 assembly line comes from the sub-assembly lines and is manually checked by the line supervisors before commencing every shift. The manually checking of the stock by supervisors is incompetent and likely to cause errors leading to shortages, inaccuracies, and overstock of raw materials. Company X understands that the existing inventory's existing manually challenging and laborious procedure is prone to errors. This assembly line needs online resource management software such as Fishbowl Manufacturing, NetSuite, E2 Shop System, IQMS ERP Software, Henning Visual Esti, Track ERP, Prodsmart, JobBOSS Katana that can provide production visibility and maintain the right inventory. This L494 assembly line needs a shift from manual inventory checking by the supervisors to online management that can seemingly keep the inventory in check.

4. *Improving production quality and accuracy*

The L494 assembly line production quality is lower than the set expectations. Every production shift is set with an acceptance of 1-2 bad quality seats. However, on average, 17-23 bad quality seats have been produced every shift. With limited shop floor visibility, it becomes challenging for line supervisors to know in real-time the stations accountable for making the bad seats. There is a constant push to increase the shop floor visibility for managers, supervisors, and operators to improve the productivity, production quality, and accuracy that is currently deteriorating. It becomes challenging to enhance the quality of seats with no real-time indicators for quality measurement linked between test and inspections station to the L494 line.

5. *Increasing health and safety awareness*

In total, 245 major and minor health and safety-related incidents occurred at company X from the six months of data collected, of which 71 occurred at the L494 line. Company X had to spend £32 million to settle the disputes and maintain high health and safety standards. The challenge is always to find a way to improvise the existing health and safety protocol and keeping it updated.

6. *Using the latest technology*

To remain competitive, managers need to utilize the latest industry 4.0, enabling technologies such as IoTs, IIoTs, CCPS, AI, and cloud computing. The major challenge is how best to implement these technologies and necessary skills requirements to accomplish key objectives such as improving the seats' efficiency and quality, reducing cost, and increasing safety. Besides, it is not enough to implement these technologies into the line without a strategy (collect, analyze, and find patterns).

4.4.4 Problems

From the data collected, the list of problems faced by operators, line supervisors, managers, and research and development team while working on the L494 assembly line is listed below:

1. Due to no process visibility within the stations, the operators find it difficult to construe the time required to execute specific tasks within each station (refer to section 4.3). Process visibility essentially means knowing the time needed for each sub-process completion within the station. Knowing cycle time to complete each process will benefit operators in completing their work on-time. Currently, operators are being displayed by production takt-time, which is not efficient enough to monitor and improve station level performance.
2. Inventory related problems such as missing seat cushion, faulty components such as heater head specification, erroneously arranged materials in the racks, etc., cause difficulties for operators in managing inventory.
3. Constantly changing work shifts for operators from one station to another means that it takes time to familiarise themselves with new station processes.
4. Apart from station cycle-time (as discussed above), no appropriate performance indicators are provided to the operators that show real-time station process cycle time, equipment availability, inventory, and tool management to help them compete for their dedicated task on-time.
5. Ineffective monitoring of the workforce is seen as the major problem that the line supervisors are currently facing. The workforce-related problems include operators absent from their stations and operators not performing their job correctly. The line supervisors require indicators to help monitor operator performance (efficiency) in real-time and avoid production delays. Due to limited shop floor visibility, the supervisors cannot efficiently monitor and improve the real-time seat quality. The current performance indicators provided to the line supervisors and managers cannot effectively monitor the real-time production rate, quality, highlight bottlenecks, and operator efficiency, therefore, compromising on overall assembly line performance.

4.4.5 Bottlenecks

The production data collected from the Sorion MES database helps to identify the bottlenecks and drill down to investigate the bottlenecks befalling at the L494 assembly line. The data collected from the line contains several parameters, for example, the average cycle time of each station, Unique Seat Identifier Number (USIN), seat option, Standard Jobs Per Day (SJPD), and number of Seats In Rework (SIR). A sample of the dataset is shown in table 25. Cycle time data related to stations 10 and 13 is not populated because they act as buffer stations. Buffer stations are installed to stabilize any fluctuations arising during the assembly line's normal working, so data related to buffer stations are not accounted for further data exploration.

Table 25 Assembly line manufacturing sample data for November 2019

Date	**Station average cycle time per day (seconds)**												
	1	2	3	4	5	6	7	8	9	11	12	**SJPD**	**SIR**
1/10	54.8	86.1	85	91.2	86.2	88	99	91	87.2	82.6	85.5	767	31
2/10	63.6	85.5	85	89.8	91.3	78	91	78.3	86.2	87.3	78	781	04
3/10	87.7	95.3	91	92.3	85.2	84	86	85.2	81.1	74.7	84.4	782	04
4/10	85.6	88	91	91.2	85.5	85	78	85.3	86.1	71.3	74.6	781	05
5/10	59.4	89.1	86	78.2	75.6	78	105	78.9	84.5	89.6	85.8	783	28
6/10	78.7	91.3	82	85.6	74.1	74	105	85.1	85	85.8	76.1	785	08
7/10	78.6	86.5	75	75.6	73.2	86	89	91.5	90.6	86.7	84.6	773	17
8/10	99.3	76.5	83	90.2	78.5	89	86	78.2	90.6	74.8	75.1	771	11
9/10	85.2	86.8	91	79.6	86.8	90	111	87.8	91.2	93.3	91.5	779	13
10/10	88.4	90.2	74	86.1	84.5	91	91	84.5	89.2	91.5	87.1	781	10

The takt time of 98.5 seconds is set throughout the production process, implying that every station should complete its operations within the set takt time. The highlighted red values in table 25 signpost the stations whose average cycle time is over the takt time. Station 7 is seen with four highlighted values in table 25, indicating that it was the main reason behind the whole assembly line delays during this production period. The assembly line produced two-seat models (A and B) with three sub-types/variants (sub-types 1, 2, and 3) based on customer specifications in the recorded data timeframe.

To understand the cause of decreased productivity and target the bottleneck stations, it is crucial to monitor these stations' performance individually over a given period. Box and whisker plots are used to show the summary of the data distribution, its variability, and its central value. These plots are the quickest way to ascertain whether the dataset is symmetric or skewed. Figure 22 shows that station 7 is the root cause of the overall decreased production line performance. The average cycle time of station seven during the whole period of data collection is 99.6 seconds against the set production takt time of 98.5 seconds.

Apart from station 7, the rest of the stations performed consistently within the takt time assigned to the production line. Next, the three evident outliers seen across station 5 are carefully investigated. The investigation realized that operators at station 5 failed to stop the process recording during the break times and shift change. Hence, these outliers are treated as lousy data points because they are caused due to human errors and unlikely to appear under normal circumstances. Note that these outliers are eliminated from further data processing.

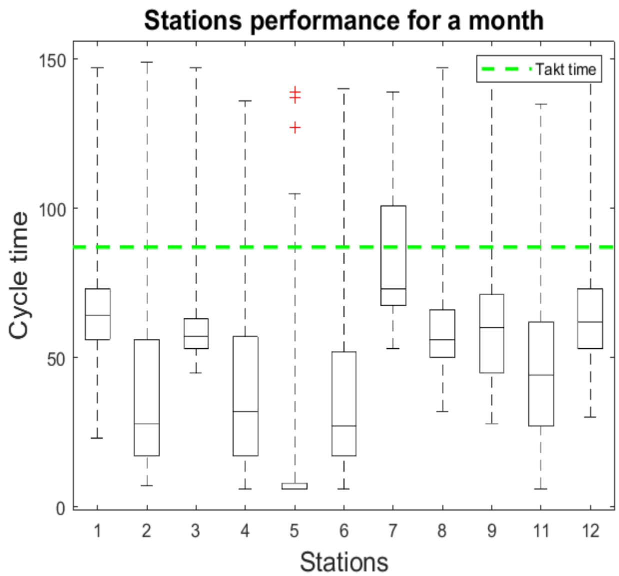


Figure 22 Box and whiskers plot for stations CT over a given period (01/09/2020)

Another inference that is derived from figure 22 is that the station 3 average cycle time is 54.8 seconds. The station 5 average cycle time is 9.9 seconds, considerably lower than the set takt time. This considerable cycle time difference points towards exploring the uneven task distribution across stations. Table 26 gives an insight into the average day cycle time of every station for 1/10/2020, showing that the task distribution over different stations is non-uniform. For instance, the average cycle time for station 5 is 16.2 seconds, followed by station 1 and station 3 with 54.8 seconds and 75.2 seconds, meaning these stations had the shortest cycle time compared to all other stations.

Table 26 Average station cycle time (sec) for a day (01/10/2020)

Station	1	2	3	4	5	6	7	8	9	11	12
Avg. cycle time	54.8	86.1	75.2	91.2	16.2	51.9	99.6	90.1	87.2	82.6	85.5

The next step is to drill down into station 7 to discover which seat model and its variants are the increased cycle time sources. By further time study data analysis, it is evident that model B with an average cycle time of 101.67 seconds (4.67 seconds more than the set production takt time) is the reason behind the increased cycle time (as shown in figure 23 (a)). Whereas, model A with an average cycle time of about 67.32 seconds, did not contribute to any production delays. Therefore, it is apparent that model B in station 7 is the main reason behind the increased cycle time. In the final step, station 7 model B is further investigated to examine which sub-process (sub-type) is responsible for the delays. Figure 23 (b) represents the different model B sub-type processes carried out at station 7. Sub-type 1 process with an average cycle time of about 165.33 seconds is the reason behind poor model B line performance, followed by the sub-type 2 processes with a cycle time of about 99.1 seconds. The sub-type 3 processes averaged a cycle time of about 90.3 seconds, under the production takt time.

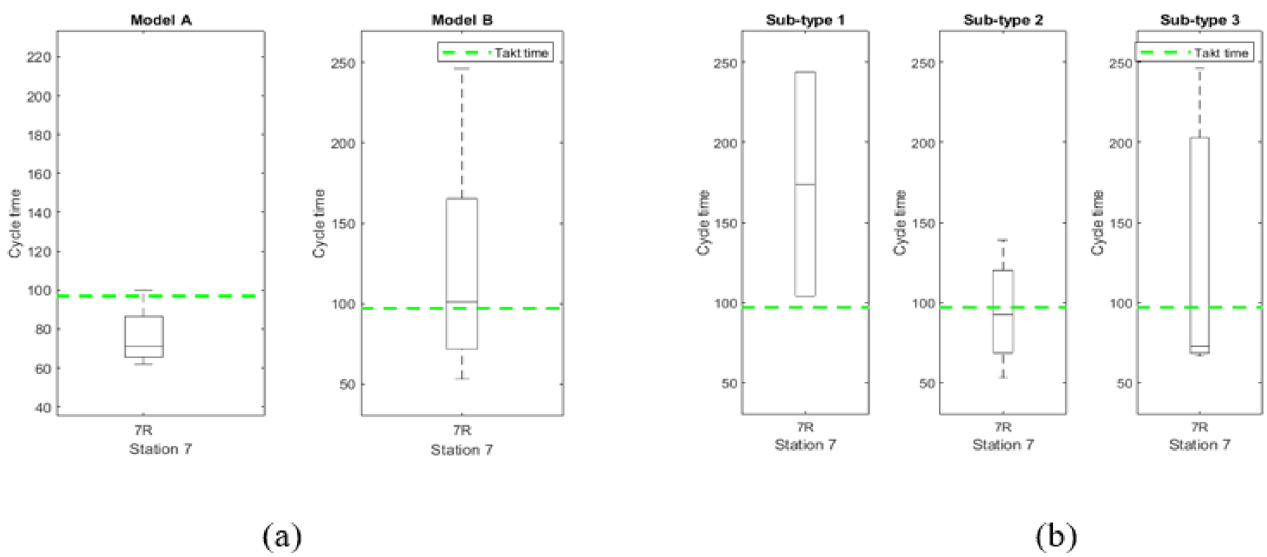


Figure 23 (a) Box and whisker plot for station 7 model A and model B. (b) Box and whisker plot for station 7 model B with sub-type1,2 and 3

Table 27 Average process cycle time for station 7 (actual vs. theoretical)

Station 7	**Actual time (sec)**	**Theoretical time (sec)**
Main operation		
Completing the airbag installation	103.6	98.5
Type		
Model A	67.5	98.5
Model B	101.3	98.5
Sub-type		
Sub-type 1	165.5	98.5
Sub-type 2	99.6	98.5
Sub-type 3	90.2	98.5

The production data study aims to spot the bottlenecks and enhance the company X seat manufacturing assembly line's production rate using time-study data analysis. By performing the time-study data analysis, it is seen that station 7 cycle time exceeds the takt time. With further drilling down, it is evident that model B with a cycle time of 101.67 seconds and sub-type 1 with a cycle time of 165.33 seconds is the leading cause of the delayed production. Due to sub-type 1, model B at station 7, the company X can produce only 18850 seats against a set target of 19080 seats that month.

Therefore, knowing the root causes behind the decreased production, the immediate suggestion that can be inferred to company X is line re-balancing, line optimization, and splitting the bottleneck process into sub-processes to meet the standard takt time and enhance the manufacturing process, as the best solution. It needs to be noted that gathering the data and identifying the bottlenecks is a continual process. Once the solution is suggested, it needs to be implemented and tested to confirm enhanced performance and check for any further possible improvements.

4.4.6 Existing Performance Measures

The company X's existing performance measures to monitor the L494 assembly line's performance can be reflected from the dashboards' snapshots shown in figures 24 and 25. The company X employs two different sets of KPIs, one for the supervisors and managers and another for the operators. The set of KPIs displayed to supervisors and managers to monitor the L494 production line's performance is takt-time, rework, production count, production loss ratio, and availability. These KPIs are shown in the L494 assembly line master dashboard (figure 24). The sequence of process steps that need to be undertaken within the station and the takt-time KPI is displayed to the operators, as shown in figure 25. In total, five KPIs are used to monitor the current assembly line's performance to achieve key business objectives. The effectiveness of the existing KPIs can be evaluated through the proposed KPI guidelines in section 4.5.

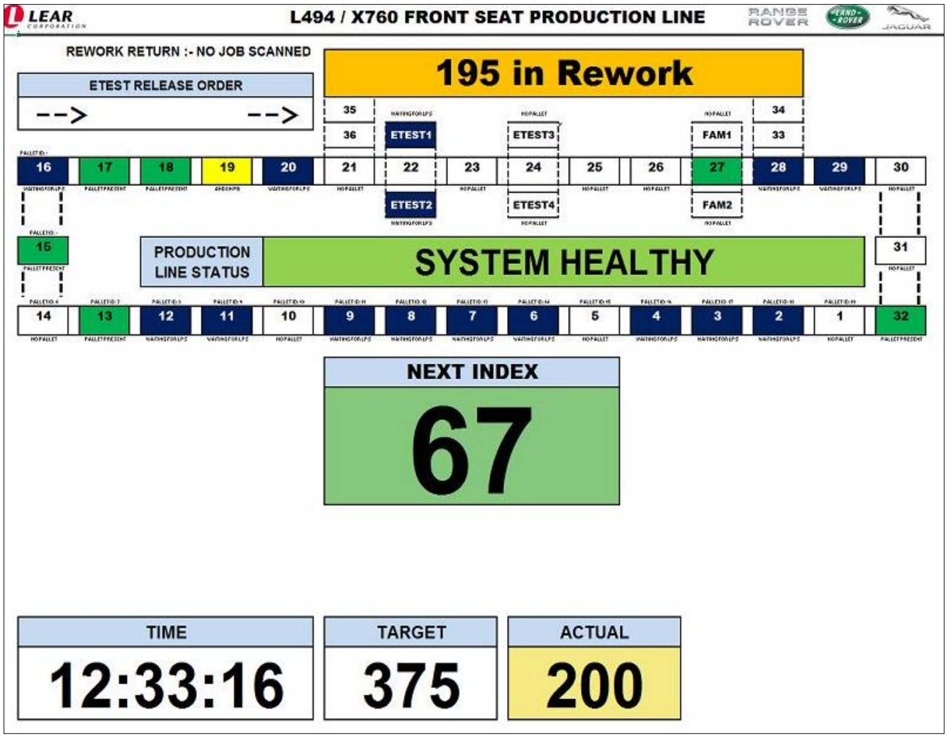


Figure 24 L494 assembly line master dashboard- accessible by the supervisors and managers

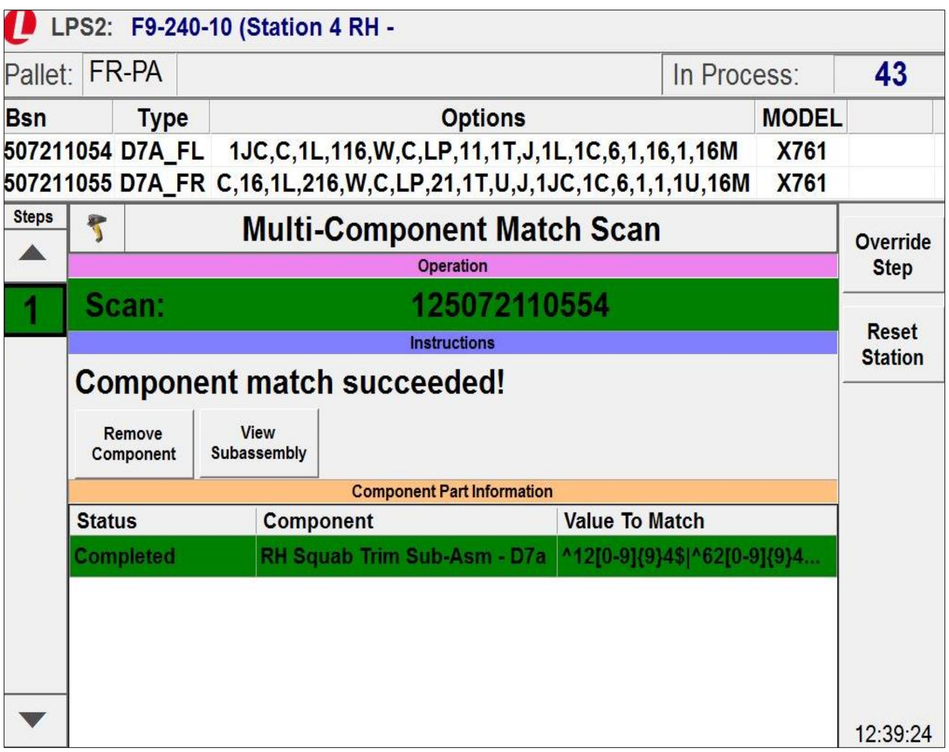


Figure 25 L494 assembly line master dashboard- accessible by operators

4.5 Assessing the Effectiveness of Existing KPIs using KPI Guidelines

In this section, company X's list of KPIs, such as takt-time, rework, production count, production loss ratio, and availability, to monitor the L494 assembly line is analyzed and compared with the set business objectives, problems, and challenges using the proposed KPI guidelines. Each existing KPI is assessed separately using KPI guidelines. The assessment results are illustrated to underline the effectiveness (or applicability) of the existing KPIs in monitoring and improving the current assembly line performance from table 28 32.

Table 28 Evaluating takt-time KPI using proposed KPI guidelines

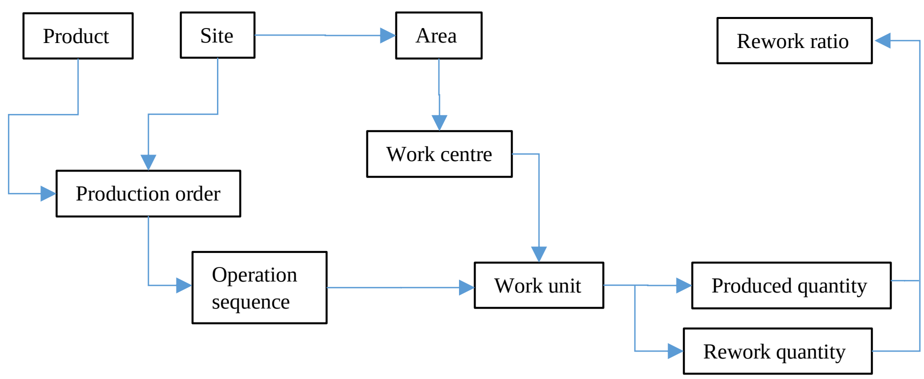
Information Stage	
Content stage	
Name	Takt-time
Description	The rate at which a finished seat needs to be completed in order to meet customer demand
Unit of Measure	Seconds
Range	Decided based on the production time and customer demand (currently set at 90.5 seconds)
Trend	Lower, the better
Context stage	
Timing	Real-time
Audience	Supervisor, manager
Production Methodology	Discrete, batch, continuous
Discernment Stage	
Type	Process
Dimension	Time
Form	Leading
Nature	Derived
Scheming Stage	
Formula	Takt-time = total available production time/ average customer demand
Equation	Total available production time, average customer demand
Equation Variable	Cycling time, blocked time, starving time, waiting for auxiliary time and bypass time, and customer demand
Origin of Data Stage	
Station PLCs, local historian, Sorion	

Station PLC: the purpose of station level PLCs is to control station motor drives, sensors, motion detectors, etc., using an automated tailored control logic mechanism. *Local historian*: this is a local database that resides on the shop floor (level 1-2 according to the ISA-95 model). This local historian is used to collect the data from all station level PLCs (belonging to a particular assembly line) to monitor and control station level performances. *Sorion*: this is an MES level (level 3, according to the ISA-95 model) database used by company X to monitor and document the transformation of raw materials to finished seats. It collects the data from every data-driven device present on the shop floor to ensure effective manufacturing operations execution from start to finish.
Assisting Technology Stage
Motion detectors, proximity sensors

By evaluating the takt-time KPI, it is apparent that the right audience for this KPI is supervisors and managers. Displaying this KPI to operators will not support the company X effectively monitoring the production rate because takt-time is explicit to the whole assembly line rather than the individual station. The operators need a performance indicator such as cycle-time specific to the station, process, and sub-process and can help monitor and maintain station-level production rate. Nevertheless, takt-time can be observed in real-time, enabling the line supervisors and managers to make swift decisions. This KPI is process-centric. Two of company X's key business objectives, namely real-time monitoring of stations and improving the production rate, can be undeniably measured and monitored using this KPI at the higher level (supervisors and managers);. In contrast, quality aspects of the assembly line cannot be measured through it. Therefore, company X will benefit from displaying this KPI to supervisors and managers but not the operators for production monitoring and improvement.

Table 29 Evaluating rework ratio KPI using proposed KPI guidelines

Information Stage	
Content stage	
Name	Rework ratio
Description	The rework ratio is the relationship between Rework Quantity (RQ) and Produced Quantity (PQ)
Unit of Measure	%
Range	0-100
Trend	The lower, the better
Context stage	
Timing	On-demand, periodical, real-time
Audience	Operator, supervisor, manager

<table>
<tr><td>Production Methodology</td><td>Discrete, batch, continuous</td></tr>
<tr><td>ER Model</td><td>
</td></tr>
<tr><td colspan="2">Discernment Stage</td></tr>
<tr><td>Type</td><td>Product</td></tr>
<tr><td>Dimension</td><td>Quality</td></tr>
<tr><td>Form</td><td>Leading</td></tr>
<tr><td>Nature</td><td>Derived</td></tr>
<tr><td colspan="2">Scheming Stage</td></tr>
<tr><td>Formula</td><td>Rework ratio = RQ / PQ</td></tr>
<tr><td>Equation</td><td>RQ, PQ</td></tr>
<tr><td>Equation Variable</td><td>Scrap quality, RQ, total PQ</td></tr>
<tr><td colspan="2">Origin of Data Stage</td></tr>
<tr><td colspan="2">Local historian, LPQS, Sorion
<u>LPQS</u>: stands for Lear Production Quality System. It is responsible for storing the quality-related production information from the test and inspection line within the company X production facility</td></tr>
<tr><td colspan="2">Assisting Technology Stage</td></tr>
<tr><td colspan="2">Laser scanners, sensors</td></tr>
</table>

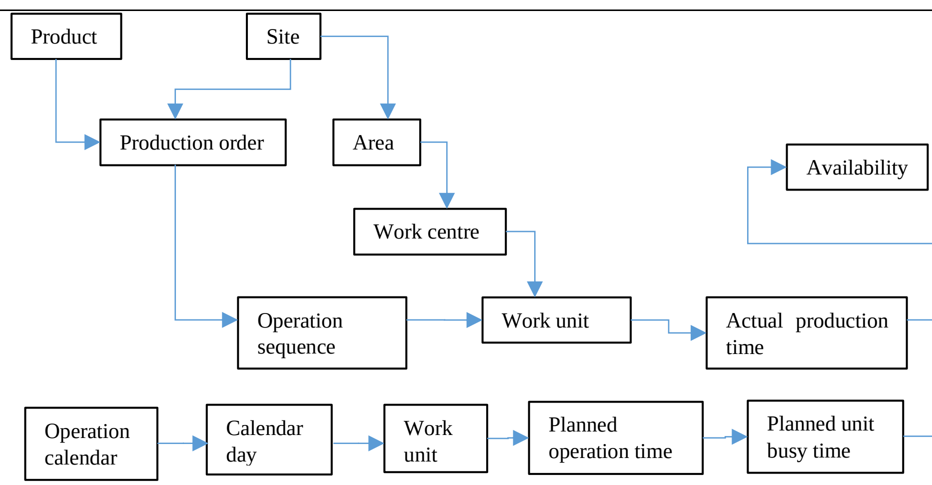
By analyzing the rework ratio KPI, it is apparent that this KPI can effectively measure the seat quality in real-time, on-demand, and periodical. With the improvement in seat quality being one of company X's key business objectives, this KPI can effectively monitor and maintain the seat quality. One point to note from the analysis is that the rework ratio is a derived KPI, meaning that it requires quite a few equation variables (also known as the data) for its calculation. They make it complicated and costly (due to the technology used for extracting the data from the shop floor). There is a various quality associated KPIs that can measure the real-time seat quality using minimal equation variables and/or cost-effective technologies. One such example is a quality count KPI that can measure and monitor the quality of seats without involving several equation variables, unlike various other KPIs that need complex and sophisticated technologies to get the right equation variables. As rework ratio KPI is solely used to measure the quality (product-centric), the production process cannot be monitored. The ER models depict where the data can be obtained within the assembly line.

Table 30 Evaluating production count KPI using proposed KPI guidelines

Information Stage	
Content stage	
Name	Production count
Description	The amount of seat produced per shift
Unit of Measure	-
Range	Decided based on the production order per shift
Trend	The higher, the better
Context stage	
Timing	On-demand, periodical, real-time
Audience	Supervisor, manager
Production Methodology	Discrete, batch, continuous
Discernment Stage	
Type	Product
Dimension	Quantity
Form	Leading
Nature	Fundamental
Scheming Stage	
Formula	-
Equation	-
Equation Variable	-
Origin of Data Stage	
Local historian, Sorion	
Assisting Technology Stage	
Motion detectors, RFID readers, scanners	

Production count KPI is displayed for computing the number of seats produced in real-time, on-demand, and periodically based on the user (audience) requirements. This KPI helps supervisors and managers know the status of seat production and aids in comparing it with the set production target. To fulfill customer demands on time, it becomes critical to track the production count's status during every production shift/order (illustrated in section 4.4.4). As seen in table 30, this KPI's nature is fundamental, meaning that no other equation variables are needed to calculate it, making it the most suitable KPI for real-time monitoring seat production. Overall, this KPI is very beneficial for company X to monitor real-time production performance.

Table 31 Evaluating availability KPI using proposed KPI guidelines

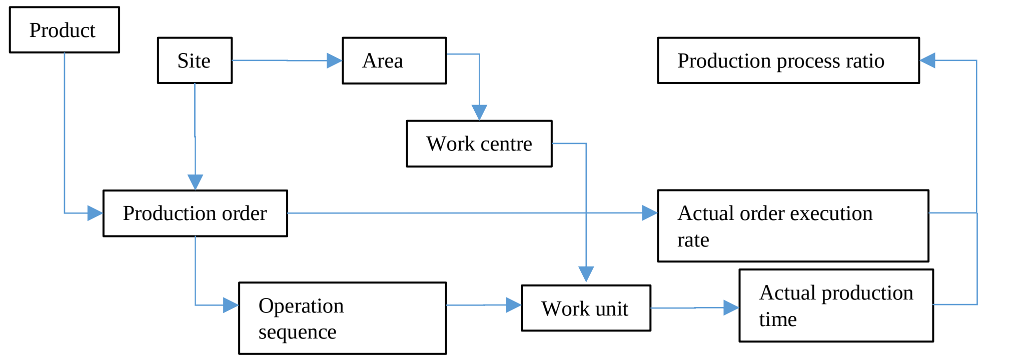
Information Stage	
Content stage	
Name	Availability
Description	It is the ratio between Actual Production Time (APT) to the Planned Busy Time (PBT)
Unit of Measure	%
Range	Min: 0% Max: 100%
Trend	The higher, the better
Context stage	
Timing	On-demand, periodical
Audience	Supervisor, manager
Production Methodology	Discrete, batch, continuous
ER Model	
Discernment Stage	
Type	Process
Dimension	Time
Form	Lagging

Nature	Derived
Scheming Stage	
Formula	Availability = APT / PBT
Equation	APT, PBT
Equation Variable	AUBT, ADOT, AUPT, ADET, AUST
Origin of Data Stage	
Sorion	
Assisting Technology Stage	
RFID reader, camera system, barcode scanners	

Availability KPI is process-centric and used to monitor the seat production rate per shift/ order, as highlighted in table 31. This KPI can only monitor the production rate on-demand and periodical (a lagging KPI); thus, it cannot make quick decisions. Supervisors and managers use availability KPI to know for how long the station(s) were available during the previous shift/order aiding them to identify the problematic station(s) and focusing on them during the next shift. This action is characterized as corrective because it is not applicable for determining the challenging station(s) in real-time production. Moreover, with the form of this KPI is derived, it cannot be used in real-time monitoring and improvement of the production of seats. It means that the results generated from this KPI are only available after the process has been ended and cannot be used by the company X to fulfill their key business objectives instantaneously.

Table 32 Evaluating production loss ratio KPI using proposed KPI guidelines

Information Stage	
Content stage	
Name	Production loss ratio
Description	The production loss ratio is the relationship of quantity lost during production (PL) to the Consumed Material (CM)
Unit of Measure	%
Range	0-100
Trend	The higher, the better
Context stage	
Timing	On-demand, periodical, real-time
Audience	Supervisor, manager
Production Methodology	Batch, continuous

<table>
<tr><td>ER Model</td><td>
</td></tr>
<tr><td colspan="2">Discernment Stage</td></tr>
<tr><td>Type</td><td>Product</td></tr>
<tr><td>Dimension</td><td>Quantity</td></tr>
<tr><td>Form</td><td>Leading</td></tr>
<tr><td>Nature</td><td>Derived</td></tr>
<tr><td colspan="2">Scheming Stage</td></tr>
<tr><td>Formula</td><td>Production loss ration = PL / CM</td></tr>
<tr><td>Equation</td><td>PL, CM</td></tr>
<tr><td>Equation Variable</td><td>CM, production count, production target, scrap count, good quality count</td></tr>
<tr><td colspan="2">Origin of Data Stage</td></tr>
<tr><td colspan="2">LPQS, Sorion</td></tr>
<tr><td colspan="2">Assisting Technology Stage</td></tr>
<tr><td colspan="2">Motion detectors, counters, sensors, laser scanners</td></tr>
</table>

Production loss ratio KPI is used to measure the amount of material that is lost during production. This KPI can be monitored in real-time, periodical, and on-demand, as illustrated in table 32. With the production methodology applicable to batch and continuous manufacturing, this KPI cannot be used in discrete manufacturing (i.e., production of seats) to efficiently measure the production loss for the given L494 assembly line and derive useful results. The reason behind that is the nature of the process undertaken within this assembly line, constantly changing production orders and raw materials, making it difficult to calculate, analyze and interpret the results after measuring this KPI. By analyzing the production loss KPI from the perspective of company X's business objectives, it was apparent that this KPI is not beneficial (section 4.2.2). Based on the literature review findings (section 2.4), in discrete manufacturing, KPIs such as scrap ratio, first-time yield, or scrap-to-rework ratio can be used if the aim is to measure the production loss as perceived in a given case-study.

After evaluating all the existing KPIs using the proposed KPI guidelines, the following main conclusion are drawn:

1. There are no useful KPI measures currently provided to the operators, which can help them monitor and improve production performance and achieve the key business objectives. The takt-time KPI supplied to the operators does not fully help in improving actual production performance.
2. To measure the quality of the seats assembled, a derived KPI (rework ratio) is employed when several other KPIs are available in the literature review, which can be straightforwardly deployed based on the easily accessible shop floor data cost-effective technology. Also, the rework ratio data is not fetched back to the operators, improving seat quality.
3. One real-time KPI, production count, and one periodical KPI, availability, are used to measure the line's production rate.
4. An inadequate KPI (production loss ratio) is currently used with zero added value to monitor the assembly line performance.

4.6 Proposed KPIs

By considering the current business objectives; understanding the challenges, problems, and bottlenecks, along with the conclusions drawn from the evaluation of existing KPIs using KPI guidelines, a list of KPIs is proposed to company X. These proposed KPIs are based on the findings of the literature review (section 2.4), expert advice and assessments using proposed KPI guidelines in addition to dividing them based on the job roles. To avoid overwhelming operators, supervisors, and managers with many KPIs, only a few best fit KPIs for each job role is proposed. Proposing the KPIs is an iterative process. It involves finding similar challenges, problems, and bottlenecks within the manufacturing shop floor domain and assessing the proposed KPIs' effectiveness. It is evaluated using the proposed KPI guidelines. The assessment results proved that the proposed KPIs could effectively monitor the overall assembly line performance and help achieve key business objectives and address the current challenges and problems (as elucidated in section 4.7). In a nutshell, the process for selecting proposed (suggested) KPIs for operators, supervisors, and managers is:

1. Identify similar objectives, problems, and challenges from the literature review
2. Think through the expert group
3. Consider KPI standards guidelines
4. Evaluate the proposed KPIs using KPI guidelines

The operator's proposed KPIs are cycle-time, utilization efficiency, and first-pass yield; supervisors are allocation efficiency, technical efficiency, and quality; for the manager, they are OEE, throughput rate, and scrap ratio. The combination of proposed KPIs and applicable existing KPIs gives the appropriate KPIs and is illustrated in table 33. From the existing KPIs, it should be noted that KPIs' production loss ratio is not included in table 33 because of its zero added value as concluded from section 4.5. The takt-time KPI previously displayed to the operators is not considered as this KPI is suitable for supervisors and managers as the audience. It should be noted that the appropriate KPIs are focused on efficiently monitoring the current state of the assembly line. In case of any changes, the proposed KPIs need to be revised. The detailed evaluation of these KPIs is illustrated in section 4.7.

Table 33 Appropriate KPIs based on job roles

Appropriate KPIs	**Operator**	**Supervisor**	**Manager**
Proposed KPIs	Cycle time	Allocation efficiency	OEE
	Utilization efficiency	Quality	Throughput rate
	First pass yield	Technical efficiency	Scrap ratio
Existing KPIs		Production count	Production count
		Rework ratio	Rework ratio
		Availability	Availability
		Takt-time	Takt-time

4.7 Assessing the Effectiveness of Proposed KPIs Employing KPI Guidelines

To test the effectiveness of the proposed KPIs, it is evaluated using KPI guidelines. All the key KPI measures and elements that can help company X monitor their business objectives ingeniously, problems and challenges are underlined, making it evident that their implementation can improve overall shop floor performance and yield rewarding outcomes in the form of improved productivity and quality. To simplify the evaluation results, they are studied independently based on job roles. The proposed KPIs for operators are cycle time, utilization efficiency, and first-pass yield. The evaluation of these proposed KPIs is illustrated in table 34, 35, and 36.

Currently, company X has employed takt-time KPI for the operators to monitor station performance. From literature, it can be established that the takt-time KPI is only useful for monitoring assembly-level performances, which means that company X does not have any KPI to monitor station level performances during the production of seats. The proposed cycle time KPI can help monitor the station level performances and support the operators in knowing the exact time required to finish their sub-tasks and overall task completion time. Moreover, cycle time KPI is process-centric and can be displayed on-demand, periodical, and real-time, making it convenient for the operators to identify the bottleneck processes in real-time within the station(s) the potential causes of the drop in production rate. The cycle time reports can further help the company X rethink the line balancing and scheduling procedures undertaken at the L494 assembly line.

Often labor-intensive semi-automatic lines are prone to process delays arising due to several human and machine-related glitches. Cycle time supports identifying the error-prone processes, thus increasing the station's visibility, process, and/or sub-process within the given assembly line. Cycle time helps to directly address three out of five company objectives, such as improving production rate, real-time monitoring of stations, and identifying the stations' bottleneck processes.

Table 34 Evaluating cycle time using KPI guidelines

Information Stage	
Content stage	
Name	Cycle time
Description	The total time from the beginning to the end of your process as defined by the production manager or customer
Unit of Measure	Seconds
Range	It depends on the manager and/ or customer
Trend	The lower, the letter
Context stage	
Timing	On-demand, periodical, real-time
Audience	Operator, supervisor
Production Methodology	Discrete, batch, continuous
Discernment Stage	
Type	Process
Dimension	Time
Form	Leading
Nature	Derived
Scheming Stage	

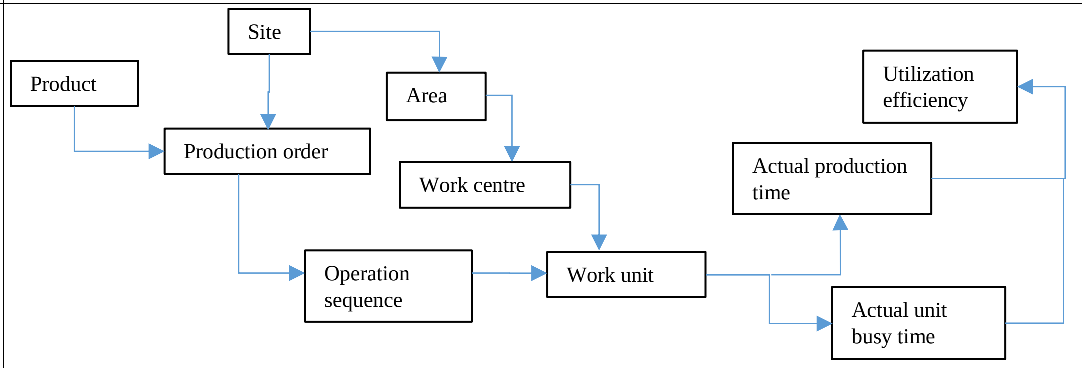
Formula	The average time between the completion of processes
Equation	APT, PBT, NOT, OPT, PRI
Equation Variable	AUBT, ADOT, AUPT, ADET, AUST
Origin of Data Stage	
Station PLC, local historian	
Assisting Technology Stage	
Sensors, motion detectors, RFID, camera detectors	

The next KPI proposed to operators is utilization efficiency; it enables the operators to know the difference between the actual production time and actual station busy time. This KPI displays the right time for which the station was operating compared with the actual production time. For intermittent lines that are typically operated on a set takt-time basis, any interruptions caused by one or several stations can negatively affect the whole production rate, utilization efficiency KPI helps to highlight both the under-performing and over-performing stations in real-time, on-demand, and periodical, enabling the operators to know how their specific station is performing throughout the production of seats.

As this KPI is process-centric, it can effectively address the key objectives, which are time-dependent. With the company X's current problems and challenges concerning the station, performance is reduced productivity. This KPI can identify the station(s) that requires an additional or reduced workforce compared to the existing workforce plan.

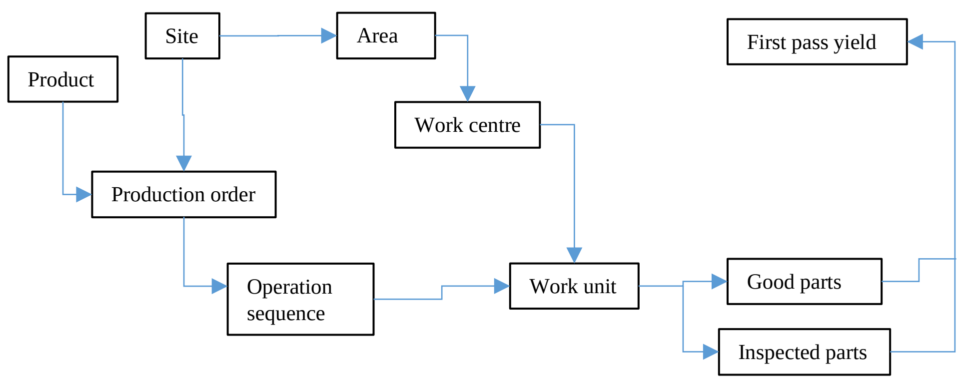
Table 35 Evaluating utilization efficiency using KPI guidelines

Information Stage	
Content stage	
Name	Utilization efficiency
Description	The utilization efficiency is the ratio between the Actual Production Time (APT) and the Actual Unit Busy Time (AUBT)
Unit of Measure	%
Range	Min: 0 Max: 100
Trend	The higher, the better
Context stage	
Timing	On-demand, periodical, real-time
Audience	Operator, supervisor, manager

Production Methodology	Discrete, batch, continuous
ER Model	
Discernment Stage	
Type	Process
Dimension	Time
Form	Leading
Nature	Derived
Scheming Stage	
Formula	APT / AUBT
Equation	APT, AUST, ADET, ADOT
Equation Variable	AUPT, ADET, APT, AUST
Origin of Data Stage	
Sorion	
Assisting Technology Stage	
Sensors	

The third KPI proposed to operators is the first-pass yield as assessed in table 36. This KPI is focused on the quality aspect of seat production. It helps the operators know the good or bad quality of seats produced in real-time, on-demand, and periodical. With a consistent decrement in the quality of seats produced by the L494 assembly line, this KPI can assist the company X, especially operators, in familiarizing themselves with the quality of seats produced so that precautionary measures can be initiated to stop the further drop in seat quality in-time. If displayed to the operators during the production, these three proposed KPIs will support the company X to address key business objectives, problems, and challenges by monitoring the critical performance measures.

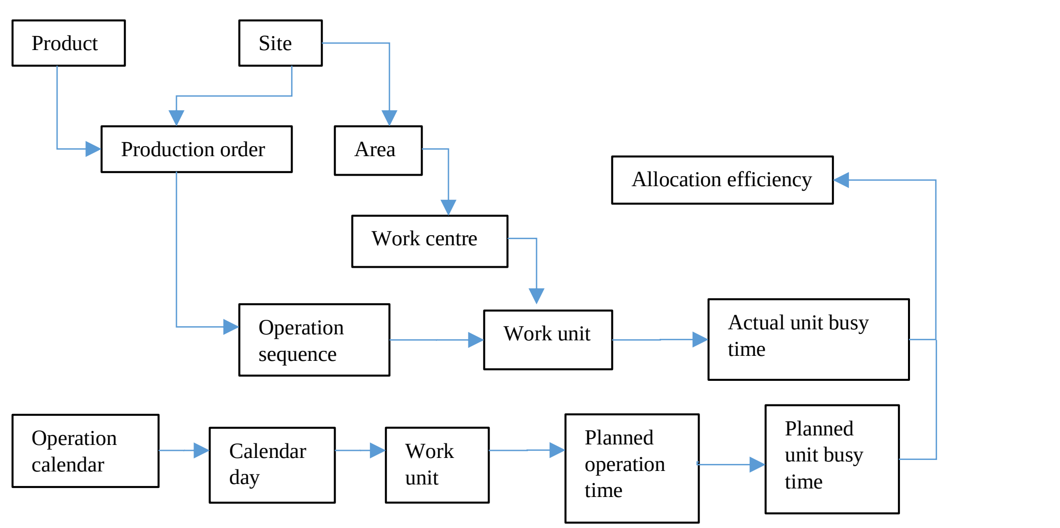
Table 36 Evaluating first pass yield using KPI guidelines

Information Stage	
Content stage	
Name	First pass yield
Description	It is the ratio between Good Parts (GP) and Inspected Parts (IP).
Unit of Measure	%
Range	Min: 0 Max: 100
Trend	The higher, the better
Context stage	
Timing	On-demand, periodical, real-time
Audience	Operator, supervisor, manager
Production Methodology	Discrete, batch
ER Model	
Discernment Stage	
Type	Product
Dimension	Quality
Form	Leading
Nature	Derived
Scheming Stage	
Formula	GP / IP
Equation	GP, IP
Equation Variable	GP, IP. Q
Origin of Data Stage	
Local historian, LPQS	
Assisting Technology Stage	

Counters, T&I scanners

Similarly, the proposed KPIs for supervisors and managers are assessed in table 37- 42. The aim behind presenting these tailor-made KPIs to supervisors and managers is to address every problem, challenge, highlight the bottleneck, and enable effective monitoring of L494 production performance. The effectiveness of these KPIs is also illustrated in table 37-42.

Table 37 Evaluating allocation efficiency using KPI guidelines

<table>
<tr><th colspan="2">Information Stage</th></tr>
<tr><td colspan="2">Content stage</td></tr>
<tr><td>Name</td><td>Allocation efficiency</td></tr>
<tr><td>Description</td><td>It is the ratio between the actual allocation time of a work unit expressed as the Actual Unit Busy Time (AUBT) and the planned time for allocating the work unit defined as the Planned Unit Busy Time (PUBT)
Note: the unit here can be referred to as equipment or station based on the user requirement.</td></tr>
<tr><td>Unit of Measure</td><td>%</td></tr>
<tr><td>Range</td><td>Min: 0
Max: 100</td></tr>
<tr><td>Trend</td><td>The higher, the better</td></tr>
<tr><td colspan="2">Context stage</td></tr>
<tr><td>Timing</td><td>On-demand</td></tr>
<tr><td>Audience</td><td>Operator, supervisor, manager</td></tr>
<tr><td>Production Methodology</td><td>Discrete, batch, continuous</td></tr>
<tr><td>ER Model</td><td>
</td></tr>
<tr><th colspan="2">Discernment Stage</th></tr>
</table>

Type	Product, Process
Dimension	Time
Form	Lagging
Nature	Derived
Scheming Stage	
Formula	AUBT / PUBT
Equation	AUBT, ADOT, PBT
Equation Variable	APT, AUST, ADOT, PBT
Origin of Data Stage	
Local historian	
Assisting Technology Stage	
Sensors, RFID, motion sensors	

Table 38 Evaluating quality using KPI guidelines

Information Stage	
Content stage	
Name	Quality
Description	The quality ratio is the relationship between the Good Quantity (GQ) and the Produced Quantity (PQ)
Unit of Measure	%
Range	Min: 0 Max: 100
Trend	The higher, the better
Context stage	
Timing	On-demand, periodical, real-time
Audience	Operator, supervisor, manager
Production Methodology	Discrete, batch, continuous
ER Model	

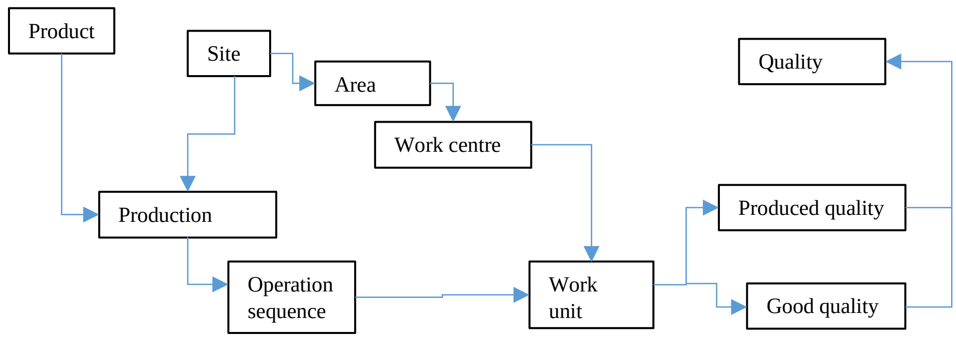
	
Discernment Stage	
Type	Product
Dimension	Quality
Form	Leading
Nature	Derived
Scheming Stage	
Formula	GQ / PQ
Equation	GQ, PQ
Equation Variable	GQ, PQ
Origin of Data Stage	
Local historian, LPQS	
Assisting Technology Stage	
Counters, T&I scanners	

Table 39 Evaluating scrap ratio using KPI guidelines

Information Stage	
Content stage	
Name	Scrap ratio
Description	It is the relationship between Scrap Quantity (SQ) and Produced Quantity (PQ)
Unit of Measure	%
Range	Min: 0 Max: 100
Trend	The lower, the better
Context stage	
Timing	On-demand, periodically, real-time
Audience	Operator, supervisor, manager

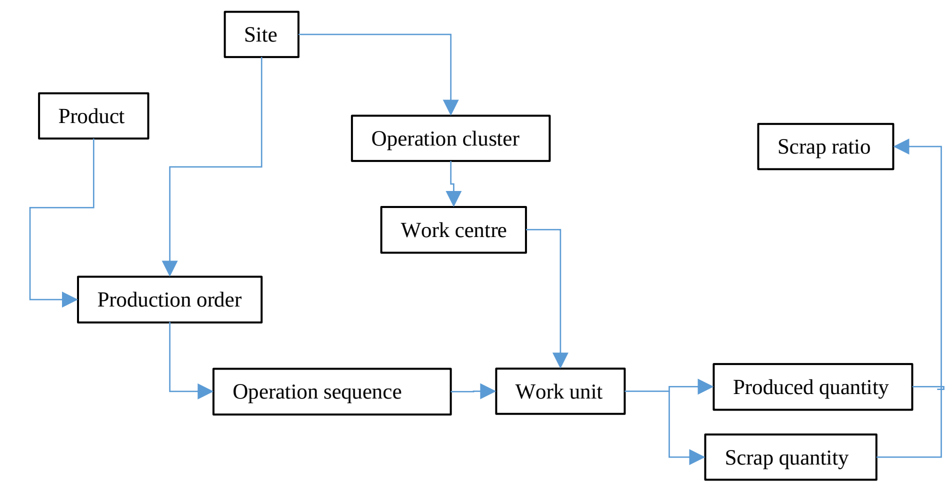
Production Methodology	Discrete, batch, continuous
ER Model	
Discernment Stage	
Type	Product
Dimension	Quantity
Form	Leading
Nature	Derived
Scheming Stage	
Formula	SQ / PQ
Equation	SQ, PQ
Equation Variable	Q, SQ, PQ
Origin of Data Stage	
Local historian, LPQS	
Assisting Technology Stage	
Counters, T&I scanners	

Table 40 Evaluating OEE using KPI guidelines

Information Stage	
Content stage	
Name	OEE
Description	It is the multiplication of availability, effectiveness, and quality
Unit of Measure	%
Range	Min: 0 Max: 100

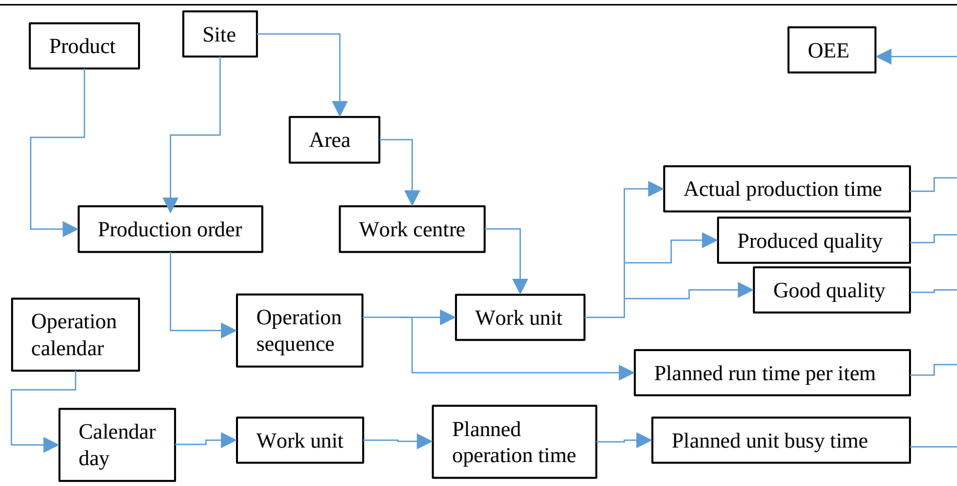
Trend	The higher, the better
Context stage	
Timing	On-demand, periodical, real-time
Audience	Operator. supervisor, manager
Production Methodology	Discrete, batch, continuous
ER Model	
Discernment Stage	
Type	Product, process, resource
Dimension	Time, quality
Form	Lagging
Nature	Derived
Scheming Stage	
Formula	Availability*effectiveness*quality
Equation	APT, PBT
Equation Variable	AUBT, ADOT, AUPT, ADET, AUST
Origin of Data Stage	
Sorion, LPQS	
Assisting Technology Stage	
Motion detectors, sensors, counters, camera detectors	

Table 41 Evaluating throughput using KPI guidelines

Information Stage	
Content stage	
Name	Throughput rate

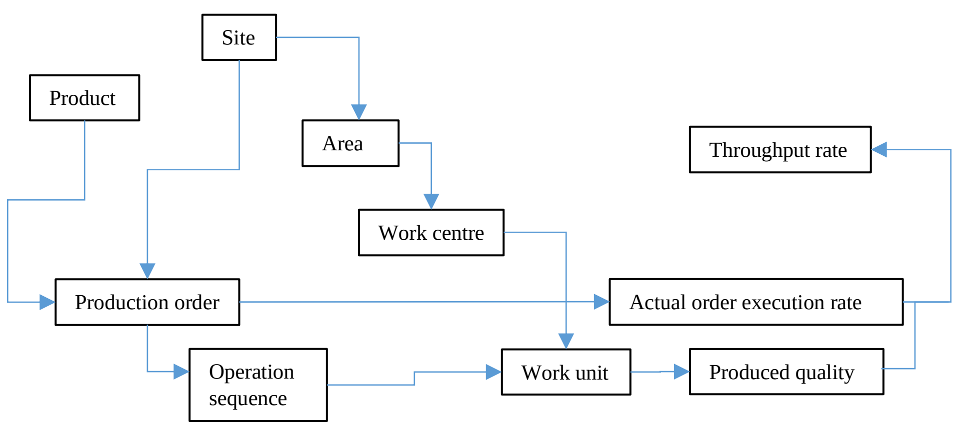
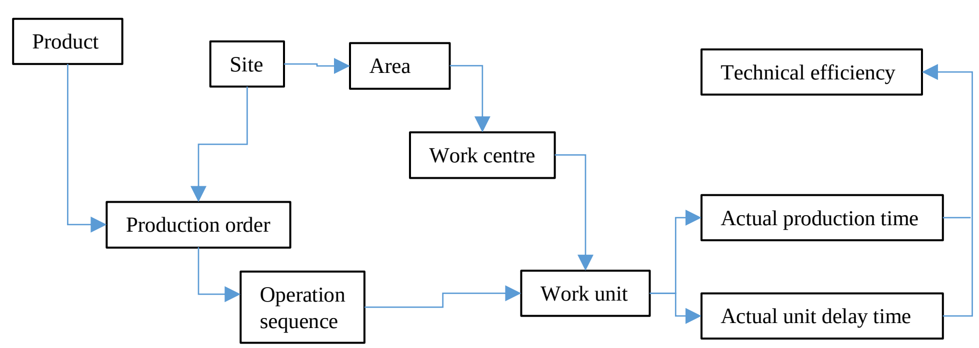
Description	It is the measure of process performance in terms of the Produced Quantity of an order (PQ) and the Actual Execution Time of an Order (AOET)
Unit of Measure	Seconds
Range	Min: 0 Max: specific to production shift/order (product-centric)
Trend	The higher, the better
Context stage	
Timing	On-demand, periodical
Audience	Supervisor, manager
Production Methodology	Discrete, batch
ER Model	
Discernment Stage	
Type	Product, process
Dimension	Time
Form	Lagging
Nature	Derived
Scheming Stage	
Formula	PQ/AOET
Equation	APT, ADET, AUST, PQ
Equation Variable	APT, ADET, AUST, PQ
Origin of Data Stage	
Local historian, Sorion	
Assisting Technology Stage	
Counters, RFID, motion sensors	

Table 42 Evaluating technical efficiency using KPI guidelines

Information Stage	
Content stage	
Name	Technical efficiency
Description	It is the relationship between the Actual Production Time (APT) and the sum of APT and ADET
Unit of Measure	%
Range	Min: 0% Max: 100%
Trend	The higher, the better
Context stage	
Timing	On-demand, periodical, real-time
Audience	Operator, supervisor, manager
Production Methodology	Discrete, batch, continuous
ER Model	
Discernment Stage	
Type	Process
Dimension	Time
Form	Leading
Nature	Derived
Scheming Stage	
Formula	APT / (APT + ADET)
Equation	APT, PBT, NOT, OPT, PRI
Equation Variable	AUBT, ADOT, AUPT, ADET, AUST
Origin of Data Stage	
Station PLC, local historian	
Assisting Technology Stage	
Sensors, motion detectors, RFID	

Other critical KPI measures that can be resulting by assessing the effectiveness of the proposed KPIs using KPI guidelines are:

1. The ER-model illustrates data (equation variables) that is required to calculate the KPIs within the manufacturing facility

2. The origin of the data stage highlights where the data can readily be available for extraction within the shop floor

3. The assisting technology stage indicates the tools required to extract the data from the shop floor

4.8 Prioritizing Key Business Objectives and Appropriate KPIs

Prioritizing key business objectives: Using the procedure as described in section 3.4, the SMART criteria is applied to the key business objectives, and results are illustrated in table 43. From the results shown in table 43, it is evident that objective 1 has the highest total effective weight, therefore ranked top in the prioritization list. This means that the company X needs to focus its attention more on achieving objective 1 before the rest because this objective fulfills all the criteria of being SMART (implicating that this objective can be the quickest to accomplish by company X).

Table 43 Prioritizing key business objectives using SMART criteria calculation

Objectives	Effective Weight calculation										T. eff Weight	Rank
	Ex-1	Ex -2	Ex -3	Ex -4	Ex -5	Ex -6	Ex -7	Ex -8	Ex -9	Ex -10		
1	5	5	4	5	4	4	5	5	5	5	47	1
2	4	4	4	4	3	4	4	4	3	4	38	2
3	3	3	3	4	3	3	3	3	4	3	32	3
4	2	3	3	3	2	2	3	2	2	3	25	4
5	2	2	3	2	2	2	2	2	3	2	22	5

Prioritizing KPIs: prioritizing KPIs is done by dividing KPIs based on their relevance/ significance on the critical business objectives. In simple words, splitting the KPIs based on the objectives and then implementing SMART criteria for prioritization. Since the appropriate KPIs are distributed based on the job roles, the separation of KPIs will also be done individually before prioritization, as illustrated in table 44. It should be noted that objective 4 has been achieved by identifying the bottlenecks in section 4.4.5, and KPIs for objectives 5 is out of this research scope.

Table 44 Dividing KPIs based on key business objectives

Operator	**Supervisor**	**Manager**
Objective1:	Objective 1:	Objective1:
Cycle time	Takt-time	Takt-time
Utilization efficiency	Availability	OEE
	Allocation efficiency	Availability
	Technical efficiency	Throughput rate
Objective 2:	Objective 2:	Objective 2:
First pass yield	Quality	OEE
	Rework ratio	Rework ratio
		Scrap ratio
Objective 3:	Objective 3:	Objective 3:
Cycle-time	Quality	Production count
Utilization efficiency	Production count	Rework ratio
First pass yield	Rework ratio	Scrap ratio
	Technical efficiency	Throughput rate

Once the KPIs are separated based on their relevance to the objectives, the next step is to implement the SMART criteria like the one used for prioritization of key business objectives, as shown in table 44. The results of implementing the SMART criteria are illustrated in table 45.

Table 45 Prioritization of KPIs based on SMART criteria

Operator	**Supervisor**	**Manager**
1. Cycle time	1. Takt-time	1. Takt-time
2. Utilization efficiency	2. Availability	2. OEE
3. First pass yield	3. Allocation efficiency	3. Availability
	4. Quality	4. Throughput rate
	5. Technical efficiency	5. Rework ratio
	6. Rework ratio	6. Scrap ratio
	7. Production count	7. Production count

4.9 Implementation and Evaluation of Appropriate KPIs within L494 Assembly Line

In this section, the implementation and evaluation of appropriate KPIs within the L494 assembly line of company X's manufacturing facility is elucidated. At first, the following steps are conducted for successful implementation.

Step 1- Gathering required data for implementing appropriate KPIs: stage 4 (origin of data stage) and stage 5 (assisting technology stage) of KPI guidelines highlighting the data needed (equation variables) and the technology required to extract the data from the L494 assembly line is identified in section 4.8. Using this information, figure 26 highlights how the flow of data right from the local historian and Sorion databases to appropriate KPIs takes place. All the relevant PLC memory bits from the local historian and Sorion database are marked by dark and light grey colors in figure 26. The respective PLC data block helps track all of the equation variables, which are later used for calculating appropriate KPIs.

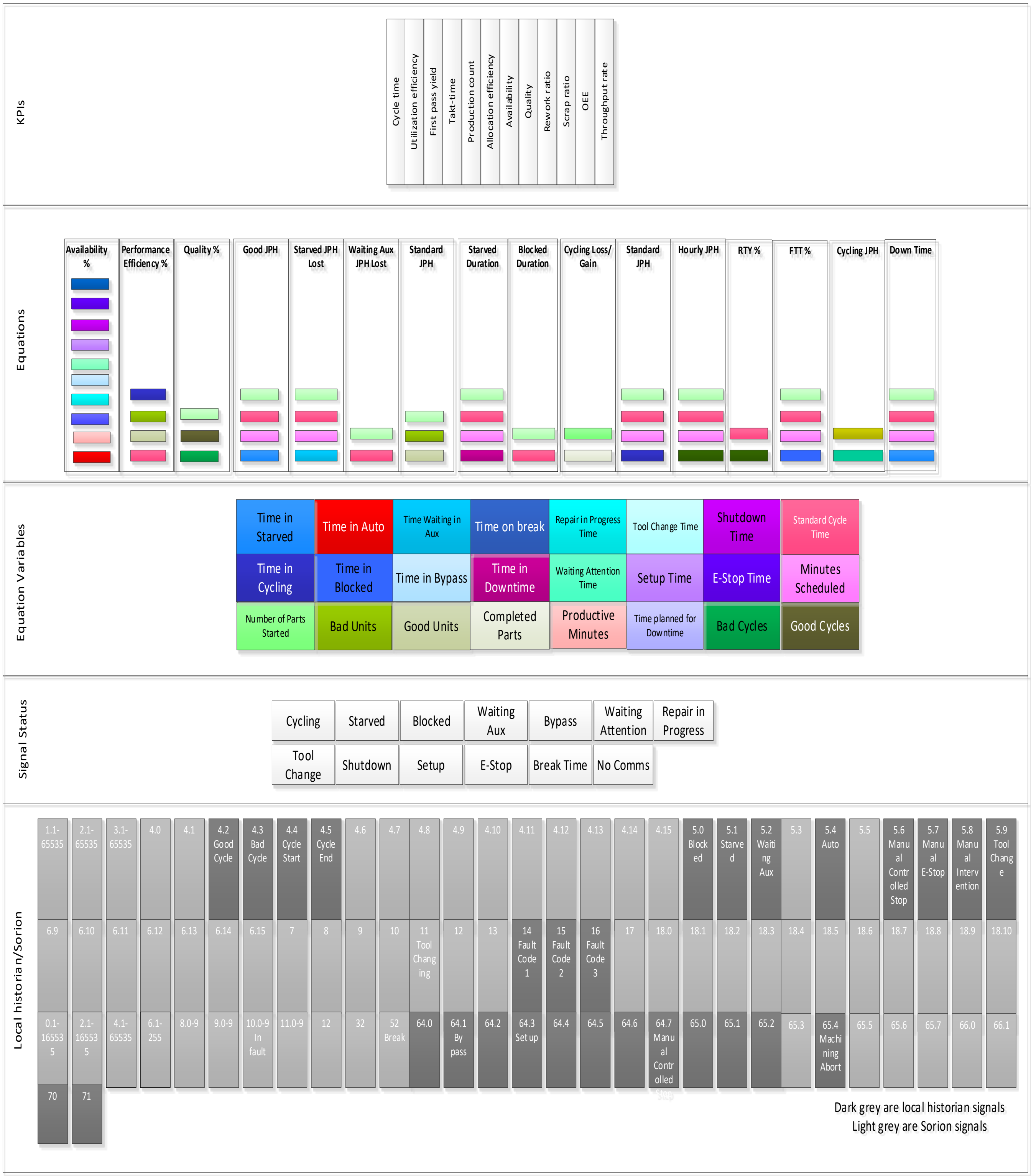


Figure 26 local historian and Sorion to KPIs-data flow

Step 2- Displaying appropriate KPIs to the audience: three dashboards are proposed for the audiences (operators, supervisors, and managers) working on the L494 assembly line. The dashboard is an essential visualization tool that tracks, analyzes, and displays KPIs to monitor a production process's health. The dashboard designs are minimal and scalable, as well as easy for the audience to understand. The design of these dashboards displaying essential KPIs for various audiences is shown in figures 27, 28, and 29.

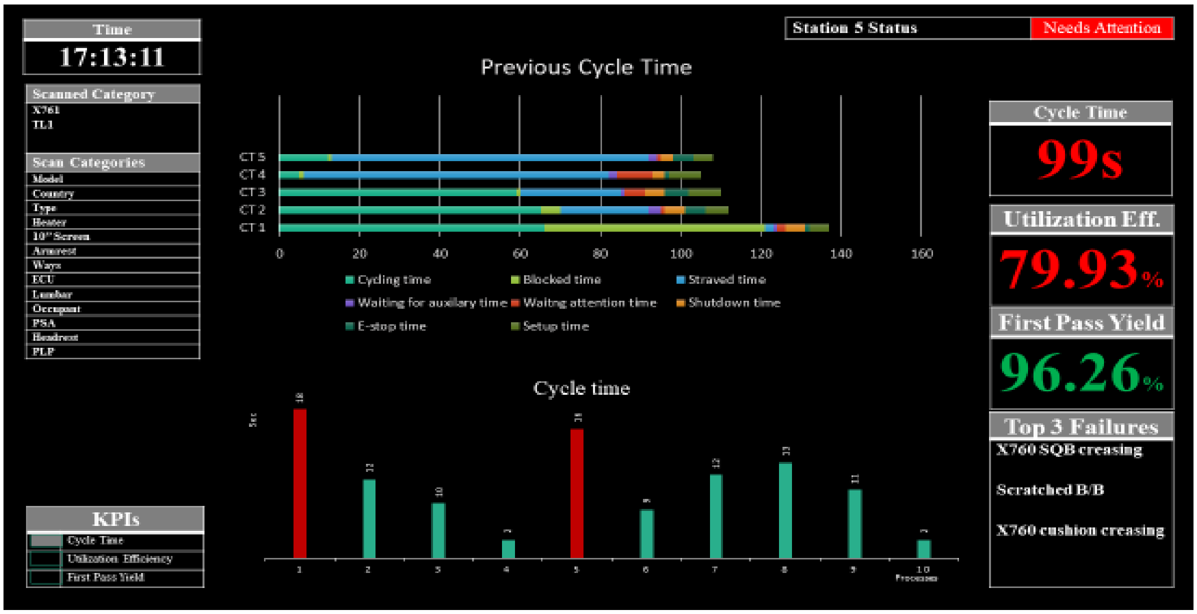


Figure 27 Dashboard designed for operators

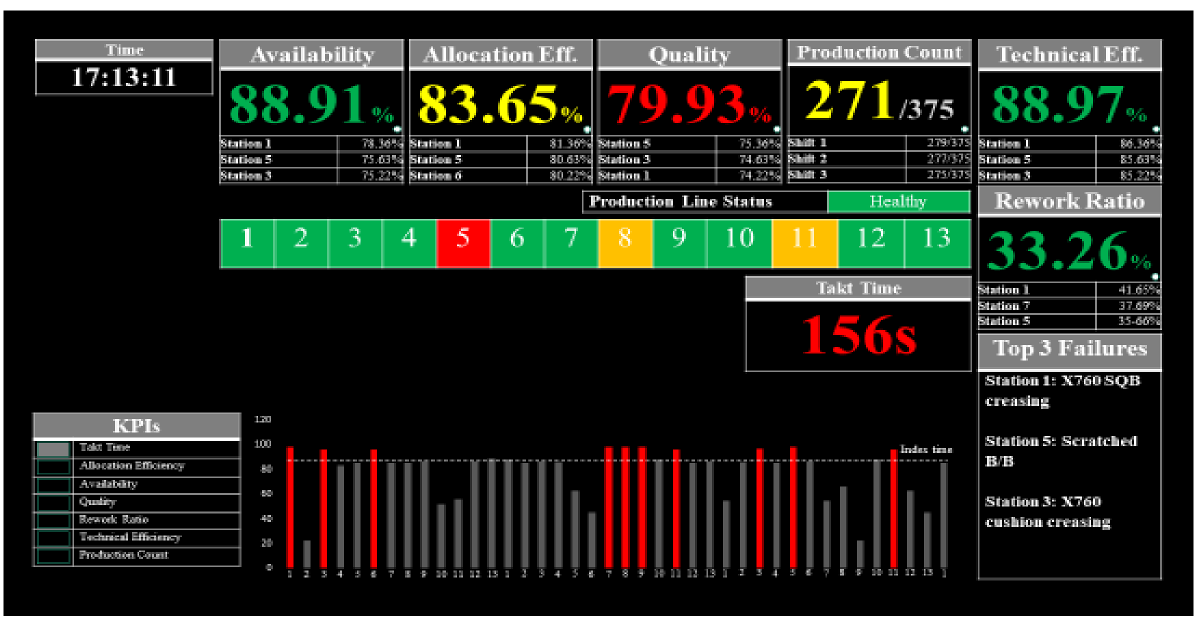


Figure 28 Dashboard designed for supervisors

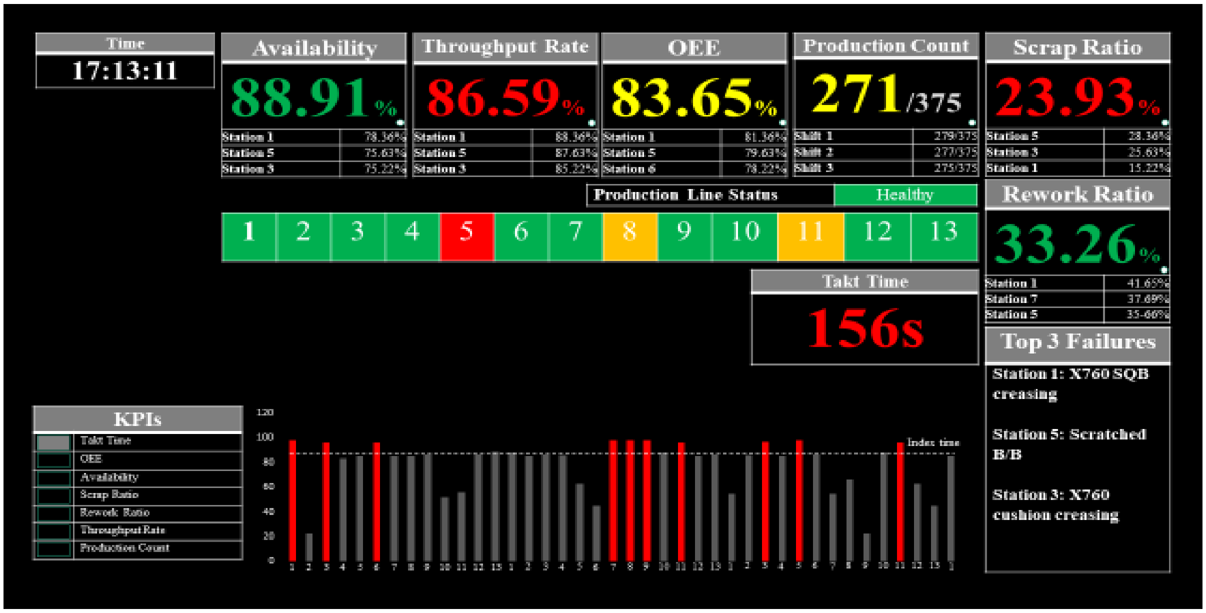


Figure 29 Dashboard for managers

Step 3-Recording new data: the last step in the implementation phase is to record the L494 assembly line's performance soon after the proposed dashboards are replaced with the existing ones. The data is set to be registered from 03/06/2020 to 03/09/2020. But due to the current on-going uncertainty causing by the Covid-19 pandemic, Company X production was drastically affected, resulting in no further approval of undertaking any research work from 01/07/2020 - 01/06/2021. Therefore, only a month (01/07/20) of data was recorded for evaluating the effectiveness of the proposed approach through the implementation of the proposed dashboards for the current L494 assembly line. The comparison of the assembly line performance is recorded in table 46.

Table 46 Comparison of L494 assembly line performance

Criteria	**Theoretical performance**	**Previous performance (01/09/2019-01/03/2020)**	**Performance recorded on 01/07/2020**
Seat production (per shift)	230-245	205-223	233-237
Overall production rate (per shift)	98	83.5	91.5
Rework seats (per shift)	1-2	17-23	7-9
Acceptable production loss limit (per order)	£200-£250	£11250-£13500	£4900-£6900

Percentage of orders delivered on-time without involving additional resources	100	81.7	92.5
The requirement of extra workers to fulfil production order on-time	0	2	0
Number of breakdowns reported during a production shift	0	23-25	2-3
Number of times the stations failed to complete assigned operations with the set takt time (per production order)	0	1350-1360	60-90

Table 46 shows that with the implementation of the appropriate KPIs, the L494 assembly line performance is considerably elevated. For instance, the seat production rate (per shift) improved from 205-233 to 233-237 per shift. The acceptable production loss also noticeably reduced from £11250-£13500 to £4900-£6900, making a substantial saving of £8350-£9600 per production order. The additional workers' requirement to fulfill the production orders on-time was no more needed as well, as the percentage of production orders delivered timely increased from 81.7% to 92.5%. The number of breakdowns reported per production shift reduced from 23-25 to 2-3. Lastly, the number of times the stations failed to complete their operations within the set takt-time improved from 1350-1360 to 60-90.

To better realize how the numerical figures mentioned in table 46 have improved by the implementation of the proposed dashboards with appropriate KPIs; comparisons highlighting the significant differences between proposed dashboard with appropriate KPIs (To-Be KPIs and dashboards) and existing KPIs dashboard (As-Is KPIs and dashboard) are tabulated table 47, 48 and 49. These comparisons are the essential points that stand out in favor of the proposed dashboard with appropriate KPIs supporting effectively monitoring the company X L494 assembly line performance. Table 47, 48, and 49 show these comparisons concerning company X objectives from the viewpoint of operators, supervisors, and managers, respectively.

Table 47 Comparisons between proposed dashboards with appropriate vs. existing KPIs dashboard- operators perspective

Company X L494 assembly line objectives	**Proposed dashboard with appropriate KPIs (To-Be KPIs and dashboard)**	**Existing KPIs dashboard (As-Is KPIs and dashboard)**
Improve the current production rate to 98% to fulfill production orders on time without involving additional workers	By effectively monitoring production rate using the cycle time and utilization efficiency KPIs, the operators can spot the station's most complicated process, assisting the operators in completing the process and analyzing potential bottlenecks on time. For example, cycle time displays the production process's status in real-time, enabling the operators to take proactive measures rather than reactive measures. The presentation of cycle-time KPI on the dashboard makes the operators aware of the time needed to complete every process within the desired station simpler and easier to deduce. Utilization efficiency enables the operators to know the difference between the actual production time and actual station busy time. This KPI displays the right time for which the station was operating compared with the actual production time. For intermittent lines that are typically operated on a set takt-time basis, any interruptions caused by one or several stations can negatively affect the whole production rate, utilization efficiency KPI helps to highlight both the under-performing and over-performing stations in real-time, on-demand, and	Takt-time is the only KPI available on the dashboard for the operators that have been used by company X for monitoring the L494 assembly line performance. After evaluating takt-time KPI (section 4.5), it is apparent that the right audience for this KPI is supervisors and managers. Displaying this KPI to operators will not support the company X effectively monitoring the production rate because takt-time is explicit to the whole assembly line rather than the individual station. Calculating the takt time depends on various internal and external factors beyond the control of company X. Having cycle time instead of takt time can be a better option for monitoring the L6494 assembly line production rate. Also, the existing dashboard presents information that is irrelevant for the operators working within different stations.

	periodical, enabling the operators to know how their specific station is performing throughout the production of seats.	
Improvement in seat quality	The first pass yield KPI is focused on the quality aspect of seat production. It helps the operators know the good or bad quality of seats produced in real-time, on-demand, and periodical. With a consistent decrement in the quality of seats produced by the L494 assembly line, this KPI can assist the company X, especially operators, in familiarizing themselves with the quality of seats produced so that precautionary measures can be initiated to stop the further drop in seat quality in-time.	There is no KPIs that can help the operators in monitoring the quality of seat produced. So, company X does not have any performance measures available for the operators to monitor the seat quality, thereby improving seat quality.
Real-time monitoring of the stations to increase visibility and quick decision-making capability	The proposed cycle time KPI can help monitor the station level performances and support the operators in knowing the exact time required to finish their sub-tasks and overall task completion time. Moreover, cycle time KPI is process-centric and can be displayed in real-time, making it convenient for the operators to identify the bottleneck processes in real-time within the station(s) that are the potential causes of the drop-in production rate. Thus, enabling quick decision-making capability with increased visibility.	Currently, there are no performance measures that can help company X to monitor the L494 assembly line performance to increase visibility and quick decision-making capability

Table 48 Comparisons between proposed dashboards with appropriate vs. existing KPIs dashboard- Supervisors perspective

Company X L494 assembly line objectives	Proposed dashboard with appropriate KPIs (To-Be KPIs and dashboard)	Existing KPIs dashboard (As-Is KPIs and dashboard)
Improve the current production rate to 98% to fulfill production orders on time without involving additional workers	KPIs such as allocation efficiency and technical efficiency are proposed to the supervisors for effectively monitoring production rate. The benefits of these KPIs in monitoring production rates are illustrated in section 4.7. These KPIs can be displayed in real-time, on-demand, and periodical based on the process. Supervisors need to enable them to analyze the production performance and take proactive measures in-time. These KPIs' information highlights the root causes that degrade the assembly line performance and help find a suitable solution. For example, technical efficiency is the effectiveness with which a given set of inputs is used to produce a seat. If the technical efficiency drops, it means that the assembly line performance is degrading and needs attention.	Supervisors have four KPIs (takt-time, availability, production loss ratio, and production count) to monitor production performance. In section 4.5, only two KPIs (takt-time and production count) help deliver relevant information for real-time performance monitoring. The data from production loss ratio KPI is not applicable for seat assembly (discrete manufacturing). The reason behind that is the nature of the process undertaken within this assembly line, constantly changing production orders and raw materials, making it difficult to calculate, analyze and interpret the results after measuring this KPI. The availability KPI is useful for undertaking proactive measures as this KPI cannot be displayed in real-time to spot the production anomalies.
Improvement in seat quality	Having real-time quality information about the seats using quality KPI helps the supervisors take necessary actions before further degrading. The quality KPI displayed on the dashboard also allows the supervisors to locate the station responsible for the decline in seat quality.	Rework ratio KPI can measure the seat quality in real-time, on-demand, and periodical. This KPI can effectively benefit them in monitoring and maintaining the seat quality. One point to note from the analysis (section 4.5) is that the rework ratio is a derived KPI. Meaning that it requires quite a few equation variables (also known as the

	It helps to locate the seat defect with the relevant station where that process was undertaken. Knowing the station where seat defects arise enables the supervisors to take necessary actions to improve the seat quality.	data) for its calculation, making it problematic and costly (due to the technology used for extracting the data from the shop floor). There is a various quality associated KPIs that can measure the real-time seat quality using minimal equation variables and/or cost-effective technologies. One such example is a quality KPI that can measure and monitor seats without involving several equation variables, unlike various other KPIs that need complex and sophisticated technologies to get the right equation variables.
Real-time monitoring of the stations to increase visibility and quick decision-making capability	The proposed KPIs, such as allocation efficiency, technical efficiency, and quality, can present production line performance in real-time, providing increased visibility for the supervisors to achieve quick decision-making capability. All the necessary information needed by the supervisors to actively monitor every individual station in real-time is displayed on the dashboard to identify the causes of any unnecessary stoppages in the production and degrade in the seat quality.	With the existing KPIs and dashboard, the company X does not have complete visibility of the L494 assembly line, and hence quick decisions cannot be made. For instance, KPI such as availability is a lagging KPI, meaning that the information obtained from this KPI cannot be displayed in real-time to make informed decisions. Whereas, takt-time KPI can help to show station performance in real-time but fails to track the station's process that causes delay offering partial visibility.

Table 49 Comparisons between proposed dashboards with appropriate vs. existing KPIs dashboard- managers perspective

Company X L494 assembly line objectives	**Proposed dashboard with appropriate KPIs (To-Be KPIs and dashboard)**	**Existing KPIs dashboard (As-Is KPIs and dashboard)**
Improve the current production rate to 98% to fulfill production orders on time without involving additional workers	Managers are provided with OEE and throughput rate KPIs for monitoring the performance of the L494 assembly line. The figures displayed by these KPIs provide managers with invaluable data that can be used as a tool to improve the production rate and enable them to fulfill the production orders on time. Based on the class of user, bespoke high-level KPIs are selected and displayed. The managers proposed the KPIs to provide them with complete information (product, process, and resource) of the production line performance. For example, OEE KPI multiplicates availability, performance, and quality providing managers with complete information.	To monitor a given L494 assembly line's performance and achieve the set objectives, company X employs the same set of KPIs and dashboards presented to the supervisors (shown in figure 24). The disadvantages of using the existing KPIs and dashboard is already mentioned in table 48; they are the same with the supervisors.
Improvement in seat quality	KPIs such as OEE and scrap ratio enable the managers to know the quality of seats produced in real-time, on-demand, and periodical. The dashboard further lists the top 3 stations with seat failure, which can help the managers improve seat quality by addressing these failures.	
Real-time monitoring of the stations to increase visibility and quick decision-making capability	After assessing the deficiencies with the existing KPIs regarding company X needs, the proposed KPIs fill the gap of lack of information needed for real-	

	time monitoring of the stations by providing full station level activity through KPIs OEE throughput rate. The proposed dashboard presents relevant information without overloading the managers with information. As the KPIs provided to the managers are high-level (demonstrating the company's overall performance). The figures displayed using these KPIs can help in decision-making.	

During the month (01/07/2020) when these KPIs were presented to the operators, the following bottlenecks (hindrances) were identified:

1. Task allocations: cycle time for stations 2 and 8 theoretically calculated through task allocation for various seat orders (3SJXCH1, 75SSTD7, 8QWE54L, etc.) significant than the set takt-time resulting in overall production delays.

2. Station wait times: high difference in task allocation resulted in few stations (station 1 and 5) always completing their task well within the cycle time. Station 1 and station 5 cycle time was 65.3 and 56.5 seconds (30-40 seconds lesser than the production takt time) respectively throughout the production.

3. Seat Quality: 89 out of 137 seat quality defects identified were due to L494X1 and L494X6 seat variants. With the increased visibility of the production line, these defects in the seats were due to armrest installation. The armrest installation process can be directly linked to stations 5 and 6, where it is undertaken.

Promptly addressing these bottlenecks using line balancing techniques, the production rate was improved.

To further understand the source of improvement in the L494 assembly line performance from the company X staff themselves, several operators, line supervisors, and managers were asked to reflect their opinions about the new dashboards displaying appropriate KPIs. Several operators mentioned the visibility of the operations and sub-operations within each station as the key to this improvement that helped them deliver their tasks timely. The cycle time KPI played a critical role in keeping the operators informed about the operations' status. With the cycle time KPI, it was easier for the operators to familiarize themselves with the processes that need attention, time-consuming from the more manageable, and completes operations in the least amount of time. They further stated that the first pass yield KPI helped them know the standard of the produced seat, which they have never been displayed in the previous dashboard. It facilitated them to watch specific procedures so that several seats can be saved from further rework. As all the KPIs showed to operators were real-time, this was coined as one of the significant factors for improving overall assembly line performance.

From the perspective of line supervisors and managers, they cited that the dashboards supported them in making informed and quick decisions. It displayed which stations, operations, and sub-operations were the root cause for overall performance decrement. The generated KPI reports helped them think and work on the existing line balancing and optimization techniques and modify them accordingly. The line supervisors were able to take preventative rather than corrective actions in breakdowns by providing insights into the current performance. Line supervisors also reported that the number of breakdowns had significantly improved after implementing new dashboards due to the increased visibility within each station. The line supervisors and managers agreed that the KPI reporting dashboards helped them discover the current assembly line's strengths and weaknesses and swiftly allocate the operator(s) based on the nature of operations within each station. It also helped them set new strategic plans and effectively monitor the current business objectives, problems, and challenges and highlight the bottlenecks.

CHAPTER 5 CONCLUSION AND FUTURE WORK

This chapter concludes the research work reported in this thesis. A comprehensive summary of the research achievements and contributions are outlined, and future recommendations are stated.

5.1 Achievements of Research Objectives

Manufacturers are pushed to engineer highly flexible, robust, and efficient manufacturing processes to produce high-quality goods at a reduced cost to combat evolving challenges and attain full economic potential in the current industrial revolution. As a result, manufacturing industries in the present time have realized the significance of shop floor data analysis. They are implementing performance measurement systems to assess and improve the performance of their manufacturing operations continually. To quantify the effectiveness and efficiency of shop floor operations, this research work develops a holistic approach that enables manufacturers to understand, analyze, select, and implement appropriate KPIs for their shop floor operations assessment. Few research objectives are defined in section 1.6 of this thesis, highlighting this holistic approach's development. This section elucidates the achievements of those objectives.

<u>*Objective 1: develop a manufacturing shop floor exploration model to identify the key business objectives, problems and challenges, crucial performance details, bottlenecks, and list of KPIs within the given manufacturing shop floor facility by using questionnaires and structured interviews along with shop floor production data*</u>.

A detailed review of existing frameworks and models within literature and industry is presented in Chapter 2, particularly in the manufacturing sector. A comprehensive literature on performance measurement assessments emphasizing these models' strengths and limitations is presented in section 2.3. From the assessments conducted in section 2.3, it was established that the manufacturing shop floor exploration model could successfully overcome the limitations of existing frameworks and models by making use of questionnaires, structured interviews along shop floor production data. In-depth development of manufacturing shop floor exploration model to identify the key business objectives, problems and challenges, crucial performance details, bottlenecks, and list of KPIs for manufacturing shop floor facility is presented in section 3.2.

2. Develop KPI guidelines by extracting every essential guiding performance measure needed for the manufacturer to understand, analyze, select, and implement appropriate KPIs. The KPI guidelines consist of five stages, namely: information stage, discernment stage, scheming stage, the origin of the data stage, and assisting technology stage. Each stage consists of measures dedicated to providing vital information to help manufacturers better monitor their shop floor operations and improve decision-making capabilities.

A detailed review of existing KPI performance measures within the literature and manufacturing industry is presented in Chapter 2. Comprehensive literature highlighting KPI measures along with relevant KPI elements is presented in section 2.4. A level of granularity throughout the process of developing novel KPI guidelines that unifies every possible KPI measure alongside the elements needed for manufacturers to understand, analyze, select and implement appropriate KPIs within their shop floor facility is illustrated in section 3.3. These guidelines help to bridge the gap between industrial needs and current research.

3. Conduct a case study on a tier 1 automotive manufacturing suppliers' shop floor facility to evaluate the proposed manufacturing shop floor exploration model's effectiveness and practicality combined with the KPI guidelines. The case study will mainly concentrate on analyzing the usefulness of the existing KPIs generated from the manufacturing shop floor exploration model in monitoring the key business objectives using KPI guidelines.

Chapter 4 demonstrates the detailed process of implementing the proposed methodology within Company X, a tier 1 automotive manufacturing suppliers' shop floor facility in the UK. Section 4.4 outlines the crucial L494 performance details, key business objectives, challenges, problems, and bottlenecks because of applying the manufacturing shop floor exploration model. Section 4.5 evaluates the effectiveness of the existing KPIs using proposed KPI guidelines. The conclusions are drawn for the L494 assembly line. There are no beneficial KPI measures currently provided to the operators, which can help them monitor and improve production performance and achieve the key business objectives. The takt-time KPI supplied to the operators does not fully help in improving actual production performance. To measure the quality of the seats assembled, a derived KPI (rework ratio) is employed when several other KPIs are available in the literature review, which can be straightforwardly deployed based on the easily accessible shop floor data cost-effective technology. One real-time KPI, production count, and one periodical KPI, availability, are used to measure the line's production rate. An inadequate KPI (production loss ratio) is currently employed with zero added value to monitor line performance.

4. From the data collected through the manufacturing shop floor exploration model and coalescing it with the focused literature review on KPIs, opinions from industrial and academic experts, and evaluating it using KPI guidelines, a set of appropriate KPIs is suggested. The benefits of implementing the appropriate KPIs in the manufacturing shop floor facility is explained.

The comprehensive evaluation of the appropriate KPIs and their possible benefits on company X's overall manufacturing shop floor performance improvement are discussed in sections 4.5 and 4.7. Some of the key benefits including real-time production and quality monitoring, tailor-made performance measures for operators, supervisors, and managers, early bottleneck detection, enabling proactive rather than reactive decision-making, and providing a cost-effective solution to deploy new performance measures. Section 4.9 explains the results of implementing the appropriate KPIs within the L494 assembly line; it also includes operators, line supervisors, and managers about the new dashboards designed to monitor production performance effectively.

5. Prioritizing key business objectives and the appropriate KPIs using SMART criteria.

Various prioritization techniques available from the literature are discussed in section 2.5. The existing prioritization techniques are compared depending on their scalability, easy-use, time-complexity, accuracy, robustness, and customer satisfaction. Based on the results generated, by comparison, SMART criteria were selected because each element in these criteria works together to create a goal that is sensibly planned, transparent, and trackable. The goal is to rank key business objectives and appropriate KPIs in order of their importance in improving current shop floor performance. The detailed process of prioritizing key business objectives and KPIs are discussed in section 3.4. The result of implementing SMART criteria in company X manufacturing facility is illustrated in section 4.8.

5.2 Research Benefits

The case study, implementation, and evaluation in Chapter 4 highlighted several benefits of adopting the proposed methodology. Below is an outline of these benefits.

1. Capturing overall shop floor performance details

By employing questionnaires, structured interviews, and shop floor production data, the manufacturing shop floor exploration model can capture through production information such as crucial performance details, key business objectives, problems, challenges, and bottlenecks. These details enable the manufacturers and the person conducting the study to familiarise themselves with specific reasons for any decrement and/or improvement in the shop floor's current performance.

2. Enabling the manufacturers to understand, analyze, select and implement appropriate KPIs

The proposed KPI guidelines are presented as a step-by-step guide consisting of five stages, namely: information stage, discernment stage, scheming stage, the origin of the data stage, and assisting technology stage. Every stage consists of different measures and corresponding elements which provide indicative information about the KPIs. The idea behind choosing a systematic approach is to lay a strong foundation for understanding KPIs without overwhelming manufacturers. Moreover, to effectively address the current industrial needs, it is deemed necessary for the manufacturers to acquire basic (general) knowledge about KPIs before sequentially obtaining detailed aspects (i.e., by following different stages). The approach will help impart KPIs knowledge, starting from providing necessary to precise details as needed by the manufacturers.

3. Evaluating the effectiveness of performance indicators

Compared with the KPI guidelines, the manufacturing shop floor exploration model results provide manufacturers with the effectiveness of the existing performance indicators. For instance, KPI guidelines break down details of every performance indicator needed by manufacturers to confirm existing performance measures' applicability in achieving their key business objectives. It enables manufacturers to know if the existing performance indicators assist in monitoring the right performances.

5.3 Novelty of the Research

1. Developing a manufacturing shop floor exploration model capable of identifying key business objectives, problems, challenges, crucial performance details, bottlenecks, and a list of KPIs within the given manufacturing shop floor facility.

2. Developing KPI guidelines for the manufacturers to understand, analyze, select, and implement appropriate KPIs.

3. Combining manufacturing shop floor exploration model with KPI guidelines to determine the effectiveness of the proposed approaches.

5.4 Further Research

The complete methodology of selecting appropriate KPIs and reviewing the manufacturing shop floor performance is a continuous process. The results, which were obtained in the current study, can be used, extended in future works as follows:

1. Application of the proposed methodology to several manufacturing facilities to confirm its effectiveness and applicability.
2. Development of web interface which can offer appropriate KPIs instantly without additional resources for research.
3. Integration of KPI measures such as financial, health and safety, and energy-related and corresponding elements to KPI guidelines.

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Appendix

Appendix 1: Confirmation of Ethical Approval

Biomedical and Scientific Research Ethics Committee
Kirby Corner Road
Coventry
CV4 8UW

Wednesday, 25 March 2020

Mr Abdul Rehan Khan Mohammed
WMG
University of Warwick
Coventry
CV4 7AL

Dear Mr Mohammed

Ethical Application Reference: BSREC 49/19-20
Title: 'A Holistic Model Required for Selecting Key Performance Indicators'

Thank you for submitting your revisions to the Biomedical and Scientific Research Ethics Committee (BSREC) for consideration. We are pleased to advise you that, under the authority delegated to us by the University of Warwick Research Governance and Ethics Committee, **full approval for your project is hereby granted.**

Before conducting your research it is strongly recommended that you complete the on-line Research Integrity training:
www.warwick.ac.uk/ritraining. Support is available from the BSREC Secretary.

In undertaking your study, you are required to comply with the University of Warwick's Research Code of Practice:
https://warwick.ac.uk/services/ris/research_integrity/code_of_practice_and_policies/research_code_of_practice/

You are also required to familiarise yourself with the University of Warwick's Code of Practice for the Investigation of Research Misconduct:
https://warwick.ac.uk/services/ris/research_integrity/research_misconduct/codeofpractice_researchmisconduct/

You must ensure that you are compliant with all necessary data protection regulations:
https://warwick.ac.uk/services/idc

Please ensure that evidence of all necessary local permissions is provided to BSREC prior to commencing your study.

Please also be aware that BSREC grants **ethical approval** for studies. The seeking and obtaining of all other necessary approvals is the responsibility of the investigator.

www.warwick.ac.uk

Any substantial changes to any aspect of the project will require further review by the Committee and the PI is required to notify the Committee as early as possible should they wish to make any such changes. The BSREC Secretary should be notified of any minor amendments to the study.

May I take this opportunity to wish you the very best of luck with this study.

Yours sincerely

pp. [redacted]

Dr David Ellard
Chair, Biomedical and Scientific Research Ethics Committee

Appendix 2: List of manufacturing shop floor KPIs identified from the literature

Serial no.	List of Manufacturing Shop Floor KPIs
1	Allocation Ratio
2	Availability
3	Average Time to Competence
4	Blocking Time
5	Build To Schedule
6	Busy Time
7	Capacity Utilization
8	Changeover Time
9	Corrective Maintenance Time
10	Critical Machine Capability Index
11	Cycle Time
12	Defect Count
13	Downtime
14	Downtime in Proportion to Operating Time
15	Emergency Stop Time
16	Employee Available Time
17	Employee Satisfaction with Training
18	Employee Scheduled Time
19	Equipment Failure Rate
20	Equipment Unavailability, Hours per year - Planned maintenance
21	Equipment Unavailability, Hours per year - Sustained fault
22	Equipment Unavailability, Hours per year - Temporary fault
23	Equipment Unavailability, Hours per year - Unplanned maintenance
24	Faults Detected Prior to Failure
25	First Aid Visits
26	First Time Through
27	First Time Yield
28	Forecasts of Production Quantities
29	Good Cycles Counter
30	Idle Time
31	Increase/decrease in Plant Downtime
32	Industry Benchmark Performance
33	Integration Capabilities
34	Interaction Level Inventory
35	Labor Performance
36	Labor Productivity
37	Machine Capability Index
38	Machine Downtime
39	Machine Modules Reuse

40	Machine Set Up Time
41	Maintenance Backlog
42	Maintenance Technician's Skill Level Improvement
43	Manufacturing Uptime
44	Mean Time Between Failure
45	Mean Time To Repair
46	Operating Time
47	Order Execution Time
48	Outage Time per Event
49	Overall Equipment Effectiveness
50	Overall Production Rate
51	Overtime as a Percentage of Total Hours
52	Percentage of Maintenance Work Orders Requiring Rework
53	Percentage of Man-Hours used for Proactive Work
54	Percentage of Scheduled Man-hours to Total Man-hours
55	Percentage of Spare Manufacturing Capacity
56	Percentage of Tasks Completed
57	Percentage Planned vs. Emergency Maintenance Work Orders
58	Percentage Reduction in Defect Rates
59	Percentage Reduction in Downtime
60	Percentage Reduction in Inventory Levels
61	Percentage Reduction in Manufacturing Lead Times
62	Percentage Reduction in Number of Employee Injuries
63	Percentage Reduction in Number of Equipment Failures
64	Perfect Order Measure
65	Performance
66	Personnel Work Time
67	Planned Hours of Work vs. Actual Situation
68	Planned Maintenance Time
69	Planned Work to Total Work Ratio
70	Predictive Maintenance Monitoring
71	Preventive Maintenance Time
72	Process Capability Index
73	Processing Time
74	Product/Service Usage Everyday
75	Production Attainment
76	Production Downtime
77	Production Target
78	Production Volume
79	Productivity
80	Project Resource Utilization

81	Quality
82	Quality Improvement
83	Quality Tracking-Six Sigma
84	Ratio of Internal versus External Training
85	Reduced Time to Productivity
86	Reject Cycles Counter
87	Repair in Progress Time
88	Reportable Health & Safety Incidents
89	Resource Utilization
90	Response time to gas or water leaks
91	Rework
92	Right First Time
93	Risk Analysis Ratio
94	Schedule Variance
95	Scheduled Production
96	Scrap
97	Setup Time
98	Shutdown Time
99	Staffing Efficiency
100	Standard Operating Efficiency
101	Starving Time
101	Station Unavailability - Planned Maintenance
102	Station Unavailability - Sustained Fault
103	Station Unavailability - Temporary Fault
104	Stop Time
105	Takt Time
106	Technical Efficiency
107	Technology used to Execute Inventory Strategies
108	Throughput
109	Time on Floor to be Packed
110	Time to Fill
111	Tool Change Time
112	Total Factor Productivity
113	Training Penetration Rate
114	Unplanned Capacity Expenditure
115	Unscheduled Down Time
116	Utilization
117	Utilization Efficiency
118	Waiting for Attention Time
119	WIP Inventory
120	Worker Efficiency

121	Workforce Stability
122	Work-In-Process

Appendix 3: Publications

Publication 1:

A. R. K. Mohammed and A. Bilal, "Manufacturing Enhancement through Reduction of Cycle Time using Time-Study Statistical Techniques in Automotive Industry," 2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS), Taipei, Taiwan, 2019, pp. 681-686, doi: 10.1109/ICPHYS.2019.8780198.

Publication 2:

M. A. R. Khan and A. Bilal, "Literature Survey about Elements of Manufacturing Shop Floor Operation Key Performance Indicators," 2019 5th International Conference on Control, Automation and Robotics (ICCAR), Beijing, China, 2019, pp. 586-592, doi: 10.1109/ICCAR.2019.8813436.

Publication 3:

A. R. Khan Mohammed, B. Ahmad, and R. Harrison, "A Holistic Approach for Selecting Appropriate Manufacturing Shop Floor KPIs," 2020 IEEE Conference on Industrial Cyber physical Systems (ICPS), Tampere, 2020, pp. 291-296, doi: 10.1109/ICPS48405.2020.9274690.

Literature Survey about Elements of Manufacturing Shop Floor Operation Key Performance Indicators

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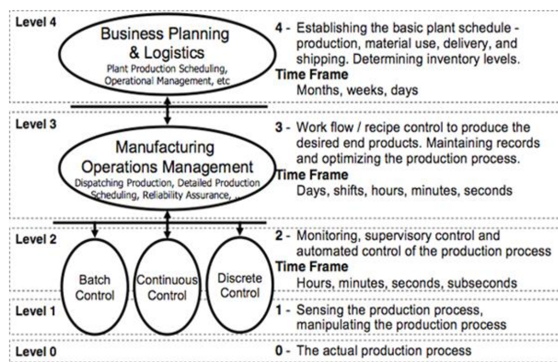
***Abstract*—In the era of globalization, manufacturing industries are compelled to continuously monitor their manufacturing operations to maintain competitiveness. As a result, manufacturers have integrated several measurement models to inspect their manufacturing operations. These models comprise of a set of Key Performance Indicators (KPIs), which are capable to enumerate the effectiveness, competence, efficiency and proficiency of manufacturing operations. This paper presents a review of manufacturing shop floor operation KPIs that has been studied in the recent literature. Based on the reviewed literature author proposes various KPI elements such as: description, category, scope, formula, unit of measure, range, trend, mode of display, viewers and manufacturing approach. These elements can help manufacturers to better describe, classify, analyze and measure the appropriate KPIs for their shop floor operations. Thus, enabling manufacturers to accomplish and uphold great quality, increased productivity and throughput.**

Keywords-performance enhancement; KPIs; manufacturing operations KPIs and manufacturing industries

INTRODUCTION

The performance of equipment, process, production line or the whole manufacturing industry is principally measured in two ways: result indicators and performance indicators. Result indicators are used to measure the effects of the operations activities but ignoring the cause. While performance indicators are used to generate the next plan of action to be taken based on the results [1]. According to International Standard ISO 22400-1 (2014) [2] and International Standard ISO 22400-2 (2014) [3], KPIs plays a vital role in swiftly and effectively providing precise and detailed statistics of a whole manufacturing industry by equating real-time performance alongside with their nominal performance to accomplish set objectives. A manufacturing industry is composed of a number of operational areas, for instance manufacturing, sales, marketing and many other related functional areas. Based on the operational areas, manufacturing industries can have diverse sets of KPIs [4].

Centred on the operational area, within the manufacturing industries functional hierarchy model: discrete, continuous or batch control of the manufacturing process is at level 1-2 [4]. Whereas, manufacturing operations management is at level 3 and business planning and logistics is at level 4. Figure 1, illustrates the different levels of manufacturing industries hierarchy model. As mentioned in IEC 62264-1 [5], manufacturing shop floor operations can further be categorised into sub operations, such as: production, maintenance, quality, inventory and other manufacturing related operations. KPIs based on each of these sub operations can be defined independently or depending on combinations of these sub operations. In this paper, level 1-3 of the below mentioned hierarchy model, predominantly focusing on manufacturing shop floor operation KPIs is addressed.



Functional hierarchy model [5].

Several manufacturing industries that uses KPIs to improve their shop floor operations often detracts from their objectives because they measure numerous KPIs, which leads to fading the emphasis on primary goals [6]. Also, many manufacturers have limited understanding about the right KPIs that can help them to enhance their manufacturing operations [7], [8]. Equally, some of the KPIs have no links related to objectives defined by the manufacturers, and a lot of them monitors one part of process not targeting other imperative processes [9], [10]. In a nutshell, many manufacturers are still struggling to find the required guiding KPI elements to enable design, measure and improve their shop floor performance. Intuiting the difficulties faced by the manufacturing industries, this paper presents a list of KPIs covering all the essentials elements required by a manufacturer before selecting the right KPIs for their manufacturing shop floor operations.

From the set standards on manufacturing KPIs so as to achieve the best industry practices, the key determinants/elements of an ideal KPI should include:

description, category, scope, formula, unit of measure, range, trend, mode of display, viewers and manufacturing approach. Some of the manufacturing shop floor KPIs presented in this paper are shown in table I.

TABLE I. LIST OF MANUFACTURING SHOP FLOOR KPIS

Allocation Ratio	Production Process Ratio
Availability	Quality
Corrective Maintenance Ratio	Rework Ratio
Cycle Time	Scrap Ratio
First Time Pass Yield	Standard Jobs Per Hour
Mean Time To Failure	Setup Ratio
Mean Time To Repair	Technical Efficiency
Overall Equipment Effectiveness	Throughput Rate
Performance	Utilization Efficiency
Production Effectiveness	Worker Efficiency
Production Loss Ratio	

The rest of the paper is structured as follows: literature review, followed by explaining the elements of KPIs. Then, list of KPIs is presented. Finally, conclusions are drawn.

LITERATURE REVIEW

To search more on this research area, a meticulous exploration of the literature linked to manufacturing industries shop floor KPIs was conducted over longitudinal basis. This literature review covers materials from the last 20 years. The notion behind setting up this time frame is: during the initial literature search on manufacturing industries shop floor KPIs via google scholar and researchgate, it was seen that this term arouse and gained popularity after the year 1998 (with only 7 publications registered during that year). Followed by 10, 11 and 13 publications in the upcoming years 1999, 2000 and 2001 respectively. The literature was examined by means of the following electronic databases: ABI/INFORM Global, ACM Digital Library, British Standards Online, Engineering Village, IEEE Xplore Digital Library, Science Direct and Scopus. Moreover, University of Warwick library search was also conducted in order to take into account all related books and dissertations.

KPIs plays an important role in assessing the effectiveness and efficiency of any given performance area within manufacturing industries. From the year 1980's, efforts in the manufacturing industries and academia have headed towards achieving high performances in the manufacturing shop floor operations [11]. Research papers, that highlights commonly used manufacturing industries shop floor KPIs are discussed below: Rahman [12], calculated CT to figure out the key downtime causes during total productive maintenance practices in a semi-automated manufacturing company. These downtimes were considered as non-value added undertakings, so minimising these downtimes helped to increase manufacturing performance, and improve the volume of production. Cao et al. [13], Meidan et al. [14] and Wang et al. [15], considered CT vital for multi-objective optimization in a semiconductor manufacturing industry to reach the set manufacturing targets on time by reducing the downtime. Thus, enabling industries to maintain a competitive advantage in global market. In order to reduce the CT, Bayesian neural model, selective naïve Bayesian classifier and adaptive logistic regression based correlation analysis models respectively, were generated to predict any variations in CT.

Lingam et al. [16], used CT to improve current production rate of t-shirt manufacturing in a textile industry using lean tools. The main focus was to decrease CT using a number of lean tools such as time and motion study, kaizen, failure mode effect analysis and value stream mapping. By doing so, the industry was able to save 82 seconds per product that was 20% reduction in CT, resulting in improved production rate along with increased savings. Ablad [17], worked on optimizing CT and UE in a multi-robot assembly cells. Working with multiple robots often creates collision glitches, which can be minimized by introducing synchronization schemes. These schemes has negative impact on CT and UE, and hence surrogate models were designed that optimises the impact and creates collision free environment inside assembly cells. Lepratti et al. [18], aimed at reducing the dynamic CT in order to deal with highly flexible manufacturing operations in automotive industries. Results proved that reducing dynamic CT by integrating scheduling and sequencing algorithms, improved the manufacturing effectiveness and material handling capabilities.

Kolte et al. [19], implemented effective preventive maintenance scheduling to enhance A, P, Q PLR, PPR and OEE of leading automobile manufacturing industry. Enhancing these KPIs, lead to the increase in continuous productivity and also, attaining higher production rate. This further lead to decrease in the maintenance cost and helped the industry to survive in the highly complex market competition. The case study which was carried on automobile engine cylinder block manufacturing line proved that by implementing the preventive maintenance scheduling: uptime was incremented, MTBF was increased and average MTTR was convincingly reduced. Juaregui Becker et al. [20], developed a new OEE method coined as machining equipment effectiveness (MEE) that focuses on optimising A, P, Q and OEE to improve routing flow, frequency of orders, production time and stability of demands. By taking an example of a high-mix-low-volume manufacturing industry, wherein both the materials and processes are varying, this method was implemented and the results proved to be feasible and effective.

Relkar et al. [21], analyzed the OEE of a leading automobile manufacturing company. By determining the performance of a present system, reference values were acquired; and then using regression analysis and various design experiments, ideal equation of OEE was developed. This equation was then used to boost the present OEE, so as to improve the A, P and Q of the company. Roriz et al. [22], demonstrated an industrial case that was concentrated on increasing the Q and OEE of production processes, using single minute exchange of die methodology. By employment of this methodology, the industry was able to efficiently organise their industry shop floor and reduce the setup time. Due to reduction in the setup time, the A of the machines increased and hence production rate significantly improved. Sowmya et al. [23], looked at the capacity problems in manufacturing industries to better A, P and OEE. The main emphasis was to improve utilization of resources and proliferate the performance of present machines using total productive maintenance tools. Similarly, Baluch et al. [24], heightened OEE of a Malaysian palm oil mills using total productive maintenance techniques. As a result there was decrease in overall downtime, improved equipment performance, reduced setup time and improved workers performance.

Meier et al. [25], evaluated KPIs related to planning and delivery of industrial services such as MTBF, UE and WE. This helped manufacturer to efficiently deliver the services by considering and managing these disruptions and uncertainties that causes these delays on-time. Gonzalez et al. [26], listed KPIs (A, MTBF, MTTR, P, RR and TE) covering operation and maintenance phase for efficient wind farm operations. This list was based on the literature review and interviews with stakeholders involved within wind farm operations. It concluded that more in depth revisions are needed within this domain for implementing right KPIs in wind farms operation and maintenance phase. Jovan et al. [27], suggested a method to measure and present the execution of production objectives in the form of introducing production KPIs such as Q, CMR and FTP yield. This KPIs enabled to minimize the production cost and increase the production rate by minimizing downtime and improving product quality.

Stylidis et al. [28], compared the manufacturing quality with the perceived quality and proposed an integrated quality framework that can improve the product quality and benefit customers. Similarly, Jain et al. [29] and Elzahar et al. [30], studied the various quality management systems practices like quality plan, supplier assessments and evaluations, customers satisfactions implemented in manufacturing industries to improve the product quality and benefit customers. Several other papers: used a various prediction methodology for continuous predicting CT, PLR, PPR and PE KPIs in a semiconductor manufacturing industry [30]. Few concentrated on measuring CT, MTTR, MTTF, TR and cycling loss KPIs to assess the impact of total productive maintenance practises on semi-automated manufacturing companies [31]. Few used selective naïve Bayesian classifier for continuous predicting CT in semiconductor manufacturing industry [32]. Heightened KPIs that are used to measure and monitor Q performance in oil and gas industry [33]. Showed how the variation of functional speeds both in material, and manufacturing handling processes leads to dynamic CTs, which enhances the system performance [34].

Chen et al. [35], mentioned the challenges that manufacturing industries are facing in measuring and deciding KPIs for increasing machine performance. Andrej et al. [36], looked after the short-term and long-term production strategic challenges through production KPIs. Garretson et al. [37], concentrated on the terminology that supports manufacturing process characterization and assessment. Borsos et al. [38], explored the relationship between the KPIs and the objectives set by the manufacturing industries in order to determine the waste in the production process. Muhammed et al. [39], cited few manufacturing KPIs and implemented them on multi robot line simulator to improve its performance from the results obtained by the KPIs. Iuga et al. [40], listed few shop floor KPIs for automotive industries based on the interviews conducted with various automotive manufacturers.

Literature review also shows that KPIs are generated mainly based on specific type of industries and only few KPI sets exists based on manufacturing shop floor operations [41]–[45]. Industrial norms for selecting, composing, defining and identifying a required set of KPIs for manufacturing shop floor operations is lacking. Every manufacturer dealing with same shop floor operations has their personalised KPI list that they are interested to evaluate, which are relatively inconsistent. This paper intends to club all these KPIs together with their elements, in order for manufacturers to understand, explore and consider the right KPIs to achieve their desired objectives. By employing the right KPIs industries can achieve increased production efficiency, uniform and high product quality and enhance their throughput. In total, more than 40 KPIs were determined in the above literature. But only 21 KPIs are presented in this paper because these KPIs are sufficient, interrelated and covers the rest of the KPIs. For instance, calculating CT, covers cycling loss as well as cycling gain. CT is a constant value fixed for a machine, station, process or whole manufacturing line. So, values below the fixed CT gives you the cycling gain and values above the fixed CT gives you the cycling loss.

Elements of Manufacturing Operation KPIs

These elements are based on the problems highlighted in the literature review as well as considering manufacturing industry best practices. Elements of the KPI can be divided into several sub classes: description, categories, scope, unit of measure, viewers, mode of display, range and manufacturing approach. Table V lists all symbols with their description used in calculating the KPIs.

Description

This section aims for describing the KPI as specific as possible, and must be clearly understood by everyone working in the manufacturing industries. Considering the International Standards ISO 22400-1&2 report [2], [3] and literature review a list of 21 KPIs have been defined, but a more specific definition based on manufacturing industrial operations is required to clearly differentiate them. Hence, table IV mentions this KPIs list with a clear manufacturing grounded description.

Categories

KPIs are categorised in several ways, subjected to the purpose of use: time, cost, quality, sustainability and flexibility; operations, control, maintenance, planning and inventory; qualitative and quantitative; product, process and resource; inventory, assembly and maintenance. Depending upon the nature of manufacturing shop floor operation and the set objective to be achieved, selecting the right category will be crucial. For example, in a packaging industry, KPIs of interest to operators, and supervisors are time and cost. So, directly monitoring those KPIs will be of interest rather than looking at product or inventory side of KPIs. Furthermore, considering product, process and resource categorisation into account the list of 21 KPIs mentioned in table IV can be divided as shown in table II. Similarly, table III categorises the KPIs based on operations, control, maintenance, planning and inventory.

These categories are mainly based on the area of manufacturing shop floor operations. So, readily finding KPIs that are categorized based on the manufacturers demands can help them to employ those sets of KPIs without being concerned about other KPIs. These categorization is done critically based on the literature surveyed. For instance, the research papers that are concentrated on product related KPIs were studied and all the list of KPIs related to this category were mentioned in the product related KPI list. Similarly, all the research papers that are focused on the resource area, were listed in resource category list.

TABLE II. CATEGORISATION OF KPIS BASED ON PRODUCT, PROCESS AND RESOURCE

Product	Process	Resource
FTP yield	A	AR
Q	CMR	PE
RR	CT	PLR
SCR	JPH	PPR
	MTTF	STR
	MTTR	TE
	OEE	TR
	P	WE
		UE

TABLE III. CATEGORISATION OF KPIS BASED ON OPERATIONS, CONTROL, MAINTENANCE, PLANNING AND INVENTORY

Operations	Control	Maintenance	Planning	Inventory
A	FTP yield	CMR	AR	TR
CT	PLR	MTTF	PE	
JPH	PPR	MTTR	STR	
OEE	RR		TE	
P	SCR		UE	
Q			WE	

TABLE IV. LIST OF KPIS AND THEIR ELEMENTS

KPI	Description	Scope	Formula	Unit of measure	Range	Trend	Manufacturing Approach	Viewers	Mode of display
Allocation ratio (AR)	It's the ratio between the actual busy times to the actual execution time for any manufacturing operations	Pr, PO, Pl	$\frac{\sum A_{ubt}}{A_{uet}}$	%	0-100 (possibility of more than 100 in case of overlapping operations)	Close to 100	D, C, B	S, M	Pd
Availability (A)	A for a machine, station, process, or whole manufacturing line takes into account all the events that stops planned production	WU	$\frac{T_r}{T_{pd}}$	%	0-100	Close to 100	C, B	S, M	Od, Pd
Corrective maintenance ratio (CMR)	CMR is used to indicate the time that has been spent on corrective tasks on the work unit	WU	$\frac{T_{cm}}{T_{cm}+T_{pm}}$	%	0-100	Close to 0	D, C, B	S, M	Od, Pd
Cycle time (CT)	It is the total time elapsed from the beginning to the end of the process as defined by the manufacturer or user. CT to move a part from one station to another station inside the shop floor is calculated in the given formulae	WU, WC, WO, Pr, Pe	$C_C^y = C_D^{y,S_n} - C_D^{y-1,S_n}$	Time	Once the CT is defined its value remains fixed	The closer to the set value, the better	D, C, B	S, M, O	Rt, Od, Pd
First time pass yield (FTP yield)	It indicates the quality of the order manufactured, and is expressed as the percentage of good products manufactured by the inspected products	WU, Pr, PO, Dt	$\frac{G_p}{I_p}$	%	0-100	Close to 100	D, B	S, M, O	Rt, Od, Pd
Mean time to failure (MTTF)	It is used to indicate the reliability of the given machine, station, process, or whole manufacturing line grounded on the basis of the know failures rates	WU	$\frac{\sum_{i=1}^{T_{fi}} T_{tf}(i)}{T_{fi}+1}$	Time	Depends on the nature of failure	The higher, the better	D, C, B	S, M	Od, Pd
Mean time to repair (MTTR)	It is used to show how quickly a machine, station, process, or whole manufacturing line can be restored after occurrence of an failure	WU	$\frac{\sum_{i=1}^{T_{tf_i}} T_{tr}(i)}{T_{tf_i}+1}$	Time	Depends on the nature of failure	The higher, the better	D, C, B	S, M	Od, Pd
Overall equipment effectiveness (OEE)	OEE is multiplication of A, P and Q. It gives the difference between the theoretical calculated production capacity to the actual production capacity of a manufacturing process	WU, Pr, Dt	$A \times P \times Q$	%	0-100	Close to 100	C, B	S, M	Od, Pd
Performance (P)	P takes into account whatever causes the manufacturing process to operate at less than the maximum possible	WU, Pr, Pl,	$\frac{T_{cd}}{T_{ad}}$	%	0-100	Close to 100	C, B	S, M, O	Rt, Od, Pd

	operating speed. In other words, it shows how efficiently a manufacturing process is performing under the influence of disturbances (slow cycles and small stops).	TP							
Production effectiveness (PE)	The ability of the manufacturing system to produce the highest number of good parts (units) by consuming least amount of resources. It helps to find the symmetry between the rate of production and the quality of parts being manufactured.	WU, WC, TP,Pr, Dt, Pl	$\frac{\hat{P}_c * b_{op}}{b_p}$	%	0-100	The higher, the better	D, B	S, M	Od, Pd
Production loss ratio (PLR)	It is used to indicate the amount of quantity lost during production	WU, Dt	$\frac{Q_{lp}}{Q_m}$	%	0-100	The higher, the better	C, B	S, M	Rt, Od, Pd
Production process ratio (PPR)	It is generally used to depict the efficiency of manufacturing production. It is expressed as the ratio of actual production time to the actual order execution time.	Pr, PO, Pl	$\frac{\sum A_{pt}}{A_{oet}}$	%	0-100	Close to 100	D, C, B	S, M	Od, Pd
Quality (Q)	Q is evaluated as the number of good pieces or products produced (pieces that passes quality and inspection test) to the total of pieces produced	WU, WC, Pr, TP, Dt, Pl	$\frac{\rho_p - \rho_d}{\rho_p}$	%	0-100	Close to 100	D, C, B	S, M, O	Od, Pd
Rework ratio (RR)	RR is used to indicate the quality that has not passed the quality and inspection test	WU, Pr, PO, Dt	$\frac{R_Q}{P_Q}$	%	0-100	Close to 0	D, C, B	S, M	Rt, Od, Pd
Scrap ratio (SCR)	It is relationship between the scrap quality and the produced quality	WU, Pr, PO, Dt	$\frac{S_Q}{P_Q}$	%	0-100	Close to 0	D, C, B	S, M	Rt, Od, Pd
Setup ratio (STR)	It identifies the proportion of time used for arrangement or setting up of a system equated to the actual time used for processing	WU, Pr, PO	$\frac{A_{ust}}{A_{upt}}$	%	0-100	Close to 0	D, C, B	S, M	Od, Pd
Standard jobs per hour (JPH)	It is used to indicate the number of jobs executed per hour, against the standards jobs	WU, WC, Pr, Pe, TP	$\frac{3600}{C_{st}} * \text{units per cycle}$	Units/Time	Depends on the type of operation	The closer to the set value, the better	D, C, B	S, M	Od, Pd
Technical efficiency (TE)	It is calculated for a work unit. It is the ratio between actual production time to the actual production time and sum of all the malfunctions and delays that caused disruptions	WU	$\frac{A_{pt}}{A_{pt} + A_{dt}}$	%	0-100	Close to 100	D, C, B	S, M, O	Rt, Od, Pd
Throughput rate (TR)	It is used to indicate the efficiency of the processes; and is expressed in terms of produced quantity of an order to the actual order completion time	Pr, PO, Pl	$\frac{P_q}{A_{oet}}$	Quantity/Time	Once the TR is defined its value remains fixed	The closer to the set value, the better	D, B	S, M	Od, Pd
Utilization efficiency (UE)	It's an indicator that detects the productivity of the operational work units, and is identified as the ratio between actual manufacturing time to the actual busy time	WU	$\frac{A_{umt}}{A_{ubt}}$	%	0-100	Close to 100	D, C, B	S, M, O	Rt, Od, Pd
Worker efficiency (WE)	It's the ratio between the actual worker operating time to the actual worker attendance time related to the manufacturing orders	W, WG, WU	$\frac{A_{wot}}{A_{wat}}$	%	0-100	Close to 100	D, C, B	S, M	Pd

WU- Work Unit, WC- Work Centre, WO- Work Order, W- Worker, WG- Work Group, Pr- Product, Pe- Personnel, Pl- Plant, PO- Production Order, Dt- Defect types, TP- Time Period, D- Discrete, C- Continuous, B- Batch, S- Supervisor, M- Manager, O- Operator, Rt- Real-time, Od- On-demand, Pd- Periodical

Scope and Unit of Measure

In general, scope is used to identify the part for which the KPI is most applicable in the manufacturing industry. For instance, product, worker, work centre (corresponds to production unit, process cell, storage zone or production line), work order or work unit. The unit of measure of KPIs can be any of following: rate, ratio, efficiency, utilisation, capability index and effectiveness (refer table IV). Based on the formula used to calculate the KPI, the unit of measurement changes. For example, unit of measure to calculate A is ratio. Whereas, unit of measure to calculate MTTR is utilization.

Viewers

It is imperative to know the viewers for whom the KPIs are being designed. Typically, KPIs are generated for: shop floor workers, supervisors and managers. Based on the type of viewer, the KPI list is designed (refer table IV). For example, PE will be helpful for manger and supervisor to make future decisions. While, for the workers PE would produce nothing fruitful.

Mode of Display, Range and Manufacturing Approach

Frequency with which KPIs has to be displayed to generate useful information is vital. For instance, displaying the KPIs for a process, station or the whole manufacturing line depends on the nature of the manufacturing operations. Therefore, KPIs that have severe impact on the manufacturing operations are often displayed in real-time. Typically, KPIs are displayed in: real-time, on-demand or periodically (refer table IV). For instance, Q KPI are often displayed on-demand or periodical. Whereas, CT KPI is displayed in real-time, on-demand and periodical.

From the industry best practices, it is recommended that before obtaining the KPI results, one must know the range of the KPI (upper bound and lower bound). Without prior understanding of the KPI outcome, the resulted value would just be a number. So, understanding the range is important in order to enhance the manufacturing performance. Lastly, manufacturing approach identifies the method of manufacturing operation for which the KPI is largely related: discrete, continuous or batch (refer table III).

TABLE V. LIST OF SYMBOLS USED TO CALCULATE MANUFACTURING SHOP FLOOR KPIS

Symbol	Description
A_{dt}	actual delay time
A_{pt}	actual production time
A_{oet}	actual order execution time
A_{ubt}	actual unit busy time
A_{uet}	actual unit execution time
A_{umt}	actual unit manufacturing time
A_{upt}	actual unit processing time
A_{ust}	actual unit setup time
A_{wot}	actual worker operating time
A_{wat}	actual worker attendance time
b_{op}	overall parts produced in the batch
b_P	amount of time required in producing the batch
C_C^y	CT of part y
C_D^{y,S_n}	departure timestamp of part y at station S_n
C_D^{y-1,S_n}	departure timestamp of part y-1 at station S_n.
C_{st}	standard CT
f_i	failure period end time
G_p	number of good parts
I_p	number of inspected parts
$\hat{P}_c$	predicted cycle-time between the completed parts
P_Q	produced quality
Q_{lp}	quantity lost during production
Q_m	quantity consumed during production
R_Q	rework quality
S_Q	scrap quality
T_{ad}	actual production time
T_{cd}	calculated production time
T_{cm}	total corrective maintenance time
T_{pd}	planned production time
T_{pm}	total planned maintenance time
T_r	run time (machine, station, process, or whole manufacturing line)
T_{tf}	total time in failure
T_{tr}	total time in repair
ρ_p	total production parts
ρ_d	defect parts

CONCLUSIONS

In this paper, a list of manufacturing shop floor operation KPIs were congregated based on the literature review. This literature review covered the most recent research articles and white papers; whose interest was to enhance the performance of manufacturing shop floor operations. Later, few challenges faced by the manufacturers related to selecting the right KPI for their shop floor operations were discussed. A list of KPIs with their detailed elements: such as description, categories, scope, unit of measure, viewers, mode of display, range and manufacturing approach were discussed. This list can help manufacturers to better describe, classify, analyze and measure the appropriate KPIs for their shop floor operations. Because, it clearly states every single details (KPI elements) about manufacturing shop floor KPIs. Thus enabling the manufacturers to accomplish and uphold great quality, increased productivity and throughput, with adequate flexibility, rapid response and negligible downtime. However, the research remains open for further exploration with the purpose of understanding manufacturing shop floor KPIs clearly.

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Manufacturing Enhancement through Reduction of Cycle Time using Time-Study Statistical Techniques in Automotive Industry

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***Abstract*— Within the complex and competitive automotive manufacturing industry, manufacturing Cycle Time (CT) remains one of the Key Performance Indicators (KPIs). Its reduction is of strategic importance as it contributes to time-to-market shortening, faster bottleneck detection, achieving throughput targets and improving production-resource scheduling. This paper presents a case study on CT analysis for early stage identification of the bottleneck stations and the processes in a manual assembly line that is responsible for increased manufacturing CT. The case study is conducted on an automotive seat manufacturing plant in the UK. For detailed CT analysis, CT of each station is recorded. Results of the case study shows that bottlenecks identification at an early stage can significantly enhance the overall performance of the production line.**

Keywords*— *automotive industry, cycle time and production line

INTRODUCTION

In automotive industry, there is a constant pressure to reduce CT and maintain required production takt time. Manufacturing CT can be defined as the time required to complete one cycle of manufacturing operation(s) at a station level to produce a product. Whereas, takt time refers to the frequency of a product that must be produced to meet customers' demand. Takt time can be typically split into CT, waiting time, idle time and starved time. Measuring CT of a manufacturing processes is critical to manufacturers; so as to evaluate job execution rate at a station level. CT of a typical manufacturing process is reliant upon various factors that include: product mix, components used, machinery involved, inventory, scheduling practices and process technology. Due to high complexity and constant change in these factors, its challenging to conduct comprehensive production analysis for CT reduction [1].

Simulation software are extensively used for carrying out comprehensive CT exploration but a number of issues impede their everyday use. For instance, with more than 65 commercial simulation software's available in the market, manufacturers finds it challenging to choose an appropriate software that fits their requirement. Additionally, due to absence of strong simulation standards or languages it becomes difficult for manufacturers to maintain these software's and requires additional simulation specialists for their support [2]. When a model is developed using these simulation software's for CT analysis, it may take from several hours and numerous repetitions to find out optimal solution to reduce CT [3]. The data fed into simulation models is mostly based on assumptions made during the design stage. The actual assembly process time is often different than the predicted by simulation. As a result, time-study statistical techniques are readily adopted by the manufacturers as a complementary solution to simulation software to help in reduction of manufacturing CT [4].

KPIs of a production line can be measured in two ways: online or real-time KPIs and offline KPIs. Online KPIs are used to report the status and performance of a production line. Offline KPIs are used to report the performance of a production line based on historical data. Online KPIs are used by operators as well as managers to make quick judgements on how to improve their current performance by rectifying problems straightaway. Offline reports are typically used by managers to assess the performance, identify problems and make necessary plans to avoid such problems in the future. Offline reports give an opportunity to compare historical data from various perspectives. This paper will be focusing on both online and offline KPI monitoring as the combination of both is significantly beneficial to identify problems and put necessary plans in place to resolve them.

Manufacturing of seats is usually characterized by linear sequence of operations which means the sequence of operations remains the same (typically increasing or decreasing by a known common difference). Due to this linearity, if any operation fails or delays, it effects the whole manufacturing process. The paper is aimed at identifying the stations that are responsible for causing the delays in the seat production, and then drilling down to investigate the processes that are responsible for the delays. Since, the line is characterized as linear sequential, the takt time plays a critical role in measuring the line performance [5], [6]. Takt time is calculated based on the available time divided by the demand (per production order or shift) [7]. Factors such as premature purchasing of raw materials; retrieval and storage of goods; and other cost related issues; which are encountered in producing ahead of demand can be totally eliminated by producing on demand.

Takt time is assigned for the whole production line and its value is decided based on the processes breakdown between each stations. Therefore, measuring and keeping up with the takt time is of great importance within automotive manufacturing industries [8]. Failing to keep up with the takt time results in reduced productivity, increased time-to-market and has negative impact on the overall manufacturing performance. The case study presented in this paper focuses on addressing the challenges faced by Company X in maintaining its takt time during production.

The methodology presented in the paper identifies the root causes of the increased manufacturing CT through step by step drill down approach. It aims to provide the specific process within the processes which is responsible for increased CT. The paper is organized as follows: section II presents literature review, section III gives an overview of the company X, its product process flow, problems with their existing assembly line and the structure of current assembly line data. Section IV describes the methodology adopted to tackle the existing problems in the company X. Section V provides the conclusion.

LITERATURE REVIEW

In the era of fourth industrial revolution, it is critical for the manufacturers to live up to on-time customers' demands and ensure customers satisfaction. Hence, manufacturers are constantly finding ways to reduce the CT of the manufacturing processes with increased performance and productivity of the whole manufacturing plant, along with maintaining high standards of product quality [9]. In a highly complex automotive industry, reducing CT is of great importance, since it contributes to faster fault detection, time-to-market shortening and realizing throughput targets [10]. There are numerous methods, tools and techniques developed to tackle CT related problems. A few of them are listed below: Sada et al. [11], used a simple spreadsheet technique to decrease CT in a semiconductor fabrication plant. The spread sheet is used to compare the theoretical CT with actual CT for each process involved in the fabrication. This comparison is done to detect the bottleneck process and by doing so the CT is improved by 24%.

Silva et al. [12], adopted statistical analysis to record every moments of parts throughout the IBM's multi-layer ceramics line. The purpose is to find all the meaningful dimensions that can allow to detect and round CT glitches. By implementing statistical analysis, IBM's microelectronic production line saw an improvement of 15% in overall CT. Yih-yi et al. [13], designed an algorithm that is used to find the shortest CT for the production process in semiconductor fabrication industry. The algorithm is based on the where-to-dispatch and what-to-dispatch mechanism. This mechanism is grounded on calculating minimal waiting time and transportation time, by embedding this mechanism it is evidenced to reduce 32.5% waiting time in the current semiconductor manufacturing industry. Chung-Jen et al. [14], proposed an Manufacturing Intelligence (MI) method to exploit the value of production data to reduce CT. The MI is based on neural networks that predicts the Work In Process (WIP) for CT reduction. To verify the method, it is tested in an integrated device manufacturer production line in Taiwan and the result is considerable improvement in CT.

Tamas et al. [15], proposed a dynamic CT setting algorithm to improve CT of an industrial open station conveyor. The algorithm is developed taking into account the complexity of the production process and product variability. Indoor positioning system along with smart wireless sensors were installed to track and record each movement of production to figure out bottlenecks and improve CT. David et al. [16], used ManSim/X manufacturing line simulator to examine the effect on CT by varying the percentage of different products on the semiconductor production line. The results proved that factors such as process complexity, operator availability, production rate and factory shut downs effected the CT. However, these results were limited to the given production line. Dharun et al. [17], worked on reducing CT of a T-shirt manufacturing plant. By employing several lean tools, namely: failure mode effect analysis, time and motion study, kaizen and value stream mapping, the plant overall CT is reduced to 20%.

Lerdlekha [5], adopted standard time analysis to reduce CT in wood product manufacturing industry. By comparing the standard times of assembling and polishing required for the manufacturing of the product with the set takt time, production capacity is increased from 560 units/month to 1200 units/month. Dinesh et al. [18], proposed a vendor rationalization strategy for streamlining the supplies to reduce manufacturing CT in an engineer-to-order Indian company. Kraljic's matrix-based model is implemented which reduced the manufacturing CT of feeder hopper from 43 days to 21 days. Similarly, various research articles discussed the CT related problems and suggested possible solutions to efficiently tackle it [19]–[21].

From the intensive literature review it is apparent that solutions pertaining to CT were resolved either using time-study analysis or developing simulations models. Papers which were based on deploying simulation models for CT reduction mainly discussed about the difficulties in understanding software language, suffered with number of software glitches and consumed ample time for generating, testing and implementing those models. Moreover, most of these articles were specific to a particular production line or manufacturing plant where the case study is carried out. For a seat manufacturing industry that develops highly customized products, developing, training, testing and implementing these simulations models can be time consuming. So, manufacturers are finding complementary solutions that can monitor their production performance before these models are generated. Plus, due to constantly changing customer demands, models developed with the help of simulation software's becomes redundant sooner and requires constant redevelopment.

Likewise, all the aforementioned research papers concluded by mentioning the bottleneck equipment, station or line responsible for the decreased manufacturing productivity and poor performance of the production plant. Bottleneck in manufacturing process perspective is identified by determining maximum CT in the production line. For example, if the maximum CT of a station is greater than the takt time, then the customers' demands are not fulfilled and vice-versa. They failed to mention precisely which process is the reason behind the poor throughput of the equipment, station or production line. Knowing the exact process could have benefitted the production line operators, engineers, supervisors as well as the managers to rethink on that particular process not the whole processes involved.

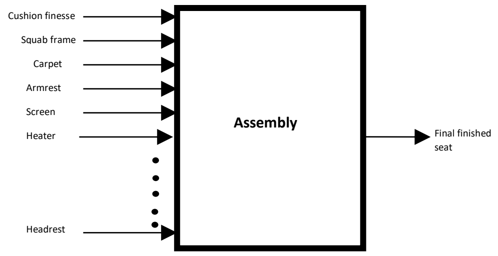
The purpose of identifying the exact process is critical to improve and enhance manufacturing efforts. For example, within a given station depending on the task distribution, station has to execute several processes. In case of CT related issues, not every process is the reason for poor line performance. So, identifying the specific process becomes vital for the manufacturer to better understand the definite cause and develop a solution to minimize the cause of increased CT. Company X where the case study is performed comprises of sequential assembly lines consisting of various operating stations. Maintaining takt time for sequential assembly lines are crucial for the manufacturers because a delay at any station can stop the whole assembly line leading to reduced productivity and effecting the overall production performance. So it is important to maintain with the takt time assigned to the production process. As a result it becomes increasingly important to specifically mention the exact process causing the CT delays.

CASE STUDY

The time-study data analysis presented in this case study is conducted on the data obtained from the company X final assembly line. To scrutinise the cause of poor production line CTs, step by step drill down is performed to specify the precise origin of the cause, i.e., the sub-process within the process. Based on the findings of time-study data, a number of solutions are suggested that can enhance the production performance. In this section, background of the company X, its product process flow and the problem faced by their existing production line is discussed.

Company background

The evolution of automotive products towards electrification and autonomy combined with data analytics is driving the development of innovative car components. Seats is one of the most complex components in a car that must integrate complex electronics systems to create safer, more connected and adaptable products built from advanced lightweight and sustainable materials. Company X UK is leading the smart manufacturing initiative for company X globally, which deals with car seat manufacturing. Company X's manufacturing UK employs 200 staff and 2000 workers across three UK plants. It manufactures seats for various cars brands, with its major customer being Jaguar Land Rover (JLR). In company X, every component that is required to manufacture a seat is pre-assembled in sub-assembly lines and final seat is primed in assembly lines within their manufacturing plants. Figure 1, is a block diagram representation of an assembly line with a list of key inputs and output. The inputs to the assembly line are fetched from the sub-assembly lines; and inputs to this sub-assembly lines are the raw materials based on the seat requirements.



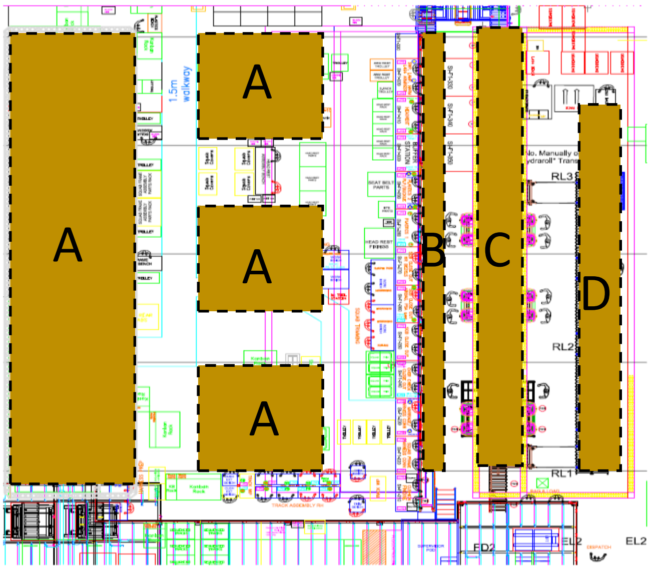
Snapshot of a assembly line with list of inputs and output

Product Process Flow

To produce a seat in this company it has to go through a final assembly line, which consist of thirteen stations excluding those stations which are dedicated for test and inspection operations and further rework. Each station involves human for process undertaking; machines for material handling; conveyors for continuous movement of production operations and buffers to link stations. This assembly line is typically an intermittent line that does not produce identical products due to highly customised and huge variety of seat options. Intermittent assembly lines are primarily know for facilitating quick assembly of comparable parts while leaving the room for customization. Every station in this assembly line has different process to undertake based on the customers requirement.

Due to high complexity involved in manufacturing, the operations carried out at the stations are mostly manual and varies with every seat based on its specifications. Various operations that takes place at different stations are mentioned in table I. Every seat that is manufactured includes various seat features, such as: model number, drive type, model year, country name, carpet type, rear frame type, heater type, articulation type, screen type, speakers type, armrest type, lumbar type, headrest type and foot-well lamp type. In addition, customers can also select the colour of the seat features. Figure 2 represents the layout of the company X, where '*A*' denotes subassemblies, '*B*' denotes final assembly line, '*C*' denotes test and inspection line and '*D*' denotes rework line.

It is necessary to inspect the reasons behind the reduced productivity of seats. As a result, to understand and investigate the bottlenecks and constraints within the final assembly line, time-study data exploration is conducted.



Company X manufacturing plant layout

OPERATIONS CARRIED OUT AT VARIOUS STATIONS IN THE FINAL ASSEMBLY LINE

Station	Process
1	placing and handling cushion finesse
2	setting up squab frame with cushion finesse
3	fixing marriage bolts on the cushion finesse
4	fixing marriage bolts on the squab trim
5	installing heaters and its connections
6	placing airbags and its components
7	completing the airbag installation
8	mounting the valance fit with its required components
9	completing the valance fixings
10	buffer station
11	fixing headrest, backboard and other necessary components
12	installing switch-pack and foot-well lamp
13	buffer station

Problems with the existing assembly line

The major problems faced by this company in the final assembly line are abrupt increase in the station CTs leading to reduced standard Job Per Hour (JPH); reduced productivity; increased blocked and starved time for various stations and poor Overall Equipment Effectiveness (OEE). The JPH for the line at full capacity is set at 98 seats but due to increased CTs, the JPH is reduced to 96 seats. To understand the root causes of reduced JPH, this study aims to analyze CT of the manufacturing processes of all stations.

The required CT data is recorded from the final assembly line starting from 1st July 2018 up to 30th July 2018. The production window (shift hours) is set to 8 hours per day excluding the operators break times. The data collected from the line contains several parameters, for example: average CT of each station, Unique Seat Identifier Number (USIN), seat option, Standard Jobs Per Day (SJPD) and number of Seats In Rework (SIR). A sample of the dataset is shown in table II.

CT data related to station 10 and 13 is not populated because these are buffer stations. Buffer stations are installed to stabilize any fluctuations arising during normal working of assembly line, so data related to buffer stations are not accounted for further data exploration. The takt time of 98.5 seconds is set throughout the production process, implicating that every station should complete its operations within the set takt time. The highlighted red values in table II signposts the stations whose average CT is over the takt time. Station 7 is seen with 4 highlighted values in table II indicating the main reason behind the whole assembly line delays during that production period.

ASSEMBLY LINE MANUFACTURING SAMPLE DATA FOR JULY 2018

Date	Station average CT per day (seconds)											SJPD	SIR
	1	2	3	4	5	6	7	8	9	11	12		
1/10	54.8	86.1	85	91.2	86.2	88	99	91	87.2	82.6	85.5	767	31
2/10	63.6	85.5	85	89.8	91.3	78	91	78.3	86.2	87.3	78	781	04
3/10	87.7	95.3	91	92.3	85.2	84	86	85.2	81.1	74.7	84.4	782	04
4/10	85.6	88	91	91.2	85.5	85	78	85.3	86.1	71.3	74.6	781	05
5/10	59.4	89.1	86	78.2	75.6	78	105	78.9	84.5	89.6	85.8	783	28
6/10	78.7	91.3	82	85.6	74.1	74	105	85.1	85	85.8	76.1	785	08
7/10	78.6	86.5	75	75.6	73.2	86	89	91.5	90.6	86.7	84.6	773	17
8/10	99.3	76.5	83	90.2	78.5	89	86	78.2	90.6	74.8	75.1	771	11
9/10	85.2	86.8	91	79.6	86.8	90	111	87.8	91.2	93.3	91.5	779	13
10/10	88.4	90.2	74	86.1	84.5	91	91	84.5	89.2	91.5	87.1	781	10

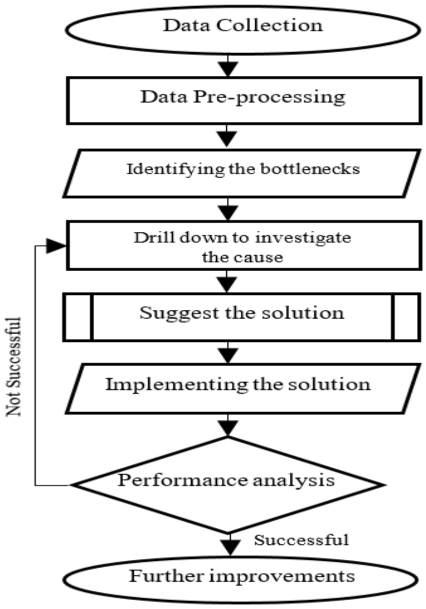
In the recorded data timeframe, the assembly line produced 2 seat models (model A and model B) with 3 sub-types/variants (sub-type 1, sub-type 2 and sub-type 3) based on customer specifications. The rate of seat production is setup at 785 seats per day (SJPD-785) with no more than 5 seats in rework (per day). The number of operators required for the whole assembly line is 26 for the final assembly line. Two operators are required per station, each operator dealing with different type of seat, namely, right hand seat and left hand seat. The total number of seats that are manufactured during the given time period is 18850 against set target of 19080 seats; which means that the assembly line is running short of 230 seats during that month.

METHODOLOGY

Once the order is received, according to build to sequence operators starts gathering the required raw material needed to fulfil the order from their warehouse. The raw material then gets pre-assembled in the sub-assembly lines. The pre-assembled parts are fed as inputs to final assembly line (typically in boxes alongside the final assembly line) where the seat gets its complete shape. To investigate the root cause of the increased production takt time, the following methodology (figure 3) is employed. Implementation of the solution is not in the scope of this paper and is considered as the future work.

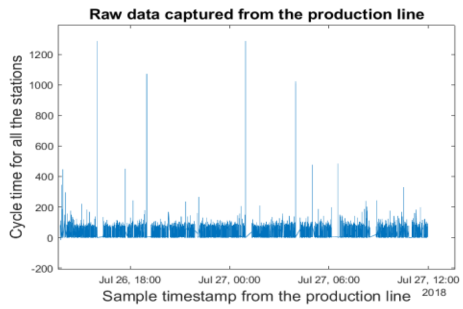
Data pre-processing

The raw historical production data from the final assembly line contained numerous parameters including CT data from all the stations, SJPH, SIR, RR and USID. The parameters which are not needed for further data processing are filtered and only CT data of assembly stations is considered. This CT data is abundant with missing data and outliers. In the data pre-processing phase, all the missing data is filtered out, next outlier-detection and replacement scheme is carried out for effective data analysis [22]. This scheme replaces those data points which deviates drastically from the given norm or average value, and subsequently interchanges it with normal data points. Average CT of all the stations at 01/10/2018 instant is shown in table III and during that instant it is noticed that station 7 CT is 99.6 seconds (higher than the set production takt time).

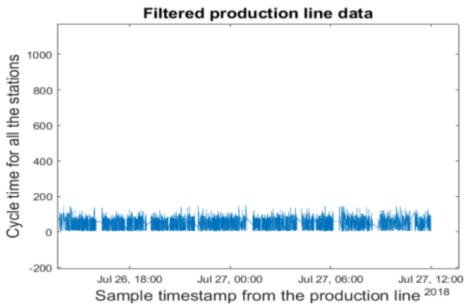


Methodology implemented in the current assembly line

Figure 4 (a) represents a snapshot of the raw data that is captured from the production line which consists of various missing data redundancies. Figure 4 (b) presents the snapshot of the data after filtering out redundant data using outlier-detection and replacement schemes.



(a)



(b)

(a) Snapshot of the raw data captured from the production line. (b) Snapshot of the filtered production line data

Identify the bottlenecks and drill down to investigate the cause

In order to understand the cause of decreased productivity and to target the bottleneck stations, it is important to monitor the performance of these stations individually over a given period of time. Box and whisker plots is used to show the summary of the data distribution, its variability and its central value. These plots are the quickest way to show whether the dataset is symmetric or skewed.

From figure 5, it is evident that station 7 is the root cause for the overall decreased production line performance. The average CT of station 7 during the whole time period of data collection is 99.6 seconds against the set production takt time of 95.5 seconds. Apart from station 7, rest of the stations performed consistently within the takt time assigned to the production line. Next, the 3 evident outliers seen across station 5 is carefully investigated. From the investigation it is realized that operators at the station 5 failed to stop the process recording during the break times. Hence, these outliers are treated as bad data points because they are caused due to human errors and unlikely to appear under normal circumstances. Note that these outliers are eliminated from the further data processing.

Few other inference that is be derived from figure 5 is: station 1 average CT is 57.8 seconds and station 3 average CT is 52.3 seconds which is nearly half of the assembly takt time. This huge CT difference pointed towards exploring the uneven task distribution within the stations. Table III gives an insight into average day CT of every station for 1/10/2018, showing that the task distribution over different stations is non-uniform. For instance, average CT for station 1 is 54.8 seconds followed by station 3 and station 6 with 65.2 seconds and 61.9 seconds, meaning these station had the longest waiting time when compared to all other stations.

Next step is to drill down station 7 to discover which seat model and its variants are the sources of the increased CT. By further time study data analysis, it is obvious that model B with an average CT of 101.67 seconds (4.67 seconds more than the set production takt time) is the reason behind the increased CT (as shown in figure 6 (a)). Whereas, model A with average CT of about 67.32 seconds didn't contribute to any production delays. Now it is apparent that model B in station 7 is the main reason behind increased CT.

In final step, station 7 model B is further investigated to examine which sub-process (sub-type) is responsible for the delays. Figure 6 (b), represents the different model B sub-type processes carried out at station 7. Sub-type 1 process with average CT of about 165.33 seconds is the reason behind the model B to perform poorly, followed by sub-type 2 process with CT of about 99.1 seconds. Whereas, sub-type 3 process averaged CT of about 90. 3 seconds which is the under the production takt time.

AVERAGE STATION CT (SEC) FOR A DAY (01/07/2018)

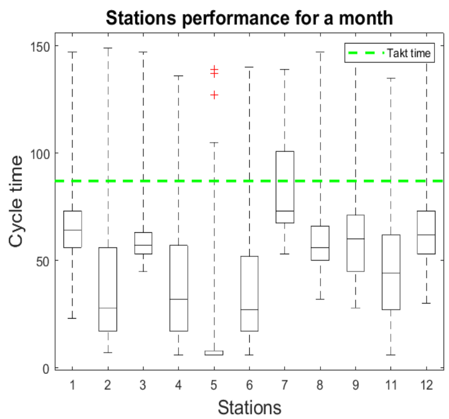
Station	1	2	3	4	5	6	7	8	9	11	12
Average CT	54.8	86.1	65.2	91.2	86.2	61.9	99.6	90.1	87.2	82.6	85.5

Suggest solutions

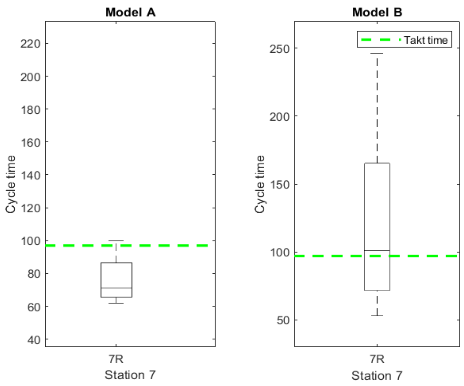
Sub-type 1, model B at station 7 is the bottleneck in the studied assembly line. It is due to this station that the SJPD, productivity and performance of the overall production line is effected. Based on intensive research on how to reduce CT and the results from data analysis, the author suggests few solutions which can help to improve the current state of the production line. Installing buffer stations well-thought-out the line and considering a change from traditional sequential conveyor line to parallel conveyor line can help the manufacturer to reduce the operations delays. But this change can be costly and will require additional resources for its normal working.

Line balancing is suggested as the best fit solution for the given problem because from the table II it is witnessed that there is a huge unbalanced task distribution between various stations. Rethinking about the current state of tasks distribution between the stations and splitting most frequent interrupted processes can help to reduce the waiting time, blocked time and starved time; thereby increasing the line throughput. By exploring the processes carried out by all the stations in the assembly line, several processes were shifted within the stations for better line balancing. Particularly, the processes undertaken at the station 7 (bottleneck station) of the assembly line is shifted to other stations and few were split within the station itself.

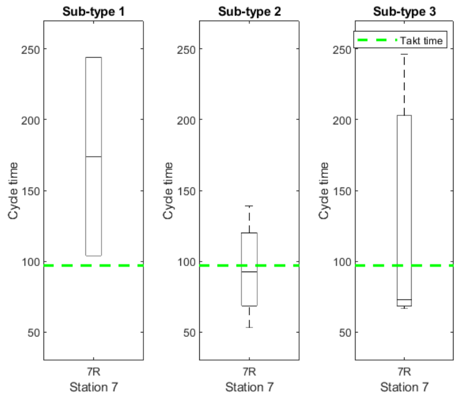
Furthermore, table IV shows the variations in the actual time taken to complete various operations at station 7 with the theoretical time. By comparing theoretical time with the actual time of the processes carried out at station 7 it is obvious that the Company X current assembly line needs line optimization apart from line balancing. If this bottleneck could have been identified at an early stage, it would have significantly enhanced the overall performance of the production line.



Box and whiskers plot for stations CT over a given period



(a)



(b)

(a) Box and whisker plot for station 7 model A and model B. (b) Box and whisker plot for station 7 model B with sub-type1,2 and 3

AVERAGE PROCESS CT FOR STATION 7 (ACTUAL VS THEORETICAL)

Station 7	Actual time (sec)	Theoretical time (sec)
Main operation		
Completing the airbag installation	103.6	90.5
Type		
Model A	67.5	90.5
Model B	101.3	90.5
Sub-type		
Sub-type 1	165.5	90.5
Sub-type 2	99.6	90.5
Sub-type 3	90.2	90.5

CONCLUSION

The study aims to spot the bottlenecks and enhance the production rate of company X seat manufacturing assembly line using time-study data analysis. By performing the time-study data analysis, it is seen that station 7 CT exceeds the takt time. With further drilling down, it is evident that model B with CT of 101.67 seconds and in particular sub-type 1 with CT of 165.33 seconds is the main cause of the delayed production. It is due to sub-type 1, model B at station 7; the company X is able to produce only 18850 seats against set target of 19080 seats that month. Therefore, knowing the root causes behind the decreased production, the author suggests line re-balancing, line optimization and splitting the bottleneck process into sub-process in order to maintain standard takt time and enhance manufacturing process, as the best solution to the tackle CT problem.

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A Holistic Approach for Selecting Appropriate Manufacturing Shop Floor KPIs

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***Abstract*—This paper presents a holistic approach that enables manufacturers to systematically select appropriate Key Performance Indicators (KPIs) for their shop floor operations assessment. The approach is based on the contemplation that KPIs can be selected on the basis of a set of measures that are theoretically grounded. The approach consists of five layers namely: information layer, discernment layer, scheming layer, origin of data layer and assisting technology to capture the data layer. Each layer consists of set of measures dedicated to provide vital information that will assist manufacturers in better monitoring of their shop floor operations and improve decision-making capabilities. The practicality of the proposed approach is demonstrated through its application to an automotive seat manufacturing company.**

Keywords— key performance indicators, KPIs, manufacturing industries, shop floor, holistic model

INTRODUCTION

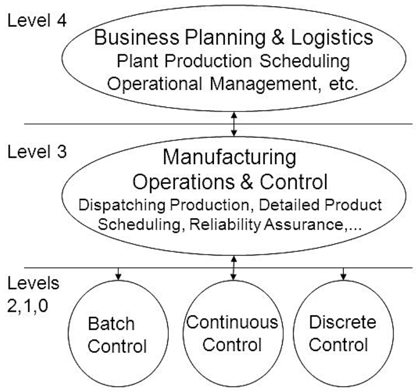
In order to survive in the current industrial revolution, manufacturers are pushed to engineer highly flexible, robust and efficient manufacturing process to produce high quality goods at reduced cost to combat evolving challenges and attain full economic potential [1]. As a result, manufacturing industries in the present time have realized the significance of shop floor data analysis and are implementing performance measurement systems to continually assess and improve the operational state of their manufacturing operations [2]. With the aim of quantifying the effectiveness and efficiency of shop floor operations, a set of comprehensive indicators are defined by International Standards Organization (ISO) to comprehend tactical goals of performance management and improvement often referred to as KPIs [3]–[6].

KPIs are critical part of an organization's capability to monitor its business performance health, facilitating to make certain that the premeditated goals of organizations are achieved. A number of researchers and think tank experts emphasises on significance of selection of right KPIs to provide business performance measure and identify bottlenecks [2], [7]–[10]. KPIs provide managers, supervisors, operators and various other decision makers with a snapshot of the business performance, highlighting the bottlenecks encountered in attaining its set business objectives [11]. Right selection and appropriate implementation of KPIs has a significant potential to assist manufacturers in improving business performance.

There is copious literature related to organizational performance measurements. Despite this, it is estimated that more than 80% of organizations fail to achieve their business objectives [5], [12], [13]. The reason for this failure is limited understanding of the business operations and associated KPIs, abundance of KPIs present in the literature for selection purposes, unnecessary large number of KPIs used by businesses for performance measurement, and technological issues that hinders its implementation [2], [7], [14], [15]. Most of the traditional methods for KPI selection are consultant-driven and ad-hoc, which lack scientific foundation essential for generalizability and repeatability approach for KPI selection [2], [16].

Selection of right KPIs is one of the major challenge faced by manufacturers in the current era of industrialization. Often managers select KPIs without accurate understanding of the shop floor operations. Selecting right KPIs from the literature can be inferred as a complex decision making process also termed as Multi Criteria Decision Making (MCDM) problem because it involves numerous factors and associated interdependencies [17], [18]. Undeniably, it is observed that a set (finite) of KPIs can be estimated and carefully chosen by means of predetermined conditions [18], [19].

ISO offers a set of KPIs, ISO 22400 (ISO 22400-2:2014+A1:2017) focusing on KPIs for manufacturing operations management also referred to as Manufacturing Execution System (MES) [20], [21]. The MOM is a term used in International Electrotechnical Commission (IEC) 62264 to address a particular level in the manufacturing enterprise functional hierarchy model as shown in figure 1 [22].



ANSI/ISA-95 functional hierarchy model [22]

KPIs mentioned in the ISO standard are described through name, description, formulae, unit of measure, production methodology and other characteristics. This standard attempts to generalise its applicability to all industries but in few statements it clearly states that 'the indicators are suitable only for discrete manufacturing' and 'limited to managers as audience'. These statements are often equivocal and imprecise and the information provided at times are fragmented. Thus, ISO standards may not be largely considered for KPI selection and deciding KPI applicability [20], [22]. Furthermore, essential KPIs required for measuring the manufacturing shop floor performances are ambiguously covered [1], [4], [7], [23].

In this context, main challenges encountered by the manufacturers in achieving their business objectives are: 1.

too many KPIs selected for monitoring which weakens the main focus on objectives. 2. KPIs selected fail to establish connection with the objectives to be achieved. 3. Lack of understanding of the KPIs, which leads to failure in reporting and monitoring of measures. With more than 1700 KPIs available in the literature, it becomes difficult for any manufacturer to understand, analyze and implement the right KPIs for monitoring their shop floor operations [16], [24].

Therefore, the author developed a KPI selection approach that guides the manufactures to understand, analyze and implement the right KPIs. The approach consists of 5 layers: information layer, discernment layer, scheming layer, origin of data layer and assisting technology layer. This approach enables decision makers to link their business objectives with appropriate KPIs. The paper is organized as follows: Section II describes the literature review and explains all the set of measures required for selecting the KPIs. Section III introduces the proposed holistic approach and discusses different layers of it. Section IV mentions the case study company wherein this proposed approach is tested and based on the company's set objectives a new set of KPIs are suggested and later tested. Finally, conclusion for the research is provided.

LITERATURE REVIEW

The performance of manufacturing industries is typically measured at MES or Enterprise Resource Planning (ERP) i.e. level 3 and 4 of ANSI/ISA 95 model [20]. The heart of manufacturing i.e. the shop floor occupies level 0, 1 and 2 of ANSI/ISA 95 model, any problems (mechanical, electrical and technological etc.) occurring at this level will severely impact the whole production. Additionally, problems such as reduced production rate, capacity and quality calculated at the higher levels of ANSI/ISA model are connected with the poor monitoring of the shop floor activities. Thus, selecting KPIs for monitoring and controlling performance of the shop floor will greatly help manufacturers to analyze their business objectives swiftly and enable them to make quick decisions [25]. Understanding the importance of an efficient working shop floor, the literature focuses on development of holistic approach for selecting appropriate manufacturing shop floor KPIs.

Level 5	Enterprise Planning: external relationships and product life cycle
Level 4	Business Planning: the basic schedule and batch management
Level 3	Operations: workflows to produce desired end product
Level 2	Control and monitoring of production process
Level 1	Laboratory equipment and testing instrumentation
Level 0	The plant: actual production process

Abstracted hierarchal layers of ANSI/ISA-95 model [22]

By combining the contributions from various literature articles [3]–[5], [9], [16], [24], it was possible to ascertain subsequent features for KPIs measurement: *Significance*: it provides important information which can make a difference in decision by facilitating manufacturers to either approve, update aforementioned expectations or to formulate predictions about the present and future measures. One of the vital features of significance is timeliness, meaning that information should reach the decision makers before they lose the ability to make informed decisions. *Reliability*: it deals with the quality of KPIs assuring that it is equitably free from inaccuracies and truly indicates its purpose. Similarly, other criteria like consistency, understandability, comparability, predictive, quantifiable, traceable, inexpensive and verifiability are critical when selecting and measuring optimal KPIs [18], [26]–[28]. The manufacturing shop floor holistic approach is carefully developed considering all of the above mentioned measurement features.

It is perceived in [29]–[32] that the most critical factor to monitor for every manufacturing industry is time. Thus, many manufacturing industries often use time related KPIs such as cycle time, takt time, shutdown time, stop time, setup time, availability and production time etc. While continuing to monitor time related KPIs, manufacturing industries failed to keep up with monitoring the overall shop floor performance. From literature it was revealed that various other factors, such as: cost, quality, safety, environment and sustainability should also be considered for monitoring overall shop floor performance [6], [33], [34].

Due to inadequate familiarity with KPIs, several manufacturing industries tend to measure and display a same set of KPIs throughout their shop floor. In fact, KPIs are job role specific i.e. management, supervisor and operator [30]. For instance, total production loss KPI is considered as manager specific as it gives the overall production losses throughout the production line, displaying this KPI may be of no use for operators. Cycle time KPI which enables the operators to monitor and improve the operations time will be useful. Furthermore, several manufacturers fail to realize KPI trend, i.e., the improvement direction (higher the better or lower the better). For example, availability KPI trend is higher the better and rework ratio trend is lower the better. Without complete understanding about the KPI trend, the KPIs measured and displayed will only remain a number [35]–[37].

KPIs in manufacturing industries are displayed in real-time, on-demand and periodical based on the audience [13], [35], [36]. It is observed that the KPI display timing plays a crucial part in KPI selection process [30]–[32]. Shop floor operations which needs to be monitored constantly, so as to identify the instant bottlenecks should be monitored using real-time KPIs [38], [39]. Selecting a periodical KPI which cannot be updated after every data acquisition event will not help the manufacturers to detect the bottleneck and make quick decisions [29].

Mohammed *et al*. [23] mentions that after selecting KPIs for monitoring purposes, the manufacturers should also identify the equation variables needed to calculate those KPIs. It is due to the fact that not every equation variable data needed to calculate the KPI would be readily available at the shop floor. The nature of KPI will help the manufacturers to decide the origin of data inside the manufacturing industry. Mostly, KPIs are of fundamental or derived in nature. From manufactures perspective, it is important to know the equation variables needed to calculate a KPI because extracting data for a certain variable on the shop floor might be challenging, costly and sometimes unfeasible due to working with legacy systems and silo systems. Knowing the equation and equation variables (equation and equation variables are part of the formulae required for its calculation) needed to calculate a KPI will benefit the manufacturers to either employ the KPI or search for an alternative [8], [40].

Lastly, many researchers' and think tank experts inclines to further reason on the technology employed for extracting the required data to calculate the KPIs [4], [7], [8], [28]. If the technology engaged for calculation is sophisticated and expensive then deploying those KPIs on the shop floor would not be recompensing. A KPI that can be deployed on the shop floor with an unpretentious technology can help manufactures to easily monitor their KPIs without spending heavily on the technology. However, the type of technology that needs to be deployed is dependent on the kind of shop floor operations undertaken.

After critically considering all the factors, criteria and methods that are required for appropriate KPI selection, the author has established that there is a need of developing a holistic and systematic approach. The approach that can account all the deemed aspects of KPIs available in the literature and which can guide the manufacturers to select appropriate KPIs. It is based on the contemplation that KPIs can be selected on the basis of set of measures that are theoretically grounded. The approach consists of five layers, with each layer consisting of set of measures dedicated to disclose vital information that will inspire the manufacturers to better monitor and improve decision-making capabilities within their shop floor operations.

PROPOSED HOLISTIC APPROACH

This paper proposes a holistic approach to select right KPIs for measuring performance of shop floor operations. The proposed approach consists of five layers namely: information layer, discernment layer, scheming layer, origin of data layer and assisting technology to capture the data layer. The reason for dividing the approach into five layers is to make it logical and systematic for the manufacturers. The first layer (i.e. information layer) covers the fundamentals of a KPI which is subdivided into content and context layers. After acquiring the essential information about KPIs from the first layer, the manufacturers can then proceed towards obtaining detailed aspects for a certain KPI from the second layer (discernment layer). Being satisfied by obtaining detailed aspects of KPIs, manufacturers can then advance to third layer which will then explain equation variables needed for KPI calculations. The fourth layer will guide manufacturers to know the origin of data required for the equation variables within their shop floor. Lastly, fifth layer will help them to know the technologies available for data capturing.

Information layer

The purpose of this layer is to enable manufacturers to acquire basic information about the KPIs. This layer is further divided into two sub-layers namely: content and context layers as shown in table I and table II. Content layer comprises of list of measures, such as: name, description, formulae, unit of measure, range and trend. The detailed explanation of each of this measures is explained in table I. Whereas, context layer comprises of list measures, such as: timing, audience, production methodology and Entity-Relationship (ER) model with detailed explanation mentioned in table II.

INFORMATION- CONTENT LAYER

Content Layer	
Measure	**Detail**
Name	Name of the KPI
Description	A brief description of the KPI
Formula	The mathematical formula to calculate a KPI
Unit of measure	The basic unit or dimension in which the KPI is stated
Range	Specifies logical limits (upper and lower) of the KPI
Trend	Is the statistics about the improvement direction, for instance, higher is better or lower is better

Information layer allows manufacturers to carefully realize KPI basics before moving forward with its selection, implementation and visualization. In the initial stages of KPI selection it is critical for manufacturers to comprehend the fundamental concepts about KPI of their interest. From the literature it is witnessed that more than 80 percent of the manufacturers fails to realise their business objectives or fail to improve their shop floor performance due to the failure of understanding the necessary concepts of KPIs [7]. Having basic knowledge about the KPIs can help the manufacturers to familiarise themselves about KPIs before further consideration.

INFORMATION- CONTEXT LAYER

Context Layer	
Measure	**Detail**
Timing	A KPI can be calculated either in *Real-time*- after each new data acquisition event *On demand*- after a specific data selection request *Periodically*- done at a certain interval, e.g. once per day
Audience	Audience is the user group typically using this KPI. Typically, the audience are *Operators*- personnel responsible for the direct operation of the equipment *Supervisors*- personnel responsible for directing the activities of the operators *Manager*- personnel responsible for the overall execution of production
Production methodology	Specifies the production methodology that the KPI is generally applicable for: *discrete, batch and/or continuous*
ER model	The effect model diagram is a graphical representation of the dependencies of the KPI elements that can be used to drill down and understand the source of the element values

Discernment layer

Discernment layer of the proposed approach covers thorough (detailed) aspects of KPI. The list of measures covered by this layer are: type, dimension, form and nature; explanation of each measure is mentioned in table III. This layer encourages manufacturers to critically comprehend the applicability of new or existing KPI with their desired business objectives. It facilitates them to think and question their current KPIs cogency in achieving astounding performance by providing their detailed aspects. This layer further aids the manufacturers to know (specifically) which measure i.e. product, process and/or resource of manufacturing shop floor can be improved using certain KPIs. Since, it has been observed from the literature that most managers are unaware of the KPI relevance, resulting in poor KPI selection [40]. This layer will help to address the KPI relevance issues by providing detailed insights of the KPIs as underlined in table II.

By identifying parameter (i.e. the elements present in each measure) to which the KPI is pertinent to with an appropriate dimension, form and nature can benefit manufacturers to accurately link their business objectives with the selected KPIs. Additionally, it will allow manufacturer to focus on particular parameters which can enable them to make quicker and informed decisions.

DISCERNMENT LAYER

Discernment Layer	
Measure	**Detail**
Type	Identification of the element that the KPI is relevant for- *Product, process and/or resource*
Dimension	Identification of the element that the KPI is relevant for- *Time, cost, quality, safety, environmental, sustainability and other*
Form	Specifies the form of KPI- *Lagging*- are typically “output” oriented, easy to measure but hard to improve *Leading*- typically input oriented, hard to measure and easy to influence
Nature	Specifies the nature of the KPI- *Fundamental or derived*

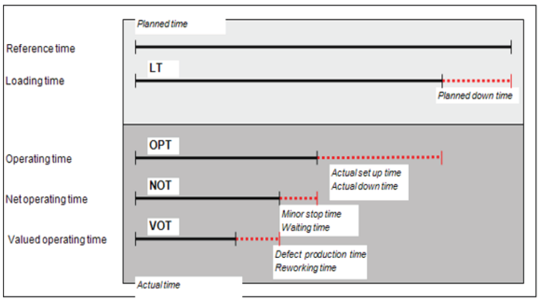
Scheming layer

After acquiring vital and thorough knowledge on fundamental and detailed aspects of the KPIs. Scheming layer provides additional measures such as equation and equation variable (usually known as data) which resembles the formulae used for KPI calculation as shown in table IV. This layer will guide manufacturers to know the variables (data) that will be required to calculate their desired KPIs. For example, the equation variables required to calculate availability KPI are operating time against the loading time.

SCHEMING LAYER

Scheming Layer	
Measure	**Detail**
Equation	It resembles the formulae used for KPI calculation
Equation variable	The variables present in the equation are termed as equation variables

For example, figure 3 elucidates that in order to calculate availability KPI, manufacturers need to know the equation variables such as: reference time, loading time, operating time, net operating time and valued operating time. Knowing these equation(s) and equation variable(s) will guide manufacturer's to effortlessly link their business objectives with the KPIs selected and also discern if the data for these variables subsists within their shop floor data model.



Equation variable for calculating availability KPI

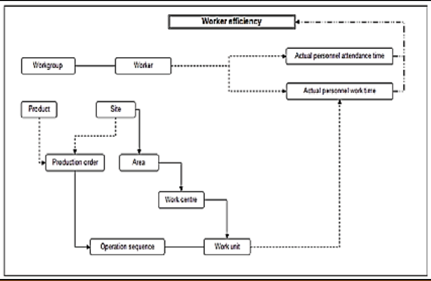
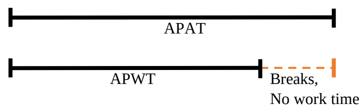
Origin of data layer

After knowing the equation variable(s) required to calculate the KPI, origin of data layer helps manufactures to identify the point of origin of these variables within their shop floor. The point of origin can be a Programmable Logic Controller (PLC) used for collecting the data from a station or an energy monitor installed for recording readings of a particular robot. It is essential for manufacturers to identify the origin of the data because under some circumstances, such as presence of legacy systems makes it difficult for data extraction. Extracting data from legacy systems remains a challenge but with numerous KPIs available, it becomes easier for manufacturers to switch to alternative KPIs with different equation variables that might not depend on data extraction from legacy system. By knowing the origin of the data, manufacturers can decide whether to proceed with data extraction of a certain KPI or else look for an alternative.

Assisting technology to capture the data layer

In order to collect data swiftly and efficiently, this layer helps manufacturers to know the assisting technology applicable for data capturing. Since, cost is a critical factor while deploying technology into the shop floor, this layer aids the manufacturers to decide and then select optimal KPI which will increase the overall shop floor performance with reasonable investment in supporting technology. For example, in order to calculate worker efficiency KPI it is necessary to capture the worker's operating and idle time inside the shop floor. The worker presence can be captured using assisting technologies such as: RFID readers, camera systems and motion detectors. It will now be up to the manufacturers to decide and select the technology that economically suits them. Table V illustrates an example of worker efficiency using the proposed approach.

KPI HOLISTIC APPROACH: WORKED OUT EXAMPLE FOR WORKER EFFICIENCY KPI

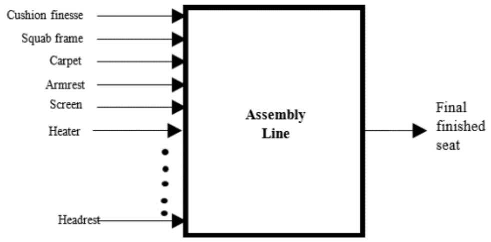
INFORMATION LAYER	
Content layer	
Name	Worker Efficiency
Description	The worker efficiency considers the relationship between the actual personnel work time (APWT) related to production orders and the actual personnel attendance time (APAT).
Formula	Worker efficiency = APWT / APAT
Unit of Measure	%
Range	Min: 0% Max: 100%
Trend	The higher the better
Context layer	
Timing	Periodical
Audience	Supervisor, management
Production Methodology	Discrete, batch, continuous
Effect Model Diagram	
DISCERNMENT LAYER	
Type	Resource
Dimension	Time
Form	Lagging
Nature	Derived
SCHEMING LAYER	
Equation	APAT, APWT
Equation Variable	APAT, APWT, Break time and no work time 
ORIGIN OF DATA LAYER	
Manufacturing Execution System (MES)	
ASSISTING TECHNOLOGY LAYER	
RFID reader, camera system, barcode scanners	

CASE STUDY

The case study is conducted on a set of KPIs obtained from the company X (automotive seat manufacturing company). Based on the set objectives to be achieved by company X, existing KPIs are studied through the proposed holistic approach. Results generated by implementing the holistic approach is compared with the set objectives to realize the existing KPIs applicability, effectiveness and performance.

Company X background

Company X UK is leading the smart manufacturing initiative for company X globally, which deals with car seat manufacturing. Company X's manufacturing UK employs 200 staff and 2000 workers across three UK plants. It manufactures seats for various cars brands, with its major customer being Jaguar Land Rover (JLR). In company X, every component that is required to manufacture a seat is pre-assembled in sub-assembly lines and final seat is primed in assembly lines within their manufacturing plants. Figure 4, is a block diagram representation of an assembly line with a list of key inputs and output. The inputs to the assembly line are fetched from the sub-assembly lines; and inputs to this sub-assembly lines are the raw materials based on the seat requirements.



Snapshot of an assembly line with list of inputs and output

Company X objectives

After analyzing company's priority intents as well as interviewing managers, line supervisors and research and development teams, it was established that the main objectives of company X (w.r.t their shop floor performances) is real-time monitoring of seat production rate while maintaining high quality. Company X mainly focuses on real-time monitoring of seats production and enhancing the seat quality. Company X are producing 98 seats/hour against 100 seats/hr, with around 5 seats failing to clear the quality inspection against 3 seats per given production window. Currently, the KPIs used in order to monitor their production line are: Allocation Ratio (*AR*), Availability (*A*), Takt-Time (*TT*), Rework Ratio (*RR*), Production Process Ratio (*PPR*) and Production Target (*PT*). These KPIs were selected by company's management team. The dashboard display that the company presently use is shown in figure 5. Furthermore, there is no separate dashboard based on the job roles (manager, supervisor and operator).

Dashboard layout for company X seat production line

Analyzing KPI's of company X through proposed holistic approach

Since, company X objectives are real-time monitoring the production rate and improving quality of the production line, the KPI's selected for that purpose should reflect the same. Table VI highlights company's objectives via KPI measures based on the proposed approach. It should be noted that only few measures of the proposed approach are mentioned by the author for establishing critical understanding and developing the clarity of set objectives.

KPI OBJECTIVE AND COMPANY X OBJECTIVE

KPI measure	Company X objective
Timing	Real-time
Type	Product and process
Dimension	Time and quality
Form	Leading

Evaluating these KPIs (*AR*, *A*, *PPR*, *PT*, *RR* and *TT*) using the proposed approach is mentioned in table VII. It is observed from table VII that four out of six KPI's used by the company X does not support real-time monitoring of production performances. For example, KPI such as *AR*, *A*, *PPR* and *PT* does not support real-time visualization i.e. these KPI cannot be updated after every data acquisition event. These KPIs supports on-demand and periodical visualization. Therefore, company X will be unable to monitor real-time shop floor performance using the given set of KPIs. Only one KPI (*RR*) is selected to monitor the seat quality. *RR* is relationship between rework quantity and produced quantity, this KPI helps to monitor number of products that has not passed quality inspection. The red highlighted boxes in table VII gives a clear indication of KPIs that will not support the company X to monitor their business objectives. Therefore, company X is in need of KPIs which can effectively monitor real-time production rate and quality of the product.

REALIZING EXISTING COMPANY X KPIS USING PROPOSED APPROACH

KPI measures	Existing company X KPIs					
	AR	*A*	*PPR*	*PT*	*RR*	*TT*
Audience	S, M	S, M	S, M	S, M	S, M, O	S, M
Dimension	T	T	T	T	Q	T
Form	La	La	La	La	Le	Le
Timing	Pe	Od, Pe	Od, Pe	Od, Pe	Od, Pe, Rt	Od, Pe, Rt
Type	Po	Po	Po, Pr	Po	Po	Pr

Pe- Periodical, Od- On-demand, Rt- Realtime, Po- Product, Pr- Process, Re-Resources, S- Supervisor, M- Manager, O- Operator, T-time, Q- Quality, La- Lagging, Le- Leading

By further investigating table VII, it is apparent that there is no KPI focusing on resource aspect, with production rate and quality being the main objective for monitoring, not involving resource related KPIs will impact company X's ability to fully improve the production rate. Additionally, with the current dashboard design installed throughout the production line, only *RR* KPI can help operators to monitor the performance of the line in real-time. Rest of the KPI are helpful for supervisors and management to timely track the production performance. Hence, the current dashboard design also shows limitations when viewed as a shop floor operator.

To sum up, by scrutinizing the current KPIs of company X through the proposed holistic approach, it has been viewed that only 1 KPI (*RR*) is directly aligned to monitor company's set objectives. Rest of the KPIs does not completely align with the set objectives and henceforth needs revision.

Company X suggested KPIs

Table VIII shows the list of KPIs which can help company X to better monitor and fulfil their set objectives. Since, there are more than 1700 KPIs available in the literature, author has carefully chosen a set of five appropriate KPIs that are directly aligned to monitor and achieve company's objectives. Unlike the existing KPIs which mostly deviates from the set objectives, the suggested KPIs directly measures their objectives. The suggested KPIs are: Cycle Time (*CT*), Good Quality (*GQ*), Overall Equipment Effectiveness (*OEE*), Takt Time (*TT*) and Utilization Efficiency (*UE*). The reason for selecting these KPIs can be clearly interpreted from table VIII, where all of the suggested KPIs are well aligned with the company's objectives.

SUGGESTED KPIS USING PROPOSED APPROACH

KPI measure	Suggested X KPIs				
	CT	GQ	OEE	TT	UE
Timing	Od, Pe, Rt	Od, Pe, Rt	Od, Pe, Rt	Od, Pe, Rt	Od, Pe, Rt
Type	Pr	Po, Pr, Re	Po, Pr, Re	Pr	Pr
Audience	S, M, O	S, M, O	S, M, O	S, M	S, M, O
Dimension	T	Q	T, Q	T	T
Form	Le	Le	Le	Le	Le

Since, the chosen KPIs are based on the author's experience both in the field KPIs as well as working with company X, in future this approach can be used to develop a model (encoded as a software package) which can list out the appropriate KPIs based on the companies' objectives.

I. CONCLUSION

Currently, standard approaches to select appropriate KPIs for manufacturing shop floor do not exist. The paper has proposed a holistic approach required for selecting appropriate KPIs for monitoring manufacturing shop floor performances based on set of measures which are theoretically grounded. To examine effectiveness of the given approach, it was implemented on company X assembly line. The proposed approach revealed that five out of six KPIs used by company X were not aligned with their business objectives. A set of five KPIs were suggested to company X which can help them to better monitor their shop floor performances. This approach not only enabled manufacturers to comprehend their existing KPIs w.r.t their business objectives but also guided them in knowing the appropriate KPIs for their shop floor performances.

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