# PRIORITIZATION OF RESPONSIVE MAINTENANCE TASKS VIA MACHINE LEARNING-BASED INFERENCE

E. Konstantinou[1*], A.K. Parlikad[2], A. Wong[3], C. Broom[3]

[1]Research Associate, University of Cambridge, Institute of Manufacturing, Cambridge, UK
[2]Senior Lecturer, University of Cambridge, Institute of Manufacturing, Cambridge, UK
[3]Redbite Solutions
* Corresponding author

**ABSTRACT** Maintenance task prioritization is essential for allocating resources. It is estimated that almost 1/3 of the maintenance cost is wasted to unnecessary activities. Task prioritization is based on risk assessment that takes into account the probability of failure and the criticality of an asset. The criticality analysis is defined by the asset owner based on several parameters, among them safety, downtime cost, productivity, whilst the probability of failure is determined based on deterioration models, regular manual inspections, or installed sensors. Currently, the latter is an extremely complicated and labour intensive procedure, when multiple and different types of assets need to be managed. This paper proposes an innovative method that exploits the advances in mobile communications, social networking, Internet of Things and machine learning to address this shortcoming. This approach brings building elements and assets online using asset tags with an online 'asset profile' linked to it. Users of assets are able to scan these tags using a mobile phone app to not only see the information about those assets, but also enter 'comments' describing issues and problems on the profiles. These comments are processed through machine learning-based inference methods to estimate the probability that a failure has occurred. This paper validates the proposed method using historical data collected from the Estate Management, of the University of Cambridge.

## 1. Introduction

It is estimated that the lifetime building maintenance cost is equal to 0.4 times the construction cost (Hughes et al., 2004). Maintenance actions aim to restore every part of a building back to its original status (British Standards Institution, 1993). Building failures and defects are common phenomena in construction. Some of the most typical types of such defects are: wall cracks, faulty electrical wiring, faulty fire/smoke detection system, not working lighting, moisture, blocked or inadequate drainage systems (Ahzahar et al., 2011; Othman, 2015). Any of these issues increase dramatically the maintenance cost. It is reported that moisture issues only, cost billions of dollars in the United States (Kubba, 2008).

Efficient and good quality planning of maintenance tasks is crucial for the wellbeing of its occupants (Brugge et al., 2010). In this regard, a well maintained ventilation system can increase productivity by 2.5-5% during an 8 hour work period (Park & Yoon, 2011). On the contrary, a delayed response to malfunctions of the heat, ventilation and air conditioning system (HVAC) can cause productivity loss that ranges between 5% to 9% (Al Horr et al., 2017; Kosonen & Tan, 2004), and Sick Building Syndrome (SBS) (Lan et al., 2011)..The latter is linked to several illnesses, among them eye, nose, and throat initiation, headaches, and allergies (Au-yong et al., 2014). Researchers proved that insufficient maintenance quality results in poor indoor environmental quality in social housing (Diaz et al., 2018; Rauh et., 2008). Poor indoor environmental quality is directly related to several health issues, especially respiratory illnesses, among them, asthma, rhinitis, bronchitis, common cold and cough (May et al., 2017). The potential savings from improving the above maintenance related health issues is estimated to be equal to 168 US dollars (Wargocki, 2018). In the UK, the annual costs incurred from asthma treatments are equal to 1 billion British Pounds (Mukherjee et al., 2014). Therefore, it is essential to devise an efficient method to improve the quality of maintenance planning of residential and office buildings.

## 2. Background

Maintenance actions are initiated either after an asset fails (corrective) or before (preventive) at regular intervals. The corrective actions in particular, need to be immediately addressed to avoid causing severe inconvenience to the building users (Le et al., 2018). Such fast response is achievable only if budget allows it. Unfortunately, the budget that is allocated for maintenance is limited (Le et al., 2018). This is mainly due to the lack of accurate estimation tools of the required maintenance funds (Yu et al., 2017). It is reported that one thirds of the maintenance cost is wasted insufficiently (Mobley, 2002). In order to accommodate the most critical maintenance needs under budget restrictions, maintenance tasks needs to be prioritized.

Most of the prioritization methods consider the probability of failure and the criticality of an asset (consequences of failure). The criticality analysis is defined by the asset owner (or organisation) based on several parameters, among them safety, downtime cost, asset importance, productivity, whilst the probability of failure is determined based on deterioration models, regular manual inspections, or installed sensors (Crespo et al., 2016). On that respect, Parlikad & Srinivasan (2016) proposed a dynamic criticality-based method to optimize maintenance plans in terms of defining the optimal repair/replacement time for an asset. Sweis et al. (2014) developed a multi-attribute prioritization model that relies on predefined major criteria of major public healthcare facilities. Ratnayake & Antosz (2017) combined fuzzy logic with a risk matrix to optimize the prioritization of machinery maintenance. Chang et al. (2004) in a different approach, proposed a knowledge-based method to prioritize the maintenance needs of public universities. However, the main

limitations of the existing prioritization methods that rely on heuristic rules and experience-based common sense are the unscheduled downtime and the waste of resources (Li & Ni, 2009). In addition, little focus is given on residential and office buildings as existing studies are predominantly designed for manufacturing and public infrastructure (e.g. hospitals).

Currently, digital twins are presented as a promising solution for improving maintenance decision making (Macchi et al., 2018; Watson, 2011). The digital twin is defined as a virtual entity that consists of sensor and transmitted data. This paper presents an innovative machine learning-based approach towards this direction to address the prioritization of maintenance tasks in an efficient way. This paper hypothesizes that the priority of maintenance tasks can be predicted through past reports of assets' defects. It features an accuracy of 59% on average in terms of classifying the maintenance tasks as "Urgent", "non-Urgent", "Critical", "High", "Medium" and "Low". The remainder of this paper is structured as follows. Section 3 analyses the overall method proposed in this paper using data from the Estate Management Department of the University of Cambridge. Section 4 presents the results. Section 5 summarizes the outcomes of this paper.

## 3. Proposed Solution

### 3.1 Internet of Things (IoT) for Maintenance

The proposed method exploits the IoT in order to establish a communication between the managers and the assets. Such communication will provide real time information to the managers about the condition of multiple assets in a cost-efficient way. Accessible assets "digital profiles" are exploited to achieve this. To access such profiles, the users scan unique identification tags attached on objects as displayed in Figure 1.

Figure 1: Asset tagging



These tags are directly linked to a software application that manages the "digital" profile of every asset (The Simple Asset Management Software, 2019) as shown in Figure 1 above. The "digital profiles" contain useful information about the location of the asset, the latest inspection and most importantly allow the users to send feedback about any potential assets' defects. Table 1 illustrates some examples of users' feedback as provided by the Estate Management Department of the University of Cambridge.

Table 1: Example of labelled input training data

| Text (input) | Label |
|---|---|
| The fire alarm in the bull pens keeps going into fault. | Urgent |
| South research house lift More than one person stuck in the lift. | Urgent |
| Magnetic door holder - cover has been removed and there are exposed wires. Could BBC engineer attend to fix please. | Urgent |
| Water pump is leaking. Pls could someone attend. | non-Urgent |
| We have some lights/bulbs out room 1.20 x1 corridor outside 1.20 x2 | non-Urgent |
| Can you please arrange for someone to visit site and look at the existing heating system as several radiators are not working and may have air in the system | non-Urgent |
| After a fire alarm test the panel has gone into alarm with a 'power supply fault' message. They can't find the source of the power supply fault. Nothing has tripped out. | Critical |
| Lift entrapment | Critical |
| PIN HOLE IN 42ml COPPER PIPE TO CAGE WASH | Low |
| Glass lift requires leveling up in the basement, (as there is half inch gap). | Low |
| Air con is leaking, pls could b & C attend. Dept said they have put bucket and towels underneath, so it should be ok for tonight, but pls could someone attend tomorrow. | Medium |
| MAIN KITCHEN GAS PUMP FAILED UNABLE TO USE COOKERS ECT. | Medium |

The users' feedback is the input of a machine learning-method that infers the criticality of every asset defect reported. A prioritization label is finally returned based on this criticality output. This label indicates the response time. At the first stage (Stage A), the proposed method classifies the maintenance tasks as "Urgent" and "non-Urgent". The former depict assets' failures with a large impact on its users, whilst the latter failures of lower importance. At the second stage (Stage B), each of these two categories is subdivided based on the response time. The urgent are classified as either "Critical" (response within half an hour) or "High" maintenance tasks

(response within 2 hours), whilst the non-urgent as "Medium" (response within 2 days) and "Low" maintenance tasks (response within 10 days).

The classification method proposed in this paper is based on the management practises followed by the Estate Management Department of the University of Cambridge that provided the historical data. To achieve such classification, the model is trained separately for each stage. Figure 2 illustrates the overall proposed framework proposed of this paper.

Figure 2: Proposed framework
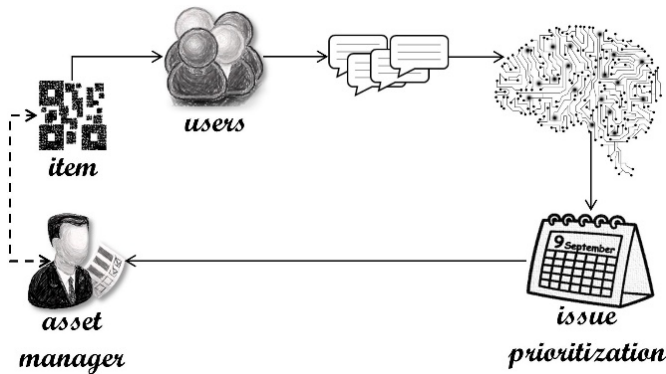


## 2.1 Machine learning-based inference of asset failure impact (criticality)

Figure 3 illustrates the machine learning-based proposed method for prioritizing the maintenance tasks. The rectangular shapes refer to input/outputs and the skewed parallelogram to methods. The inputs of the method are free text provided by the users of the assets through itemit application and historical data. The proposed method is trained with historical data. These data are text messages that report multiple assets defects.

Figure 3: Proposed machine learning-based prioritization of responsive maintenance tasks
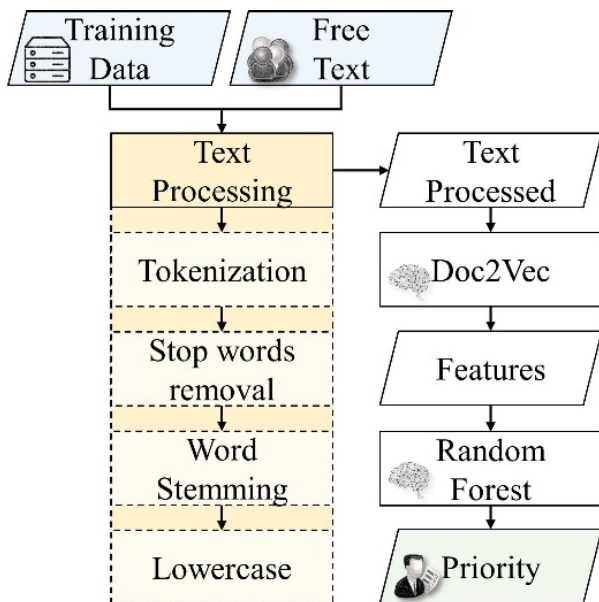


Initially, natural language processing techniques are exploited to pre-process the inputs. This includes: a) tokenization for splitting the sentences into a sequence of strings i.e. tokens, b) removal of stop words, c) lowercasing, and d) word stemming for converting the words to their root form. Secondly, Paragraph Vector (Mikolov & Com, 2014), an unsupervised algorithm, is trained to convert the processed texts (inputs) into feature vectors. This approach uses stochastic gradient descent calculated via backpropagation. One of the main advantages of such approach is that: a) takes into account word semantics, and b) considers the word order. The Paragraph Vector has two versions, the Distributed Bag of Words (PV-DBOW) and the Distributed Memory (PV-DM). The PV-DM is trained to predict the word following a text window, whereas the PV-DBOW is trained to predict the words within a text window. The PV-DM is selected for this paper as it proven to perform better (Mikolov & Com, 2014), an unsupervised algorithm is trained to convert the processed texts (inputs) into feature vectors. This approach uses stochastic gradient descent calculated via backpropagation.

Thirdly, a random forest is trained to classify each of the inputs into the 4 response labels as described in the previous section. The scope of this papers is to prioritize a large variety of maintenance tasks efficiently. This implies imbalanced classes as the inputs will depict different types of assets failures. This paper selects random forest as they perform well with such data (Khoshgoftaar et al., 2007). Random forests are collections of decision trees that perform well with overfitting issues.

## 4. Implementation and Results

### 4.1 Data analysis

The data used were provided from the Estate Management Department from the University of Cambridge. They depict actual maintenance reports raised over a period of 4 years (2014-2018). They cover a variety of assets and building types (residential, office, teaching). The data are prioritized by experts with a response time as described in the previous section, considering the level of impact that the assets failure have on the residents, such as productivity, health and safety. A percentage of 80% of the training data is randomly selected for training and the remaining 20% for testing. Figure 4 displays the frequency the "Urgent" and "non-Urgent" classes of Stage A, whilst Figure 5 presents, the training data of Stage B (Critical, High, Medium, and Low). In these figures, it appears that the training data are strongly imbalanced. To achieve a reliable performance, the classes with the largest training data are down-sampled to the size of the smallest class.

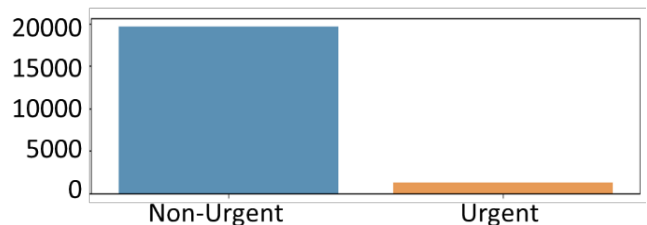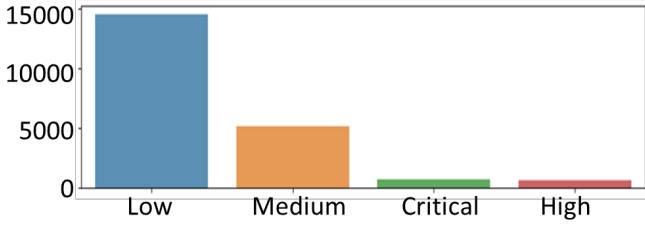Figure 4: Training data frequency (Stage A)

Figure 5: Training data frequency (Stage B)



The training dataset contains 178 different types of assets in total. Table 2 illustrates some of them categorized as Mechanical, Electrical, Plumbing and Architectural.

## Table 2 Type of assets

| Mechanical Assets | Total | Architectural Assets | Total |
|---|---|---|---|
| lift | 1396 | door | 2507 |
| air conditioning | 1144 | window | 722 |
| boiler | 700 | roof | 336 |
| radiator | 614 | wall | 260 |
| chiller | 366 | lock | 162 |
| plant room | 353 | gate | 131 |
| fan | 320 | work top | 89 |
| heater | 113 | stair | 75 |
| Building management system (BMS) | 99 | slab | 71 |
| Air Handling Units (AHU) | 94 | shelf | 69 |
| freezer | 39 | desk | 63 |
| air handling unit | 35 | cabinet | 45 |
| pressurisation unit | 33 | whiteboard | 34 |
| control panel | 31 | noticeboard | 34 |
| cooling unit | 15 | seat | 24 |
| duct | 11 | keypad | 10 |
| dumbwaiter | 8 | pin board | 6 |
| heat exchanger | 5 | shelter | 5 |
| air compressor | 3 | paver | 5 |
| electric heating | 1 | dispenser | 4 |
| **Plumbing Assets** | | **Electrical Assets** | |
| toilet | 3049 | lighting | 3728 |
| tap | 544 | fire system | 965 |
| sink | 460 | outlet | 384 |
| drain | 416 | smoke detector | 104 |
| pipe | 307 | camera | 44 |
| shower | 193 | intruder alarm | 39 |
| humidifier | 81 | sounder | 32 |
| cistern | 70 | card access | 32 |
| water pump | 54 | cooker | 19 |
| water tank | 43 | security detector | 10 |
| basin | 41 | bell | 3 |
| sewage | 28 | dishwasher | 1 |
| inverter | 14 | | |
| hot water system | 11 | | |
| water cooler | 9 | | |
| grease trap | 5 | | |
| gulley | 5 | | |

*4.2 Performance*

The performance of the method presented in this paper is evaluated with a python implementation developed in PyCharm framework, running in a Windows 8.1 operating system. To display the performance of the proposed method 4 classification metrics are used, accuracy (see Equation ((*1*)), precision (see Equation (2) recall (see Equation (3)), and F1_score (see Equation (4)). Accuracy returns the fraction of correct predictions. Precision depicts how well the proposed method avoids from labelling as positive a sample that is negative (true negatives), whilst recall represents the efficiency of the classifier to find all the true positive samples (true positives). Lastly, the f1_score is the weighted average of precision and recall. Table 3 shows the performance of the proposed method.

$$accuracy = (TP + TN)/(TP + TN + FP + FN) \qquad (1)$$

$$precision = TP/ (TP + FP) \qquad (2)$$

$$recall = TP/(TP + FN) \qquad (3)$$

$$f1_{score} = 2 * (precision * recall)/(precison + recall) \qquad (4)$$

## Table 3: Performance of proposed method

| Class | Accuracy | Precision | Recall | f1 |
|---|---|---|---|---|
| Urgent | 0.62 | 0.59 | 0.69 | 0.64 |
| Non-Urgent | | 0.64 | 0.54 | 0.58 |
| Critical | 0.57 | 0.59 | 0.67 | 0.63 |
| High | | 0.55 | 0.46 | 0.50 |
| Medium | 0.58 | 0.58 | 0.69 | 0.63 |
| Low | | 0.60 | 0.48 | 0.53 |
| Average | 0.59 | 0.58 | 0.59 | 0.61 |

Each stage (A, B) is separately evaluated. In general, Table 3 shows that all classification steps perform equally well under all 4 metrics. The proposed method returns an accuracy of 62% in terms of classifying samples as "Urgent" or "non-Urgent", features an accuracy of 57% in classifying samples as "Critical" or "High", and lastly scores an accuracy of 58% in labelling samples as "Medium" or "Low". However, the main limitation of the proposed method is that the accuracy of Stage A affects the performance of Stage B, since samples are first classified as "Urgent"/"non-Urgent" before being classified as either "Critical" vs "High" or "Medium" vs "Low". One of the main reasons that the proposed method does not achieve a higher accuracy is that experts were not entirely consistent through the years when labelling the training data. Table 4 presents such an example. In this table it is shown that the same maintenance issue (i.e. same importance and asset type) it is tagged with difference response time. For instance, in #1 and #2, a faulty fire door is labelled as "non-Urgent" (response from 2-10 days), whilst the same issue in #3 and #4 is labelled as "Urgent". In addition, as shown in Figure 4 the classes of Stage A are strongly imbalanced. This is mainly because not all assets had a "Critical" or "High" label. This occurs mainly with the architectural assets as the issues related with such assets are mostly of "Medium" or "Low" importance.

Table 4: Non-consistent labelling of training data

| # | Text (input) | Label | Asset |
|---|---|---|---|
| 1 | GROUND FLOOR CORRIDOR FIRE DOOR DROPPED FRAME ISSUE REPAIR BROKEN DOOR | non-Urgent | Door |
| 2 | GROUND FLOOR TO BASEMENT THE FIRE DOOR IS BROKEN | non-Urgent | Door |
| 3 | Replace worn fire door that is not closing on alarm | Urgent | Door |
| 4 | Replace worn fire door seal to room SW02 | Urgent | Door |
| 5 | Taken from Email Good afternoon, We have a blocked toiler in the men's fitness changing rooms. Would someone be able to come and unblock it? Thank you | Low | Toilet |
| 6 | Basement toilet is blocked | Medium | Toilet |
| 7 | The air conditioning unit in the SP clean room is not working. Please can someone attend. | Medium | Air conditioning |
| 8 | Air Con is not working in room M113C. Pls could B & C attend. | Low | Air conditioning |
| 9 | The radiator in room 416 is not working. | Low | Radiator |
| 10 | The heating in this office is not working properly. One of the radiators is like warm, the other is not working at all. | Medium | Radiator |

## 5. Conclusion

Up to present, while the maintenance cost remains high the budget that is allocated for it is limited. The wellbeing of occupants is directly linked with a good quality of maintenance management. Several studies are proposed focusing on prioritizing the maintenance works. However, they remain inefficient as they cause downtime and waste of resources. This paper exploits IoT and machine learning inference in order to prioritize maintenance tasks in a time and cost-efficient way. It hypothesizes that the priority of maintenance tasks can be predicted through past reports. The proposed method features a classification accuracy of 59% on average. The main limitations of the proposed method are the non-consistent labelling of the historical data by the asset managers, and the strongly imbalanced classes. Future work will focus on: a) standardizing the labelling process in order to avoid such issues and increase the performance, b) focusing on assets with the most frequent issues in order to avoid strongly imbalanced training data, and b) establishing a semantic-based linkage with the digital twin of the building in order to increase the accuracy of estimating the impact that the failure of assets have on its users.

## 7. References

Ahzahar, N., Karim, N. A., Hassan, S. H., & Eman, J. (2011). A Study of Contribution Factors to Building Failures and Defects in Construction Industry. In *Procedia Engineering/ The 2nd International Building Control Conference 2011* (Vol. 20, pp. 249–255). https://doi.org/10.1016/j.proeng.2011.11.162

Al Horr, Y., Arif, M., Kaushik, A., Mazroei, A., & Elsarrag, E. (2017). Occupant productivity and indoor environment quality : A case of GSAS. *International Journal of Sustainable Built Environment*, 6(2), 476–490. https://doi.org/10.1016/j.ijsbe.2017.11.001

Au-yong, C. P., Ali, A. S., & Ahmad, F. (2014). Improving occupants ' satisfaction with effective maintenance management of HVAC system in office buildings. *Automation in Construction*, 43, 31–37. https://doi.org/10.1016/j.autcon.2014.03.013

British Standards Institution. (1993). *BS 3811:1993 Glossary of terms used in terotechnology*. London: British Standards Institution.

Brugge, D., Welker-Hood, K., Kosheleva, A., & Saddler, S. (2010). Association and Correlation of Self-Reported Home Environmental Factors and Health Symptoms. *Archives of Environmental & Occupational Health*, 8244. https://doi.org/10.3200/AEOH.61.1.33-41

Chang, C.-Y., Chang, Y.-C., & Huang, S.-M. (2004). Prioritization System for Building Maintenance Applications in Public Universities. In *roceedings of the 21st ISARC*. Jeju, South Korea. https://doi.org/https://doi.org/10.22260/ISARC2004/0027

Crespo, A., Pedro, M., León, M. De, Rosique, A. S., & Fernández, J. F. G. (2016). Criticality Analysis for Maintenance Purposes : A Study for Complex In-service Engineering Assets. *Quality and Reliability Engineering International*, (February 2015). https://doi.org/10.1002/qre.1769

Diaz, E., Patino, L., & Siegel, A. (2018). Indoor environmental quality in social housing : A literature review. *Building and Environment*, 131(December

2017), 231–241.
https://doi.org/10.1016/j.buildenv.2018.01.013

Hughes, W., Ancell, D., Gruneberg, S., & Hirst, L. (2004). EXPOSING THE MYTH OF THE 1 : 5 : 200 RATIO RELATING INITIAL COST , MAINTENANCE AND STAFFING COSTS OF OFFICE BUILDINGS. In *Proceedings 20th Annual ARCOM Conference* (Vol. 1, p. 373/381). London : BSI, 1993.

Khoshgoftaar, T. M., Golawala, M., & Van Hulse, J. (2007). An Empirical Study of Learning from Imbalanced Data Using Random Forest. In *19th IEEE International Conference on Tools with Artificial Intelligence* (pp. 310–317). https://doi.org/10.1109/ICTAI.2007.46

Kosonen, R., & Tan, F. (2004). The effect of perceived indoor air quality on productivity loss. *Energy and Buildings*, *36*, 981–986. https://doi.org/10.1016/j.enbuild.2004.06.005

Kubba, S. (2008). *Architectural Forensics*. McGraw Hill Professional. https://doi.org/10.1036/0071498427

Lan, L., Wargocki, P., Wyon, D. P., & Lian, Z. (2011). Effects of thermal discomfort in an office on perceived air quality , SBS symptoms , physiological responses , and human performance. *INDOOR AIR*, (2006), 376–390. https://doi.org/10.1111/j.1600-0668.2011.00714.x

Le, A., Domingo, N., Rasheed, E. O., & Park, K. S. (2018). Building Maintenance Cost Planning and Estimating : A Literature Review. In *Proceeding of the 34th Annual ARCOM Conference* (pp. 707–716). Belfast, UK.

Li, L., & Ni, J. (2009). Short-term decision support system for maintenance task prioritization. *Int . J . Production Economics*, *121*, 195–202. https://doi.org/10.1016/j.ijpe.2009.05.006

Macchi, M., Roda, I., Negri, E., Fumagalli, L., Macchi, M., Roda, I., … Fumagalli, L. (2018). Exploring the role of Digital Twin for Asset Lifecycle Management Exploring the of Digital Twin for Asset Lifecycle Management Exploring the of Digital Twin for Asset Lifecycle Management Exploring the role of Digital Twin for Asset Lifecycle Management. *IFAC-PapersOnLine*, *51*(11), 790–795. https://doi.org/10.1016/j.ifacol.2018.08.415

May, N., McGilligan, C., & Ucci, M. (2017). *Health and Moisture in Buildings*. Retrieved from http://www.ukcmb.org/health-and-moisture-in-buildings-report

Mikolov, T., & Com, T. G. (2014). Distributed Representations of Sentences and Documents. *ArXiv.Org*, *32*.

Mobley, R. K. (2002). *An Introduction to Predictive Maintenance* (2nd ed.). Elsevier Inc. https://doi.org/https://doi.org/10.1016/B978-0-7506-

7531-4.X5000-3

Mukherjee, M., Gupta, R., Farr, A., Heaven, M., Stoddart, A., Nwaru, B. I., … Davies, G. (2014). *Estimating the incidence , prevalence and true cost of asthma in the Estimating the incidence , prevalence and true cost of asthma in the UK : secondary analysis of national stand-alone and linked databases in England , Northern Ireland , Scotland and Wal.* https://doi.org/10.1136/bmjopen-2014-006647

Othman, N. L., Jaafar, M., Mariah, W., Harun, W., & Ibrahim, F. (2015). A Case Study on Moisture Problems and Building Defects. *Procedia - Social and Behavioral Sciences*, *170*, 27–36. https://doi.org/10.1016/j.sbspro.2015.01.011

Park, J. S., & Yoon, C. H. (2011). The effects of outdoor air supply rate on work performance during 8-h work period. *INDOOR AIR*, 284–290. https://doi.org/10.1111/j.1600-0668.2010.00700.x

Parlikad, A. K., & Srinivasan, R. (2016). Towards Dynamic Criticality-Based Maintenance Towards Criticality-Based Assets. *IFAC-PapersOnLine*, *49*(28), 103–107. https://doi.org/10.1016/j.ifacol.2016.11.018

Ratnayake, R. M. C., & Antosz, K. (2017). Development of a Risk Matrix and Extending the Risk-based Maintenance Analysis with Fuzzy Logic. *Procedia Engineering*, *182*(1877), 602–610. https://doi.org/10.1016/j.proeng.2017.03.163

Rauh, V. A., Landrigan, P. J., & Claudio, L. (2008). Housing and Health - intersection of Poverty and Environmental Exposures. *Reducing the Impact of Poverty on Health and Human Development: Scientific Approaches*, *1136*(1), 276–288. https://doi.org/10.1196/annals.1425.032

Sweis, G., Sweis, R. J., Hussein, R. A., & Hiyassat, M. (2014). Priority Setting for Healthcare Facilities Maintenance. *Life Science Journal*, (February 2015).

The Simple Asset Management Software. (2019). Https://itemit.com/.

Wargocki, P. (2018). Productivity and Health Effects of High Indoor Air Quality. *Reference Module in Earth Systems and Environmental Sciences*. https://doi.org/https://doi.org/10.1016/B978-0-12-409548-9.01993-X

Watson, A. (2011). Digital buildings – Challenges and opportunities. *Advanced Engineering Informatics*, *25*, 573–581. https://doi.org/10.1016/j.aei.2011.07.003

Yu, A. J., Shields, B. A., & Simonton, J. (2017). Risk-Based Prioritization of Maintenance Tasks. In *Proceedings of the 2017 Industrial and Systems Engineering Conference* (pp. 794–800).