PRIORITIZATION OF RESPONSIVE MAINTENANCE TASKS VIA MACHINE LEARNING-BASED INFERENCE

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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.

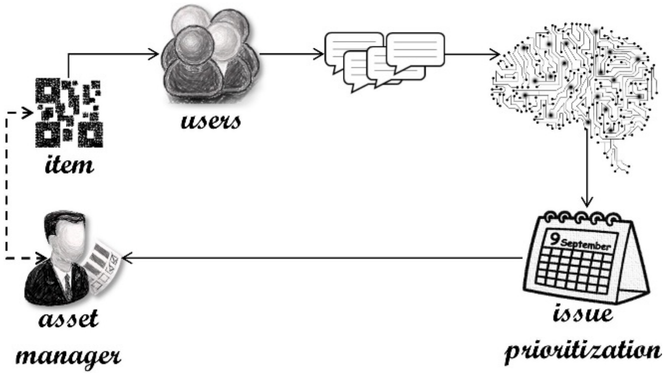
Table 1: Example of labelled input training data

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.

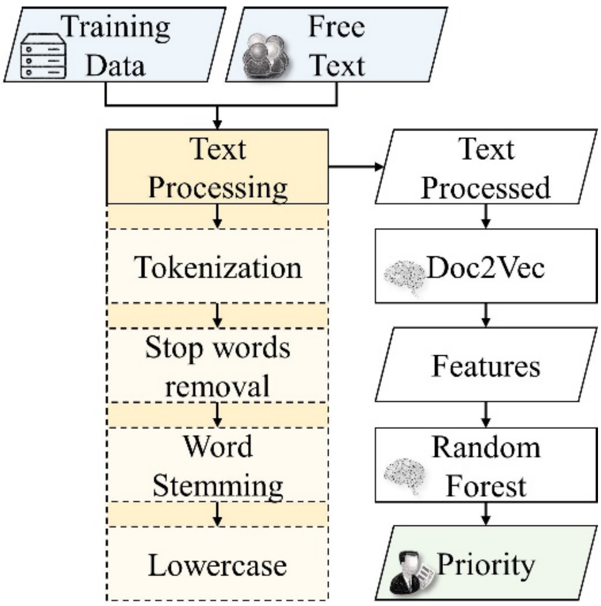
Figure 2: Proposed framework



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)

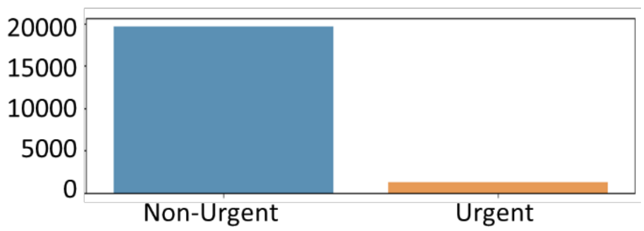
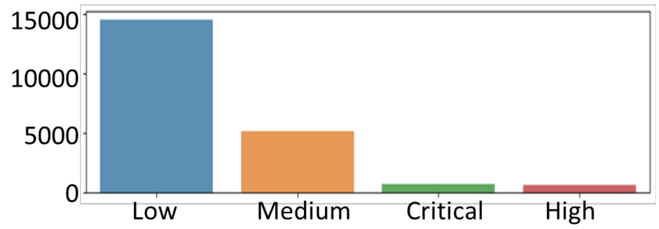


Figure 5: Training data frequency (Stage B)



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.

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

$$precision = TP/\,(TP + FP) \quad (2)$$

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

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

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.

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