Scalable Machine Learning Architectures for IPA-Driven Maintenance Task Allocation in Large-Scale Building Portfolios

Zhimeng Huang
School of Computing, Engineering and Built Environment
Edinburgh Napier University
Edinburgh, United Kingdom
z.huang2@napier.ac.uk

Xiaodong Liu
School of Computing, Engineering and Built Environment
Edinburgh Napier University
Edinburgh, United Kingdom
x.liu@napier.ac.uk

Imed Romdhani
School of Computing, Engineering and Built Environment
Edinburgh Napier University
Edinburgh, United Kingdom
i.romdhani@napier.ac.uk

Chi-Sheng Shih
College of Electrical Engineering and Computer Science
National Taiwan University
Taipei, Taiwan
cshih@csie.ntu.edu.tw

Abstract

This research presents a groundbreaking approach to Building Maintenance Management (BMM) by introducing an Intelligent Process Automation (IPA)-Driven Building Maintenance Management (IBMM) model. This innovative model harnesses the synergies between Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) technologies to transition from reactive to proactive and predictive building maintenance strategies. The study highlights the critical gap in current BMM practices—the absence of intelligent systems for anticipating and addressing maintenance issues before they escalate. Through an extensive literature review, the transformative potential of AI and IoT for enhancing building maintenance management within smart cities is explored, establishing a foundation for the IBMM model's application. The core of this research lies in its novel application of scalable machine learning architectures to automate and optimize maintenance task allocation in large-scale building portfolios. The practicality of the IBMM model is demonstrated via a proof of concept (POC) in an industrial setting, evidencing its capacity to improve efficiency, reduce costs, and bolster sustainability in building maintenance operations. The model epitomizes a paradigm shift in BMM by integrating IPA, which combines AI and ML, facilitating automated, intelligent decision-making and task allocation. Among its advancements, the IBMM model introduces enhanced predictive maintenance through real-time data analysis, adaptive learning and optimization, automated decision-making, and human-machine collaboration, contributing to energy efficiency and alignment with smart city objectives. The paper delineates the methodology, design, and implementation of a machine learning model for engineer task assignments, culminating in a case study that validates the model's efficacy. This research not only signifies a significant advancement in BMM by leveraging IPA technologies for autonomous process refinement but also proposes a unique IPA-driven procedure that incorporates IoT technology and a novel smart device fixer to guide BMM processes. Anticipated outcomes include more accurate maintenance scheduling, cost efficiency, enhanced performance, and the fostering of a collaborative community through an open online documentation platform for BMM. Looking forward, the research aims to refine the IBMM model further by exploring advanced AI algorithms for more precise predictive maintenance and integrating real-time data analytics and IoT networks for improved maintenance strategy responsiveness. This work pioneers a smarter, more efficient, and sustainable approach to building maintenance, marking a new era in the management of urban infrastructure.

CCS Concepts

• **Machine learning algorithms**; • **Real-time operating systems**; • **Software development process management**;

Keywords

Building Maintenance Management (BMM), Machine Learning (ML), Intelligent Process Automation (IPA), Decision Tree

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1 INTRODUCTION

The rapid urbanization of contemporary society necessitates innovative approaches to building management, demanding that infrastructures not only accommodate the present needs but also adapt proactively to future changes. This research delves into the intersection of smart building infrastructure and urban innovation, focusing on the integration of Intelligent Process Automation (IPA) and Internet of Things (IoT) technologies within Building Management Systems (BMS). The emergence of smart cities underscores the need for intelligent building maintenance that aligns with the

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broader vision of urban efficiency, sustainability, and adaptability. This paper identifies a critical gap in current building maintenance management — the lack of proactive, intelligent systems capable of predicting and mitigating issues before they escalate.

In response to this identified need, this paper proposes the 'IPA-Driven Building Maintenance Management' (IBMM) model. This novel model leverages the synergistic potential of AI and IoT to enhance building maintenance operations, transitioning from reactive to proactive and predictive management. The IBMM model is underpinned by an extensive literature review that highlights the transformative impact of AI and IoT on building maintenance, setting the foundation for its application in smart cities. This paper outlines the sophisticated data model and algorithmic structure of IBMM, optimized for the integration of AI and IoT in building maintenance.

The practical viability of the IBMM model is demonstrated through a proof of concept (POC) system implemented in an industrial setting, showcasing the model's capability to enhance efficiency, reduce costs, and improve sustainability in building maintenance management. This POC serves as a testament to the model's applicability and effectiveness, providing a tangible example of its benefits in a real-world environment.

By integrating IPA, a convergence of robotic process automation (RPA), artificial intelligence (AI), and machine learning (ML), the IBMM model represents a paradigm shift in building maintenance management. It embodies a novel, efficient, and sustainable approach, leveraging the latest technologies to automate routine tasks, learn from data patterns, and make intelligent and data-driven decisions.

The effectiveness of the IBMM model has been verified and evaluated with an industrial-scaled case study on a building maintenance company to identify the current task assignment problem. The key problems solved by the IBMM model include Manual Coordination, Mismatched Skills, Inadequate Human Relation and Emotions, and Wrong Decisions caused by misunderstanding.

The paper focuses on the automated decision making for effective task allocation through IPA concept, using AI machine learning model to predict the proposed engineers. The integration of IPA within the IBMM model introduces several ground-breaking advancements:

Enhanced Predictive Maintenance: By leveraging AI and ML algorithms, IPA can analyse vast datasets from IoT sensors in real-time, predicting maintenance needs before they become critical issues. This not only extends the lifespan of building infrastructure but also significantly reduces downtime and maintenance costs.

Adaptive Learning and Optimization: IPA systems can continuously learn and adapt from ongoing operations. This means the IBMM model can become more efficient over time, adjusting maintenance schedules and protocols based on historical data, current performance metrics, and predictive analytics.

Automated Decision-Making: IPA facilitates a higher level of automation in decision-making processes. For instance, in the event of a detected anomaly, the system can automatically initiate a maintenance protocol or alert human operators, thereby enhancing response times and operational efficiency.

Customization and Scalability: The flexibility of IPA allows for customization according to specific building requirements and scalability to larger building networks or smart city infrastructures. This makes the IBMM model versatile and applicable to a wide range of urban settings.

Energy Efficiency and Sustainability: By optimizing maintenance operations and ensuring the efficient functioning of building systems, IPA-driven solutions contribute to energy conservation and sustainability goals, aligning with the broader objectives of smart city initiatives.

Human-Machine Collaboration: IPA introduces a new dimension in human-machine collaboration, where maintenance personnel are aided by intelligent automation, leading to more effective and less labor-intensive maintenance processes.

To summarize, the value of IPA in the IBMM model is multifaceted, encompassing efficiency, predictive capabilities, adaptability, sustainability, and enhanced human-machine collaboration. This novel approach not only revolutionizes building maintenance management but also aligns seamlessly with the evolving dynamics of smart city environments.

The rest of this paper is organized as follows: section 2 disuses the traditional BMM methods and how IPA BMM revolutionize the methods by enabling predictive maintenance, optimizing resource allocation, and automating routine tasks. Session 3 present the IBMM methodology to collect the data forming the algorithm, design and implementing the machine learning model for the BMM engineer assignment to a task. Session 4 and 5use a case study to demonstrate the machine learning model, describes the experiments and performance evaluation respectively. The conclusion and future outlook of the paper is presented in section 6.

2 RELATED WORK

Building Maintenance Management (BMM) refers to the process of ensuring that buildings and their associated services meet the requirements of the occupants and are maintained to a standard that preserves or improves the asset's value (Wood, 2005) [1]. It involves planning, controlling, and implementing maintenance activities for buildings and their infrastructure.

BMM encompasses various tasks, including but not limited to, routine maintenance (like cleaning), repair works (fixing a broken window), preventive maintenance (like HVAC servicing), and predictive maintenance (identifying potential problems before they occur).

The importance of BMM is manifold:

Preservation of Asset Value: Proper BMM practices help in preserving or even enhancing the value of a building. Regular maintenance can prevent deterioration and prolong the lifespan of building components (Chanter & Swallow, 2007) [2].

Health and Safety: BMM is essential to ensure the health and safety of a building's occupants. Adequate maintenance ensures that facilities, such as fire safety systems, are in good working condition and can perform effectively when needed (Seeley, 1997) [3].

Functional Efficiency: Regular maintenance helps to ensure that the building and its systems function efficiently. For example, the regular servicing of heating systems can ensure they operate at optimal efficiency, reducing energy usage and costs (Wood, 2005) [1].

Legal Compliance: There are often legal requirements for certain maintenance activities. Regular maintenance helps to ensure compliance with these regulations, avoiding penalties or legal issues (Chanter & Swallow, 2007) [2].

The importance of BMM, therefore, cannot be overstated. However, traditional BMM methods are often resource-intensive and reactive. There is a growing need for innovative, data-driven solutions to enhance the efficiency and effectiveness of BMM practices, a subject that forms the core of this research.

The current BMM is typically done by many buildings maintenance management company by implementation of standardized maintenance procedure, including schedule checks and repairs. Most of them use a BMMS or CAFM to handle the procedure, the system usually contains maintenance (corrective and preventive) scheduling and tracking, assets management, quote management, purchase order management, finance management, timesheets . . .etc. (Xiao & Proverbs, 2003) [4] These traditional approaches have achieved varying degrees of success in preserving asset value and ensuring compliance, however, they often lack efficiency by human collaboration with not much automation or historical dataset understanding, leading to increased operation costs and potential downtime.

With IPA implementation on top of the traditional BMM, the resource allocation will be effective and efficient, the AI driven analysis on the real time parameters and data set collected from the database, could potentially overcome the following problem in the traditional BMM:

Reactive Nature of Maintenance: Traditional BMM is often reactive. IPA can shift this paradigm towards a more predictive maintenance approach, identifying potential issues before they become problems, thus reducing downtime and maintenance costs. (Ahuja & Yang, 2019) [5]

Inefficient Resource Allocation: Conventional methods may not optimally allocate resources. IPA, with its AI-driven analysis, can ensure that maintenance tasks are assigned to the most suitable personnel, enhancing operational efficiency. (Mehta & Pandit, 2020) [6]

Lack of Real-Time Data Analysis: Traditional BMM doesn't fully leverage real-time data. IPA systems can analyze data from IoT sensors in real-time, allowing for more timely and informed decision-making. (Lopez et al., 2017) [7]

Limited Predictive Maintenance: While some predictive maintenance may be in place, it's often not as advanced. IPA can use machine learning to analyse historical data and predict future maintenance needs with greater accuracy. (Jardine et al., 2006) [8]

Manual Scheduling and Monitoring: A lot of scheduling and monitoring tasks are manual, which can be time-consuming and prone to human error. IPA can automate these processes, improving accuracy and freeing up human resources for more complex tasks. (Swanson, 2001) [9]

Customization and Adaptability: Traditional systems may not be highly adaptable to changing building needs. IPA allows for greater customization and scalability, making it easier to adjust maintenance strategies as building usage and technologies evolve. (Ramos et al., 2018) [10]

Table 1: Variable Explained

Variable	Meaning
D_{client}	client profile, client building information and contact information
$D_{location}$	problem location, using hospital as an example, emergency department > east wing > radiation room . . .etc.
D_{time}	Time information usually stands for the response time, it defines the severity of the problem, is it a not trading issue, a restricted trading issue, a common defect, or an emergency. It states how fast the problem need to be repaired.

3 APPORACH – METHODOLOGY FOR IPA DRIVEN TASK ALLOCATION

3.1 Maintenance management

A maintenance is carried out for a fix or a service to a specific building asset. Such as boiler is not working, pest control, toilet broken. . .etc. Proper building maintenance management is pivotal in leveraging the "Smart Readiness Indicator" (SRI) to assess energy savings and the effectiveness of improvements in retrofitted buildings. (Al Dakheel et al., 2023) [11]. In the current CAFM, to log a case, usually the set of information is required. Variable D means data, data subject, problem, maintenance type and discipline.

$$D_{maintenance} = \{D_{subject}, D_{problem}, D_{maintenace\_type}, D_{discipline}$$

However, in the real CAFM, the collected data are not only maintenance data, but also other information required to resolve a problem. Typically, client information, location information and time information are required. Thus, the data set of reporting a problem, a more usual way will be:

$$D_{input} = D_{maintenance} \cup D_{client} \cup D_{location} \cup D_{time}$$

We explained maintenance information above, some basic detail of D_{client}, $D_{location}$, D_{time} are (Table 1):

The paper focuses on the assigning task stage for two typical types of maintenance, corrective maintenance, and preventive maintenance.

- Corrective Maintenance

The type of maintenance is carried out immediately when there is a failure occurred or detected. It usually has impact to the business. Health and safety issues such as gas, fire or boiler issues could cause business not trading or restricted trading. A totally malfunctioning equipment fix could be clarified as reactive maintenance; A part malfunctioning equipment fix could be clarified as corrective maintenance due to it may still working.

To define a corrective maintenance, severity data may require to be collected to clarify it's a corrective maintenance or a reactive maintenance. Different from preventive maintenance, it doesn't mandatory require the asset data to keep the service record, usually carried out a one-time fix. Thus, the data input formula will be:

$$D_{corrective\_maintenance} = D_{maintenance} \cup D_{severity}$$

- Preventive Maintenance

The type of maintenance is a proactive maintenance strategy to schedule regular inspection and maintenance to an equipment, to prevent the failure of the equipment. Critical equipment without proactive maintenance could cause health and safety issues once the equipment failed, also incurs a much higher amount of fix cost due to urgent repair. a manufacturing big data solution can be used for active preventive maintenance in manufacturing environments. (Wan et al., 2022) [12]

A planned preventive maintenance (PPM) usually in relation to an asset, the maintenance required the data for the asset to keep the tracking of the maintenance record. Hence the maintenance input formula state as:

$$D_{preventive\_maintenance} = D_{maintenance} \cup D_{severity} \cup D_{asset}$$

3.2 Maintenance Scheduler

Operation managers handle the scheduler to allocate their engineers to maintenance tasks. Scheduler contains important maintenance attributes, time, engineer, and geolocation. The following article explain under two different maintenance severities how operation manager schedules a maintenance task.

The imperative of assigning an engineer to a maintenance task, particularly under circumstances deemed urgent due to potential health and safety implications, necessitates a strategic approach to scheduling that prioritizes immediacy without compromising on the appropriateness of the assigned personnel. This process involves a comprehensive evaluation of the engineer's availability, geographic proximity to the task location, and possession of the requisite skill set for the task at hand. The availability status of engineers may vary, encompassing scenarios where they are on standby, en route to a task, engaged in an assignment, or unavailable due to personal commitments such as holidays.

In the context of immediate scheduling, where the temporal aspect takes precedence over cost considerations, the operational strategy focuses on identifying and deploying the most proximate engineer who also embodies the specific competencies required for the maintenance task. This decision-making framework ensures that the response to urgent maintenance needs is both swift and effective, thereby mitigating any potential risks to health and safety. The assignment process, therefore, underscores the importance of an agile operational management system capable of dynamically matching maintenance tasks with the optimal engineering resources based on current availability, geographical positioning, and technical expertise. This approach not only enhances the efficiency of maintenance interventions but also aligns with best practices in risk management and safety assurance.

In instances where a maintenance task is deemed non-urgent, allowing for a more flexible scheduling timeframe, the focus shifts towards optimizing resource allocation to enhance operational efficiency and profitability. This paradigm is characterized as a "common scheduler" approach, which seeks to meticulously balance the engineer's availability with the objective of maximizing economic returns from each task undertaken. The intricacy of this scheduling challenge necessitates a sophisticated algorithmic solution, designed to navigate the complexities inherent in coordinating maintenance assignments.

The algorithm employed for this purpose is predicated on a multifaceted analysis that encompasses several critical dimensions. Firstly, it evaluates the availability of engineers, considering their current assignments, projected task durations, and personal schedules. This evaluation ensures that the allocation of resources does not impinge upon previously committed engagements or violate labor regulations concerning rest periods.

Secondly, the algorithm incorporates a skill matching mechanism, which aligns specific maintenance tasks with engineers possessing the requisite technical expertise. This dimension is crucial for ensuring that tasks are executed proficiently, thereby minimizing the likelihood of rework or delays that could erode profitability.

Thirdly, the algorithm considers geographical logistics, aiming to assign engineers to tasks in a manner that minimizes travel time and associated costs. By optimizing the spatial distribution of assignments, the system enhances overall operational efficiency.

Finally, the algorithm integrates a profit maximization model, which assesses the relative economic value of each potential assignment. This model factors in direct costs, anticipated revenue, and strategic considerations such as long-term client relationships and market positioning.

The culmination of these considerations within the algorithm results in a sophisticated scheduling system that not only addresses the immediate operational needs but also aligns with the overarching business strategy. This approach facilitates the judicious utilization of engineering resources, ensuring that each assignment contributes positively to the organization's profitability and service quality standards.

A typical maintenance task scheduling is decided by the following algorithm: e.g.: a maintenance task requires one engineer to do the work:

The $Mainteance_{task}$ should has attributes location, time, severity, discipline, and other detail.

$$Maintenance_{task} = M_{location} \cup M_{time} \cup M_{severity} \cup M_{discipline} \cup M_{other}$$

To assign to an engineer, there is a set of engineers {Engineer, Engineer, . . .} to select, each engineer's has attributes availability, location, skillset, and labour rate. The best scenario engineer is often based on the performance or cost, the result maybe various based on the situation.

$$Engineer_{candidate} = E_{location} \cup E_{avalability} \cup E_{skillset} \cup E_{rate}$$

Assume balancing performance and cost are the key to do the assignment, we have some functions to filter the set of engineers:

$$Candidate_{location} = \int(M_{location}, \{E_{location}, \ldots\})$$

$$Candidate_{time} = \int(M_{time}, \{E_{availablity}, \ldots\})$$

$$Candidate_{discipline} = \int(M_{discipline}, \{E_{skillset}, \ldots\})$$

$$Candidate_{speed} = \int(M_{duration}, \{E_{duration}, \ldots\})$$

$$Candidate_{cost} = \int(\{E_{rate}, \ldots\})$$

The option candidate finally will be for the maintenance task is (Candidate = C):

$$Candidate_{engineers} = C_{location} \cap C_{discipline} \cap C_{time} \cap C_{speed} \cap C_{cost}$$

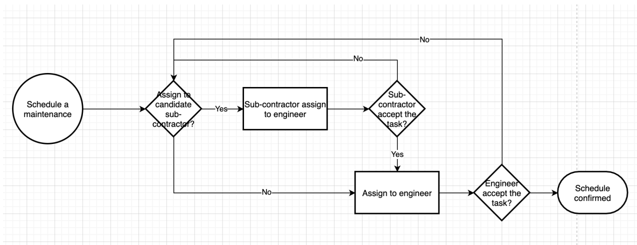

Figure 1: Maintenance Scheduling

The maintenance scheduling reply on the acceptance of a sub-contractor and engineers to complete the workflow cycle. State in the diagram below (Figure 1).

4 CASE STUDY

A case study on a building maintenance company has been carried out at industry scale to identify the current task assignment problem. The company location is at Basildon, Essex. The clients are the Commercial Building Owners includes Franchise Restaurants, Hotels, Property Service Company. The Maintenance Management Team includes Project managers, FM managers experienced in managing diverse specialists handling electrical, HVAC, plumbing, and general repairs.

The key problems targeted by the IBMM model are:

Manual Coordination: Maintenance tasks are assigned manually by a facilities manager, leading to delays and occasional miscommunications.

Mismatched Skills: Sometimes, engineers are assigned tasks that don't align with their primary skill set, leading to suboptimal fixes and increased time on tasks.

Human Relation and Emotions: Some skilled engineer who performed well is not assigned due to the relation and emotions from the management team.

Wrong Decision: Management team make wrong decision due to lack of understanding or memory from the large historical dataset.

The proposed solution is to implement IPA in Building Maintenance Management, in particular, it's the Automated Task Detection and Assignment. The IPA system, equipped with AI classification algorithms, analyses data from historical datasets, generate precise machine learning model. The IPA approach has a database of engineers' skills and current workload, with turning the dataset through machine learning classification model, it automatically proposes or assigns tasks to the most suitable engineer based on the machine learning model.

In this paper, the dataset for a maintenance issue is comprehensively defined to encompass all aspects of the maintenance task. It includes the company managing the maintenance issue and the client who has raised the requirement. The building where the issue has occurred is logged for location specifics, accompanied by a brief subject title and a detailed description of the maintenance issue. The type of maintenance, crucial for task scheduling, is categorized typically as Planned Preventative Maintenance (PPM) or Reactive, while the discipline involved is specified to determine the appropriate contractor company. The severity of the issue is noted for prioritizing tasks, along with the client-set budget. The dataset also captures both expected and actual start and end times for the maintenance tasks, offering a timeline of the events. Users involved in reporting, managing, and serving the issue are recorded, along with the status of the maintenance task.

Similarly, the dataset for an engineer undertaking a maintenance task is meticulously detailed. It includes the company responsible for serving the maintenance task and the specific user or engineer carrying out the work. Maintenance information is included, noting that a single maintenance issue might involve multiple tasks or engineers for resolution. The dataset also details the expected and exact start and end times for the engineer's site visit, providing a schedule and actual account of the work. The task's geographical data is crucial for calculating the engineer's travel and on-site labour costs. The rate at which the engineer is compensated, typically a fixed or hourly rate in the building maintenance industry, is recorded. Finally, the maintenance status post-visit is updated to reflect the completion or continuation of the task. This comprehensive dataset ensures that every aspect of the maintenance task, from inception to completion, is thoroughly documented and analysed.

From the data set above, we prepare the initial dataset for the model training with thousands of rows (Table 2 Engineer Dataset to Train Machine Learning Model):

To determine the most suitable machine learning classification model for assigning an engineer to a task based on speed and cost using the provided dataset, it's essential to consider the nature of the dataset and the specific requirements of the task assignment process. The dataset contains features such as postcode, discipline, time, speed, cost, and the engineer assigned. The goal is to predict the most appropriate engineer for future tasks, considering the minimization of response time (speed) and cost.

Several classification models could be considered, each with its strengths and applicability to the scenario (Appendix B: Classification Model Comparison):

Decision Trees: Decision trees are versatile models that can handle both numerical and categorical data. They are particularly useful for their interpretability, as they provide clear decision paths. However, they might suffer from overfitting, especially with complex, high-dimensional data.

Random Forest: An ensemble method that uses multiple decision trees to improve prediction accuracy and control overfitting. Random forests can handle the dataset's mixed types of features well and are robust against overfitting compared to single decision trees. They are also capable of estimating feature importance, which could be useful to understand which factors (speed, cost, discipline) most influence the engineer assignment.

K-Nearest Neighbours (KNN): KNN is a simple, instance-based learning algorithm where the classification of a sample is determined by the majority class among its k-nearest neighbours. KNN is very intuitive and easy to implement but can become computationally expensive as the dataset grows, and it requires a meaningful metric of distance in the feature space.

Neural Networks: Deep learning models, such as neural networks, are highly flexible and can model complex nonlinear relationships. They might be overkill for this dataset, given its relatively straightforward nature, but could be considered if the dataset's size

Table 2: Engineer Dataset to Train Machine Learning Model

postcode	discipline	time	speed	cost	engineer
SE10 OBB	Fire Door PPM	30/05/2023 23:00	66524	747	Engineer 11
B2 4DU	Gas safety	30/07/2023 23:00	89	207	Engineer 33
CM77 8YJ	Gas safety	29/06/2023 23:00	122	320	Engineer 37
PE9 2DB	Gas safety	29/06/2023 23:00	62	128	Engineer 5
B40 1PU	Gas safety	30/07/2023 23:00	201	248	Engineer 75
LN1 1YW	Gas safety	30/07/2023 23:00	131	271	Engineer 80
PO19 1HX	Kitchen extraction clean	31/07/2023 10:33	344	423	Engineer 59
RG21 7NT	Kitchen extraction clean	30/06/2023 10:42	208	500	Engineer 66
L1 8JF	Kitchen extraction clean	30/06/2023 12:24	355	745	Engineer 90
WF17 9AD	Kitchen extraction clean	31/07/2023 10:23	375	379	Engineer 58
TW18 4BL	Gas safety	30/07/2023 23:00	100	332	Engineer 72
KT1 1ET	Gas safety	30/07/2023 23:00	70	686	Engineer 50
TA1 1SB	Grease management	31/07/2023 11:24	1	353	Engineer 7
SW5 9QF	Kitchen extraction clean	30/06/2023 14:46	480	445	Engineer 93
RM20 2ZN	Kitchen extraction clean	30/06/2023 14:12	480	383	Engineer 98
WR14 4 PZ	Kitchen extraction clean	30/06/2023 14:12	450	774	Engineer 27
...	...	...	...	...	...

and complexity grow or if there are intricate patterns in how engineers are assigned to tasks.

Given the requirements—to assign an engineer based on speed and cost—Random Forest would likely be the best starting points. it can handle the dataset's mixed feature types and can capture complex patterns in the data without the extensive pre-processing that some other models might require. They also offer robustness against overfitting through their ensemble approaches, making them suitable for a dataset with thousands of rows.

The implementation visualizes the data analysis with average speed of each engineer (Figure 2), speed and cost distribution (Figure 3), speed vs cost diagrams (Figure 4).

The implementation trains the model with Random Forest Classifier with 80% of data and 20% of test data. visualize the tree diagram (Figure 5):

With an example of input {'postcode': ['LN1 1YW'], 'discipline': ['Gas safety'], 'time': '2023-11-30 00:00:00'}, the output through the machine learning model will be:

Predicted Engineer: Engineer 37 (alias)

Predicted Speed: 106 minutes.

Predicted Cost: GBP 667

The implementation evaluated the engineer model by accuracy score, and the speed, the score prediction is evaluated by the RMSE.

5 EVALUATION

This section evaluates the implementation of Intelligent Process Automation (IPA) in the domain of Building Maintenance Management (BMM), with a specific focus on the automated allocation of engineers to tasks. The analysis encompasses the effectiveness, accuracy, and efficiency of the IPA-driven model, assessing its impact on the overall management process. This evaluation is essential to understand the practical implications, benefits, and potential areas for improvement in this novel approach.

To collaborate with human to enhance analysis of how accurately the IPA system assigns engineers to tasks based on their skills and workload. Evaluating the time and resource savings achieved through the IPA-driven allocation process. Assessing the effectiveness of the system in predicting maintenance needs and preventing critical issues.

With the case study above, the initial training model had been very helpfully collaborated with the Essex company with valid predicted data before the operating manager to assign a task to an engineer. The company continue the collaboration with the IPA engineer allocation to maintenance tasks is a great success for further model training.

Some discussion might bring up to the topics, such as discussing the broader impact of the findings on building maintenance management. Critically analysing the strengths and weaknesses of the IPA-driven allocation system. How IoT could be implemented in the IBMM procedure.

The research is exploring more opportunities for further development and refinement of the IPA BMM procedure, such as the environmental impact on the maintenance, transport impact on the maintenance within the smart city concept.

6 CONCLUSION

The research presented herein marks a significant stride forward in the field of Building Maintenance Management (BMM), leveraging the capabilities of Intelligent Process Automation (IPA) to revolutionize traditional practices. The core contribution of this study lies in its successful integration of current IPA technologies to autonomously refine BMM procedures, thereby aligning with the dynamic demands of modern infrastructure management.

Key to this advancement is the research's focus on identifying, assessing, and ranking crucial criteria influencing BMM. This systematic approach ensures that the most relevant and impactful

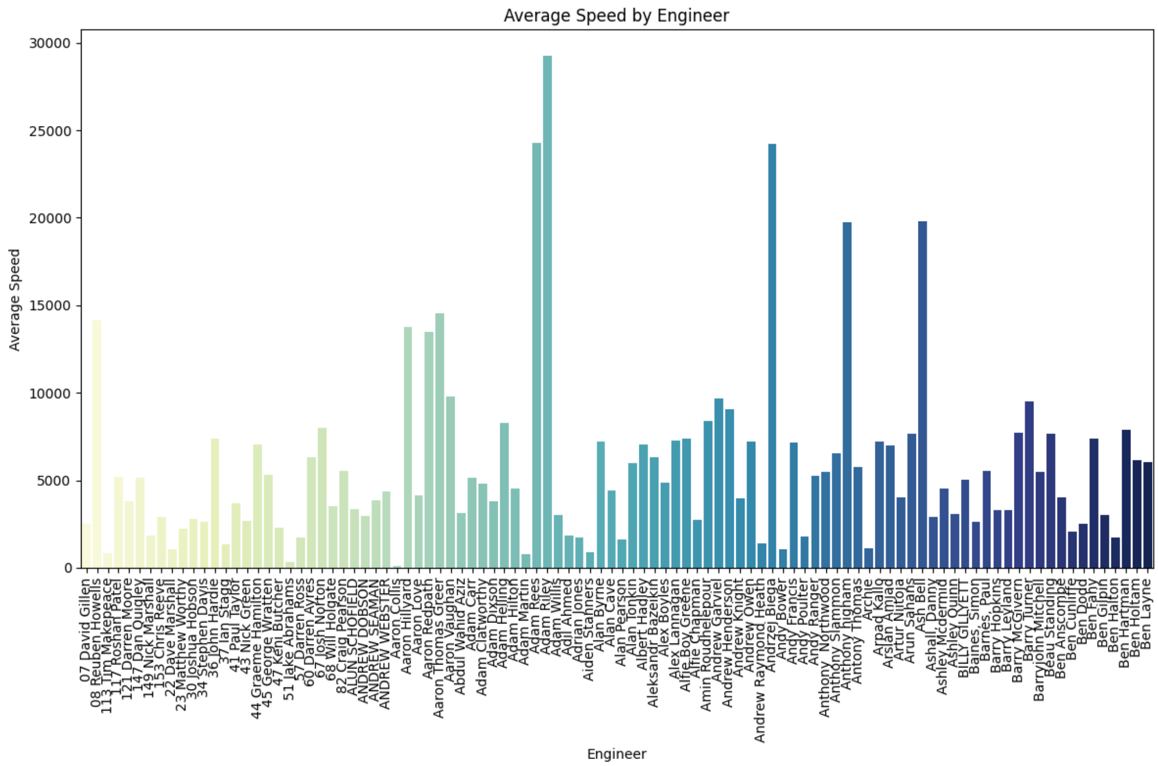

Figure 2: Average Speed Per Engineer

factors are considered when designing and implementing maintenance strategies. The research's novelty is further accentuated by the proposal of a unique IPA-driven BMM procedure, which not only incorporates Internet of Things (IoT) technology but also introduces the development of an innovative smart device fixer. This tool is poised to guide and enhance BMM processes significantly.

The research outlines the basic data required to influence and predict maintenance work effectively. These insights form the foundation of a more informed and data-driven approach to BMM, moving away from traditional reactive models to proactive, predictive strategies. The study also delineates a basic process flow for integrating machine learning into BMM, showcasing how AI can be effectively utilized to streamline and optimize maintenance operations.

The anticipated outcomes of this research are multifaceted and far-reaching. The implementation of these findings is expected to yield more accurate maintenance scheduling, cost efficiency, enhanced performance, and value-oriented building maintenance practices. These improvements are not just incremental; they represent a paradigm shift in how building maintenance is approached and executed.

Furthermore, the introduction of an open online documentation platform for building maintenance is a testament to the research's commitment to collaborative and continuous improvement. This platform will serve as a repository of knowledge, experiences, and best practices, accessible to professionals worldwide. It will facilitate the sharing of insights and innovations, fostering a community of practice that can collectively push the boundaries of what is possible in BMM.

In conclusion, this research does not merely propose a new methodology; it heralds a new era in building maintenance management. By harnessing the power of IPA and IoT technologies, it enables smarter, more efficient, and more sustainable building maintenance practices. This work will lead towards a more intelligent, integrated, and interconnected approach to building maintenance.

Moving forward, the research will aim to further refine and expand the IPA-driven BMM model by exploring advanced AI algorithms for even more accurate predictive maintenance. Future work will also involve the integration of real-time data analytics and more complex IoT networks to enhance the precision and responsiveness of maintenance strategies. Additionally, there will be a focus on scalability and customization of the model to cater to a wider range of building types and maintenance scenarios. By continually advancing the technology and methodologies, the aim is to not only anticipate but also innovatively respond to the evolving landscape of urban infrastructure and maintenance needs.

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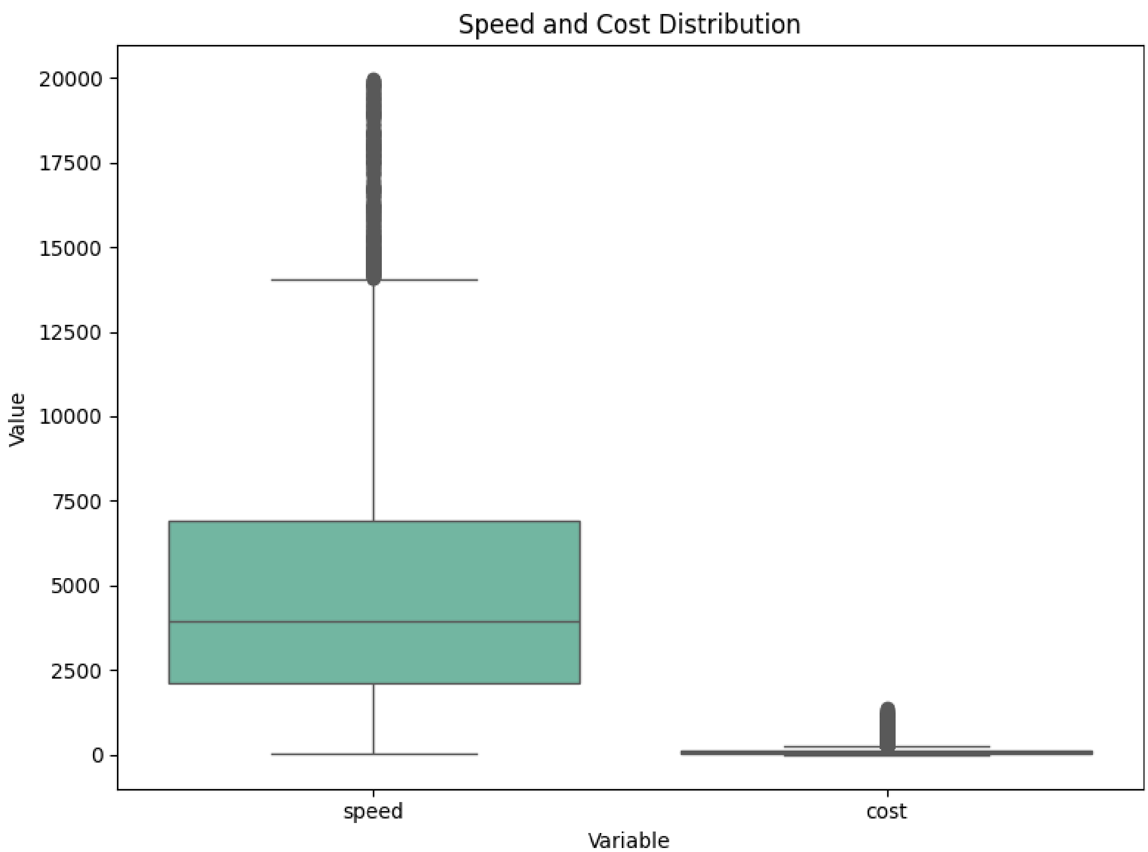

Figure 3: Speed and Cost Distribution

Figure 4: Speed vs Cost

were invaluable in demonstrating the applicability and effectiveness of our proposed model in actual operational environments. This partnership not only facilitated the empirical validation of our research but also underscored the practical relevance and potential impact of our findings within the domain of building maintenance management. We extend our profound gratitude to RNW for their indispensable support and collaboration, which played a pivotal role in the successful realization of this study.

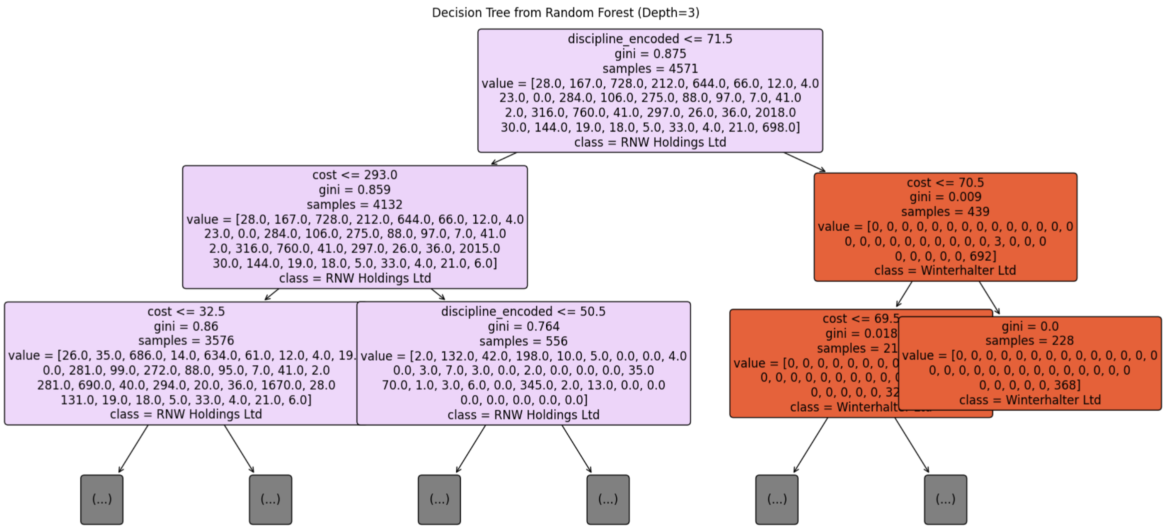

Figure 5: Random Forest Tree

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