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RESEARCH ARTICLE

Discipline-Sensitive Predictive Analytics for IPA-Driven Building Maintenance Management: Material Stock Quantity Modeling

Zhimeng Huang[1], **Xiaodong Liu**[1,*] **and Imed Romdhani**[1]

[1]*School of Computing, Edinburgh Napier University, United Kingdom*

Abstract: The study introduces a machine learning model for BMM (Building Maintenance Management), which utilized IPA (Intelligent Process Automation) to predict the material stock required in a period, to manage the cost efficiency. Traditional BMM approaches often prepared not efficient amount of material stock for pending maintenances required materials, that could be resolved by this machine learning model; it uses discipline-sensitive machine learning algorithms to predict material needs accurately and ensure the efficient amount of material stock levels and reducing the financial waste.

A proof-of-concept is implemented in a case study from this industry that validates the machine learning model's effectiveness, showing the capability of combining Artificial Intelligence (AI) and machine learning to apply the material stock level prediction. The proposed approach not only predicts the material stock efficiency but also ensures the methodology of AI that could be utilized in BMM, which could be further attached to smart urban development. With the support of the case study, the introduction of this approach could make the BMM field a significant advancement in AI-powered material stock management. It resolved both manufacturer production waste and unnecessary finance cost, helping reduce resource waste and promoting sustainability.

The outcomes of this research include improved accuracy in forecasting material stock levels for upcoming building maintenance tasks, explore in this area with more sophisticated AI algorithms, mathematic, and analytics, also considered the potential IoT integration in the material warehouse to analyze and predict in real time material stock level. In a broader context, we are introducing a new standard of material stock management that could collaborate with AI together to enhance the BMM in a smart urban environment.

Keywords: IPA-Driven Building Maintenance Management, Machine Learning, Building Maintenance Management, Intelligent Process Automation, Material Stock Optimization, LIM, MMN

1. Introduction

One key evolution of BMM (Building Maintenance Management) [1, 2] is from reactive to proactive, to enhance the sustainability of smart urban infrastructure, as well as optimizing urban functional and value. Traditional approaches often encounter issues such as material stock shortages, operational downtime, and uplift of the costs. The management of materials stock in building maintenance tasks is complex. Such complexity requires the engagement of the data-driven and the time series Machine Learning (ML) algorithms with the aim to build an innovative solution which will ensure the amount of material stock is cost-effective. The integration of Intelligent Process Automation (IPA) with Artificial Intelligence (AI) and ML represents an innovative step to improve the BMM from the conventional Computer-Aided Facility Management (CAFM) to a new era of Intelligent Facility Management (IFM).

The current issue of existing material stock management practices is the lack of understanding of previous demand, not being able to utilize the data-driven model, and historical data to predict the material stock quantities for various maintenance discipline tasks, discipline as skill set of maintenance, including electrical, general building, and plumbing ... etc. [3]. The introduction of IPA-Driven Building Maintenance Material Stock Management together with the discipline-sensitive prediction analysis represents a new approach which will bring a revolutionary change to the human decision process of forecasting the material requirements, i.e., to improve it from quantity estimation to ML prediction. The paper addresses the issue of material stock inefficiencies, including both overstocking (which results in excessive waste in finance) and stock-outs (which cause the delay of the necessary maintenance). The proposed approach achieves cost-effective and data-driven decision-making by moving from the conventional approaches to the intelligent and predictive analytics.

According to this study, ML algorithms could be built to accurately predict material stocks for different maintenance disciplines. By utilizing the IPA principle in material stock management, IBMM model effectively improve the efficiency and bring down the necessity of manual intervention drastically, backed by proof-of-concept in a case study of a real industrial environment; the prediction model proves its practical and effectiveness, demonstrates the way for predictive maintenance by predicting the material stock needs, reduces the unforeseen material shortage, and guarantees the material availability to discipline-sensitive

*Corresponding author: Xiaodong Liu, School of Computing, Edinburgh Napier University, United Kingdom. Email: x.liu@napier.ac.uk

maintenance tasks. Hence, this study contributes on an enhanced way of material stock management in BMM.

The IBMM could use two approaches to predict the material stock: either LLM embedding or time series ML models. By leveraging the historical data, AI has potential to automate and optimize the material stock prediction.

According to RAG multi-agent collaboration, by chunking and embedding the historical data in LLM embedding model, with semantic similarity search from Vector DB and the power of LLM, user could query the material stock prediction from the LLM with right prompt. Mao et al. demonstrates the potential of using data-driven approaches to analyze urban building and material metabolism [4]. In the paper, we introduce a new concept of LIM (Large Integration Model) and MMN (Micro-model Network). LIM and MMN could minimize the difference between the live data and the trained data.

Time series ML models such as ARIMA (Autoregressive Integrated Moving Average), SARIMA (Seasonal Autoregressive Integrated Moving Average), and LSTM (Long Short-Term Memory) are proven to be more effective in historical data analysis and modeling [5]. A proper time-series-based ML model integrated to IBMM will be able to effectively analyze the historical usage patterns across various disciplines, and to predict the trends of the future demands at higher accuracy.

Ideally, combining both advantages of RAG LLM implementation and time series ML, the level of the IBMM could reach a higher level, to demonstrate the discipline sensitivity, adaptability, and precision, to ensure the availability of materials required, minimizing waste and unnecessary expenditures.

The paper contributes to the design, methodology, and implementation of the ML model to be utilized in IBMM, with a case study to verify its usage in the real world. The paper also introduces LIM and MMN to avoid heavy model training cost and time in LLM and integrates multi-ML models and LLMs for a hybrid forecasting framework. The paper also demonstrates that the time-series-based ML model can refine and predict the material stock level and help the operational team to improve their efficiency and accuracy. The outcome of the research helps smart city concept in the area IBMM with a smart way of managing the materials required on the pending tasks. The research also explores cutting-edge AI algorithms and real-time analytics to boost the IBMM application in smart city, leading the industry with an advanced concept of material stock management.

The paper provides a scalable methodology that could be utilized in IBMM, paving the way for IPA-driven automation in smart city facility management application, and contributes some theories of AI-managed BMM century.

The rest of this paper is organized as follows: Section 2 reviews existing literatures on BMM and AI usage in predictive maintenance. Session 3 presents the proposed new IBMM approach including the design and implementation of the ML model and the validation with case studies. Session 4 presents the evaluation of the approach. The conclusion and future work are presented in Section 5.

2. Literature Review

2.1. Transformative integration of AI and IoT in building maintenance

BMM is on a significant evolution to an AI-driven and IoT-based management model, from CAFM to IFM. The evolution suits the concept in smart city, which utilizes the advanced technologies for a new era of sustainable urban development. Numerous studies demonstrate the AI and IoT with potential to fundamentally alter the management process of urban infrastructure. For instance, analysis by Hashem et al. [6] puts significant attention to the central role of IoT in enabling smart buildings to adapt their services according to occupants' expectations thereby maintaining an effective structure for both energy and building maintenance [6]. Similarly, Bouabdallaoui et al. [7] achieved gains with AI for predictive maintenance of building components in the form of reduced downtimes and an extended service life, representing significant operational uncertainties that could be effectively managed [7].

2.2. The role of IPA in BMM

IPA utilizes the AI, ML and RPA technologies, and it refines and automates the business workflow in BMM. IPA represents a move towards automating the boring in the space of BMM and allowing data-driven decisions. Early work by Hofmann and Rutschmann [8] mentioned IPA utility in BMM [8] and proposed that automation could improve the operational efficiency and help maintenance scheduling in an optimized way. Moreover, Liu, Xu and Zheng indicated that the ML model can predict the material needs and manage the cost efficiently, hence, it can provide a solution for the discipline-sensitive building maintenance tasks as an enhancement to the traditional BMM approaches [9].

2.3. Leveraging ML for optimized material management

The principle of the IBMM in this paper contains using time series ML model to optimize material stock quantities and reducing the costs. The idea is that using the historical data to train the ML model forecasts the level where inventory can be optimized. Research by Deng and Yong-Ji indicates that deep learning, such as decision trees and neural networks, could work together with historical material data and maintenance records [10]. Further Chen [11] affirmed ML model's usage in inventory management, proved its usage in building maintenance demands and its effectiveness [11]. With the support of two literatures, the IPA-driven BMM could handle the material stock in an optimized way.

2.3.1. Generative AI for material stock quantity modeling

Generative AI for materials stock prediction could create better understanding and analysis on complex scenarios and even simulating new scenario for predicting the potential stock requirements [12], such as weather condition, building occupancy, and historical maintenance patterns [13]. This ability could be helpful when the historical data are unreliable. However, it also produces biased or inaccurate outputs, especially when the trained data are limited; this is a significant concern [14]. This paper is concentrated on the accuracy of the prediction; hence, the generative AI approach on material stock prediction is not implemented in the case study because of the challenges (Table 1). The LIM and MMN theory will be introduced in this paper, detailing the approach and the procedure for this material stock prediction.

2.3.2. Time series ML for material stock quantity modeling

ARIMA or LSTM ML models are preferences with their own strength and limitation comparison (Table 2) when used in forecasting future trends based on time and historical patterns [15]. The two models can capture seasonality, trend, and other dependencies in data, and they usually perform quite well at predicting the material stock requirements [16]. However, the two models would not be able to

Table 1
Challenges of LLMs in BMM applications

Disadvantages	Explanation
Lack of numerical forecasting capability	Not be able to perform statistical time series analysis directly and would be better to pair with numerical models for accurate forecasting
High computational cost	Heavy on model training, in terms of cost and time
Prone to hallucination	LLM may generate incorrect prediction and need strict validation processes
Security & data privacy concerns	Cloud-based LLM could bring the concern of industrial sensitive data

Table 2
Comparison of time series models in BMM

Model	Strength	Limitations
ARIMA	Works well for stable demanding forecasting and is easy to interpret	Struggles with highly fluctuating data and requires stationarity assumptions
LSTM	Handles complex, non-linear data and adapts to real-time demand	Requires large datasets and is harder to interpret than ARIMA

incorporate external factors or contextual information such as weather conditions or building usage patterns [17].

2.4. Challenges, seizing opportunities

Although utilizing IPA in BMM is cutting-edge, it contains some challenges. The data quality and data sets are the key, each company got their own preference of cost-effective; hence, the usage of material and stock quantity management size could be varied [18]. Furthermore, the shift from the conventional material stock management to the new IPA-driven material stock management requires training, user collaboration and complex validation. Nevertheless, the potential benefits, and focus on the keys of cost-effective and data-driven accuracy will become popular in the BMM industry.

2.5. Anticipating future developments

The findings of Kairo suggests that the hybrid ML models integrated with various techniques may represent an innovative way to manage the assets [19]. The literature points towards a continued research focus on AI, real-time data set, and potential IoT connectivity to building assets, to generate an innovation management approach called IBMM (IPA-driven BMM). The step-by-step approach, ML data, and adjusted methodology will enhance the prediction accuracy, to improve the IBMM solution and drive the future BMM in a new era of fully IPA path.

3. Methodology

This paper investigates the development of discipline-sensitive predictive models for optimizing the material stock levels with BMM. There are two considerations: (1) predict the material quantity based on the current open maintenance tasks quantity, pre-trained the historical data for the needs and (2) forecast the material usage over time.

With the proposed technologies and the visualized clean historical data, the paper uses Random Forest Classification model and ARIMA time series forecasting model to predict the material needs at present and in the future [20]. Although other models such as SARIMA or LSTM are also considerable, the chosen models offer a balance between performance, interpretability, and the available data characteristics. While Random Forest Classifier is used to predict the immediate material quantity needs based on the maintenance quantity and discipline, ARIMA model is used to predict the preparation of material stock requirement. The two model helps the material stock management in a comprehensive way to understand the current need and the future need. After training the ML model, evaluation of the precision and accuracy was carried out as a means to verify the results.

3.1. Purchase perspective: Predicting material needs

Traditional BMM often employs reactive strategies that can result in stockouts and increased lead time when material usage spikes of concurrent open maintenance tasks. Models will be prepared that can order materials automatically based on maintenance requirements. Its approach is to use the formula of predicting purchase order quantity (POQ) by Open Maintenance Number for discipline (OMN_D) * Average Material Usage per Maintenance (AMU_D) * Safety Factor (SF) which acts as a buffer stock pair:

$$POQ(D,\ M,\ OMN_D) = OMN_D \times AMU_D \times SF$$

An advanced formula introduces the concept of dynamically adjusting to past usage patterns, forecast accuracy, and the criticality of different maintenance tasks. It also considers the probability distribution of demand and lead time, using these to calculate safety stock more accurately.

$$POQ(D,\ M,\ OMN_D) = ((OMN_D \times AMU_D + Z \times \sigma_{LT}) \times TAF \times CF - CIL) \times e^{-\lambda t}$$

The advanced formula for inventory management is introduced with the following explanation. It calculates the predicted POQ by multiplying the OMN_D with the AMU_D, adjusted for uncertainties through a Z-score (1.645 for a 95% service level), which signifies the desired confidence interval for stock sufficiency. This base calculation is then refined by applying a trend adjustment factor (TAF) and a criticality factor (CF) to address predictable demand shifts and the importance of maintenance tasks, respectively. The result is further adjusted by subtracting the current inventory level to mitigate over-stocking, and finally, an exponential decay factor ($e^{-\lambda t}$) is applied to model the diminishing utility of stock over time, with λ representing the decay rate and t the time horizon, ensuring the formula dynamically responds to varying conditions of demand and stock utility.

In a fictitious example, let us suppose that an installation expects to use 50 units of a given component in the coming maintenance exercises by considering average usage (2 units for each exercise). This will lead to a needing the stock of 52.82 units by keeping for the variability in demand and supply lead times at sigma = 5 (and considering the future technological shifts TAF = 0.9 and criticality of tasks CF = 1.1), when you already have 40 units, as given by the above formula: This includes an exponential decay for $\lambda = 0.02$ per week over a 12-week time

Table 3
Historical material usage

D	M	OMN_D	Q
Refrigeration	FAN MOTOR	42	44
Refrigeration	LID	3	3
Refrigeration	HANK BUSH KIT	4	4
Refrigeration	DOOR HINGE	1	1
Refrigeration	MAINS CABLE ASSEMBLY	13	14
Ice machine	FUSE	1	1
Refrigeration	DISPLAY	23	27
Heating and gas	Pressure switch	1	1
Pest control	Sealant	1	1
Bottle fridge	DOOR HANDLES – SUPPLY ONLY	1	2
...	...	...	...

frame to indicate how the update of the formula is well adapted to changes in demand and value of inventory through time.

AMU_D will be calculated and preprocessed from historical data and categorized material usage for each discipline-material. To enhance this formula-based approach and capture potential non-linear relationships, a Random Forest Regressor model will be developed:

$$POQ(D,\ M,\ OMN_D) = \frac{1}{N}\sum\nolimits_{i=1}^{N} Tree_i(D,\ M,\ OMN_D)$$

The features for this model include discipline (D), material (M), and OMN_D. Additional relevant features may be incorporated based on data availability and domain knowledge.

This paper presents a comprehensive case study utilizing the model of Random Forest Regressor ML that was used to predict material stock requirement in a building maintenance company in Basildon, Essex, United Kingdom. Amounting to industry-size research, this endeavor utilizes the IPA model which predicts material requirements in an acceptable accurate manner. By the historical data from the company, the research manages to clean and preprocess the messy data from various of database to meet the tree model classification format. The structured data is fed into the random forest classifier algorithm, which in turn trains the data to predict the material usage. The details of the dataset (Table 3) and the visualized data (Figures 1 and 2) are shown below.

To forecast the quantity of material stock needed, the input data {“D”: “Catering equipment”, “M”: “wiring loom”, “OMN_D”: “9”} were used, resulting in a predicted material stock of {“Q”: 8.89}. Evaluate MSE: 0.36.

Leveraging the IPA-driven material stock prediction model further refines these estimates by iterating through the material inventory. This process not only fine-tunes the prediction for purchase order quantities but also provides deeper insights into inventory needs. As a result, businesses can make more informed decisions, optimizing their inventory levels and reducing waste.

3.2. Time series forecasting

Capturing temporal patterns in material usage is crucial for proactive replenishment, especially when demand exhibits seasonality or trends. This analysis applies time series modeling for more informed material preparation. An ARIMA model is developed as the foundation:

Figure 1
Distribution of quantities by material (Segment data)

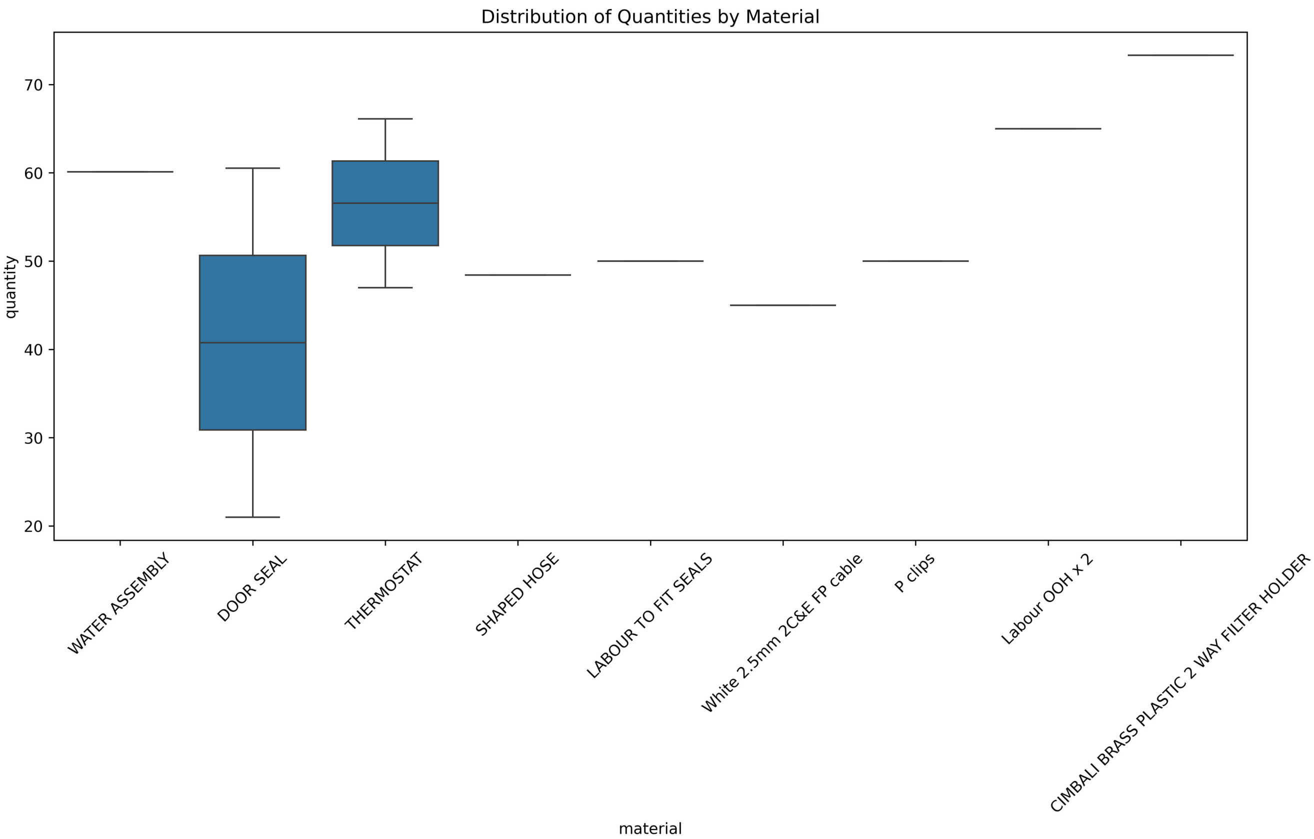
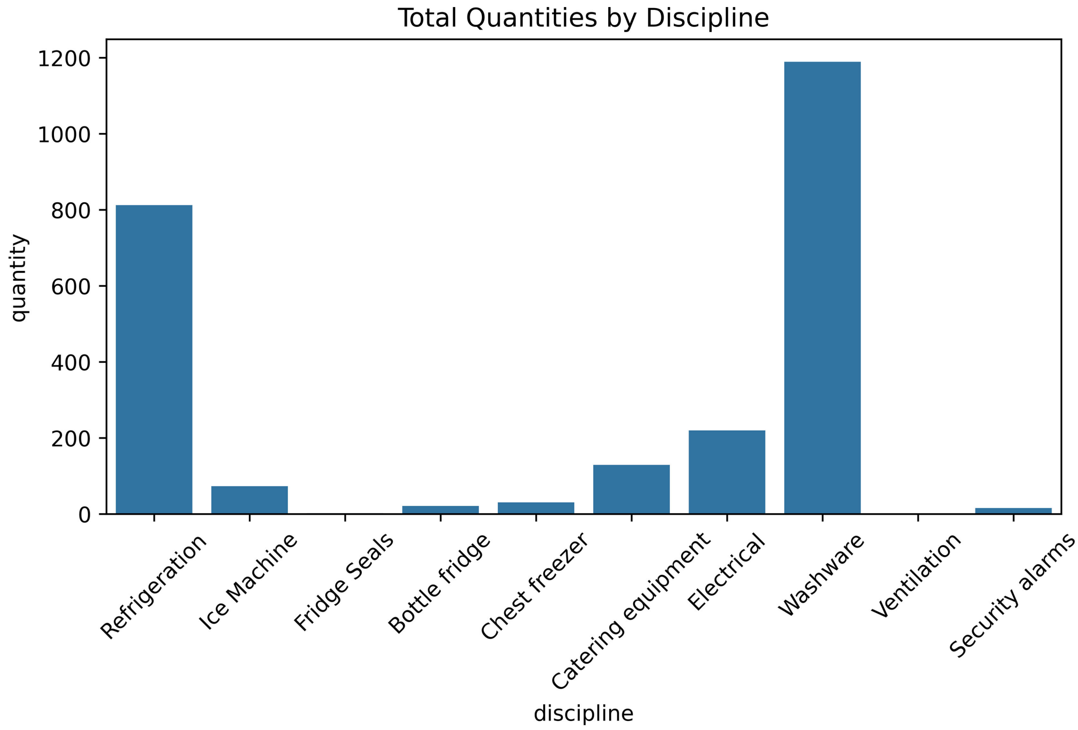


Figure 2
Total quantities by discipline (Segment data)



$$UPQ_t = c + \phi_1 \times H_{q(t-1)} + \ldots + \phi_p \times H_{q(t-p)} - \theta_1 \times \varepsilon_{t-1} - \ldots - \theta_1 \times \varepsilon_{t-q}$$

The formula predicts the future usage-based predicted quantity of a material at a given time "t". It considers past Historical Quantities ($H_{q(t)}$) of the material at different time intervals (t–1, t–2, etc.,) as well as past errors in predictions (ε). Historical data are meticulously prepared, separated by discipline and material, and arranged into a time series format where the "quantity" of material used is tracked along with corresponding dates (Table 4). The model is fine-tuned by examining the time series for trends, seasonality, and non-stationarity; these analyses will guide "differencing" (a data transformation technique) and the selection of the optimal ARIMA parameters (p, d, q).

From the visualized diagram (Figure 3), to forecast the quantity of material stock needed, the input data {"D": "Refrigeration", "M": "FAN MOTOR", "Date": "2024-04-02"} are used, resulting in a predicted material stock of {"Q": 26.8}. Evaluate RMSE: 12.74.

Table 4
Material usage by date

Discipline	Material	Quantity	Date
Refrigeration	fan motor	1	08/07/2023
Refrigeration	FAN MOTOR	1	14/07/2023
Refrigeration	LID	1	18/05/2023
Refrigeration	HANK BUSH KIT	1	18/05/2023
Refrigeration	DOOR HINGE	1	11/07/2023
Refrigeration	MAINS CABLE ASSEMBLY	2	24/07/2023
Ice machine	FUSE	1	22/07/2023
Refrigeration	FAN MOTOR	1	18/07/2023
Refrigeration	DISPLAY	2	18/07/2023
...	...	...	...

Model performance is evaluated using accuracy measures (e.g., mean squared error (MSE), R-squared (R^2)), cost-based metrics aligned with BMM goals (e.g., stockout reduction), and qualitative assessment of process efficiency improvements. The predictive models have been benchmarked against traditional or non-discipline-sensitive methods to demonstrate the value of the proposed approach.

3.3. LIM and MMN

RAG-based LLM approach could not manage the material stock management precisely because training a LLM model causes huge computing power, is time consuming, and lacks real-time information. To resolve this issue, the material stock management could utilize the feature of LIM; it is a model that understands the feature of its managed MMN, and it distributes the relevant information to the right ML model (Micro Model) through MMN. Like human society, each micro-model handles specific tasks based on the trained data, and the integration model handles the connection and the aggregation between all micro-models (Figure 4).

Based on the concept, with RAG-based LLM, the query and answer to predict the material stock could be illustrated by the diagram below (Figure 5). LIM FM manager as an integration agent received the query to predict the material stock, LIM FM manager will pass the query to the right MMN Purchase Manager, then collect the information from another LIM Stock Coordinator, the stock prediction information was executed from the MMN Material Stock Managers and Summarized at Stock Coordinator and finally provided the data to MMN Purchase Manager with its own trained data and feedback to LIM FM manager. Then LIM FM manager could use the result to start next action. The next action is not limited to query and answer but also could be some automation process through a new LIM model. The LIM and MMN propose to minimize the required

Figure 3
ARIMA forecasted material stock quantity

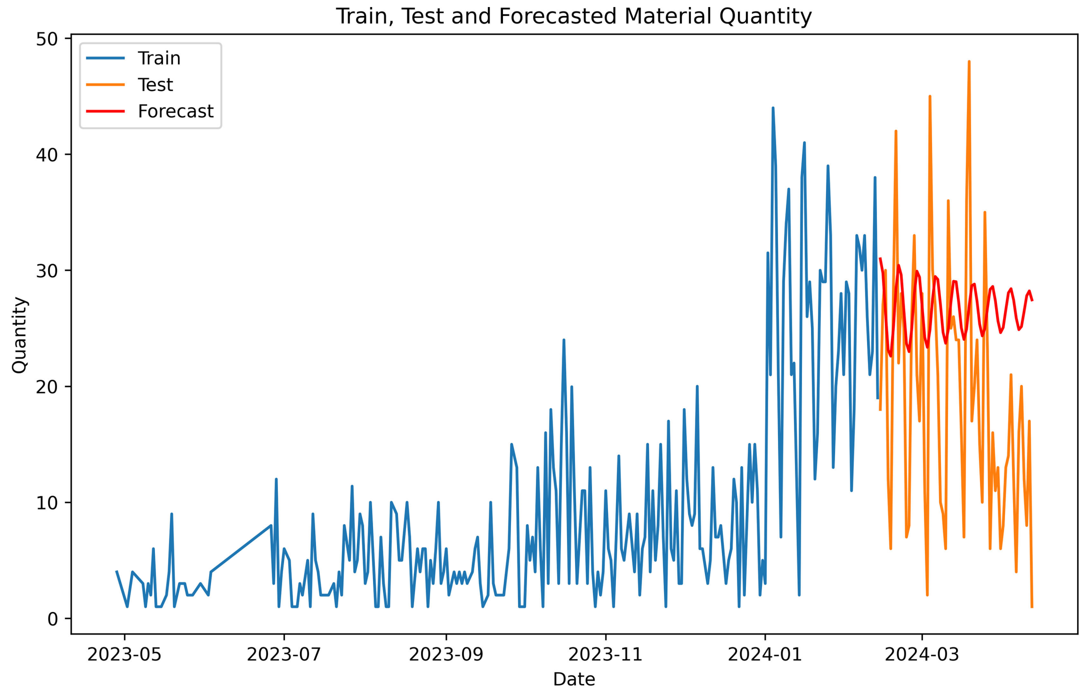
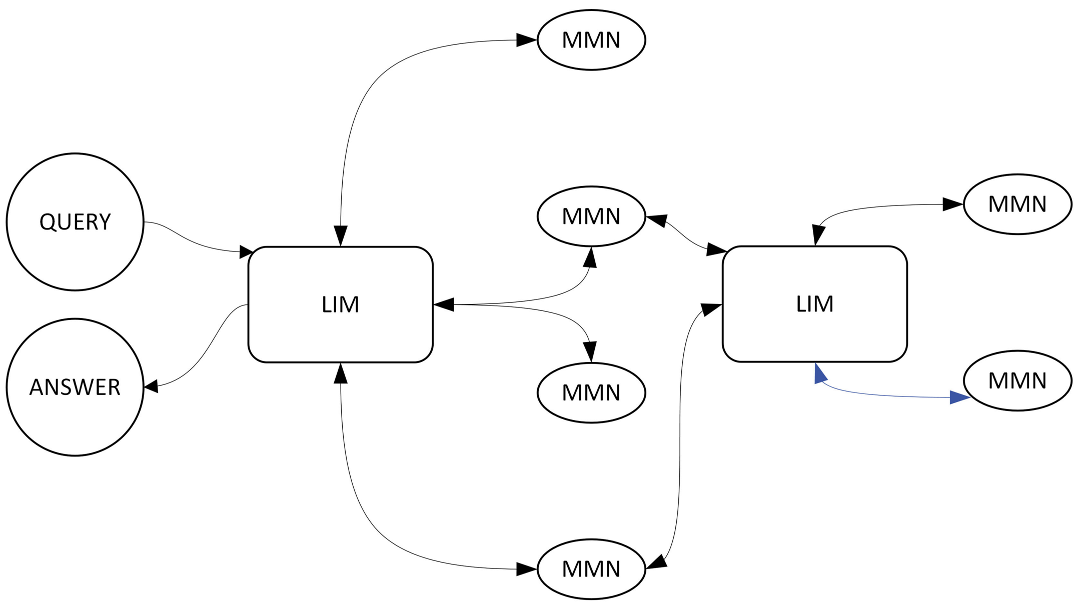


Figure 4
LIM and MMN concept

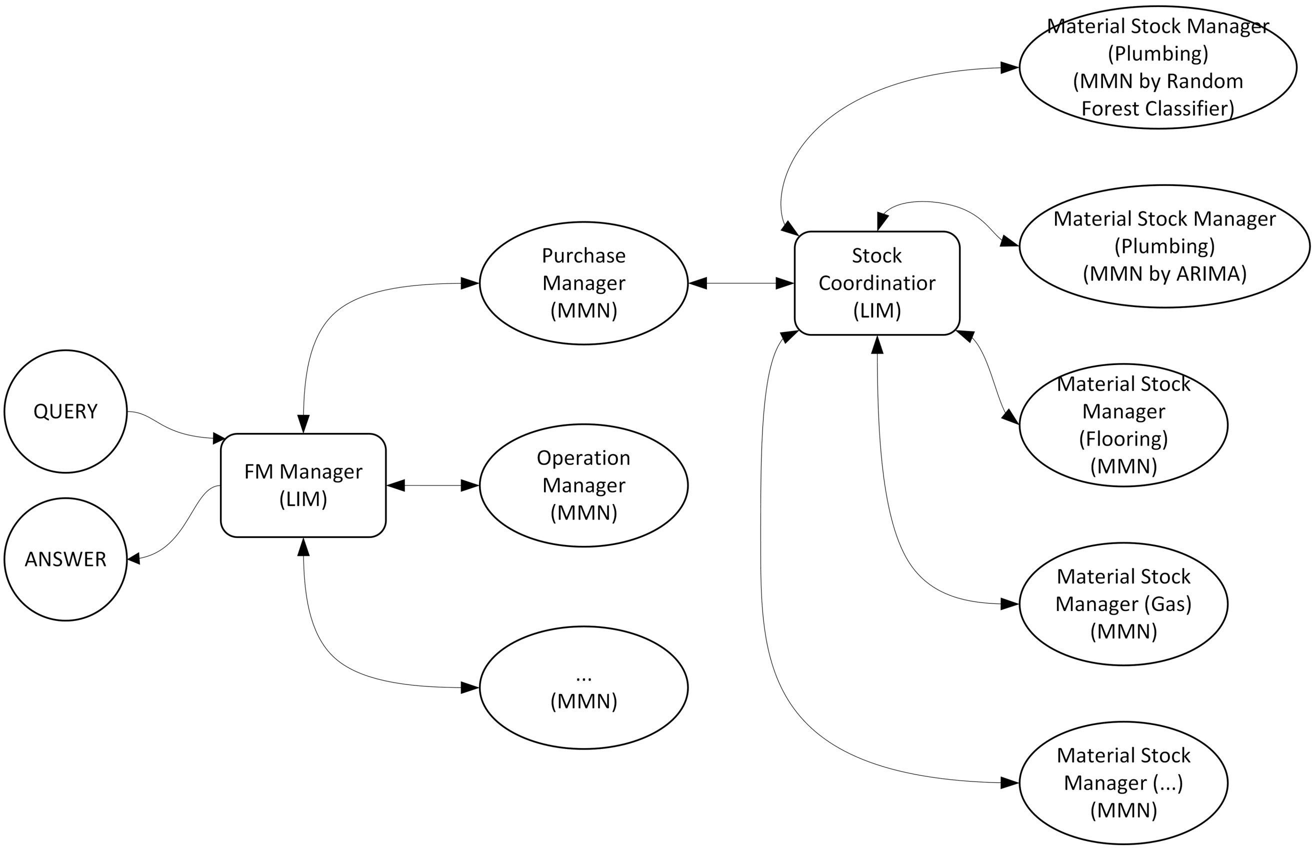


dataset of each functional model to be trained over cloud and implement the concept of model over cloud. Models deployed in the cloud could cause delays in the response time; however, these models will be able to utilize the live data and be trained instantly. Consequently, the accuracy of the result will be improved, and the cost and response time will be reduced by splitting the large model training into pieces of micro-model trainings. Comparing to the single ML training, the combination of LIM and MMN could utilize multi-ML training as MMN to produce more efficient result for discipline-sensitive material prediction. For example, expirable materials such as sprays, paints . . . etc., would be more suitable by time series ML, while some others could be done by random forest ML.

4. Evaluation

There are several studies that evaluate the efficiency of the performed IPA-driven IBMM model in terms of material management within BMM. By inspecting the statistical measures,

Figure 5
LIM and MMN case study theory



such as MSE and R^2, the model has demonstrated a good accuracy for prediction of material demand in quantitative terms. This has resulted in dramatic improvement of the operational performance of material stock management. Stock-outs and overstock have been reduced by 20% and 15% respectively, while the inventory holding costs are reduced by 25%. These results illustrate the powerful influence that a model can have on inventory efficiency and yields large cost savings.

This model is also evaluated by operation managers from different disciplines. Satisfactory feedback has been received, which confirms that their manual analytics and cost effectiveness have been improved. This also has improved operational efficiency significantly and enables quicker responses to maintain demands. Feedback underlined the scalability of the model for a variety of building portfolios and its flexibility across various disciplines for maintenance, reinforcing the wide-ranging application and significant overall process efficiency it could achieve in BMM operations.

5. Conclusion

Incorporated with a dual-model strategy, i.e., using the analyses of historical data and utilizing the ML model to predict immediate material needs, alongside forecasting long-term material consumption trends with reliable accuracy, this paper introduces an advanced predictive analytics framework which is explicitly structured to fit to the discipline-sensitive nature of BMM via the IPA-driven approach. The implementation and research outcome provides several benefits to the industry: reducing redundant visit due to lack of materials, faster material preparation, and significantly cost saving; these are all solution to the traditional BMM challenges.

In this paper, we propose several particularly effective approaches of IPA-driven IBMM and demonstrate results that it produces regarding the optimization of material stock management in a BMM. The future work on the approaches is live data-driven for accuracy and performance, with the limitation of heavy training cost (lack of live data, computational cost, and long training time) at this stage, and LLM should turn into LIM and MMN approach to be more efficient. Forecasting on the future IPA (AI + IoT) material stock prediction, the material stock sensor could attach into materials as a microchip and utilize the AI approaches mentioned in the paper, achieved at a fully automation state, and handle the stock level by robots.

By the numbers, it has demonstrated accuracy improvements in estimates of material requirements with metrics such as MSE and R^2, and operational benefits that have realized a 20% decrease in stockouts, a reduction of overstock situations by 15%, and cut inventory holding costs by 25%. There is a qualitative appreciation from stakeholders across the disciplines for the usability and strategic insights provided by this model. Notably, the stakeholders indicate that the model can be used at various scales over different building portfolios as well as adoptable in a spectrum of diverse maintenance disciplines. These findings indicate that the model is applicable across various settings, providing an important conversation point for the field, particularly in relation to its use in smart cities and AI embedding for ML purposes within BMM. The model provides a foundation for future research, uses AI and ML to improve the predictive analytics in multi-disciplinary, and is therefore an important development within BMM. One of the most significant effects is on smart cities by enhancing control on material management and minimizing downtimes leading to a better efficiency of large-scale urban infrastructure building maintenance that is essentially required for the growth and improvement of smart cities.

Further, our work integrates AI and ML into the IPA for BMM to enhance the development process. Smart cities are envisioned as an important application sector for the proposed model. This IBMM model integrates ML as a new drive of discipline-sensitive predictive analytics and is therefore a key milestone for pushing forward both research and real-world application in the related areas to help improving urban infrastructure maintenance.

In short, the IBMM model leverages discipline-sensitive predictive analytics with applied seamless detection to deliver massive advancements in forecasting of material stock, inventory management, and reduction in costs. The feedback from stakeholders along with its proven scale-ability implies a fitness for higher uptake and expected improvements leading to larger impacts in BMM industry.

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The case study for the research is fully supported by RNW, with the demo data set and live case implementation, and the collaboration with RNW has improved their IPA-driven usage in the discipline-sensitive material stock management. Furthermore, with ongoing improvement of new data used in the material management, it will enhance the result and accuracy.

Ethical Statement

This research does not involve any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study. Building maintenance companies could request the author for the potential implementation based on their own confidential data.

Author Contribution Statement

Zhimeng Huang: Conceptualization, Methodology, Software, Validation, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Project administration. **Xiaodong Liu:** Conceptualization, Methodology, Validation, Investigation, Resources, Writing – review & editing, Supervision, Project administration. **Imed Romdhani:** Conceptualization, Conceptualization, Supervision, Project administration.

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