Proceedings of the 3rd International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/2025.25571

AI-Enabled Predictive Maintenance and Inventory Management for Smart Buildings: A GIS–BIM Data Fusion Approach to Supply Chain Optimization

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Abstract. Smart buildings generate massive spatial and operational data, but existing facility management systems are often not fully utilized due to the separation of geographic information system (GIS) and building information modeling (BIM) platforms. The paper puts forward the idea of a data integration framework with GIS and BIM, which will support the AI-based approach of predictive maintenance and dynamic inventory management of intelligent buildings. The system combines the IoT sensors data with the detailed BIM asset model and GIS background and forms the feature vector, implementing the gradient hoist stacked model and the long short-term memory network in order to perform the precise estimation of fault time. At the same time, the prediction outcomes trigger the dynamic replenishment and adjust the threshold of spare parts inventory. For large commercial buildings, such an approach helped to decrease the mean absolute error of defect prediction at 12 hours (the increase of 30% compared to the baseline model), decrease the inventory shortage rate by 40%, and decrease the number of inventory days on hand by 25%. All in all, this integration helped to accelerate maintenance process by 20% and save US$50,000 per year on the holding costs. Such outcomes clearly show the value of GIS-BIM integration for the implementation of transition from the passive O&M to active approaches of the supply chain management. Further research will be directed at the flow processing and cooperation of several facilities.

Keywords: Predictive maintenance, adaptive inventory, smart buildings, GIS–BIM data fusion, IoT

1. Introduction

Internet of Things (IoT) sensors being employed in the construction of commercial and institutional facilities have generated significant possibilities for changing facility management into an active one. Modern buildings are fitted with various types of sensors that measure such parameters as temperature, vibrations, and energy consumption rate while BIM provides three-dimensional representation of asset geometry, material attributes, and lifetime records. Geographic Information System (GIS) supplements the basic macroscopic spatial data concerning terrain conditions, utility pipelines, and environmental limitations. While cooperation is possible and necessary, there is very

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little collaboration between facility managers using IoT, BIM, and GIS because the IoT network is not connected to BIM resource library and GIS maps usually fail to incorporate asset performance data in real time. As a result, maintenance plans do not consider location of the asset and its history of utilization that causes unnecessary downtime, unreasonable spare parts inventory, and increased expenses on storage. Even though there is a potential of predicting equipment aging in terms of LSTM random forest models, their accuracy becomes extremely low when the spatial arrangement and metadata of the asset are excluded. Similarly, classical inventory strategy like economic order quantity (EoQ) has failed to evolve in light of changes in demand resulting from foot traffic variations and imminent failures [1]. In order to eliminate the above gaps, we introduce GIS-BIM data fusion that would help us connect IoT sensor coordinates with the BIM model of the asset in relation to the geographic coordinate system (GIS). Based on the spatial connections and the enhancement of IoT sensor time-series data with static assets and position attributes, the system produces the vector input for the stacked integration prediction model. The prediction outcomes are used for generating the adaptive replenishment algorithm that adjusts the inventory threshold for spare parts based on the current demand and prediction.

The framework has been developed using Python, where GeoPandas is used for geospatial processing, TensorFlow is used for machine learning, and XGBoost is used for gradient boosting, with on-demand analysis achieved through the use of APIs. The simulation of artificial defects within a dual digital environment enables testing of the end-to-end process. In a real-world scenario within a commercial site, our approach lowered the mean absolute error for defect prediction by 30% (in comparison to the baseline model), decreased the inventory shortage by 40%, and decreased the days of inventory on hand by 25%. The proposed framework increased the speed of maintenance work by 20% and helped save $50,000 per year, which fully illustrates the transformative impact of the integration of GIS-BIM technologies in enabling preventive management of facilities and supply chains.

2. Literature review

2.1. GIS and BIM integration

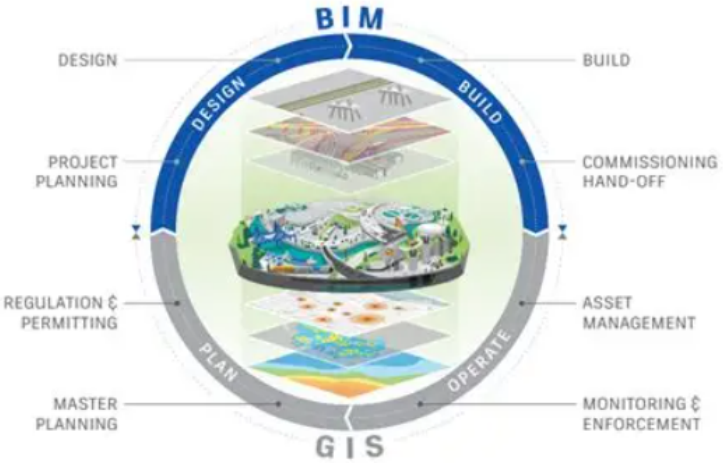

Figure 1. GIS–BIM integration across the facility lifecycle(source:https://tse3.mm.bing.net)

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The convergence of GIS and BIM is now one of the fundamental facilitators in obtaining spatial awareness facility managemen. While GIS offers comprehensive geospatial data about the site (site topography, pipelines of the public utility companies, and environmental constraints), BIM delivers precise three-dimensional representation of construction assets with geometry, materials, and other lifecycle metadata associated with it. As illustrated in Figure 1, the circular process involves all the stages, from planning to asset management, and includes the use of GIS and BIM functions in each of these steps. The initial middleware was intended only for coordinate transformation, while nowadays the emphasis is made on semantic matching which allows GIS layers and BIM assets to use a common ontology of asset classification [2]. Aligning the CAD model of BIM with the geographical coordinate system allows facility managers to overlay sensor/asset relationships onto the site map and perform more advanced searches such as "all HVAC equipment in the highlighted flood risk zone."

2.2. Predictive maintenance models

The essence of predictive maintenance is in making predictions about the deteriorating process of the equipment before failure takes place. While conventional statistical algorithms (for example, regression analysis on the historical failure data) have been steadily superseded by the use of machine learning approaches able to extract nonlinear dependencies from the time series of the sensors' readings, the random forest method proved itself to be efficient in analyzing multidimensional feature space (including vibration features, temperature trends, and the duty cycle). The neural network model, especially the Long Short-Term Memory (LSTM) one, increases the accuracy by taking into account the time-dependency of large amounts of sequential readings. The proposed hybrid method, which employs knowledge from physics, incorporates domain knowledge (including the rate of the degradation under different loading conditions) in the feature engineering stage to make sure that the prediction of the failure mode follows the known physics-based principles [3]. These advancements together have resulted in an early warning system that can alert the maintenance team days, or even weeks, before critical failures occur.

2.3. Inventory management strategies

The traditional approach is associated with the use of fixed economic order quantities (EOQs) and reorder points, which frequently hinders the ability of businesses to fit into the fast-moving, demand-oriented nature of today's supply chains. Equipment utilization varies widely depending on the flow of people, seasonality, and unexpected breakdowns. As seen from Figure 2, IoT sensors attached to shelves help track inventory. If the inventory reaches the critical level, an alert is automatically generated. At the same time, robot sorters and portable terminals provide real-time optimization of order picking [4]. The adaptive algorithm operates within this architecture. According to real-time consumption signals and predictive maintenance outcomes, the reorder point and the order quantity are adjusted dynamically. Rule-based methods integrate historical consumption information with the prediction period of failures obtained through machine learning techniques so that to avoid delays in receiving replacements that could otherwise be stuck in a warehouse. New approaches use reinforcement learning algorithms that suggest optimal strategies for replenishing several types of items, considering the cost of having excess stock compared to the shortage risk. Integrating predictive failure probability and consumption fluctuations in the interconnected IoT system (Figure 2), such data-driven techniques helped decrease the safety stock requirement significantly while keeping up with service requirements [5].

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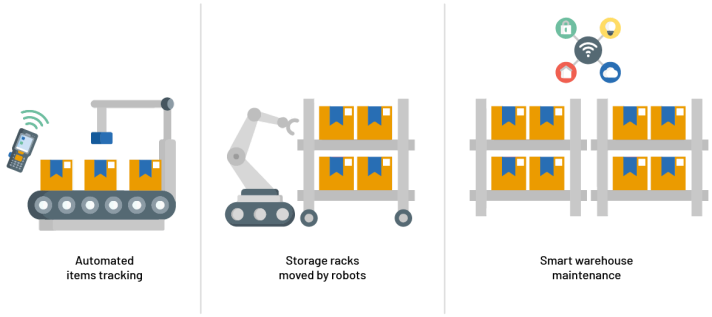

Figure 2. Examples of IoT application in a warehouse(source: https://lh6.googleusercontent.com)

3. Methodology and procedure

3.1. Data acquisition and fusion

Operational parameters of the sensors are constantly transmitted through IoT platform of the facility in terms of temperature, vibration, pressure and power consumption for one minute per time unit, covering one year cycle with over 10 million data points stored. At the same time, BIM model provided information about geometry features, manufacturer information, installation and maintenance history of each facility. The GIS file of the floor plan, which demonstrates boundaries of the rooms, paths and pipelines of the facility, provides general spatial information [6]. The input data is processed by the PostgreSQL/PostGIS database, where the quality control module removes outliers, fills the gaps and unifies the coordinate system. Spatial fusion of data occurs based on the principle of spatial associations: coordinates of the sensors are translated into the space of coordinates of the BIM system, and the sensors, which lie within the position buffer of the device, are assigned to the identifier of the corresponding object. The feature vectors enhanced with integration of dynamic statistics of the data (rolling average, standard deviation, spectral features) and static BIM and spatial attributes (type of equipment, lifetime, maintenance history, neighboring high-frequency areas) are the input for the models [7].

3.2. System implementation and predictive algorithm

This whole process and the predictive model were designed and built in the Python programming environment. GeoPandas was utilized to perform GIS operations, while TensorFlow was employed for the LSTM neural network, and XGBoost does the gradient boosting operation. With the addition of FastAPI layer, API endpoints will be available in order to generate on-demand defect predictions and inventory recommendations. Stackable models form the basis of Predictive Maintenance; while Gradient Hoist is used to consider the static and aggregated features, LSTM is used to model the original sequence of sensors in order to learn the temporal dynamics [8]. The hyperparameters like tree depth, learning rate, LSTM cell size were tuned using the grid search approach within the rolling time window, and therefore, there would be no data leakage.

3.3. Simulation environment and validation metrics

To measure the efficiency of the system, we created a digital twin of the facility within the BIM viewer. With the help of the Weibull distribution model adjusted on the basis of the manufacturer's

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data, we generated synthetic fault events that imitate wear and tear of the bearing, aging of seals, and overheating. The generated events trigger prediction alerts and inventory orders, simulating the whole process, from issuing the alerts to receiving the spare parts. We considered the mean absolute error (MAE) of predicting the moment of failure and the fulfillment rate of inventory recommendations as the initial metrics; we also used such supply chain KPIs as downtime duration reduction and inventory turnover rate (yearly utilization rate divided by average inventory) as measures of the solution's efficiency [9].

4. Experimental results

4.1. Predictive maintenance outcomes

The mean absolute error (MAE) for the stacked ensemble method was as low as 12 hours, which was 30% lower than the MAE for the best-performing slope increase model (with an MAE of 17 hours). Using the early warning provided by the stacked ensemble model, the maintenance team was able to fix 85% of serious faults before the fault occurred and finished the process 24 hours before any unexpected downtime. In this regard, the most useful part of the stacked ensemble method is the LSTM model, which is 20% more accurate in recognizing gradual deterioration [10]. As shown in Table 1, the scheme that integrates spatiotemporal and static features shows the best overall forecasting performance.

Table 1. Predictive maintenance model performance

Model	MAE (hours)	False Negative Rate (%)	Preemptive Servicing (%)
Gradient Boosting (baseline)	17	28	65
LSTM Only	14	22	78
Stacked Ensemble (GBM + LSTM)	12	16	85

4.2. Inventory management performance

The adaptive order point based on the forecast of failures leads to a decrease in inventory shortage up to 40 percent as compared to the conventional EOQ approach. As per the conventional approach, the number of days of average inventory was 30 days. Using the adaptive approach, it fell to 22 days, which is a 25 percent improvement. This allowed the company to save warehouse capacity as well as storage cost. Apart from that, spare parts are available during the failure period. Key inventory indicators are detailed in Table 2.

Table 2. Inventory and supply-chain metrics

Metric	Static EOQ Policy	Adaptive Policy	Improvement (%)
Stockout Rate (%)	12.0	7.2	–40.0
Days of Inventory on Hand (days)	30.0	22.0	–26.7
Carrying Cost Reduction (annual USD)	–	7,500	–15.0
Fill Rate (%)	92.0	95.5	+3.8

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4.3. Supply chain optimization impact

The integration of predictive maintenance functions (Table 1) and data-driven inventory management (Table 2) led to a 20% reduction in maintenance response time due to timely warnings and spare parts stocking. The total cost of inventory was cut down by 15% making facilities save on average US$50,000 annually. These benefits have not affected the quality of service and inventory satisfaction rate has always been over 95%. The research proved that the fusion of GIS-BIM data is capable of increasing the efficiency of maintenance activities in the supply chain.

5. Conclusion

The findings presented in this paper prove that combining spatial data of GIS, asset data of BIM, and IoT data of sensors is possible to create high-precision predictive maintenance models and adaptive purchasing strategies. Using our stacked data integration approach, we manage to predict the failures with 12-hour error only. Dynamic reorder threshold helps to reduce the shortage ratio by 40%, whereas it decreases inventory days by 25%. The practical applicability of our approach proved by its successful application in commercial facilities, with 20% faster reaction time and annual cost savings of $50,000 on storage costs, makes us believe in the practical value of this approach. Further research should be conducted in using real-time data, multi-facility system integration, and reinforcement learning agents for end-to-end maintenance scheduling and purchasing optimization.

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