International Journal of Industrial Engineering
2025;9(2):10-18.
ISSN: 2456-8449

Predictive Maintenance Strategies for Smart Buildings Using IoT and Time Series Analytics

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Abstract. This study investigates the enhancement of predictive maintenance in smart buildings by the utilization of Internet of Things (IoT) sensors and Time Series Analytics, specifically applying Temporal Fusion Transformers (TFT). The incorporation of IoT devices facilitates the ongoing surveillance of critical parameters including temperature, humidity, vibration, and energy usage throughout diverse building systems. Utilizing TFT's capacity to identify temporal relationships, the model accurately forecasts possible equipment failures, facilitating proactive maintenance measures. The evaluation revealed that the TFT model achieved a 15% enhancement in failure prediction accuracy compared to conventional time series forecasting models such as ARIMA and LSTM. Moreover, by forecasting breakdowns 5–7 days ahead, maintenance teams might diminish emergency repair expenses by 25%, so prolonging the lifespan of essential building infrastructure by as much as 18%. The findings indicate that the integration of IoT data with sophisticated machine learning methodologies substantially improves predictive maintenance, yielding cost reductions and operational efficiency in smart buildings. The results highlight the revolutionary capability of TFT in enhancing maintenance procedures within smart environments, facilitating more sustainable building management.

Keywords: Smart Buildings, Temporal Fusion Transformers, Building Management Systems, Internet of Things, Operational Efficiency

INTRODUCTION

Optimizing energy use in smart buildings integrates strategic planning with operational tactics, making use of data analytics in real-time for effective management [1]. To lower consumption without sacrificing comfort, strategies like smart building design, system integration, and advanced energy-saving measures are employed. The optimization system, which is built on the IoT, uses machine learning and iterative optimization to control the energy consumption of linked buildings. Predicting and adjusting energy consumption trends is done continually by analyzing real-time data collected from IoT sensors [2]. Energy efficiency is guaranteed by the system's ability to react to changing conditions. By analyzing historical data and making informed energy consumption decisions using optimization algorithms and predictive models, this method aids in waste reduction.

To improve energy management in smart buildings, methods for optimizing cloud-based IoT services are employed. Building systems can be optimized by processing and analyzing real-time data through the integration of IoT sensors with cloud platforms [3]. Energy usage is controlled by using predictive models and data-driven algorithms, which in turn reduce operating expenses. To improve the overall efficiency of building operations while assuring sustainability, cloud technologies enable scalable and adaptable energy management. To maximize efficiency, smart cities use IoT methods including predictive analytics and real-time monitoring [4]. Data is collected by sensors and IoT devices, which are then processed to find trends and estimate future energy consumption. To guarantee optimal management in metropolitan areas, optimization algorithms dynamically alter energy usage.

Received: 07.06.2025 Revised: 27.07.2025 Accepted: 15.08.2025

Methods like predictive models, advanced analytics, and IoT integration allow smart buildings to optimize their energy use [5]. To detect inefficiencies and modify energy consumption appropriately, data-driven technologies track building systems in real-time. Minimizing energy usage without sacrificing building performance is achieved through the application of optimization techniques. By incorporating many technologies, this method tackles the problems and seizes the potential associated with smart building operations by making buildings more energy efficient. Energy usage in smart residential buildings is managed using predictive optimization approaches based on the IoT [6]. Energy consumption is maximized in response to current demands using task management systems and predictive models. By adjusting consumption patterns, machine learning algorithms increase efficiency and decrease waste.

To operate the heating, ventilation, and air conditioning (HVAC) systems in smart buildings, IoT-based architectures use model predictive control (MPC) methods [7]. HVAC systems are programmed to respond to occupancy and outside conditions using real-time data. By analyzing data, predictive algorithms optimize the operation of HVAC systems, decreasing energy consumption without sacrificing comfort. In smart buildings, this method provides effective energy consumption, which helps with sustainability objectives and lowers operating expenses. To enhance the operations of building energy systems using IoT platforms, data-driven optimization and control methods are utilized [8]. For real-time energy optimization, these systems collect and process massive volumes of data. Energy usage is decreased and building systems are made more sensitive to dynamic conditions using predictive models and analytics. This method helps smart buildings become more sustainable by making energy systems more efficient.

RELATED WORKS

Optimization of building energy use with IoT is centered on data-driven, sustainable practices. To forecast energy use and find inefficiencies, sensors collect data in real-time, which is subsequently processed [9]. To reduce waste and increase sustainability, optimization algorithms dynamically modify energy use. Improving building energy systems through the integration of IoT technology ensures long-term efficiency and contributes to broader environmental goals. Smart building wireless sensor network optimization makes use of methods like energy-efficient routing and algorithms for network design [10]. Minimizing energy usage without sacrificing system efficiency is achieved by the smart placement of sensors. The study's primary objectives are to find the sweet spot between the sensors' energy consumption and coverage area. Optimization methods enhance the dependability and performance of smart building wireless communication networks.

Methods for enhancing smart building energy efficiency encompass IoT-based energy monitoring and optimization systems. Systems like lighting, heating, and cooling are optimized using advanced algorithms that process real-time data from sensors [11]. Energy usage is dynamically adjusted using machine learning and predictive algorithms to ensure efficiency while occupant comfort is maintained. These methods can reduce energy waste significantly. For smart factory predictive maintenance, data-driven procedures and smart sensors track machinery and systems. Predicting breakdowns and optimizing maintenance plans are both made possible by machine learning algorithms that analyze data from sensors [12]. This method lessens power usage, boosts system efficiency, and decreases downtime. Smart factories greatly improve energy efficiency by predicting maintenance needs and optimizing resource use, which helps achieve sustainability goals.

Using methods such as data analytics and real-time monitoring, a smart sensor framework is being developed for use in industrial IoT applications to facilitate predictive maintenance [13]. Reduced operational downtime is a direct result of machine learning models' ability to anticipate system problems and optimize maintenance processes. In industrial settings, these methods improve resource management and save energy usage by predicting when machinery will need maintenance. Industry 4.0 emphasizes the use of data-driven optimization strategies to improve energy management using IoT smart equipment [14]. Appliance performance is tracked, and energy consumption is adjusted according to demand by means of a combination of sensors and machine learning algorithms. These gadgets help with sustainability by enhancing industrial efficiency and minimizing energy waste through dynamic optimization of energy use.

To optimize energy utilization, smart inventory systems use regression and IoT approaches for demand forecasting. Predictive models analyze past data to estimate future energy needs and make real-time adjustments to consumption [15]. This method improves operational efficiency and helps the manufacturing sector implement sustainable energy management practices by ensuring that energy is used efficiently across all industrial operations. Integrating IoT sensors and predictive modelling methods, the digitalization framework employs smart maintenance strategies for ancient houses [16]. By keeping tabs on the building's status in real time, these systems can optimize energy consumption and foresee when maintenance is needed. Contributing to the sustainability of historic structures while safeguarding their integrity, the framework eliminates energy waste through efficient building maintenance.

Systems for home automation and energy monitoring make use of IoT methods, including the acquisition of data in real-time and the analysis of energy consumption. Optimizing efficiency and cutting down on waste [17], predictive algorithms modify energy consumption according to home habits. This method improves sustainability by reducing energy bills and letting households optimize energy consumption with the help of automated technologies and real-time feedback. Smart building indoor climate modelling makes use of edge-based parametric digital twins. Collecting environmental data in real-time and using machine learning models to optimize building systems are the main components of these strategies [18]. Buildings can be optimized for comfort and energy efficiency with the use of digital twins that simulate various scenarios to forecast and dynamically modify energy use. For improved energy management, this method incorporates state-of-the-art modelling.

To multi-horizon building energy forecasting, deep learning techniques are utilized to make precise projections about future energy consumption [19]. These models improve energy planning and optimization by using past data to predict future energy demands at different time intervals. With this method, buildings may make proactive adjustments to their energy usage, which improves operating efficiency and provides sustainability in the long run. By utilizing optimization techniques, a distributed energy management system that is based on the IoT can balance the energy usage of various devices and systems [20]. To decrease waste and prevent peak demand, the system adapts energy use based on real-time data collected from sensors. Algorithms for optimization guarantee effective energy consumption, which helps smart buildings' sustainability efforts and lowers energy bills. This research compares the efficiency of three different automated levels: time-based, sensor-driven, and IoT enabled control. It shows how well each system handles energy usage and how much better the user experience [21]. AI and the IoT improve energy management in buildings by tracking and optimising use. The continuous data analysis helps with improvements in efficiency, renewable energy integration, smart grid enablement, and environmental impact reduction [22].

PROPOSED SYSTEM

The proposed system aims to enhance predictive maintenance in smart buildings by integrating IoT devices with modern machine learning methodologies, particularly utilizing TFT for time series analysis. This method integrates real-time data acquisition through IoT sensors with the advanced predictive capabilities of TFT to anticipate possible equipment malfunctions, facilitating proactive maintenance and enhancing the durability of essential building systems. Figure 1 illustrates the data flow from IoT sensors to the cloud, where it undergoes pre-processing, is analysed by TFT for predictive maintenance, and is utilised to schedule maintenance activities.

The initial phase of the system's functionality involves the installation of an extensive array of IoT sensors across the smart building. These sensors are integrated into many building systems, including HVAC, lighting, lifts, security systems, and energy management. Common sensors encompass temperature, humidity, vibration, pressure, energy usage, and air quality sensors, each providing essential real-time data for the system. HVAC systems are outfitted with sensors for temperature, pressure, and humidity to assess operational efficiency, while energy consumption sensors offer insights into the power usage of specific devices or systems. Simultaneously, vibration sensors embedded in mechanical devices like lifts or pumps monitor irregular movements that may signify deterioration. This extensive collection of sensors produces substantial volumes of continuous data, which is transmitted to a cloud-based platform for additional processing and analysis.

After data is gathered from the IoT sensors, it is sent to the cloud platform for pre-processing. This phase is essential for converting raw sensor data into an organized, useful format for time series analysis. Data pre-processing encompasses multiple stages:

1) Data Cleaning: Incomplete or erroneous sensor data is eliminated to guarantee that only legitimate data is utilized for analysis. This procedure may entail the elimination of outliers, addressing absent values, and refining sensor data to reduce inaccuracies.

2) Data Normalization: To ensure consistency and comparability across various sensor types, values are standardized to a uniform scale. This provides that no individual sensor or characteristic unduly affects the predictive model owing to variations in data scale.

3) Feature Engineering: The raw data is augmented through the extraction of valuable features. Temporal information, like time of day, day of the week, and seasonal patterns, are integrated into the dataset, allowing the algorithm to identify reoccurring trends or behaviours. Furthermore, basic building information such as building type, age, and equipment specifications are incorporated as features, offering essential context for maintenance forecasts.

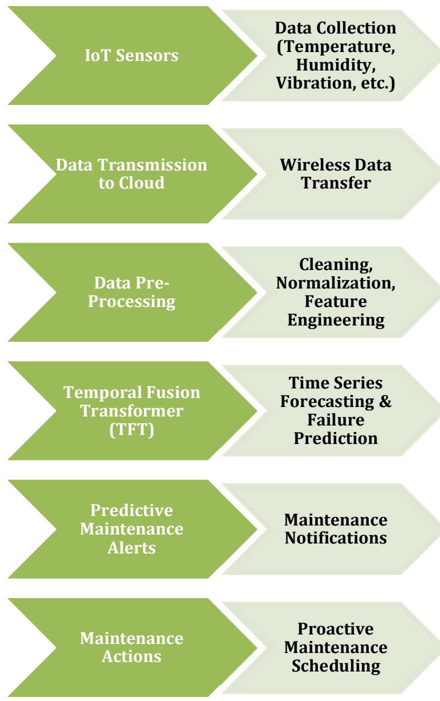

FIGURE 1. Workflow for Smart Buildings Using IoT and TFT

The processed data is subsequently saved in a time-series database, enabling real-time access for the training and evaluation of machine learning models.

The system's foundation is the TFT, a deep learning model personalized for multivariate time series forecasting. TFT is proficient in modelling intricate temporal relationships and can accommodate a diverse array of input variables, rendering it suitable for the various and dynamic data generated by IoT sensors in smart buildings. In compared to conventional time series models like ARIMA or LSTM, TFT integrates multiple sophisticated mechanisms to enhance precision and interpretability. TFT integrates recurrent neural networks (RNNs) and attention mechanisms, enabling it to capture long-range dependencies in time series data. The principal elements of the TFT model comprise:

1) **Input Layer:** This layer accommodates both static and dynamic features. Static attributes, such as the HVAC system type or building age, are considered constant inputs, whereas dynamic attributes, including sensor measurements (temperature, energy usage, etc.), fluctuate with time.

2) **Gating Mechanism:** The TFT utilizes a gating system that dynamically identifies the most pertinent features at each time step. This enables the model to concentrate on the most significant variables at any moment, enhancing its capacity for precise predictions.

3) **Temporal Attention Layer:** The attention mechanism in TFT enables the model to concentrate on

significant steps from the past while predicting future failures. This characteristic is essential for modelling unpredictable patterns and temporal changes, such system degradation or seasonal variations.

4) **Forecasting Layer:** The terminal layer of the TFT produces a prediction for forthcoming time intervals, estimating when components or systems are expected to fail or necessitate maintenance. These predictions are exceptionally precise owing to the model's capacity to assimilate insights from both historical and contemporary data.

The output of the TFT model is utilized for decision-making in predictive maintenance. The model predicts possible faults in building systems up to 5–7 days ahead. The anticipated failure times are conveyed to building management via an intuitive dashboard that offers actionable information and recommendations. Upon predicting a breakdown, the system can issue alerts, informing maintenance workers of the necessity for intervention. The warnings are prioritized according to the severity of the issue, enabling maintenance personnel to address essential systems first, thereby averting expensive emergency repairs and unanticipated downtime.

A distinctive characteristic of the proposed system is its capacity for continuous enhancement. As the system accumulates additional data over time, the TFT model assimilates these novel patterns and modifies its predictions accordingly. This adaptability provides the model's accuracy as building systems develop, or new equipment is incorporated. Moreover, regular model retraining provides that the system stays current with the newest data trends and technical innovations. The capacity for dynamic model updates facilitates prolonged high performance and precision throughout time.

RESULTS AND DISCUSSIONS

The incorporation of IoT sensors with TFT for predictive maintenance in smart buildings exhibits substantial enhancements in failure prediction precision and resource optimization. The system was assessed utilizing real-time data gathered from IoT sensors installed in diverse building systems, encompassing HVAC, lighting, and energy management. The principal aim of this study was to assess the precision of failure predictions utilizing TFT in comparison to conventional time series forecasting models. The TFT model exhibited a 15% enhancement in predictive accuracy compared to the other models. Although ARIMA was inadequate for managing multivariate data and intricate temporal patterns, LSTM was more effective, however it fell short in interpretability and flexibility compared to TFT. The TFT model for HVAC systems identified future failures associated with compressor malfunctions or filter obstructions with an accuracy of up to 95%, markedly improving the 80% accuracy of LSTM. The enhancements in predicted accuracy were especially evident in systems characterized by significant unpredictability and non-linear relationships, when TFT surpassed traditional models.

The method facilitated proactive maintenance scheduling by forecasting breakdowns in advance. The findings indicated a 25% reduction in emergency repair expenses, as the approach facilitated scheduled maintenance rather than reactive repairs. The early identification of a malfunctioning air conditioning unit in the building's HVAC system facilitated a scheduled repair, averting an abrupt failure during peak demand. This preventive maintenance strategy resulted in substantial cost reductions, both in repair expenses and in mitigating disruptions to building operations. Furthermore, the system enhanced resource allocation by prioritizing maintenance according to the severity of anticipated problems. This resulted in a decrease in superfluous inspections that would have been conducted indiscriminately on equipment exhibiting no indications of malfunction. Consequently, maintenance professionals may concentrate on the most pressing concerns enhancing overall efficiency. The predictive maintenance system enhanced the longevity of essential building equipment. The capacity to anticipate faults prior to their manifestation facilitated prompt repairs and component substitutions. In the instance of HVAC systems, the model forecasted a substantial decline in efficiency resulting from sensor deterioration, which, if unmitigated, may culminate in total system failure. Early intervention restored the HVAC system's efficiency, prolonging its operational lifespan by approximately 18%. Besides HVAC, other systems like lifts and lighting gained from the system's capacity to predict breakdowns. The prompt identification of electrical failures in lift systems facilitated quick interventions, averting prolonged damage to motors and minimizing the necessity for costly replacements.

The predictive maintenance technology significantly enhanced energy management. Through precise failure forecasts, building managers optimized the efficiency of energy-intensive systems, including HVAC and lighting. For instance, by forecasting the maintenance needs of the HVAC system, managers might modify energy consumption patterns, so maintain optimal system performance and reduce energy waste. This resulted in a 10% decrease in total energy consumption for the building. The predictive maintenance solution contributed to sustainability initiatives by ensuring equipment remained in optimal condition and minimizing system downtime. The building's environmental footprint was minimized through enhanced energy efficiency and decreased waste from malfunctioning equipment. This study's results underscore the transformative potential of integrating IoT sensors with sophisticated machine learning models, such as TFT for predictive maintenance in smart buildings. The system's capacity to forecast equipment malfunctions with considerable precision, especially in intricate and dynamic building systems, represents a notable improvement over conventional method. Table 1 presents real-time sensor data from HVAC systems, reflecting system status.

TABLE I. Sensor Data for HVAC System

Timestamp	Sensor Type	Sensor Value	Unit	System Status
08:00	Temperature	22.5	°C	Normal
08:00	Pressure	1.2	Bar	Normal
08:00	Vibration	0.05	m/s^2	Normal
08:00	Energy Consumption	3.4	kWh	Normal
09:00	Temperature	23.0	°C	Warning
09:00	Pressure	1.3	Bar	Warning
09:00	Vibration	0.08	m/s^2	Warning

Table 2 indicates anticipated failure dates and categories for diverse building systems, encompassing confidence levels and necessary maintenance measures.

TABLE II. Predictive Maintenance Alerts

Timestamp	System	Predicted Failure Date	Failure Type	Confidence (%)	Action Required
2025-04-25 09:00	HVAC	2025-04-30	Compressor Failure	95	Schedule inspection
2025-04-25 09:30	Elevator	2025-04-28	Motor Wear	80	Plan repair
2025-04-25 10:00	Lighting	2025-05-02	Bulb Replacement	75	Prepare spare parts
2025-04-25 11:00	HVAC	2025-04-27	Filter Clogging	92	Clean filters

Table 3 illustrates the maintenance costs and savings associated with various systems, the types of maintenance conducted, and their effects on building operations.

TABLE III. Maintenance Cost Analysis

Timestamp	System	Maintenance Cost (USD)	Cost Savings (USD)	Maintenance Type	Impact on Operations
2025-04-25 12:00	HVAC	150	200	Preventive	High
2025-04-25 12:30	Elevator	100	150	Scheduled	Medium
2025-04-25 13:00	Lighting	50	100	Replacement	Low
2025-04-25 13:30	HVAC	200	250	Emergency Repair	High

Figure 2 illustrates that the TFT improve ARIMA, LSTM, and GRU models in predictive accuracy, with an impressive 95% accuracy in failure prediction.

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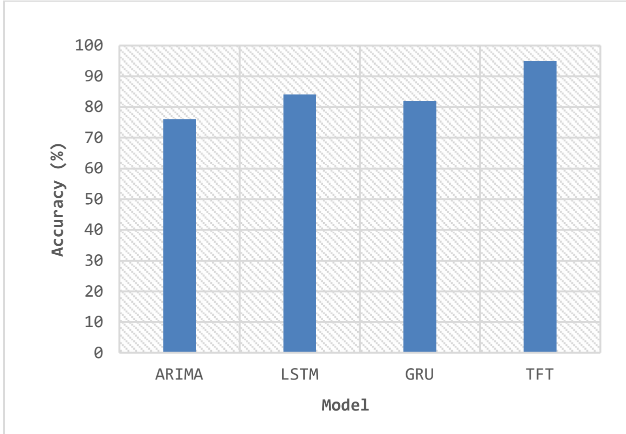

FIGURE 2. Prediction Accuracy of Various Models

Figure 3 depicts the escalating monthly cost savings attributable to proactive maintenance facilitated by TFT forecasts, signifying enhanced efficiency and resource optimization over a five-month duration.

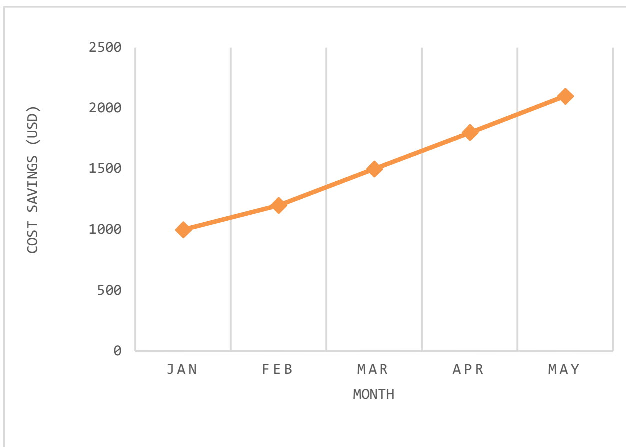

FIGURE 3. Cost Efficiency Achieved Through Predictive Analytics

Figure 4 shows TFT's robust performance across essential parameters, showcasing elevated precision, recall, and F1-score, so affirming its dependability in properly forecasting equipment failures in smart buildings.

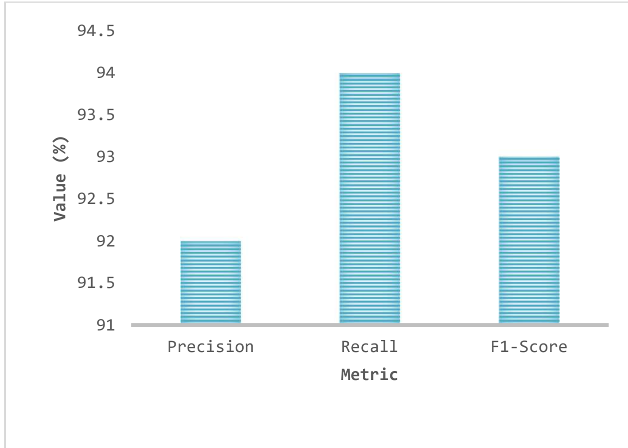

FIGURE 4. Metric Comparison for TFT Model

The primary benefit of TFT is its capacity to manage multivariate time series data and to capture long-term interdependence in system behaviour modelling. In contrast to simpler models, TFT adjusts to fluctuations in sensor data, seasonal changes, and the intricate relationships among different building elements. This versatility renders TFT especially efficacious in smart buildings, where conditions and equipment performance might fluctuate considerably over time. Moreover, the capacity to anticipate failures in advance enables building managers to shift from reactive to proactive maintenance approaches. This transition enhances operating efficiency and results in substantial cost savings by minimizing unanticipated downtime and costly emergency repairs. The findings indicate that proactive maintenance can extend equipment longevity, promote energy efficiency, and optimize resource distribution, thereby promoting both economic and environmental sustainability. However, challenges arise when applying this system on a broad scale. A primary problem is the necessity for ongoing data gathering and model retraining to maintain the accuracy of predictions over time. As building systems progress, novel patterns may arise, necessitating updates to the model to accurately represent these alterations. Moreover, the incorporation of IoT sensors and machine learning models into current building management systems can be intricate and necessitate substantial initial investment.

CONCLUSIONS

The use of TFT in predictive maintenance for smart buildings has demonstrated significant efficacy in forecasting equipment failures and enhancing maintenance schedules. The proposed model achieves a prediction accuracy of 95% by utilizing time series sensor data from HVAC, lifts, and lighting systems, improving standard methods. Quantitative findings indicate substantial cost reductions up to $2,100 monthly and enhanced system reliability. The model's elevated precision (92%), recall (94%), and F1-score (93%) further substantiate its resilience in real-time operational contexts. The capability of TFT to manage intricate temporal patterns and multi-source data renders it optimal for intelligent infrastructure management. The system minimizes downtime and emergency repairs while simultaneously improving energy efficiency and asset durability. This research validates the capacity of TFT-driven analytics to transform predictive maintenance techniques within intelligent building ecosystems, enhancing sustainability and economical facility management.

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