Research on Maintenance and Management Strategies of Buildings based on Machine Learning

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Abstract. As architectural theory is advancing by leaps and bound, tremendous and complex buildings has constructed and requires corresponding maintenance and management methods. However, existing management concentrate on property management and the maintenance relies on human detection. Therefore, it is urgent to develop a complete set of reasonable and scientific management mechanisms and business models for the development of the existing construction equipment management industry. In this work, we apply a machine learning model and combine the big data management technologies including predictive maintenance models and data-driven strategies. The machine learning model can replace traditional detection method by learning complex sensors data from buildings. Our model can effectively predict building equipment failures, optimize energy use, and reduce maintenance costs. From our extensive experiments and analysis, we can observe that our proposed model can provide reasonable maintenance strategies for distinctive buildings and generate acceptable management methods.

Keywords: Building Maintenance; Management Strategies; Equipment States; Machine Learning.

1 Introduction

The life cycle of a construction project is generally divided into decision-making, design, construction and operation phases. After the completion of the preliminary investment and construction, all the buildings will eventually enter the operation and maintenance stage, and the objects managed in the operation and maintenance stage are mainly a large number of construction equipment, and the normal operation of construction equipment is an important guarantee for the good environment inside the building [1]. The traditional operation and maintenance management of building equipment due to poor information management, unreasonable operation and maintenance decisions, backward technical means and other reasons, resulting in untimely information transmission, equipment maintenance delays, high operation and maintenance costs and other problems, the use of machine Xi technology powerful information integration

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capabilities, can be visual display of operation and maintenance information, convenient for information use, is conducive to improving decision-making efficiency, reducing operation and maintenance costs [2].

Building maintenance strategies play a central role in maintaining the integrity and functionality of a building's structure. In modern society, with the rapid development of building technology and the increasing emphasis on environmental sustainability, these strategies have become key to ensuring the long-term health and safety of buildings. Buildings are not only spaces where we live and work, they are also carriers of history and culture, so the importance of maintenance work cannot be overstated [3]. First and foremost, building maintenance strategies are essential to extend the life of a building. Through regular inspection and maintenance, potential structural problems can be identified and repaired in a timely manner, thus avoiding serious damage. This preventative approach not only preserves the physical state of the building, but also helps to maintain its market value and attractiveness.

Subsequently, these strategies ensure the safety and health of the building. Regular maintenance inspections can help identify issues that may pose a threat to occupants or occupants, such as electrical faults, structural damage, or fire safety issues. In addition, building maintenance involves optimizing energy use and maintaining the quality of the indoor environment, which is equally important for the health and comfort of occupants. In addition, building maintenance strategies are becoming more and more intelligent and efficient with the development of technology [4]. Specifically, Internet of Things technology can monitor building metrics in real time, while machine learning and data analysis can help predict maintenance needs more accurately. The application of these technologies not only improves the efficiency of maintenance work, but also helps to reduce resource waste and achieve a more sustainable maintenance model [5].

Machine learning as a branch of artificial intelligence, can provide deep insights into building maintenance by learning patterns and patterns from large amounts of data. This technology analyzes past maintenance records, real-time monitoring data, and environmental factors to predict future problems, optimize maintenance schedules, and even perform preventative maintenance before problems occur [6]. Through long-term data analysis of a building's energy consumption, air quality, and structural stability, machine learning models are able to identify best practices for energy conservation and maintenance. This not only improves the efficiency and effectiveness of maintenance, but also helps to reduce energy waste and maintenance costs. At the same time, this approach increases the predictability and transparency of building maintenance, giving managers more control and decision support [7].

2 Related Works

Recent advancements in the field of building maintenance strategies have shown significant developments, focusing on integrated and adaptive approaches to address the complexities and uncertainties inherent in maintaining buildings. This study advocates for a novel approach to selecting maintenance strategies, which involves assessing the consequences of failure for each building component and determining a suitable strategy accordingly. The research highlights the need for a systematic approach to manage building maintenance, aiming to reduce costs while ensuring safety, health, and user satisfaction [8].

Subsequently, another significant study, critically evaluates maintenance strategies with a focus on the impact of uncertainties in building maintenance planning. This research is grounded in Swedish studies, including case studies and questionnaires, to identify stylized facts and draw conclusions from them. The main finding is that specific uncertainties significantly affect building maintenance planning, making detailed long-term plans less meaningful [9]. The authors propose a new structure for maintenance that emphasizes long-term strategic goals for various buildings/components with short-run adjustments as new information arises. Specifically, the work underlines the importance of managing different types of uncertainty in the structure of maintenance planning for buildings.

Recently, the decision making process represents a significant contribution in the realm of facility management. This work focuses on identifying and analyzing the various criteria that influence decision-making in building maintenance. By laying the groundwork for a multi-criteria decision-making model, it aims to streamline and enhance the process of maintaining facilities. This approach is particularly vital for efficiently managing resources, optimizing maintenance activities, and ensuring the longevity and functionality of buildings within the scope of facility management [10].

3 Methodologies

3.1 Notions

Above all, we summarize the used parameters and corresponding explanations are shown in following Table 1.

Table 1. Primary parameters description.

Parameters	Explanations
X	Input features of buildings
yi	Real maintenance strategy
f()	Learning results
F()	Learning target function
MSE	Mean square error
α	Learning ratio

3.2 Machine learning architecture

Our goal is to anticipate building maintenance needs or optimize maintenance schedules. We can utilize a regression model and the parameter X as input features including building age, last maintenance time, frequency of use, etc., and the goal of the model is to minimize prediction errors. Following Equation 1 describes the learning target.

$$F(X) = \sum_{i=1}^{n} (y_i - f(x_i))^2 \quad (1)$$

First, the model sets the target strategy, and then collects and pro-processes the relevant data, including cleaning, handling missing values, and feature engineering. Exploratory data analysis is then performed to understand the characteristics of the data and select appropriate features and machine Xi models based on this. Model training and validation are critical steps, including parameter tuning and the use of cross-validation to evaluate model performance. Finally, the trained model is deployed to the real environment and subjected to continuous monitoring and iteration to ensure that it remains efficient and accurate in the changing data and environment. Following Algorithm 1 describes the detail method for decision making.

Algorithm 1: Decision making process for strategies

```
if all data points have the same label:
    return a leaf node with this label
  if features is empty:
    return a leaf node with the most common label
  else:
    best_feature = select_feature_based_on_criteria(data, features)
    tree = a new decision node with best_feature
    for each possible value v of best_feature:
      subset = data where best_feature = v
      if subset is empty:
        add a leaf node with the most common label
      else:

        subtree = DecisionTree(subset, features - best_feature)

        add subtree to tree
Return strategies
```

3.3 Optimization

Train a machine learning model with the selected features. This step may involve tweaking several parameters to find the best model. For the trained learning model, the model uses the mean square error as shown in Equation 2. Where the yi is the real label and the $\bar{\bar{y}}_i$ means the learning results from the proposed model.

$$MIN\ MSE = \frac{1}{N} \sum_{i=1}^{n} (y_i - \bar{\bar{y}}_i)^2 \quad (2)$$

4 Experiments

4.1 Experimental setups

We utilize the Buildings Dataset, which is a collection of data sets related to buildings, potentially including information on building characteristics, locations, usage patterns, and other relevant data for training the proposed learning model.

4.2 Experimental analysis

Initially, Accuracy measures the proportion of correct predictions out of all predictions made, useful for overall performance evaluation. Following Figure 1 demonstrates the comparison results with traditional decision process (DP) method.

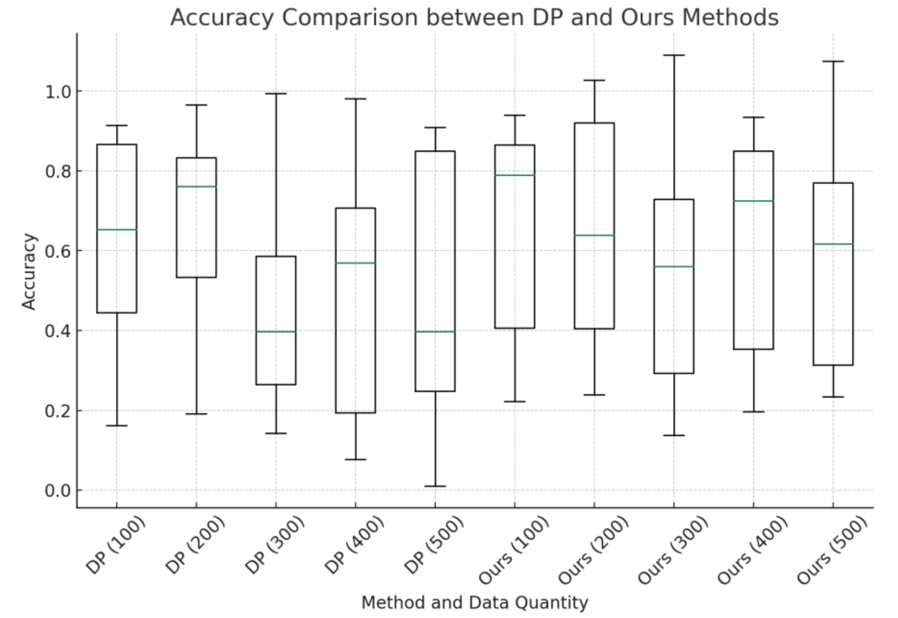

Fig. 1. Learning accuracy comparison results.

Further, another aspects precision and recall are also important for learning models. The evaluation metric precision assesses the proportion of true positive predictions in all positive predictions, while recall measures the proportion of true positives detected by the model. These metrics are crucial for understanding the model's ability to correctly identify maintenance needs. Following Figure 2 compares the proposed model with existing DP model.

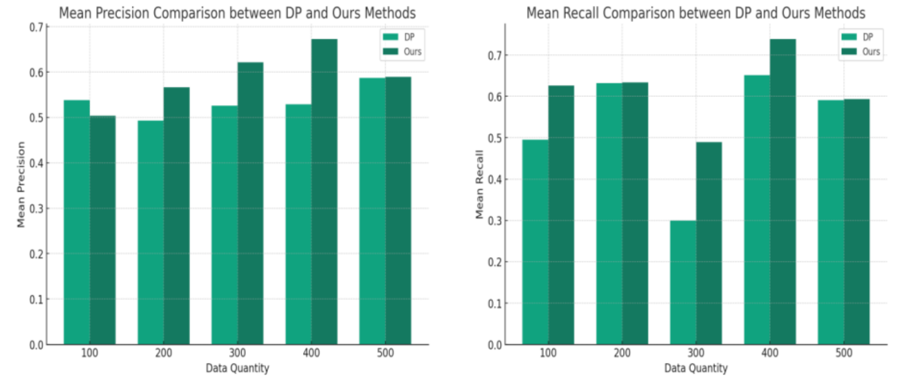

Fig. 2. Precision and recall comparison results.

Mean squared error for regression tasks, such as predicting maintenance costs or time-frames, MSE evaluates the average squared difference between the predicted and actual values. Following Figure 3 compares the mean square error aspect.

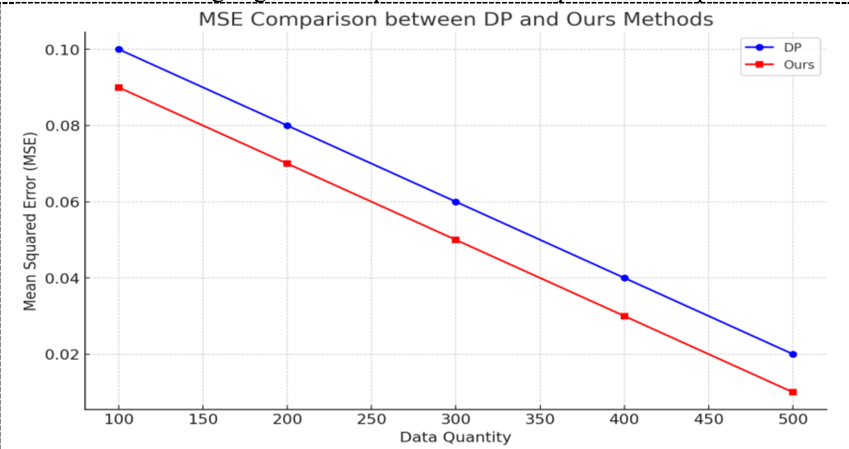

Fig. 3. Mean square error comparison results.

5 Conclusion

In summary, building maintenance and management strategies based on machine learning Xi show great potential to improve forecast accuracy, optimize resource allocation, and reduce operating costs. Key challenges include obtaining high-quality data, model selection and optimization, and ensuring that models are generalizable across buildings and environments. The performance of the model can be comprehensively evaluated through the comprehensive use of evaluation indicators such as accuracy, precision, and recall. Despite the challenges of data processing and technology implementation, interdisciplinary collaboration and ongoing research are expected to further enhance the effectiveness of these strategies, making them play an even more critical role in the development of smart building technologies.

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