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Room Maintenance Analysis using a Clustering Method

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Abstract *This research explores an application of K-Means clustering to analyze hotel room maintenance operations, focusing on three key aspects: room analysis, type of work analysis, and workload balance among technicians. The study aims to identify patterns and inefficiencies in maintenance tasks, providing data-driven insights to optimize operational efficiency. The clustering analysis revealed that certain areas of the hotel, particularly specific towers, are prone to more frequent maintenance requests, indicating a need for tailored maintenance strategies. Additionally, the analysis of work types highlighted the varying time requirements for different tasks, enabling more effective resource allocation. Finally, the workload analysis identified imbalances in task distribution among technicians, suggesting opportunities to improve workforce efficiency. The findings were presented to the hotel's management team, who confirmed that the results accurately reflected their current operational challenges. Management recognized the potential of K-Means clustering as a valuable tool for enhancing room maintenance processes, ultimately leading to improved service quality and guest satisfaction. This research demonstrates the practical application of machine learning techniques in the hospitality industry, offering a novel approach to optimizing hotel maintenance operations.*

Keywords: *Hotel Room Maintenance, K-Means Clustering, Room Analysis, Type of Work Analysis, Workload Balance*

INTRODUCTION

The hospitality industry in Thailand is experiencing significant growth in 2024, driven by an increase in both domestic and international tourism. Thailand ranks as the ninth most visited country globally, with millions of tourists contributing to its economy. In the first two months of 2024, Thailand welcomed over 5 million foreign tourists, generating significant revenue of 290,921 million baht (Ministry of Tourism and Sports, 2024). This influx of tourists is expected to generate substantial revenue, including contributions from domestic tourism and emerging markets from China, Malaysia, Russia, South Korea, and India.

The hospitality industry is increasingly embracing advanced technologies to enhance operational efficiency and guest satisfaction. The adoption of smart technologies, such as contactless check-ins, mobile room keys, virtual concierge services, and AI-powered voice assistants, is significantly enhancing the guest experience. These innovations cater to modern travelers' expectations and improve operational efficiency (Duetto, 2023). The integration of AI into business operation has a profound impact on the usage of automation, optimization of revenge and potential use of resources (Bhardwaj et al., 2023).

The application of Machine Learning (ML) in the hospitality industry, particularly in hotels, is transforming operations, enhancing guest experiences, and driving profitability. ML algorithms and models analyze vast amounts of data to provide insights, predictions, and automated decisions that improve various aspects of hotel management. Lee et al. (2018) provides evidence of the benefits of using ML for operational decision-making, particularly in areas like inventory management and resource allocation. Samala et al. (2020) highlights the effectiveness of ML in enhancing customer personalization, showing that ML algorithms can analyze customer preferences and behavior to provide tailored services, resulting in higher satisfaction and loyalty.

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As the industry grows, the demand for efficient and reliable hotel maintenance systems becomes imperative to ensure guest satisfaction and operational efficiency. The question is how to adapt ML to the hotel maintenance system.

K-Means clustering, a widely used algorithm in data analysis and ML, is particularly effective for partitioning datasets into clusters based on feature similarity. First introduced by Stuart Lloyd in 1957 as a method for vector quantization, K-Means has since found extensive applications in various fields, including hotel room maintenance, where it optimizes resources and predicts maintenance needs. The algorithm works by grouping data into clusters based on similarity. In hotel room maintenance, this technique can be used to optimize maintenance schedules, predict maintenance needs, and reduce costs by grouping rooms with similar characteristics or maintenance requirements.

Therefore, this article explores the implementation of a new hotel maintenance system in Thailand, leveraging machine learning to predict maintenance needs, reduce costs, and enhance service quality in various aspects.

LITERATURE REVIEW

Room Maintenance in Hotel Industry

Traditional maintenance practices in Thai hotels often rely on reactive strategies, where issues are addressed only as they arise. This approach leads to higher operational costs, frequent equipment failures, and decreased guest satisfaction due to unexpected disruptions. These inefficiencies underscore the need for more advanced, proactive maintenance solutions.

Predictive maintenance involves the use of data-driven techniques to predict equipment failures before they occur, allowing for timely maintenance interventions. According to Jardine, Lin and Banjevic (2006), predictive maintenance can significantly reduce maintenance costs and equipment downtime by enabling more accurate scheduling of maintenance activities. The primary benefit of implementing ML-based maintenance systems in hotels is the enhancement of operational efficiency. As reported by Tsang (2002), predictive maintenance reduces the frequency and severity of equipment failures, thereby minimizing disruptions to hotel operations and improving service quality. Law et al. (2019) examine the role of ML in predictive maintenance for hotel operations, demonstrating that predictive maintenance systems powered by ML can reduce maintenance costs and improve operational efficiency by predicting equipment failures and scheduling timely repairs. Mobley (2002) indicates that predictive maintenance can lead to substantial cost savings. By preventing major equipment failures and reducing the need for extensive repairs, hotels can lower their maintenance expenses. Additionally, the ability to schedule maintenance during off-peak times helps avoid costly disruptions and emergency repairs. Improved maintenance practices have a direct impact on guest satisfaction. According to Jeong and Oh (1998), hotel guests value reliability and the smooth functioning of hotel facilities. By ensuring that equipment operates reliably, hotels can enhance the overall guest experience, leading to increased positive reviews and repeat business.

Factors Related Room Maintenance

Maintaining hotel rooms in good condition is a critical aspect of hospitality management that directly influences guest satisfaction, operational efficiency, and long-term profitability. Various studies and literature explore different aspects of room maintenance, ranging from preventive maintenance strategies to the use of technology and data analysis.

Preventive maintenance is a proactive approach that involves regular inspections and timely repairs to prevent equipment failures and maintain the overall condition of hotel rooms. Alsyouf (2009), preventive maintenance can significantly reduce downtime and extend the lifespan of equipment; thereby ensuring that rooms remain in good condition. This strategy is not only cost-effective in the long run but also enhances guest satisfaction by minimizing unexpected disruptions. Tsang (2002) discusses the application of data-driven maintenance strategies, where historical maintenance data is analyzed to identify patterns and optimize maintenance schedules. This approach helps in maintaining rooms in good condition while also reducing maintenance costs through optimized resource allocation.

Rooms that are frequently closed for maintenance may suffer from underlying construction or material issues. Ali et al. (2016) highlight how poor-quality construction materials or outdated infrastructure can lead to frequent repairs. By analyzing maintenance records, hotels can identify whether certain rooms consistently require attention due to structural deficiencies and consider long-term solutions, such as renovations or upgrades, to address these issues. Environmental factors, such as humidity, temperature fluctuations, or proximity to high-traffic areas, can also contribute to the wear and tear of specific rooms, leading to frequent maintenance. Kasim and Ismail (2012) emphasize the importance of considering environmental impacts when analyzing maintenance needs. Understanding these factors can help in making informed decisions about room location, material choices, and maintenance schedules.

Guest behavior and usage patterns can also influence the frequency of maintenance needs. Baker (2013) found that rooms with higher occupancy rates or those frequently used by families or groups may experience more wear and tear, leading to increased maintenance requirements. Analyzing guest usage patterns can help hotels implement targeted maintenance strategies, such as more frequent cleaning or inspections for high-use rooms.

Preventive maintenance involves regular inspections and servicing to address potential issues before they arise. This includes routine checks of plumbing, electrical systems, HVAC units, and room fixtures. The goal is to ensure that all systems function properly and to prevent wear and tear from leading to bigger problems. This type of maintenance is planned and scheduled regularly to reduce the likelihood of emergency repairs (Alsyouf, 2009).

On the other hand, corrective maintenance, also known as reactive or breakdown maintenance, occurs when something has already failed or is malfunctioning. This can include repairing a broken air conditioning unit, fixing a leak, or replacing a faulty light fixture. While necessary, corrective maintenance is often more costly and time-consuming than preventive maintenance because it usually requires immediate attention and can disrupt operations (Tsang, 2002). Therefore, understanding the types of work related to room maintenance is crucial, as it helps the management team identify which tasks require more attention. Analyzing these tasks can also help pinpoint the root causes of recurring problems within the property.

Workload management is critical in allocating tasks to technicians, ensuring that work is distributed evenly and according to each technician's capacity. According to Wong and Fung (2012), proper workload management helps prevent burnout and increases job satisfaction among technicians. Techniques such as workload balancing and shift scheduling are often used to ensure that no single technician is overburdened. Assigning tasks based on technicians' skills and experience levels is a key factor in effective work allocation. Smith et al. (2013) argue that aligning tasks with technicians' competencies leads to higher efficiency and reduces the likelihood of errors. For example, more experienced technicians may handle complex HVAC systems, while newer technicians focus on routine maintenance tasks.

Proper work allocation is directly linked to the quality of maintenance and, consequently, guest satisfaction. Tsang (2002) suggests that when technicians are given tasks that match their expertise, the quality of work improves, leading to fewer repeat issues and less downtime for hotel facilities. This underscores the importance of strategic work allocation in maintaining high operational standards. Efficient work allocation in a hotel's engineering department is essential for ensuring smooth operations and maintaining high service standards.

To conclude, the key factors related to room maintenance in hotels are as follows:

- Room Analysis
- Type of Work Analysis
- Workload Analysis

Machine Learning Techniques

Machine learning algorithms, particularly those involving supervised and unsupervised learning, play a crucial role in predictive maintenance. Supervised learning algorithms such as decision trees, support vector machines, and neural networks are commonly used to predict equipment failures based on historical data (Khan & Yairi, 2018).

Unsupervised learning techniques, like clustering and anomaly detection, are also employed to identify patterns and deviations that may indicate potential failures (Wang, Ma & Zhou, 2020). K-means clustering is a popular unsupervised machine learning algorithm used to partition data into distinct, non-overlapping subsets (clusters) based on feature similarity. The objective is to minimize the variance within each cluster while maximizing the variance between clusters (Jain, 2010).

Predictive maintenance involves using historical data to predict and preempt equipment failures before they occur. K-means clustering aids in identifying patterns and anomalies in maintenance data, leading to more accurate predictions (Lee, Ni, Djurdjanovic, Qiu & Liao, 2006). Hotels can use clustering to group rooms with similar maintenance needs, thereby optimizing maintenance schedules and reducing downtime. By identifying clusters of rooms that require similar types of maintenance, resources can be allocated more efficiently (Samala et al., 2020). Clustering allows for a more efficient use of maintenance resources, reducing labor and material costs. By predicting maintenance needs and optimizing schedules, hotels can avoid costly emergency repairs (Law et al., 2019).

A study by Zhang et al. (2019) applied K-means clustering to Heating, Ventilation, and Air Conditioning (HVAC) maintenance data in hotels. The rooms were clustered based on HVAC usage patterns, which helped identify rooms with higher energy consumption and potential HVAC issues. This clustering approach enabled more targeted maintenance, reducing overall energy costs. Law, Leung and Chan (2019) implemented K-means clustering to predict maintenance needs in hotel rooms. By clustering rooms based on historical maintenance logs, the study was able to predict which rooms were likely to require maintenance, allowing for proactive scheduling. This approach reduced emergency maintenance calls and improved guest satisfaction.

Proactive maintenance based on clustering reduces room downtime and ensures that maintenance issues are addressed before they impact guests. This leads to higher guest satisfaction and positive reviews (Samala et al., 2020).

Challenges in Implementation

Preliminary implementation in several Thai hotels has demonstrated significant benefits. Key performance indicators (KPIs) such as equipment downtime, maintenance costs, and guest complaints have shown noticeable improvements. The machine learning system has enabled more accurate predictions of equipment failures, allowing hotels to address issues before they impact operations.

One of the significant barriers to adopting ML-based maintenance systems is the high initial investment required for hardware, software, and training. As noted by Al-Turki et al. (2014), the cost of installing sensors, purchasing ML software, and training staff can be substantial, particularly for small and mid-sized hotels. The successful implementation of ML-based systems requires technical expertise that may be lacking in many hotels. Daugherty and Wilson (2018) highlight the need for skilled personnel to manage and interpret ML algorithms, which can be a significant challenge for hotels without a strong technical background.

The effectiveness of ML algorithms depends on the quality and quantity of data available. Zhang, Yang and Chen (2017) emphasizes the importance of clean, accurate data for training ML models. Integrating ML systems with existing hotel management systems can also pose challenges, requiring seamless data flow and interoperability.

Several studies have documented the successful application of ML-based maintenance systems in the hospitality industry globally. For instance, Smith and Brown (2021) demonstrate how a leading hotel chain in the United States reduced maintenance costs and improved operational efficiency using ML-driven predictive maintenance.

While specific case studies on the implementation of ML-based maintenance systems in Thai hotels are limited, the potential benefits are significant. As the Thai hospitality industry continues to grow, adopting advanced technologies like ML can provide a competitive edge. Studies by the Thai Hotel Association (2023) suggest that hotels in Thailand are beginning to explore ML applications to enhance their maintenance practices and improve guest experiences.

RESEARCH METHODOLOGY

Data Collection

The first step involves gathering data relevant to room maintenance activities. This data can be collected from the hotel's maintenance management system. The data was collected and will be analyzed, the example of the room maintenance data can be shown in Fig. 1.

Order No.	Tower	Room Number	Assigned By	Detail	Submitted Date	HK Done	Type of Wrok	Assigned to	Remark	Eng Done	Finished Date
57701	C	405	Chompoo	Painting in the living room	12/27/2022	Yes	Painting	Kae	0	Yes	1/3/2023
57702	C	405	Chompoo	Painting in the bedroom	12/28/2022	Yes	Painting	Kae	0	Yes	12/30/2022
57763	B	405	Chumpol	Painting in the toilet	12/28/2022	Yes	Painting	Thawatchai	0	Yes	12/30/2022
57765	B	405	Chumpol	Painting entrance door	12/28/2022	Yes	Painting	Thawatchai	0	Yes	1/11/2023
57778	B	402	Kanokwan	Painting in the toilet	12/29/2022	Yes	Painting	Thawatchai	0	Yes	1/1/2023
57779	B	402	Kanokwan	Chair broken	12/29/2022	Yes	Furniture	Kae	0	Yes	12/31/2022
57782	A	802	Chompoo	Painting ceiling	12/29/2022	Yes	Painting	Sunti	0	Yes	1/10/2023
57783	A	802	Chompoo	Painting bathroom ceiling	12/29/2022	Yes	Painting	Kae	0	Yes	1/2/2023
57784	A	802	Chompoo	Painting in the bedroom	12/29/2022	Yes	Painting	Kae	0	Yes	1/6/2023
57785	A	802	Chompoo	Air-conditioning problem	12/29/2022	Yes	Air Conditioning System	Wanchai	0	Yes	12/29/2022
57790	B	1205	Chumpol	Paint below the window	12/29/2022	Yes	Painting	Wichien	0	Yes	1/5/2023
57791	C	404	Kanokwan	Painting in the living room	12/29/2022	Yes	Painting	Sunti	0	Yes	1/2/2023
57792	C	403	Kanokwan	Painting toilet	12/29/2022	Yes	Painting	Sophon	0	Yes	12/31/2022
57793	B	1002	Kanokwan	Air-conditioning problem	12/29/2022	Yes	Air Conditioning System	Sophon	0	Yes	12/29/2022
57798	B	509	Kanokwan	Painting toilet	12/29/2022	Yes	Painting	Sophon	0	Yes	1/3/2023
57801	B	501	Kanokwan	Grounting shower room	12/29/2022	Yes	Grounting Work	Kae	0	Yes	12/30/2022
57802	C	601	Thanarat	Painting toilet	12/29/2022	Yes	Painting	Sophon	0	Yes	1/1/2023
57809	B	203	Kanokwan	Wall paper below the window	12/30/2022	Yes	Wallpaper	Kae	0	Yes	1/9/2023
57815	B	503	Kanokwan	Painting toilet	12/31/2022	Yes	Painting	Sophon	0	Yes	1/14/2023
57816	B	503	Kanokwan	Paint toilet ceiling	1/1/2023	Yes	Painting	Kae	0	Yes	1/10/2023
57817	B	506	Kanokwan	Kitchen	1/1/2023	Yes	Furniture	Kae	0	Yes	1/2/2023
57818	B	604	Kanokwan	Paint kitchenceiling	1/1/2023	Yes	Painting	Wanchai	0	Yes	1/1/2023
57821	B	510	Kanokwan	Water leaking	1/1/2023	Yes	Piping System	Wichien	0	Yes	1/2/2023
57825	B	808	Chumpol	Water leaking	1/1/2023	Yes	Piping System	Wichien	0	Yes	1/2/2023
57828	C	402	Kanokwan	Exhaust not working	1/1/2023	Yes	Technical Work	Wichien	0	Yes	1/2/2023
57834	B	109	Chompoo	Check waterproof	1/1/2023	Yes	General Work	Sophon	0	Yes	1/2/2023

Fig. 1: The Example of Work Order

After that, the data will be synthesized to be used for data analysis on different topics:

- *Room Analysis Data:* Information about room usage, the frequency of maintenance requests over one year, and the time since the last maintenance. These measurements are chosen to reflect the room's condition, as they may indicate deterioration.
- *Type of Work Data:* Details about the different types of maintenance work performed, including the number

of each type of work and the average time spent on each task. This data is useful for identifying potential issues. For example, if painting tasks take 12 hours to complete and there are 300 requests in one year, while another task takes only 1 hour and has 100 requests, the management team should investigate abnormalities in the painting work.

- *Workload Data:* Records of the number of tasks assigned to each technician and the performance of each engineer. This data will be used to analyze and ensure that work distribution within the engineering department is balanced.

All data should be collected over a significant period, ideally 12 months, to ensure the analysis captures seasonal variations and other trends.

Data Preprocessing

Before applying the K-means clustering algorithm, the collected data needs to be preprocessed to ensure accuracy and relevance. This includes:

- *Data Cleaning:* Removing any missing or inconsistent data entries, such as maintenance tasks without completion times or incomplete room records.
- *Normalization:* Scaling the data so that all features contribute equally to the clustering process. For instance, the number of maintenance requests may need to be normalized if it has a much larger range than other features like task completion time.
- *Feature Selection:* Identifying the most relevant features for clustering to ensure that the analysis focuses on the key aspects of the data.

K-Means Clustering Application

The K-means clustering algorithm is applied to preprocessed data to identify patterns and group similar instances together:

- *Choosing the Number of Clusters (K):* The number of clusters is determined using the Elbow Method. For each value of K, the Sum of Squared Distances (SSD) between data points and their corresponding cluster centroids is calculated, known as the Within-Cluster Sum of Squares (WCSS). The optimal number of clusters is typically chosen where the WCSS begins to level off, forming an “elbow” in the plot.
- *Clustering Process:* The K-means algorithm is then run on the selected features. The algorithm iteratively assigns each data point to one of the K clusters based on feature similarity, with the goal of minimizing the variance within each cluster. This process continues until the cluster assignments no longer change or converge to a stable solution.

Methods for Determining K

Various methods have been developed to determine the optimal K value, with Python being a popular tool for implementing these techniques due to its extensive libraries and ease of use. Several studies have demonstrated the effectiveness of these methods in various domains. For instance, Xanthopoulos et al. (2013) applied the Elbow Method and Silhouette Analysis to determine the optimal number of clusters in market segmentation. Similarly, Kodinariya and Makwana (2013) discussed the theoretical aspects of K-means clustering and provided a Python-based approach for determining K. Consequently, the Elbow Method will be applied using Python in this research.

Cluster Analysis

Once the clustering is complete, the resulting clusters are analyzed to derive insights into various aspects of room maintenance:

- *Room Analysis:* The clusters can reveal patterns, such as rooms that require frequent maintenance, specific recurring issues, or rooms that are more prone to certain problems based on their location or usage.
- *Type of Work Analysis:* Clustering can identify which types of maintenance tasks are often grouped together, indicating common maintenance challenges or areas where preventive measures could be improved.
- *Workload Analysis:* By clustering tasks based on workload data, insights can be gained into the distribution of work among technicians. This analysis can help identify any imbalances in task allocation, ensuring that the workload is evenly distributed and that technicians are not overburdened.

Sample Hotel Used in the Study

The hotel is a well-established 4-star property located in the vibrant city center of Bangkok, Thailand. Operating since 1998, it has built a strong reputation for providing excellent service and comfortable accommodations to both business and leisure travelers.

The property comprises three buildings, Building A, Building B, and Building C, with a total of 176 rooms. Building A houses 26 rooms, Building B accommodates 110 rooms, and Building C includes 40 rooms.

The hotel’s engineering team plays a crucial role in maintaining the facilities to ensure guest comfort and safety. The team consists of 11 dedicated professionals: 1 Chief Engineer, 1 Assistant Chief Engineer, 3 Engineering Supervisors, and 6 Technicians. This structure allows the hotel to efficiently manage maintenance and technical needs across its three buildings, ensuring that the facilities are well-maintained and meet the high standards expected by guests.

Evaluation and Validation

The results of the clustering analysis are evaluated to ensure they are both meaningful and actionable:

- *Cluster Quality:* The quality of the clusters is assessed using the Within-Cluster Sum of Squares (WCSS) to determine how well the data points fit within each cluster.
- *Practical Relevance:* The clusters are reviewed by maintenance managers or experts to ensure that the insights derived align with operational realities and are practically applicable.
- *Implementation of Insights:* The findings from the clustering analysis are used to make data-driven decisions regarding room maintenance strategies, technician workload distribution, and preventive maintenance planning.

RESEARCH RESULT

The objective of this research is to apply a machine learning approach to predict maintenance needs, reduce costs, and enhance service quality by analyzing factors related to room maintenance. The key factors considered are room analysis, type of work analysis, and workload analysis. To validate the data for each factor, the K-Means clustering algorithm is applied, with the value of K set to 3 in each analysis.

The selection of K=3 is based on the Elbow Method, which may have identified a noticeable "elbow" at this point, suggesting that it balances the within-cluster variance and the number of clusters. Beyond three clusters, the reduction in variance becomes marginal, making three a logical choice.

The Elbow Method involves plotting the Within-Cluster Sum of Squares (WCSS) against the number of clusters (K), where WCSS measures the sum of squared distances between each data point and its assigned cluster center. As K increases, the WCSS decreases; however, after a certain point, the decrease becomes less significant, forming an "elbow" in the plot. The optimal K is typically at this elbow point, where adding more clusters does not significantly improve the clustering.

Room Analysis Results

This analysis compares the frequency of maintenance requests across different room clusters within the engineering department using K-means clustering. The y-axis represents the frequency of maintenance requests over the past year, while the x-axis denotes the time since the last maintenance (in months). The centroid coordinates for the three clusters are as follows: Cluster 1 (3.405, 10.184), Cluster 2 (3.712, 3.712), and Cluster 3 (10.937, 2.215).

The sum of squares method was applied to assign each room to its closest cluster, effectively dividing all rooms into three distinct groups. The clustering process revealed clear groupings of rooms based on their maintenance needs, as illustrated in Fig. 2.

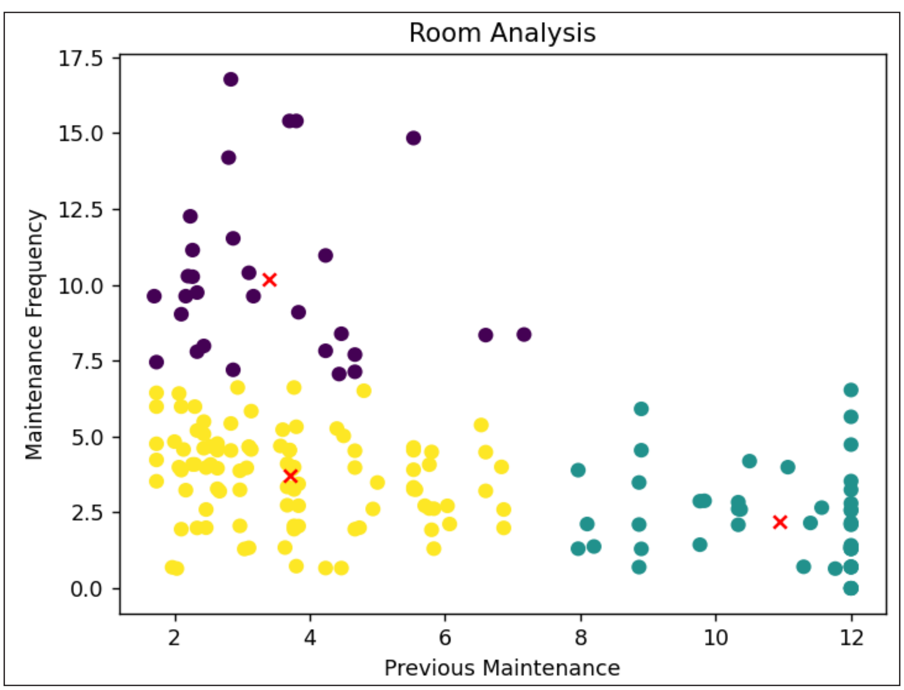

Fig. 2: Scatter Plot for Room Analysis

Cluster 1 (Tower A)

- *Characteristics:* Moderate frequency of maintenance requests (3.405/year) and a long time since the last maintenance (10.184 months).
- *Implication:* Rooms in Tower A might be left without maintenance for extended periods, leading to a buildup of moderate issues. Proactive maintenance strategies could help prevent these problems from escalating.

Cluster 2 (Tower B)

- *Characteristics:* Low frequency of maintenance requests (3.712/year) and a moderate time since the last maintenance (3.712 months).
- *Implication:* This cluster indicates effective maintenance management in Tower B, resulting in fewer issues. The balanced maintenance activities seem to keep problems under control.

Cluster 3 (Tower C)

- *Characteristics:* High frequency of maintenance requests (10.937/year) and a short time since the last maintenance (2.215 months).
- *Implication:* Despite recent maintenance, rooms in Tower C continue to experience frequent issues. This suggests potential underlying problems that are not fully addressed, requiring more frequent and perhaps more thorough maintenance interventions.

Type of Work Analysis Results

This analysis uses K-means clustering to compare the distribution and characteristics of different types of work within the engineering department. The y-axis represents the average time spent on each type of work (in days), while the x-axis denotes the frequency of each work type. The centroids for the three clusters are as follows: Cluster 1 (467.000, 7.124), Cluster 2 (139.667, 2.281), and Cluster 3 (50.833, 2.700). The sum of squares method is applied to determine the optimal number of clusters (K) for each type of work, resulting in the division of all work types into three groups. The clustering process identified distinct groups of work types based on the given data, as shown in Fig. 3.

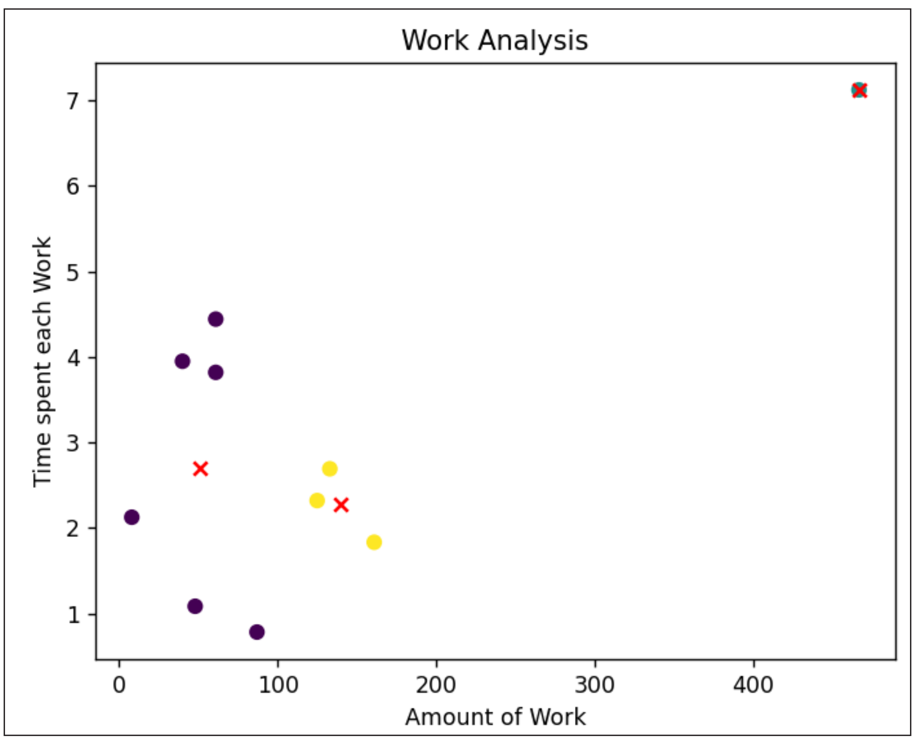

Fig. 3: Scatter Plot for Type of Work Analysis

Cluster 1: High Time Investment, Low Frequency (Painting Work)

- Cluster 1, with a centroid at (467.000, 7.124), includes only Painting work. This cluster indicates that painting tasks require a significant amount of time (an average of 467 days per task) but occur relatively infrequently (about 7.124 instances). This suggests that painting is a time-intensive process, demanding substantial resources despite its rarity. The high average time per task likely reflects the complexity and meticulousness involved in painting jobs within the engineering context.

Cluster 2: Moderate Time Investment, Low Frequency (Piping System, Furniture Work, General Work)

- Cluster 2, with a centroid at (139.667, 2.281), encompasses Piping System, Furniture Work, and General Work. This cluster shows a moderate average time spent on each task (139.667 days) with a lower frequency of occurrence (2.281 instances). The types of work in this cluster are varied, suggesting that while each task might be complex and time-consuming, they are not frequently required. This may reflect the occasional nature of these maintenance activities, which need specialized skills and considerable time investment when they do arise.

Cluster 3: Low Time Investment, Moderate Frequency (Communication System, Air Conditioning System, Electrical System, Technical Work, Grouting Work, Wallpaper)

- Cluster 3, with a centroid at (50.833, 2.700), includes a range of tasks such as Communication System, Air Conditioning System, Electrical System, Technical Work, Grouting Work, and Wallpaper. This cluster is characterized by a lower average time per task (50.833 days) and a slightly higher frequency of occurrence (2.700 instances). The tasks in this cluster are typically less time-intensive and may involve regular, routine maintenance that can be completed relatively quickly. The moderate frequency suggests these tasks are more common in the department's workload.

The analysis of these three clusters reveals distinct patterns in how different types of work are distributed within the engineering department. Cluster 1 highlights painting as a significant time investment, while Cluster 2 includes moderately time-consuming but infrequent tasks. Cluster 3 represents more routine and frequent maintenance activities that require less time to complete. Understanding these clusters facilitates better planning and resource allocation, ensuring that time-intensive tasks are managed efficiently while routine maintenance is handled effectively.

By identifying these clusters, hotel management can better allocate resources and schedule maintenance tasks to minimize disruptions to guests. Understanding the types of work that dominate each cluster helps in allocating the right resources at the right time, ensuring that technicians are not overburdened and repairs are completed promptly.

Workload Analysis Between Technicians

This analysis compares the workload distribution among three clusters identified using K-means clustering. The y-axis represents the number of tasks assigned to each technician, while the x-axis denotes the performance of each engineer. The centroid coordinates for the three clusters are as follows: Cluster 1 (2.569, 108.35), Cluster 2 (2.755, 83.224), and Cluster 3 (2.662, 42.269). The sum of squares method is used to determine the optimal number of clusters (K) for each technician, resulting in the division of all technicians into three groups. The clustering process identified distinct groups of technicians based on the given data, as shown in Fig. 4.

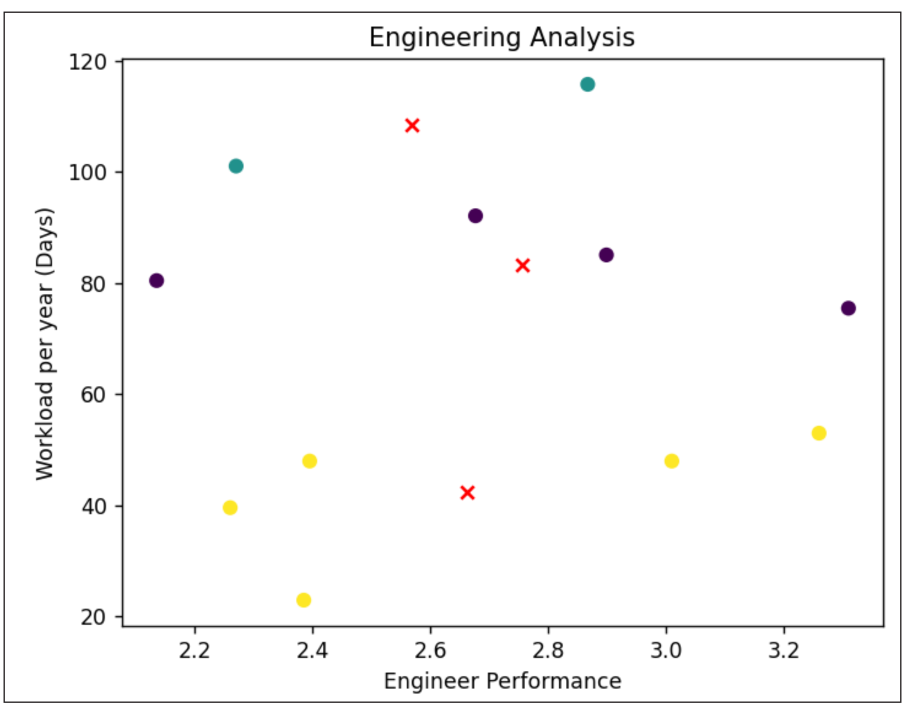

Fig. 4: Scatter Plot for Workload Analysis

Cluster 1: High Workload, Moderate Performance

- Cluster 1, with a centroid at (2.569, 108.35), represents a group of technicians with a high number of tasks assigned (108.35) but only moderate performance levels (2.569). This cluster likely includes technicians who are either overburdened or struggling with task complexity, which may affect their performance. The high task count suggests that these technicians might benefit from additional support, training, or a redistribution of tasks to optimize their performance.

Cluster 2: Balanced Workload and Performance

- Cluster 2, centered at (2.755, 83.224), shows a more balanced relationship between workload and performance. With a slightly higher performance score (2.755) compared to Cluster 1 and a reduced task load (83.224), these technicians appear to handle their assignments efficiently. This cluster likely represents an ideal scenario where the workload is well-matched to the technicians' capabilities, leading to optimal performance without overburdening them.

Cluster 3: Low Workload, High Performance

- Cluster 3, with a centroid at (2.662, 42.269), highlights technicians with a significantly lower number of tasks (42.269) but relatively high performance (2.662). This cluster may include technicians who are either highly efficient or underutilized. The low workload suggests that these technicians could potentially take on additional tasks without compromising their performance, indicating an opportunity for better workload distribution within the department.

The analysis reveals distinct patterns in workload distribution and performance among the three clusters. Cluster 1's high workload may hinder performance, while Cluster 2 shows a balanced scenario. Cluster 3 represents a situation where technicians are underutilized despite high performance. These insights suggest that reallocating tasks could improve overall departmental efficiency.

The clustering results indicate that redistributing tasks among technicians could lead to a more balanced workload, reducing the risk of burnout and enhancing overall efficiency. Additionally, the analysis suggests a need for additional training for technicians handling emergency repairs and a more balanced scheduling system to ensure that no technician is overworked.

Discussion of Results

The application of K-Means clustering in analyzing hotel room maintenance has proven highly beneficial, offering valuable insights into three critical aspects: room analysis, type of work analysis, and workload balance analysis. When presented to the management team of the studied hotel, the findings resonated strongly with their current challenges, validating the relevance and practicality of this approach.

K-Means clustering effectively categorized rooms based on maintenance frequency and the time since the last maintenance. This segmentation revealed distinct patterns across different clusters of rooms, allowing management to identify high-risk areas that require more frequent attention. By pinpointing specific rooms prone to frequent issues, the hotel can implement more targeted and efficient maintenance scheduling, thereby reducing downtime and improving guest satisfaction.

In analyzing the types of work performed, K-Means clustering identified the most time-consuming and labor-intensive tasks. This insight enables the hotel to allocate resources more effectively, ensuring that critical tasks are prioritized. Additionally, understanding the most performed tasks aids in planning and budgeting for future maintenance needs, leading to more proactive rather than reactive maintenance strategies.

The clustering approach also highlighted imbalances in workload distribution among technicians. By identifying clusters with varying levels of task assignments and performance metrics, the hotel can reallocate tasks more evenly, improving overall efficiency and preventing technician burnout. A balanced workload ensures timely completion of tasks, enhancing operational efficiency and reducing maintenance backlogs.

The management team found that the K-Means clustering analysis accurately reflected their challenges, such as frequent issues in specific rooms and uneven workload distribution among technicians. They recognized the tool's value in providing a data-driven approach to understanding and addressing maintenance challenges. The insights gained are crucial for optimizing maintenance operations, reducing costs, and enhancing the overall guest experience.

The implementation of K-Means clustering as a maintenance analysis tool is now regarded by management as a significant step forward in their efforts to maintain high standards of room quality and operational efficiency.

Smith and Lee (2020) explore integrating technologies like CMMS and AI in hotel maintenance, emphasizing the benefits of predictive maintenance strategies for improving operational efficiency and guest satisfaction. Villa et al. (2022) applied machine learning methods to design sustainable building facility maintenance, leveraging an IoT sensor network and a BIM (Building Information Modeling) model. Their proposed framework demonstrates how anomaly prediction models manage data within a 3D building model.

CONCLUSION

The integration of machine learning into hotel maintenance systems marks a significant advancement for the Thai hospitality industry. By transitioning from reactive to predictive maintenance, hotels can achieve cost savings, enhance operational efficiency, and improve guest satisfaction. Continuous evaluation and adaptation of the system will be crucial to fully realize its potential and address emerging challenges. Athuraliya and Farook (2018) demonstrates a method for analyzing hotel reviews to identify and highlight maintenance-related issues in a format that is actionable for hotel management. This method utilizes machine learning techniques, specifically Support Vector Machines (SVM), to analyze the data.

The implementation of machine learning-based maintenance systems in hotels offers numerous benefits, including improved operational efficiency, cost savings, and enhanced guest satisfaction. However, challenges such as high initial costs, the need for technical expertise, and data quality issues must be addressed. As the hospitality industry evolves, further research and practical applications of machine learning in hotel maintenance are essential to fully realize its potential. K-Means clustering, a powerful and widely used technique for identifying patterns in data, is popular due to its ease of use and efficiency, despite its limitations.

The clustering analysis revealed distinct groupings of rooms based on maintenance frequency and the time since the last maintenance. For example, Cluster 1 (Tower A) showed frequent maintenance needs after longer intervals, while Cluster 3 (Tower C) exhibited frequent maintenance requests shortly after previous maintenance. This suggests that specific areas, such as Tower C, may require more proactive and frequent maintenance scheduling to prevent recurring issues, while other areas might benefit from different maintenance strategies.

The analysis also identified variations in the types of work required and their frequency. Cluster 1, for instance, primarily involved time-consuming but infrequent tasks like painting, whereas Cluster 3 included a variety of more frequent but less time-intensive tasks such as electrical and air conditioning maintenance. Understanding this distribution allows the hotel to optimize resource allocation, schedule time-intensive tasks more efficiently, and potentially reduce downtime.

Additionally, the clustering revealed imbalances in task distribution among technicians. Some technicians were assigned a higher number of tasks but had lower performance metrics, while others had fewer tasks with higher efficiency. Addressing these imbalances can lead to a more equitable distribution of tasks, enhancing overall efficiency, and ensuring timely completion of all tasks, which can improve maintenance effectiveness and staff satisfaction.

The clustering analysis has provided actionable insights into room maintenance operations, helping to identify areas for improvement and optimize maintenance strategies. The management team can now make data-driven decisions to enhance efficiency, reduce operational costs, and improve guest satisfaction by ensuring that rooms are well-maintained and issues are addressed promptly.

The effectiveness of K-Means clustering depends on the quality and availability of historical maintenance data. Incomplete or inaccurate data can lead to incorrect clustering and suboptimal maintenance decisions (Jain, 2010). Although K-Means clustering is computationally efficient, its application in large hotels with thousands of rooms may require significant computational resources. Future research could explore more scalable clustering algorithms or hybrid approaches (Lee et al., 2006). The integration of K-Means clustering with IoT and smart systems presents a promising direction for future research. IoT sensors can provide real-time data on room conditions, enhancing the accuracy of clustering and predictive maintenance models (Law et al., 2019).

Future research could expand the scope of clustering analysis by incorporating additional variables such as guest satisfaction scores, seasonal variations, and the impact of different maintenance strategies on room availability. This would provide a more comprehensive understanding of the factors influencing maintenance needs and help in developing more effective predictive maintenance models. While K-Means clustering has proven useful, exploring other clustering algorithms, such as hierarchical clustering or DBSCAN, could offer improved accuracy or insights for categorizing maintenance tasks. A comparative analysis of different algorithms could identify the most effective method for this application. Further research could also analyze the impact of implementing clustering-based maintenance strategies on operational costs, involving a detailed cost-benefit analysis to quantify the financial benefits of optimized maintenance schedules and improved task allocation.

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