Proactive buildings: A prescriptive maintenance approach

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Abstract. Prescriptive maintenance has recently attracted a lot of scientific attention. It integrates the advantages of descriptive and predictive analytics to automate the process of detecting non nominal device functionality. Implementing such proactive measures in home or industrial settings may improve equipment dependability and minimize operational expenses. There are several techniques for prescriptive maintenance in diverse use cases, but none elaborates on a general methodology that permits successful prescriptive analysis for small size industrial or residential settings. This study reports on prescriptive analytics, while assessing recent research efforts on multi-domain prescriptive maintenance. Given the existing state of the art, the main contribution of this work is to propose a broad framework for prescriptive maintenance that may be interpreted as a high-level approach for enabling proactive buildings.

Keywords: Prescriptive maintenance · Time series analysis · Proactive buildings

1 Introduction

Prescriptive maintenance (PsM) is a type of data analytics that supports making better judgments by analyzing raw data. It takes into account information about potential conditions or scenarios, available resources, previous and present performance, and recommends a plan of action that optimizes equipment maintenance. It may be used to make decisions across any time horizon, from the present to the long term. It uses Machine Learning (ML) to comprehend and advance from the data it collects, evolving as it goes. ML and Internet of Things (IoT) enable the processing of massive amounts of data, which are now available. PsM software solutions automatically adjust to make use of new or extra data as it becomes available, in a process that is exhaustive and faster than that afforded by human skills.

To be effective, PsM requires the training of a ML model using past sensor and service data. The more high-quality information supplied, the more accurate the ML model will be in detecting more maintenance requirements and failure signals, whilst providing fewer false positives. Before feeding data to the ML algorithm, it may be necessary to clean it. Sensor readings, for example, may need to be updated to account for changes in calibration or to standardize how various faults are recorded by human operators. When training a PsM algorithm, higher-level knowledge about an organization may be submitted to the ML algorithm. This enables the PsM software to analyze critical factors like maintenance costs and manufacturing downtime. Anomaly identification, residual usable life assessment and optimal algorithmic and metrics selection are common issues that impede PsM attempts.

Because of the equipment they employ, most systems are linked to signals, which are not always time series. Predictive maintenance (PdM) gets data from condition monitoring. Then, using complex algorithms, it detects a possible failure. A misalignment, for example, will be detected by vibration analysis around three months before it causes a breakdown. Nonetheless, asset managers must take action. They must analyze facts, make a decision, and develop a work order. In such situation, PsM would generate and submit a work order to technicians to repair the misalignment. It does not require asset managers' interaction and maintains equipment on its own. This results in increased availability and productivity, as well as the capacity to do remote maintenance.

Moreover, PsM offers the same advantages as PdM, but goes a step further. In general, once customized to meet the needs of a use case, it leads to i) less unplanned downtime and higher productivity as a result of maintenance optimization, ii) higher profitability as a result of higher productivity, iii) more virtual collaboration as data is available remotely, and finally, iv) digital PsM enables significant prospects for scalability.

This work examines PsM and proposes a framework that envisions practical implications that can be conceptualized within the context of proactive buildings. The goal is to predict and prescribe actions for minimizing operational costs and downtime of home appliances as a high-level approach (considering high data granularity). We believe that the proposed framework can facilitate processes supporting feature data requirements and system architecture for enabling prescriptive analytics in household and small-scale industrial solutions, while posing as an all around generic solution for modeling and enabling PsM.

The remainder of this article is structured as follows: Section 2 showcases related work, while Section 3 analyzes the developed concepts/methodology of the proposed PsM framework. The paper concludes with Section 4, discussing final thoughts, implications and future prospects.

2 Related work

This section introduces different types of maintenance analytics and reviews recent attempts in PsM in a multi domain manner.

Electric utilities cover a wide geographic range of assets. They have been migrating from time-based maintenance planning to establishing a proactive and intelligent asset health management approach to address the conflicting constraints of decreasing customer downtimes, fulfilling regulatory standards, and managing increasing infrastructure. An advanced analytics strategy tries to model asset health and network dependability by projecting asset aging, determining the remaining lifespan, and computing network resilience. The analytics use data from business asset management, sophisticated metering infrastructure, weather systems, and other sources. The outcomes include a health score and risk ranking, as well as a proposed ideal maintenance approach based on cost limitations. [1].

Big data analytics is quickly developing as a critical IoT endeavor aimed at giving valuable insights and assisting with optimal decision making despite time limitations. Prescriptive analytics seeks to make judgments that are adaptable, automated, limited, time-dependent, and optimum. Estimations, on the other hand, present major issues, due to the uncertainty resulting from improper user input, noisy data, and the non-stationarity of real-world data feeds. A suggested method solves sensor-driven learning issues linked to uncertainty arising from time dependent characteristics, such as user input, sensor noise, and gives estimates that lead to more trustworthy prescriptions. [2].

One of the primary advantages of the railroads' digital transformation is the ability to improve asset management efficiency via the use of information modeling and decision support systems. Tracking circuits of an Italian urban railway network are used to demonstrate an actual railway signaling use case, covering from field data collecting through decision support and asset status. The acquired knowledge is then used to completely automate the prioritization of asset management actions using an optimization logic [3] and operational limitations. The goal is to improve i) maintenance activity scheduling, ii) service dependability, and iii) resource utilization and possession times while avoiding (or reducing) contractual fines and delays. [4].

Nowadays, maintenance management methodologies are being turned into automated knowledge-based decision support systems. PriMa, which consists of four layers, is proposed. These are i) data management, ii) a predictive data analytics toolset, iii) a recommendation and decision support dashboard, and iv) an overarching layer for semantic-based learning and reasoning. As a result, two functional capabilities in a real-world production system are enhanced, i) efficiently processing large amounts of multi-modal and heterogeneous data, and ii) effectively producing decision support measures and suggestions for improving and optimizing upcoming scheduled maintenance, thereby reducing production downtime. [5].

The digital revolution has had an influence on industrial processes and maintenance models, resulting in new needs, difficulties, and possibilities for ensuring and enhancing equipment utilization and process stability. A model is proposed that i) aids in the implementation of a PsM strategy and the assessment of its maturity level, ii) enables the integration of data-science techniques to predict future events, and iii) specifies intervention fields to achieve a higher target maturity condition and thus greater predictive accuracy. [6].

PsM planning is a critical facilitator of intelligent, highly adaptable manufacturing processes. Traditional maintenance procedures are insufficient to meet today's production requirements due to rising complexity. Multimodal data analysis and simulation techniques are used in an unique method to analyze historical data, such as quality of product, machine malfunction, and production planning. Validation includes real-world applications in the automobile manufacturing field, where recognized data associations and real-time machine data are used to forecast system problems and provide fixes [7].

A dynamic maintenance plan is described that takes into account the amount of deterioration and aging, as well as the system failure rate. It is commonly expected that repair would always bring positive impact in the health of the system. Nevertheless, in the case of locomotive wheel-sets, restoration decreases the system age while increasing the deterioration levels. After conducting a dependability analysis it is observed that the best maintenance plan is achieved by reducing the long-run cost rate as a function of the repair cycle and dynamically determining the appropriate inspection time. [8].

An end-to-end PsM approach that incorporates maintenance analysis, equipment, and operational data with predictive solutions and feedback to create actionable insights is offered. Workforce scheduling, supply chain optimization, field-replaceable unit control, process efficiency, and knowledge management are among the features used. The implementation has been validated in several datasets, including the data integration, feature reduction/selection, filling missing data, and noise removal stages. It detects faults at the individual equipment and fleet levels before offering a mechanism for full repair solutions, such as service staff scheduling and equipment downtime control. The findings result in an extendable PsM equipment maintenance architecture that achieves significantly decreased unexpected equipment downtime at an optimal cost. [9].

Another framework is presented for achieving optimal future-failure awareness and safety-conscious production and maintenance plans while taking system complexity and resource allocation into account. Utilizing equipment condition data, ensembles of nonlinear support vector machine classification models were used to forecast the timing and probability of future equipment breakdown. To develop optimal processes and maintenance schedules, multi-objective optimization of predicted profit and a safety metric were also employed. Ensemble models had an average accuracy and an F1-score of 0.987 and they were 3% more accurate and sensitive than individual classifiers, and the Pareto-optimal process and maintenance schedules were established as equally acceptable alternative options for decision making. [10].

One of the primary issues in smart manufacturing is interpreting information and deriving insights from data. A use case in the steel industry takes advantage of recent advances in ML in PdM and PsM analytics by utilizing corporate and operational data to assist operators on the shopfloor. Recurrent Neural Networks are used for predictive analytics, and Multi-Objective Reinforcement Learning is used for prescriptive analytics [11].

PsM is also used in the aviation sector finding application in a tire pressure indicator system, with the goal of lowering operating costs and boosting operational stability. However, research has been confined to calculating remaining usable lifespan while ignoring the influence on surrounding processes, changes in the aims of the associated stakeholders, and so on. The maturity level of the condition monitoring system must be considered when evaluating the potential of a fault diagnosis and failure prognosis system, including its implications on neighboring maintenance procedures. A PsM strategy is proposed by modeling the many stakeholders engaged in aircraft and line maintenance operations, as well as their functional connections. The findings are validated using an automated condition monitoring system that generates discrete-events and an agent-based simulation setup based on one-month's flight plan data [12].

Moreover, the aviation business is under increased competition to reduce operational costs, while features such as sustainability and customer experience are critical for differentiating from rivals. Aircraft maintenance accounts for about 20% of the total cost of airline operations. Consequently, maintenance providers must reduce their cost fraction and contribute to a more dependable and sustainable aircraft operation. The primary objective is to reduce costs while improving aircraft availability. A framework is established for the use case of an Airbus A320 tire pressure measuring task, allowing the optimization target for the proposed approach to be adjusted to integrate performance attributes other than the often used financial indicators [13].

In the PsM use case of a chemical complex system and a cooling water system, there is the possibility for anomalous operations and an unwanted increased occurrence of process safety events. A study proposes a multi-feature based paradigm for process control that is safety-aware, maintenance-aware, and disruption-aware. For fault detection, it employs ensemble classification using ML classifiers. Also, mixed integer nonlinear programming for integrated safety-aware production and maintenance scheduling, and hybrid multi-feature model predictive control for fault-tolerant set point tracking. In terms of fault detection accuracy, sensitivity, and specificity, the findings reveal that the ensemble classifier beats the individual classifiers. The designed controllers can alter control actions based on process disruption data. [14].

The high equipment intensity and complexity of semiconductor manufacturing processes results in severe facility availability requirements in this competitive sector. A conceptual approach that enables PsM in the use case of etching equipment for semiconductor production addresses such issues. ML methods forecast time-to-failure periods, whereas Bayesian Networks identify the core cause of a malfunction. When these procedures are combined, prescriptions for maintenance planning routines are generated, while system availability is increased. [15].

PsM is also used in protective coating systems against steel corrosion for tower components of big onshore wind turbines. The inspection, condition monitoring, and maintenance of such systems is an intensive and time-consuming task that necessitates a significant amount of human labor. The notion of a digital twin is introduced, with the initial guiding principle being an on-site virtual twin for producing reference regions for condition monitoring. The integration of an online picture annotation and processing tool, a maintenance strategy, corrosive resistance characteristics, structural load indicators, and sensor data is described in this study [16].

The state of the art in PsM finds applications in a variety of use cases. These include, but are not limited to energy sector and electric utilities, IoT and sensors, railway networks and circuit tracking, Industry 4.0 with deterioration, aging and equipment downtime, steel industry operations, aviation and the tire pressure measuring task, chemical complex systems with water cooling systems, semiconductor etching equipment and protective coating systems.

3 Framework proposal

This section proposes a framework for prescriptive maintenance in proactive buildings, as depicted in Fig. 1. It consists of three main components, i) the IoT data storage that gathers all IoT device data into a central database, ii) a decision support system that implements the prescriptive maintenance engine, anomaly detection, failure diagnosis and suggests prescriptions and iii) the knowledge extraction that handles the graphical user interface of the proposed framework offering functionalities, such as device health monitoring, options for maintenance and maintenance scheduling.

3.1 Data warehousing

The proposed approach will be implemented in various and heterogeneous buildings situated in four European countries: Greece, Spain, Germany and the Netherlands. The provided datasets will vary based on the actual, historical or forecasted [17] user energy habits, activities and also the climate. Indicatively, different climate zones result in different heating, cooling or ventilation systems and technologies.

Specifically, in Greece and Spain, due to high temperatures during the summer, Air Conditioning (AC) or Heating, Ventilation and Air Conditioning (HVAC) systems are more likely to exist compared to Germany and Netherlands. Furthermore, there are buildings that have a central heating system (e.g., central

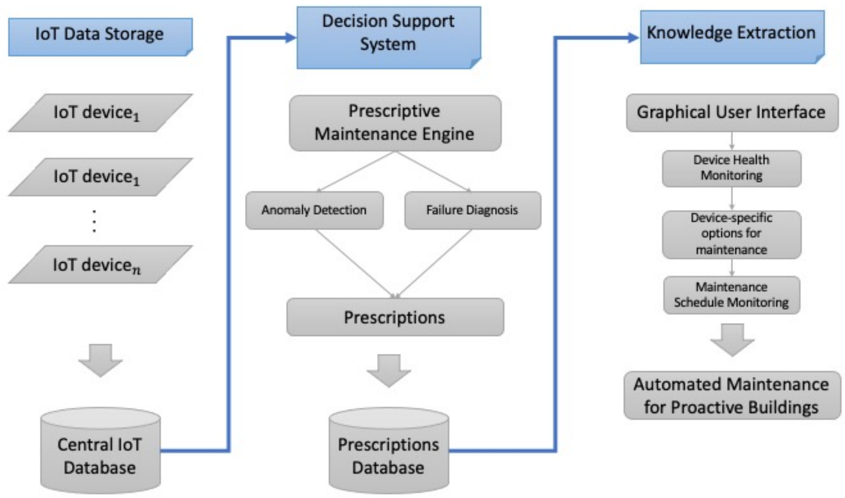

Fig. 1. Overview of framework architecture

heat pump), while others have a heating system per apartment. A summary of the data that will be used is presented in Table 1.

3.2 Anomaly Detection

Anomalies are identified by detecting uncommon observations that differ considerably from the given dataset [18]. Recognizing non-standard device behavior is seen as a major duty in the energy business. Small-scale residential and industrial environments can benefit from anomaly detection on device condition, maintenance needs, and unavailability, which can lead to lower infrastructure costs.

Furthermore, anomaly detection is widely used in data pre-processing [19] to remove outliers from records. This is a procedure that is being carried out for a variety of reasons. For example, once anomalies are eliminated, data metrics, such as the mean and standard deviation become more accurate, but also data presentation may be improved. When implementing a supervised learning task, removing anomalous data usually results in a statistically significant increase in accuracy. Anomalies are typically the most essential findings to be uncovered in IoT [20].

There are numerous methods for detecting irregularities in a number of application scenarios, including prescriptive appliance maintenance. These may include machine and deep learning approaches such as Support Vector Machine (SVM), Convolutional Neural Networks (CNN), Long Short Term Memory Networks (LSTM), CNN-autoencoder, LSTM-autoencoder and more as well as their respective outcomes measured using a variety of common metrics such as Precision, Recall, F1 Score and more.

Table 1. Overview of the data warehousing

	Greece	**Spain**	**Germany**	**Netherlands**
Building structure	concrete	concrete	brick	brick
Domestic hot water	solar system combined with electricity	decentralized-local electric boiler or heat pump	centralized from the building boiler room	decentralized-local electric boiler or heat pump
Infrastructure	electricity, heating, water system, internet and cable	electricity, water system, central heating system, HVAC, internet and cable	electricity, heating, water system, internet and cable	electricity, heating, water, internet and cable
Home appliances	television, fridge, AC, water heater, oven, microwave, washing machine, dishwasher and dryer	television, fridge, electric water heater, oven, stove, HVAC splits, dish washer, washing machine and dryer	television, fridge, electric stove, washing machine	fridge, electric heater, electric oven, washing machine and dryer
Electrical vehicle	two charging spots for electric vehicles	N/A	N/A	N/A

3.3 Failure diagnosis and prescriptions

Initially, an error is recognized in the device's regular behavior as a result of a specific problem. This error is classified to specific faults through a diagnostics process and then prescriptions are sent to the user. Such failures and recommended prescriptions are indicatively presented for widely-used home appliances (Table 2). The devices include faults (diagnosis) and course of action (prescriptions) for common household appliances like the fridge, the washing machine and the AC.

3.4 Knowledge extraction

Knowledge extraction comes as a software-as-a-service implementation fostered by a graphical user interface that offers the following services. i) Device health monitoring, ii) device-specific options for maintenance, and iii) maintenance schedule monitoring. Generally, Knowledge Extraction and Application (KEA) methods intend to analyze all gathered information, data, models and methods

Table 2. Failure diagnosis and prescriptions for widely-used home appliances

Device	Diagnosis	Prescription
Fridge	-Freezer is not cold enough -Unit is cycling too often -Frost buildup -Refrigerator is freezing food	-Check compressor and clean any dust -Set the temperature higher or remove the dust buildup or debris around the condenser coils -Inspect the damper door for air leakage -Replace the thermostat
Washing machine	-Washing machine moves around -Washing machine is noisy -Draining issues/ Washing machine does not fill with water	-Level washing machine to the ground, check suspension rods -Remove items from the washing drum or contact a technician -Check the filter for blockages -Locate the hoses and check for blockages or kinks
AC	-Refrigerant leaks -Low performance -Cycle constantly or behave erratically -Drainage issues	-Contact a technician -Contact a technician for maintenance -Thermostat sensor problem -Check the condensate drain and clean it

to facilitate the decision making. KEA improves all available information and data by contextualizing information and knowledge. The result is an automated maintenance for proactive buildings. Taking into consideration infrastructures' current and historical information is the the first step towards knowledge extraction.

Having a record of the devices' normal consumption pattern and behaviour under certain circumstances will facilitate detecting any anomalies and diagnosing any potential health device problems. Device health monitoring intends to keep a check on the devices behaviour and performance while detecting any perplexing motifs. Consequently, home appliances and devices are meant to constantly operate and perform well over the years. Proper devices' maintenance will help the devices to extend their life-span. As a result, device-specific options for maintenance will alert the owner to take immediate actions that will maintain a smooth operation. Finally, a report about scheduled maintenance ensures that periodic maintenance actions will occur.

4 Conclusion

In reality, PsM is even more proactive than PdM. PdM forecasts when a failure is likely to occur so that repair may be scheduled ahead of time. PsM seeks to prevent particular types of failure completely. This paper investigates the state of the art in PsM reporting on multi-domain use cases and conceives a theoretical framework that enables PsM for proactive buildings that may also be considered as microgrids [21].

This work sets the grounds for the deployment and operation of proactive residential buildings. It will implement and test a prescriptive and proactive building energy management system that will learn and will be self-managed, -monitored and -optimized regarding the building operation. This research will focus on delivering supervised and unsupervised ML technologies capable of detecting and predicting the potential malfunctions in the building appliances, and to recommend appropriate actions.

At the current status of framework implementation limitations can be attributed to the fact that this research does not consider data granularity [22] due to the absence of open data sources for experimenting with the conceived approach. The absence of such details renders the conception of the PsM framework for proactive buildings, a theoretical approach. Therefore, an analytical and comparative analysis regarding the options of open dataset is not possible. Also, appropriate data gathering and extraction of features are beneficial in enhancing algorithm performance for classic ML algorithms, however for Deep Learning algorithms, deeper network architecture and larger dimensional feature vectors are more essential for achieving better metric evaluation scores.

PsM can detect capital expenditure requirements considerably sooner than human perception would. PsM tools, for example, can act as a digital testing environment, particularly when combined with a digital twin architecture, allowing the consequences of adding or replacing equipment to be simulated before making a purchase. This enables asset managers to arrange purchases and acquisitions more intelligently, decreasing both appliance downtime and operational expenses.

To sum up, this paper acts a as concrete baseline for experimenting with real data for generating prescriptions for proactive buildings. The main outcome of this work conceptualizes a theoretical framework as a PsM tool that enables building pro-activeness. It poses as a generic solution when engaging in PsM and considering building assets. The aim is to improve this study investigating the following aspects.

- Continue tracking the growth of PsM and analytics with a focus on household appliances. Improve the implement the conceived PsM framework by addressing constraints and extending our understanding of the data granularity, that is necessary for more informed prescriptions.
- Improve the proposed PsM framework by further automating the process of outputting prescriptions so that it may function as a stand-alone program with only the necessary input datasets.
- Examine and integrate environmental Key Point Indicators (KPIs) such as energy bills, water bills, purchase records, emissions to air, emissions to water, emissions to land, and resource usage while offering appliance prescriptions.

– Elevate the proposed PsM framework's business viewpoint by addressing additional practical applications as well as expanding the evaluation to small scale industrial setups.

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