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ENHANCING OPERATIONAL EFFICIENCY IN INDUSTRY 4.0: A PREDICTIVE MAINTENANCE APPROACH

Abstract

Advancements of Industry 4.0 has revolutionized manufacturing operations, among them predictive maintenance (PdM) acts as one of the most demanding approaches. It effectively optimizes maintenance schedules and ensures efficient and uninterrupted work. Article provides a comprehensive literature review, offering insights into theoretical foundations, historical developments, and practical applications of predictive maintenance. The methodology section explains the research approach in detail, focusing on the development of a MATLAB-based code to generate the predictive model in accordance with the remaining useful life of the machine. Exploration into the application of PdM is made through the establishment of Bayesian Inference model informed by Pearson correlation analysis. This study underscores the possibilities of predictive analytics in enhancing operational accuracy and effectivity across various industries. As the demand for reliable manufacturing processes continues to grow, the findings of this research offer insights into the development of advanced PdM strategies and achievement of operational excellence in terms of smart manufacturing.

Key words: predictive maintenance (PdM), remaining useful life (RUL), industry 4.0, reliability.

Introduction

Over the past few years, our world in terms of technology has significantly changed, with the great contribution from the Fourth Industrial Revolution (Industry 4.0). It introduces a completely new approach to manufacturing operations, that is mainly based on the massive introduction of information technology, large-scale automation, and emergence of artificial intelligence. Many studies show that the concept of Industry 4.0 is directed to reduce expenditures, effectively manage resources, and increase the production time and quality [1].

The high level of competitiveness encourages companies to develop effective enterprise strategies, shift from traditional manufacturing methods into smart manufacturing. Smart factory is defined as a factory, where each equipment is linked over the Internet to exchange data with each other, thus providing full representation of operations and achieving safe, faster, and efficient control [2]. One of the key branches in the context of this approach, is predictive maintenance. This is becoming an inevitable tendency for many companies, as it provides a reliable solution for the management of equipment's "health status" [3]. Predictive maintenance models are mostly used as tools for early detection of anomalies. Thorough analysis of relevant data from critical equipment, detection of correlations between sensors, usage of historical data and visual analysis can provide a clear schedule and reduce unnecessary maintenance costs [4].

Companies from a wide variety of economic sectors and industries – be it oil and gas, metallurgy, food and beverage production, etc. – are actively seeking to modernize their production facilities with the introduction of digital technologies. They are particularly interested in the use of predictive analytics to anticipate future failures and optimize work processes, as the tendency shows that the traditional methods apply only after a failure occurred [5]. Current situation in Kazakhstan, especially recent news, show that country's facilities do not have any specific maintenance strategy. In example, the situation in thermal power plant in Ekibastuz. The high level of equipment wears and no clear maintenance, repair, and overhaul strategy, have led to a large-scale accident, which left most of the city without heat supply at air temperature down to minus 30 degrees [6]. This example is a great proof that the plants need to be modernized and digitalized.

Overall, the topic of predictive maintenance is not new. The bibliometric analysis of the Scopus database shows that there have been published research works from the 1980s. Figure 1 indicates that the analysis has yielded a comprehensive collection of 20 187 scholarly documents, with the growing trend. This means that with each year, interest towards this field of study has become more popular. Analysis of documents by subject area shows that a quarter of articles contributed to the field of engineering, while medicine and computer science occupy about 15% each.

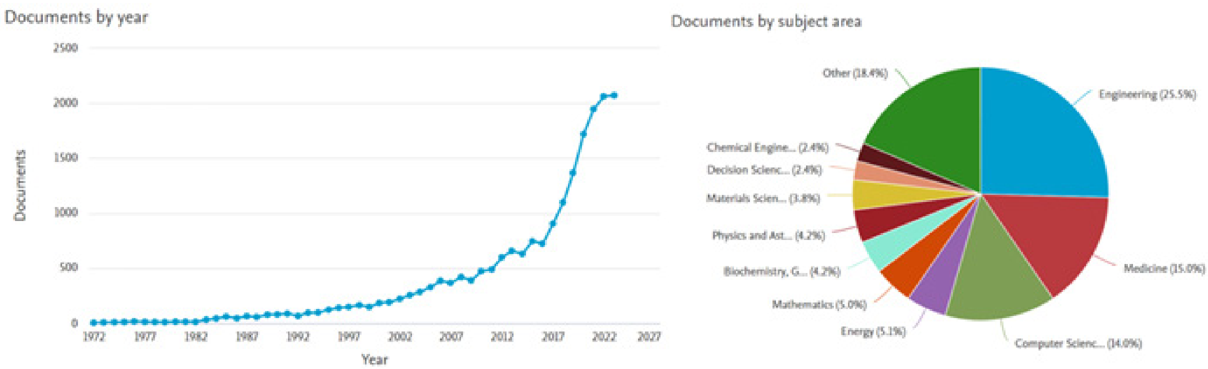

Figure 1 – Bibliometric Analysis

Literature Review

To uncover foundational theories and pivotal studies on the topic of predictive maintenance, exploration of the vast landscape of scholarly research is made in the section of literature review.

In the article [7], authors provide a systematic review on PdM application within Industry 4.0 across different manufacturing sectors. The main object of the study is to categorize maintenance by solutions and identify impact on operational efficiency. Researchers were able to determine that the data-driven applications are most common, which was proven through increasing interest in recent years in sectors, such as machinery, equipment manufacturing etc. Zhang et al. conducted a survey on the methods of predictive maintenance, which are model-based, knowledge-based, and data-driven prognosis [2]. Various factors, such as technological readiness, practical implementation, prove that the data-driven method is the most efficient as well as, the most widespread method in terms of PdM. This approach is based on analysis of historical and real-time data from sensors to further identify the patterns that show potential failures [8].

Article [9] showcases general overview of predictive maintenance. Authors explained in detail the life cycle of the solution implementation. Figure 2 demonstrates that the process initially starts with data collection (gathering necessary information), data pre-processing (determining relevant data), and model training for further establishment.

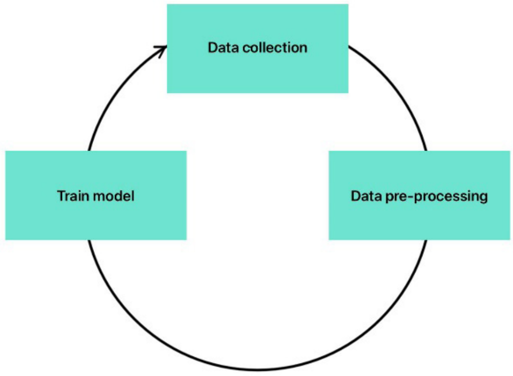

Figure 2 – Lifecycle

The main purpose of PdM is to reduce expenses by minimizing the time of repair, and by avoiding unnecessary maintenance works [10]. In terms of this perspective, Lie et al. outlines that prediction recognizes the failure with focus on identifying the leading cause of the fault to avoid similar problems in the future [11]. Analysis of healthy and unhealthy states of machines is helpful for fault prognosis for prediction of remaining useful life (RUL) [12]. RUL is an index for estimating the time left before an equipment reaches the end of its service [13].

In the work of “Challenges and Opportunities of Condition-based Predictive Maintenance: A Review”, authors outline that PdM makes the balance between costs of maintenance and performance [14]. Maintenance is scheduled in accordance with the measures such as efficiency, productivity and remaining useful life (RUL). Zuo et al. established that the physical composition of machines and its failure patterns are closely linked, thus serving as a basis for preventing unexpected issues [15].

There have been many case studies regarding the application of predictive maintenance. One of the examples is the Rolls-Royce company, known for their production of aircraft engines. Implementation of forecasting techniques through the usage of digital platforms, helped company in preventing delays by controlling maintenance requirements [16]. Another great example is Hyundai Motors, the world’s largest manufacturer. The company mainly uses artificial intelligence (AI) to determine vehicle failure based on the sensor detection system, which analyzes vibrations and therefore identifies engine abnormality [17]. The system has been proven to be effective, as the experiment results showcase that the accuracy rate from experts was nearly 9%, while the accuracy of the AI was approximately 10 times bigger [18].

Overall, research papers related to the current topic demonstrates that the trend for predictive analytics is positive and many manufacturing companies show interest in implementing this kind of technologies on their plants.

Methodology

The implementation process of PdM model on a real plant may take up to 6 months in terms of duration, due to internal processes, such as data preparation, pre-modeling, model training, project execution, service, and maintenance. For much newer plants this may take much longer, because it is necessary to have a historical database with equipment's operation properties. The general project implementation process is shown on the figure below.

Table 1 – Roadmap of the project

№	Stage
1	Data Acquisition Plant documents (P&IDs) Historical database backup Alarm list Maintenance logs, reports
2	Database Preparation Data integrity check Data clean-up Correlation matrix calculation
3	Pre-modeling Equipment definition Healthy periods & validation periods identification
4	Data Modeling & Training Modeling based on identified training periods Model validation
5	Results presentation Data analysis document Identify potential quick wins and actionable insights
6	Project Execution
7	Service & Maintenance

First, the process of establishing predictive maintenance model starts with the data acquisition, where the plant documents, historical database, alarm list etc., are gathered. During this stage data undergoes thorough check, where corrupted data is removed, and dimensionality of the dataset is reduced. The quality of the data directly affects the performance of the model; therefore, it is highly important to keep only relevant information [19].

In the next stages, exploratory analysis is made on the dataset. The relevant sensors are selected based on the correlation, which describes the time-related dependency between sensors [20]. The sensor's mode of operation shows a different behavioral pattern. Modes are divided into 3 categories: 1) period before a long shutdown, 2) period after long shutdown and 2) sensor failure. The figure 5 indicates how the long shutdown is represented.

The crucial factor in the application of PdM is determining correct metrics. As John Schultz, certified maintenance, and reliability professional, said the following: "... to improve something it is necessary to measure it, and to prove the productiveness of the program, clear and compelling data needs to be used" [21]. Based on the analysis of the data, the most important equipment will be chosen. Model will be built considering the historical data. The main algorithm used for the model training is Bayesian Inference, which allows improving model with each addition of newer data [22]. The maintenance algorithms will be implemented as soon as the model is trained and validated after thorough check.

Considering that obtaining real world datasets can be challenging, due to companies' privacy regulations and other reasons, a synthetic dataset is chosen for this research paper. This dataset is designed to emulate real predictive maintenance scenarios that may be encountered in the industry. The dataset contains 10, 000 data points with 14 features, such as temperature, torque, failure type etc.

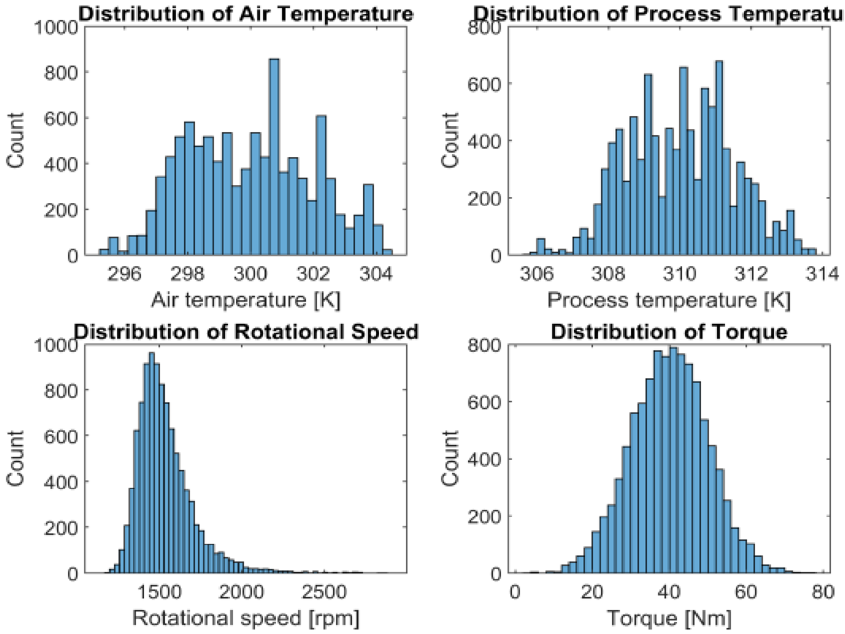

Figure 4 – Dataset visualization

Figure 4 outputs the distribution of key metrics in the dataset. Regarding the air temperature, distribution is normally distributed with a slight skew to the left, which means that there are more observations on the lower end of the temperature range. In comparison, process temperature is more spread out with multiple peaks. The rotational speed has a peak in approximately 1500 rpm, with common operational speed range with variations likely due to operational demands or machine settings. Torque displays a normal distribution, peak is at 40 Nm, with data clustering around the center of the range.

Results and Discussion

In this research, the main programming platform for creating the predictive model is MATLAB, which is widely used by engineers and scientists. As it was mentioned in the methodology section, dataset is prepared and loaded into software in a CSV (Comma-Separated Values) format.

After dataset preprocessing, the Pearson correlation matrix is created, where each correlation coefficient represents the certain relationship: 1 – displays the perfect positive linear relationship, -1 – displays the perfect negative linear relationship, while 0 – showcases no linear relationship [23]. The output of the matrix is demonstrated in the table below.

Table 2 – Pearson Correlation matrix

	Air temp	Process temp	Rotation speed	Torque	Tool wear	Target
Air temp	1.0000	0.8761	0.0227	-0.0138	0.0139	0.0826
Process temp	0.8761	1.0000	0.0193	-0.0141	0.0135	0.0359
Rotational speed	0.0227	0.0.193	1.0000	-0.8750	0.0002	-0.0442
Torque	-0.0138	-0.0141	-0.8750	1.0000	-0.0031	0.1913
Tool wear	0.0139	0.0135	0.0002	-0.0031	1.0000	0.1054
Target	0.0826	0.0359	-0.0442	0.1913	0.1054	1.0000

According to the table 1, air and process temperature have a correlation coefficient of 0.8761, which is a strong and positive correlation. Conversely, rotational speed and torque have a correlation coefficient of -0.8750, this shows that as rotational speed increases, torque decreases. As the tool wear increases, equipment tends to have a failure, which is logical. In terms of 'Target', in the dataset it is a binary variable that indicates whether maintenance is needed or not. Target has positive correlation with air temperature and torque, with torque being the most relevant predictor for the target among all the other variables in the dataset.

```
X = table2array(data(:, {'AirTemperature_K_', 'ProcessTemperature_K_', 'RotationalSpeed_rpm_', ...
    'Torque_Nm_', 'ToolWear_min_'}));
Y = data.Target;
cv = cvpartition(size(X,1),'HoldOut',0.3);
idx = cv.test;
XTrain = X(~idx,:);
YTrain = Y(~idx,:);
XTest = X(idx,:);
YTest = Y(idx,:);
BayesModel = fitcnb(XTrain, YTrain, 'DistributionNames', 'kernel');
YPred = predict(BayesModel, XTest);
```

Figure 5 – Bayesian Inference Model

Furthermore, the Bayesian inference model is implemented, code part of the model is shown in the figure below. Firstly, the dataset was divided into two groups, where 70% of the data is used for training the model, while remaining 30% would be used for testing the performance of the model. Next, data training is accompanied by the Naïve Bayes classifier, which is considered as a probabilistic classifier that can generate accurate results [24].

```
accuracy = sum(YTest == YPred) / length(YTest);
fprintf('Model Accuracy: %.2f%%\n', accuracy * 100);
```

```
Model Accuracy: 96.83%
```

Figure 6 – Model Evaluation

To evaluate the model, accuracy is calculated. It shows that it is equal to 96.83%, which means that the effectiveness of the model is high. Using predictive maintenance, it was possible to detect sudden anomalies as well as slow changes of the process in systems of multiple highly correlated sensors. Moreover, generation of early warnings for problems which finally lead to unplanned plant shutdowns.

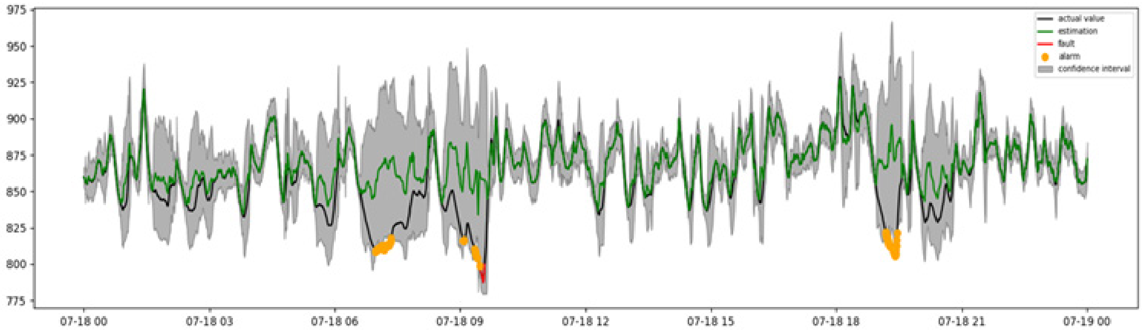

Figure 7 – Prediction visualization

Figure 7 shows the records of the equipment, there are actual values, estimated values, fault, alarm and confidence interval. Enlarged version of is displayed in the figure 8. These figures are used to make a better visualization of the predictive maintenance model.

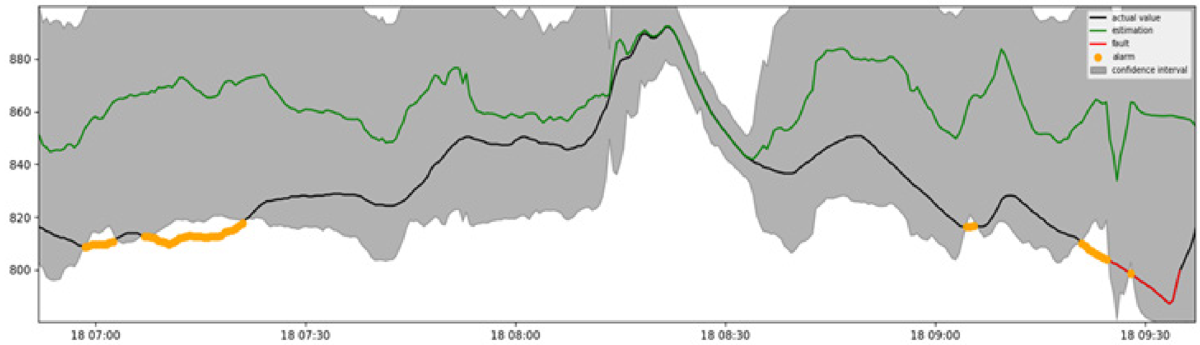

Figure 8 – Enlarged version

The predictive maintenance model generates alarm around 2.5 hours earlier than failure itself occurs. The yellow lines show the first ever alarm happens at 7:00 and at 9:04, with the failure occurring at 9:22. Thus, the figure suggests that the predictive maintenance method works accurately.

Conclusion

Predictive maintenance is an approach that involves usage of data from intellectual sensors and identification of patterns that indicate potential equipment failures. Application of PdM methodologies for equipment failure prediction has proven to be a valuable and effective approach in enhancing the reliability and performance of industrial assets.

Through a systematic analysis of failure modes, their consequences, and the implementation of predictive maintenance strategies, this study aimed to improve the overall equipment reliability and reduce unplanned downtime. As industries embrace advanced technologies and data-driven approaches, the role of PdM in equipment failure prediction becomes increasingly pivotal for achieving sustained operational excellence.

Although many studies performed a successful job in the implementation of software, there are still certain areas that needs more improvements. Manufacturing processes are becoming unpredictable with a high degree of variability and uncertainty. Industrial plants require trouble-free operation with minimum downtime. Thus, it is highly necessary for making further developments in this field of study.

In terms of this research, there are limitations regarding the dataset and model training. For further studies it would be better to establish a predictive maintenance model on a real-life dataset from the working plant. Additionally, connect the predictive maintenance model or realize the prognostic diagnosis with the high-level SCADA systems, as they are directly connected to the equipment and monitored in their own databases.

Overall, this research paper acts as a foundation for making predictions on maintenance, repair and overhaul works on much bigger plants. Tendency demonstrates that the interest towards this is high and will be more in-demand in near future.

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ИНДУСТРИЯ 4.0 ОПЕРАЦИЯЛЫҚ ТИІМДІЛІГІН ЖАҚСАРТУ: ПРЕДИКТИВТІ ҚЫЗМЕТ КӨРСЕТУ ТӘСІЛІ

Аңдатпа

Индустрия 4.0 жетістіктері предиктивті қызмет көрсету тәсілдерін қамтыған өндірістік операцияларда төңкеріс жасады. Бұл әдіс техникалық қызмет көрсету кестелерін тиімді оптимизациялау және үздіксіз жұмыс істеуін қамтамасыз ету арқылы маңызды тәсілдердің бірі. Зерттеу жұмысында алдын ала техникалық қызмет көрсетудің теориялық негіздері, тарихи оқиғалары және практикалық қолданылуы туралы кешенді әдебиет шолу ұсынылған. Әдістемелік бөлімде жабдықтың қалған қызмет ету мерзіміне сәйкес предиктивті модель жасау үшін MATLAB негізіндегі кодты әзірлеуге назар аударыла отырып, зерттеу тәсілі мұқият түсіндіріледі. Алдын ала техникалық қызмет көрсетуді қолдану зерттеуі Пирсон корреляциялық талдауына негізделген Байес шығармашылығы моделін құру арқылы жүргізіледі. Бұл зерттеу операциялық дәлдік пен тиімділікті әртүрлі салаларда арттыруда болжамдық аналитиканың мүмкіндіктерін атап өтеді. Сенімді өндірістік процестерге сұраныс өсе түскен сайын, бұл зерттеудің нәтижелері техникалық қызмет көрсетудің озық стратегияларын дамыту және интеллектуалды өндірістің тұрғысынан операциялық шеберлікке жету туралы түсінік береді.

Тірек сөздер: предиктивті қызмет көрсету, пайдалы қызмет мерзімі, индустрия 4.0, сенімділік.

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УЛУЧШЕНИЕ ОПЕРАЦИОННОЙ ЭФФЕКТИВНОСТИ В ИНДУСТРИИ 4.0: ПОДХОД ПРЕДИКТИВНОГО ОБСЛУЖИВАНИЯ

Аннотация

Достижения индустрии 4.0 произвели революцию в производственных операциях, среди которых присутствует метод предиктивного обслуживания. Данный метод выступает одним из наиболее требовательных подходов за счет эффективной оптимизации графиков технического обслуживания и обеспечения продуктивной и бесперебойной работы. В статье представлен всесторонний обзор литературы, дающий представление о теоретических основах, исторических событиях и практическом применении прогнозного обслуживания. В разделе методологии подробно объясняется подход к исследованию, уделяется особое внимание разработке кода на основе MATLAB для создания прогнозной модели в соответствии с оставшимся сроком службы оборудования. Исследование применения предиктивного обслуживания проводится путем создания модели Байесовского вывода, основанной на корреляционном анализе Пирсона. Это исследование подчеркивает возможности прогнозной аналитики в повышении операционной точности и эффективности в различных отраслях. Поскольку спрос на надежные производственные процессы продолжает расти, результаты этого исследования дают представление о разработке передовых стратегий предиктивного обслуживания и достижении операционного совершенства с точки зрения интеллектуального производства.

Ключевые слова: предиктивное обслуживание, срок полезного использования, индустрия 4.0, надежность.