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ЕЛЕКТРИЧНИЙ ТРАНСПОРТ, ЕНЕРГЕТИЧНІ СИСТЕМИ ТА КОМПЛЕКСИ

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Real-Time Assessment of the Technical Condition of Traction Motors Using Machine Learning and IoT Technologies

Purpose. The purpose of this research is to analyze machine learning algorithms, select the most accurate and efficient algorithm for diagnosing the technical condition of an induction traction motor based on operating parameters such as temperature, noise, and vibration, and study the features of using Internet of Things (IoT) technology to assess technical conditions in real time. **Methodology.** The machine learning algorithm suitable for diagnosing the technical condition of asynchronous traction motors was identified through analysis and comparative methods. **Findings.** Machine learning algorithms were analyzed, and two distinct algorithms, K-means and Extreme Machine Learning (EML), were selected for diagnosing the technical condition of asynchronous motors. The algorithms were compared based on performance metrics such as accuracy, specificity, sensitivity, positive predictive value, and negative predictive value. The results revealed that the EML algorithm outperformed K-means in these metrics, achieving an overall performance score of 93%. **Originality.** A novel system was proposed that integrates a machine learning model with IoT technology for real-time diagnostics of the technical condition of traction electric motors. This innovative approach enables dynamic monitoring of the motor's technical state. Compared to traditional temperature diagnostic systems, such a multi-parameter system will allow you to determine a specific malfunction. **Practical value.** The proposed system, based on a machine learning model, evaluates the technical condition of traction motors in real-time using IoT. It provides recommendations on when maintenance should be performed, based on the actual condition of the motor. The system allows for maintenance planning based on real-time diagnostics, facilitating a shift from scheduled maintenance to predictive maintenance strategies. This, in turn, increases operational lifespan and minimizes unplanned downtime. By leveraging IoT, the diagnostic system can integrate with motor control systems or SCADA systems, enabling remote monitoring and control of motor operations.

Keywords: traction motor; technical condition monitoring; fault detection; intelligent diagnostics; machine learning algorithms; predictive maintenance

Introduction

Nowadays, asynchronous motors are the most widely used electric machines to drive mechanisms in various fields such as transportation, manufacturing, petroleum, and energy systems industries. 40–60% of the electric energy produced in the world is consumed by asynchronous motors with high reliability and efficiency, low cost, and stable operating speed. In addition to the high reliability of asynchronous motors, it is also possible to have some inevitable failures due to overloads, mode changes, especially during transportation, variable environmental effects, failures during installation and maintenance, etc. It is known that failures associated with asynchronous motors are generally divided into two broad categories: electrical failures and mechanical failures [2, 7].

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Electrical faults consist of stator faults and rotor faults, while mechanical faults include eccentricity (imbalance), bearing, and shaft faults. Statistically, among these, mechanical faults, especially bearing faults, are a serious problem for motors.

Purpose

Bearings being an important equipment in the traction motor, the main purpose of its application is to ensure high speed and less friction. Heavy loads, increased mechanical stress, pollution, etc., cases can cause defects in the form of cracks on the surface of the bearings. In addition, increased loads can increase the severity of cracks, which are the main cause of bearing failure. To overcome these challenges, faults must be detected and diagnosed early as part of preventive maintenance. Early diagnosis and detection of faults is also one of the most important issues in transportation, as it is an important tool to prevent damage that can cause disruptions in the entire system.

Preventive maintenance is based on monitoring the condition of the traction electric motor (TEM) and allows for the prediction and prevention of faults in time before they occur. This increases the reliability of the TEM and reduces maintenance costs. Condition monitoring of the TEMs consists of several main stages: determining the fault location; detection of faulty parts; diagnosis of faults and their causes in the relevant parts; prediction of faults and prevention of faults before they occur.

These stages are carried out with the help of sensors installed in the TEM that measure voltage, current, temperature, vibration, and noise level. Recently, the monitoring of the technical condition of devices based on machine learning methods (ML) has become more and more important [1, 4, 10, 11].

Today, the development of ML has become a leading direction in fault diagnosis. The ML model is a subset of artificial intelligence (AI), and it collects data using various sensors placed on the TEM under different operating conditions.

Methodology

The main machine learning algorithms used to determine the technical condition of TEMs are:

Fault detection with unsupervised learning. K-means clustering helps to identify faulty conditions by grouping various operating parameters. Density-Based Spatial Clustering of Noisy Applications – DBSCAN is an unsupervised learning algorithm known as the density-based clustering method. DBSCAN defines clusters based on the density in a dataset and is mainly used to identify abnormal or noisy points in the data. Principal Component Analysis – PCA – facilitates the detection of abnormal conditions in motor operation through dimensionality reduction and feature detection.

Diagnosis of faults with supervised learning. Decision Trees and Random Forests are used to make diagnostic decisions by classifying different types of faults. Support Vector Machines – SVM – performs classification by drawing a boundary to separate normal and faulty motor conditions. Neural Networks – improve fault diagnosis by learning complex fault models.

Fault detection based on reinforcement learning. Q-learning and Deep Q-Nets – DQN – dynamically monitor the operating status of TEMs and suggest strategies to minimize the risks of failures by determining the most suitable operating mode.

Time series analysis. Recurrent Neural Networks – RNN and Long Short-Term Memory – LSTM – help to predict the long-term status and possible failures of the TEM by examining changes in sensor data over time. Integrated Moving Average with Auto Regression – ARIMA – predicts what changes will occur in the future based on the history of TEM parameters.

Deep learning for predictive maintenance. Convolutional Neural Networks – CNN – predict different types of failures by extracting features from large amounts of sensor data, such as vibration or noise analysis. Autoencoders – learn the normal operating mode and detect anomalies, especially in cases where the TEM parameters deviate from the standard profile.

Feature extraction and selection algorithms. Wavelet Transforms and Fourier Transforms – analyze vibration and noise signals to extract features that may indicate changes and failures in the TEM. Mutual Information and Correlation Analysis – ensures that only information that directly affects the condition of the TEM is used, identifying the most important characteristics.

Thus, with the combination of these algorithms, it is possible to accurately and effectively determine

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the technical condition of electric motors. The applied methods are selected and optimized based on the type of data received from the motor, the amount of data, and the type of faults [4, 8, 10, 16, 19].

The machine learning algorithms used to determine the technical condition of electric motors can vary depending on factors such as the quality and quantity of data, as well as the nature of specific faults.

Support Vector Machines – SVM. SVM, one of the supervised learning methods, is one of the algorithms effectively used in diagnosing motor faults. This algorithm is especially suitable for classifying nonlinear and complex data. SVM is superior in detecting motor faults due to a number of basic features:

Signal processing and classification. Electric motors produce different types of signals while operating, and in the event of a fault, there are changes in these signals. SVM can distinguish between normal and faulty situations by classifying these signals. At this point, it is important to select and process the features correctly, because the classification accuracy of SVM depends on it.

Linear and nonlinear detection. SVM can classify motor fault types as linear and nonlinear. For nonlinear problems, SVM maps the data to a higher dimension using kernel functions, thus enabling nonlinear classification.

Vibration and noise analysis. One of the most common faults in electric motors is bearing failure, which is reflected in vibration analysis. SVM can detect abnormalities and determine the type of fault by processing the vibration data.

Detection accuracy. SVM can accurately determine the type of fault by classifying it into two or more classes based on training data. This approach allows you to determine the exact type of fault and take timely repair or replacement measures.

Working with large-scale data. The data collected from the motor is large and has a complex structure. SVM is ideal for working with large volumes of data and processing them with high accuracy. This helps to detect the fault at an early stage.

Diagnosis of motor faults with the help of SVM is carried out in the following order.

Data collection and processing. Real-time or historical data is collected from the motor. This data is first processed and separated into features, for example, features are extracted by methods such as spectral analysis of the current or the Fourier transform of vibration.

Algorithm training. Based on the collected features, the algorithm is trained. Labeled data representing normal and faulty states are fed to the SVM, and the SVM draws a boundary between these classes. Choosing the correct kernel function and parameter values during training increases the accuracy of the SVM.

Testing and performance evaluation. After training, the algorithm is tested and its performance is evaluated according to criteria such as precision, sensitivity, and recall. Hyperparameter tuning of SVM parameters is important for high performance.

Real-time monitoring. The trained SVM model is applied for real-time signal processing and instant error type determination. The model can detect potential errors in time by analyzing new data.

SVM has advantages such as high-accuracy classification, non-linear data structuring, fault detection and prediction at an early stage, long training time for large data, difficulties in adjusting parameters correctly, and proper selection of kernel (the choice of kernel affects the performance of the algorithm) [3, 9, 10, 16, 19].

The SVM algorithm is very useful in the fault diagnosis of electric motors because it supports the reliable operation of motors with features such as accuracy, stability, and overcoming nonlinear problems.

The main purpose here is to classify the signals received from TEM and determine their faulty or normal states. Let's consider the SVM-based motor fault diagnosis sequence.

Selection and preparation of features. Various signals are analyzed to determine the status of electric motors. From these signals, the necessary features for detecting faults are extracted. The following steps are taken to create the features. Frequency and amplitude analysis – there are changes in vibration and current frequencies in faulty motors. Frequency and amplitude data are obtained from the signals by analysis methods such as FT. Statistical parameters – statistical parameters such as mean, variance, maximum, and minimum

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signals are calculated. The specified features are used as input data in the SVM model.

Determination of the objective function. The objective function of SVM is expressed as follows and is optimized to classify the motor signals into two classes: normal and faulty.

$$\min f \cdot \frac{1}{2}\|\tau\|^2$$

here, τ – defines the direction of the optimum separation line between the features received from the motor. Minimizing the objective function maximizes the difference between the classes, allowing for a more accurate separation of the classes.

Application of limiting conditions. For fault detection, each state of the motor must be classified according to the limiting conditions of the SVM:

$$y_i\left(\omega \cdot x_i + v\right) \geq 1$$

here y_i – indicates the class label; in the fault case it is set to $y = -1$ and in the normal case it is set to $y = +1$, x_i – is the feature vector, v – is a free parameter.

These conditions are ensured so that the properties of the fault states remain on one side of the separation line and the normal states remain on the other side. Constraints increase the classification accuracy of the model and allow more accurate separation of failure states.

Choosing a Kernel function. In electric motors, Faults may incorporate nonlinear data. To improve performance of SVM in such situations, Kernel functions are employed. RBF kernel helps in classifying motor signals by non-linear separation of patterns from the separation line.

Kernel functions, such as RBF, aid in the advanced recognition of faults within the signals from the motor. The RBF kernel allows for motor signal components non-linear to the fault detection oscilloscope to be non-linearly separated. The Kernel function is the tool that divides non-linear classes in the lower dimensions and classifies them in the higher dimensions.

Training and testing models. The SVM model is trained with the available training data. The training set employs the features of the received signals from the motor with respect to the normal operational condition as well as the fault operational condition. After training the model, it is subjected to the test data so that the results can be measured against criteria such as accuracy, quality, and recall.

Optimally tuning kernel parameters together with the C parameter yields precise results for the SVM model sustenance. This parameter controls the trade-off made between the margin and the number of misclassifications. This value ought to be determinable within a reasonable range to fulfill the timely detection of failing motors.

Real-time application. Once the SVM model is trained, it can monitor signals from the motor in real-time and instantly identify any fault conditions. In a real-time setting, the model integrates new features to anticipate failure scenarios and issue alerts for prompt intervention. This method not only extends the lifespan of motors but also lowers maintenance expenses and reduces the likelihood of accidents that could arise from failures.

SVM is a machine learning model that linearly classifies different classes of data. This model can learn even with a small number of examples and has high generalization ability. The structure of SVM is shown in Figure 1.

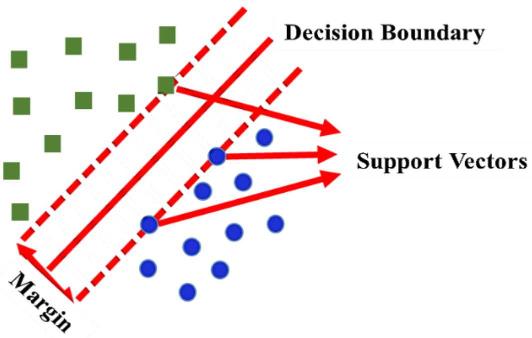

Fig. 1. Support vector machine architecture

A hyperplane is a decision boundary that linearly classifies the data; and the support vectors are the data closest to the hyperplane. Margin refers to the distance between the support vectors and the hyperplane.

In SVM, the hyperplane is expressed as:

$$d(x) = wx_i + b$$

where x_i – is the input data, w – is the weight vector perpendicular to the hyperplane, and b – is the bias. The length of the margin is calculated by the following equation:

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$$\text{margin} = \frac{2}{\|w\|} + C\sum_{i=1}^{n}\xi_i$$

where, ξ_i – is a smoothness variable added to adjust the misclassification rate when the data cannot be linearly classified in SVM, and C is a user-defined parameter. The higher the C value, the lower the allowable misclassification rate. In SVM, a hyperplane that maximizes the margin size should be selected. For this purpose, we set the minimum value of w. This is an optimization problem, and the constraint and objective function are given by Equations (1) and (2), respectively. The Lagrange emphasis method was used for optimization. The Lagrange emphasis method obtains a variable solution with partial derivative value equal to zero for all variables from the equation, which is obtained by multiplying the value of the constraints on the objective function by a new variable α. The final classification function of SVM obtained using the Lagrange emphasis method is expressed as follows:

$$f(x) = \sum_{i=1}^{N} a_i y_i K(x_i, x) + b$$

where a_i – is the Lagrange emphasis, y_i – The output data, N, represents the number of samples in the training data, and K – is the kernel. The kernel is used to transfer data to higher dimensions in non-linear classifications where the data cannot be linearly classified. A radial basis function (RBF) kernel was used in this study. The RBF kernel is expressed as:

$$K(x_i, x) = \exp\left(\frac{-\|x_i - x\|^2}{2\gamma^2}\right)$$

where γ – is a user-defined parameter that controls the flexibility of the decision boundary.

Decision Trees and Random Forest. The application of Decision Trees and Random Forest algorithms is effective for determining faults of electric motors. These algorithms help classify motor failure types and identify potential problems based on features in the data. These algorithms are particularly useful for monitoring the condition of components such as bearings, stators, rotors, etc. in electric motors and determining faults.

Decision Trees are a simple and effective classification algorithm. Based on the data collected from the electric motors, the tree structure is built by selecting the features.

The decision tree algorithm operates based on the following steps:

Feature selection. Data gathered from the motor, such as vibration, current, and temperature, serve as features for classification. Each feature can significantly influence the representation of fault conditions in the motor. For instance, in the case of a bearing fault, the vibration feature is crucial, whereas for a stator fault, changes in current are more telling.

Classification setup. A decision tree formulates decision rules at each node by selecting the optimal classification points (splits) based on the features. For example, a decision node might state «Vibration > 0.5 mm/s» or «Temperature > 90 °C» Each node aids in pinpointing the fault condition, thereby enhancing the classification process.

Metrics for classification. Decision trees identify the best split points using methods like entropy or the Gini index during data splitting. These techniques help improve the accuracy of the classification within the tree.

The Random Forest algorithm is a very powerful algorithm that consists of a combination of several decision trees. Random Forest is widely used to improve accuracy in fault diagnosis of electric motors. The working principle of the Random Forest algorithm is implemented in the following order.

Random Forest is built by creating several decision trees, each trained on different subsets of data and features. By using bootstrapping, each tree learns to develop its own classification rules, allowing for varied analyses of motor faults.

During the creation of each tree, features are chosen at random. This randomness helps the model remain flexible and ensures that decisions are made based on a diverse set of features.

The final classification in Random Forest is determined through majority voting. Each decision tree casts its vote, and the most common classification among them is selected. This approach minimizes the chances of misclassification and enhances the overall reliability of the outcomes.

Decision Trees and Random Forest algorithms build decision rules in a tree structure using various features in the data to classify electric motor faults.

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The theoretical foundations and formulas of these algorithms play an important role for fault determination.

K-means algorithm. K-means is an unsupervised learning algorithm (ULA) that combines datasets into unique subsets. It is also called center-based clustering algorithm [4]. Unique subgroups are called clusters. It takes the data as the center value and minimizes around the center according to the data distance. The function of the K-means algorithm is expressed as follows:

$$J(V)=\sum_{i=1}^{a}\sum_{j=1}^{a_i}(\|b_i-c_i\|)^2$$

where, a – is the number of cluster centers; a_i – is the number of data points in the first cluster; b_i and c_j – are the Euclidean distance (closest distance) between b_i and c_j; b_i – is a set of data points; and c_j – is the set of cluster centers [1, 8–11, 16, 19].

The sequence of operation of the K-means algorithm consists of the following:

– Randomly determines the center (i) from the given data points (bj);

– Compares other data points according to the nearest center;

– Still recalculates the surrounding data set for the center and forms another set;

– Convergence is checked and step II is performed again, and so on.

Extreme Machine Learning algorithm. Extreme machine learning (EML) is a supervised learning model that combines several learning models to improve ML results. The EML algorithm is divided into two groups, basic and advanced techniques. The EML and its activation function (Ψ_i) are expressed as follows:

$$a_n=\sum_{i=1}^{h}\beta_i\psi_i(b_n)=\sum_{i=1}^{h}\beta_i\psi_i(x_i b_n+\gamma_i)$$

where, h – hidden nodes; weight vector between input node x_i and hidden node i; β_i – is the weight vector between the output node and the ith hidden node; and γ_i – is the threshold for the ith hidden node.

The steps involved in the EML algorithm are as follows:

– Launch data subgroups for training;

– Captures data sets and builds a system to better predict and summarize performance;

– A decision is made using any of the clustering techniques.

Single-hidden Layer Feed-forward Neural Network (SLFNN) is used as a classifier to classify traction motors in good condition and requiring maintenance [5, 9-13]. In addition, a differentiator function is used to select the input significances and biases of the hidden layer.

Combined use of machine learning algorithms in fault determınation of electric motors. The combined use of K-means, External Machine Learning, Decision Tree, and Random Forest Algorithms in determining the faults of electric motors requires the synthesis of mathematical models and algorithmic approaches. This model combines the advantages of each algorithm to provide more accurate and reliable fault diagnosis. Now let's consider the mathematical models of these algorithms and their joint use.

K-means clustering involves dividing the data into $X=\{x_1, x_2,...,x_n\}$ clusters. The objective of this model is to identify the cluster centers and allocate the data points to the clusters that are nearest to these centers.

– Cluster centers $C=\{c_1, c_2,...,c_k\}$ are selected.

– Data are divided into clusters:

$$\arg\min_j \|x_i-c_j\|^2$$

where i = 1, 2,..., n and j = 1, 2,..., k

– Renovation of centers:

$$c_j=\frac{1}{|S_j|}\sum_{x_i\in S_j}x_i$$

where S_j – is the set of elements in the jth cluster.

Extreme Learning Machine (ELM) utilizes random weights and biases in the input layer. This model enables a quicker training process, allowing for accurate output predictions.

– Connection between input and output:

$$H=f(W\cdot X+b)$$

where H – is the hidden layer, W – is the input layer weights, b is the bias, X – is the input data, and f – is the activation function.

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– Output prediction:

$$Y = H \cdot \beta$$

where Y – is the output of the model and β – is the weights of the output layer.

– Weight adjustment:

$$\beta = \left(H^F H\right)^{-1} H^F F$$

where F – is the target output.

Decision Tree classifies data by making partitioning decisions at each node. The core idea behind the decision tree model is to enhance the information gained from each data partition.

– Gini index (to measure the homogeneity of the classification):

$$Gini(D) = 1 - \sum_{i=1}^{c} p_i^2$$

where p_i – is the probability of class i.

– Section by feature:

$$Gini\left(D, A\right) = \sum_{v \in A} \frac{\left|D_v\right|}{\left|D\right|} Gini\left(D_v\right)$$

– Choosing the optimal feature:

$$\arg\min_A \; Gini\left(D, A\right)$$

4. Random Forest. Random Forest consists of several decision trees, and the results of each tree are combined to obtain a final result.

– Adjustment of decision rules for each tree:

$$Y_i = f_i\left(X\right)$$
$$i = 1, 2, ..., n$$

where f_i – is the function of the ith tree.

– Final forecast:

$$Y_{final} = \frac{i}{n} \sum_{i=1}^{n} Y_i$$

Using the Collaborative Model. The joint use of these algorithms occurs in the following stages:

– Clustering with K-means. Motor data is clustered with k-means. As a result, the centers of each given group are found.

– Learning with ELM. The clustered data are fed into the ELM model. The output of the ELM model is used to determine the fault type.

– Classification with Decision Tree and Random Forest. The results from ELM are fed into Decision Tree and Random Forest models. The prediction of each tree is combined to obtain a final fault classification.

With the joint application of the mentioned models, more accurate, fast, and reliable results can be obtained in the detection of faults of electric motors. Mathematical models of each algorithm provide a complete analysis of data and effectively implement the process of fault determination. The joint model is also useful for identifying new fault patterns with adaptive learning capabilities.

Thus, the aim of the research work is to create and implement an intelligent system to monitor the technical condition of TEMs operated in transport in real time by applying various machine learning algorithms and methods.

The article used two ML algorithms to evaluate the technical condition of the motor in real-time.

One of the most common components to fail in a TEM is the bearings. Bearing failures can occur due to overheating, fatigue, corrosion, contamination, excessive mechanical loading, and other factors. In this study, key diagnostic parameters such as voltage, current, temperature, noise level, and vibration are measured for 200 different TEMs (100 in good condition and 100 requiring repair). The data obtained from the TEM in the form of signals through sensors is analyzed using various transformations and methods. Signals generated under normal and abnormal conditions are examined. Additionally, the signals collected are fed into the machine learning unit as input data to assess the technical condition of the TEMs (Figure 2).

Thus, ML algorithms, i.e., K-means and EML draft, are used as classifiers for real-time assessment of technical states of TEMs and classification of faults. In addition, the effectiveness of the two different classifiers was measured in terms of accuracy, specificity, sensitivity, negative predictive value (NPV – which shows what percentage of the model's predictions for the negative category are correct and adds it to the sum of the actual values for the negative category), positive predictive value (PPV – which shows what percentage of the model's predictions in the positive category are correct and is calculated using various

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indicators such as the sum of the actual values in the positive category).

The advantages of both classifiers are analyzed, and the best classifier is determined. Furthermore, the best classifier is used for the real-time Raspberry Pi-based hardware system. Figure 2 shows a block diagram for a real-time Raspberry PI-based hardware system.

The main operating parameters of TEM are measured by five different analog sensors such as current sensor, voltage sensor, temperature sensor, vibration, and sound sensor. In addition, the analog signals from the sensors are converted to digital signals using the PCF8591 analog to digital converter (ADC) module.

In addition, the digital signals from the PCF8591 module are pre-processed using feature extraction methods, and these extracted informative features are passed as input to the ML classifiers.

Finally, the ML classifier provides support for deciding whether the traction motor is in good condition or requires maintenance. 85% of the data (both the traction motor in good condition and the traction motor requiring maintenance) is used to train the supervised learning classifier, and 15% of the data is used to test the supervised training classifier. Since K-means and EML are suitable for smaller size, numerical and continuous data, both ML algorithms are used as classifiers in the proposed work.

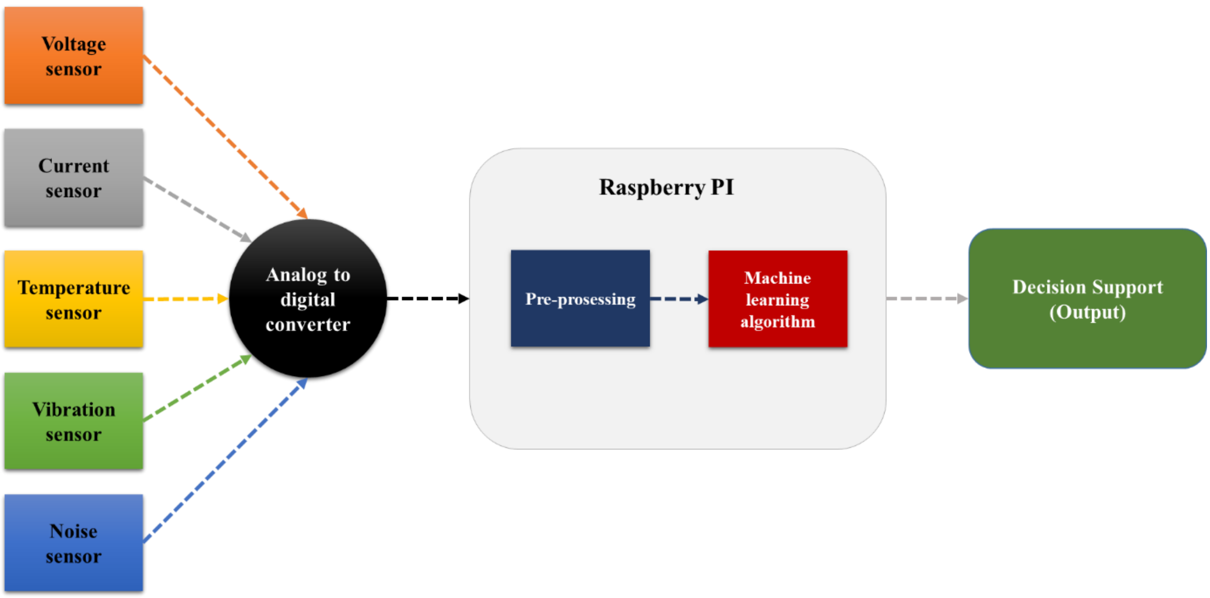

Fig. 2. Block diagram of the decision support unit

Findings

Comparative analysis of modeling results. Figures 3 and 4 show the average accuracy and sensitivity values for the K-means and EML algorithms, respectively, in diagnosing the technical condition of TEMs. A total of 200 TEMs were analyzed for both the K-means and EML classifiers within the TEM intelligent monitoring system. Of these 200 motors, 100 are in good condition, while the remaining 100 require maintenance, and these were used to train two different machine learning classifiers for monitoring purposes. In addition, 10 of the good-condition TEMs and 10 of the motors requiring maintenance were used to test the machine learning classifiers.

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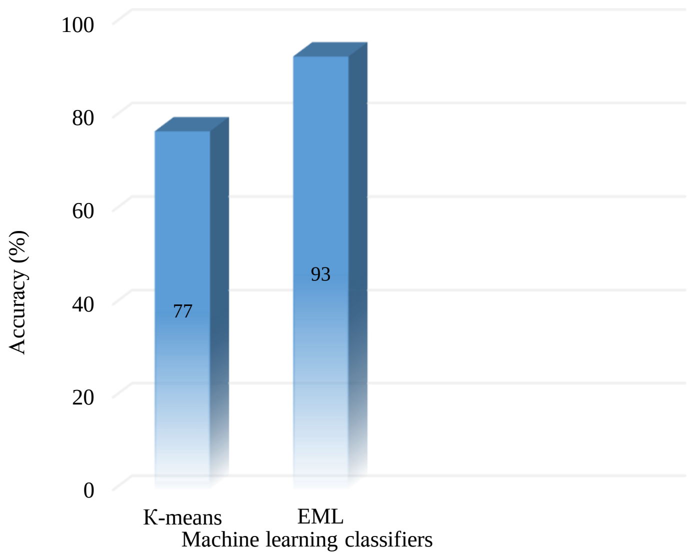

Fig. 3. Accuracy of TEM monitoring K-means and EML classifiers

The performance indicators of two different machine learning classifiers for TEM monitoring, specifically the K-means and EML classifiers, are presented in Table 1. During the testing of the monitoring system, it was found that the accuracy of the K-means classifier was 77%, while the accuracy of the EML classifier reached 93% (see Fig. 3). Additionally, the sensitivity and specificity for the K-means classifier were 73% and 81%, respectively, whereas for the EML classifier, these metrics were both 93% (refer to Figure 4 and Table 1).

Moreover, the positive predictive value (PPV) for the K-means classifier was 84%, and the negative predictive value (NPV) was 71%. It was also noted that the performance characteristics, including sensitivity, accuracy, specificity, NPV, and PPV, were all at 90% for the EML classifier. Furthermore, the average performance of the EML classifier was found to be superior to that of the K-means classifier. Given that the EML classifier is more significant than the K-means classifier, it has been implemented on the Raspberry PI using Python. It is also evident that diagnostics of the technical condition of the TEM can be conducted using the Raspberry Pi-based device.

Table 1

Performance indicators of TEM monitoring, K-means and EML classifier

No.	Indicators	K-means	EML
1.	Accuracy	77 %	93 %
2.	Specificity	81 %	93 %
3.	Sensitivity	73 %	93 %
4.	NPV	71 %	92 %
5.	PPV	84 %	92 %

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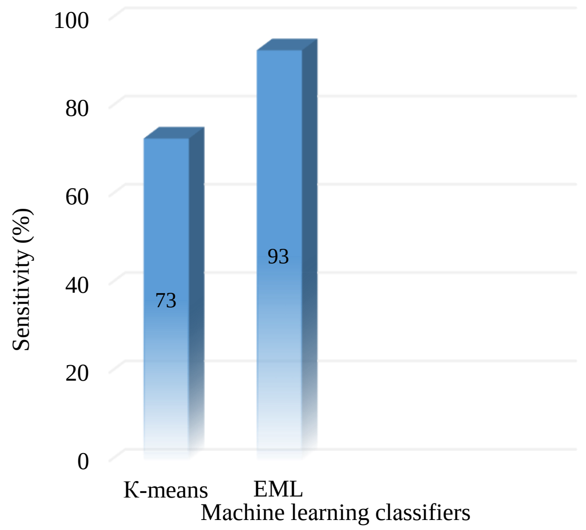

Fig. 4. TEM monitoring K-means and sensitivity of EML classifier

A monitoring system based on the Internet of Things. Recently, attention has been paid to the creation of a system for monitoring the technical condition of devices using the Internet of Things (IoT) system [3, 5, 6, 9, 14, 16, 19]. A typical IoT instrument contains the sensor to collect data, signal processing for sensor output, an ADC, digital logic, and internet connectivity for decision-making, and signal processing to activate an actuator in response to detected input. Smart sensors have the intelligence to provide direct digital data for measured parameters, ready for transmission to the gateway.

Digital logic and signal processing are part of these sensors. Digital logic consists of a microprocessor unit (MPU) that performs algorithmic functions such as filtering, compensation, and other signal converters. The built-in MPU of smart sensors can also be used to provide calibration data for the sensor, monitor abnormality in production parameters, make quick and immediate decisions during malfunctions, and issue alarms to prevent malfunctions. This will reduce the processing load on the digital processing processor of IoT systems. Smart sensors usually communicate with a central processing system in case of major faults or exceptions. Some of the smart sensors have a self-diagnostic feature, which is achieved by having two sensing elements in the sensor. The results are sent by the sensor to the central processing unit after comparing the outputs of both elements [3–5, 6, 9, 14, 19].

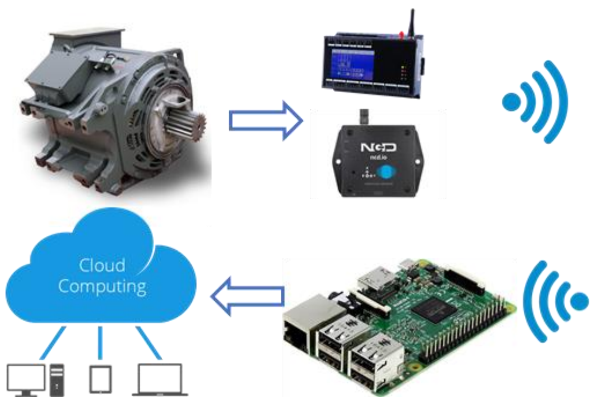

Fig. 5. Data collection from the TEMs with IoT-based sensors and transmission to the cloud system

Taking into account the characteristics of these sensors, it is possible to achieve a real-time assessment of the technical condition of TEMs operated in transport by measuring the main operating parameters. The IoT-based motor diagnostic monitoring system is specially designed to monitor the technical condition and performance of electric motors using IoT technology. This type of system uses sensors, connectivity, data analytics, and diagnostic algorithms to continuously assess the condition of traction motors and predict potential problems [1, 4, 6, 12, 15, 17–19].

Sensor placement. Sensors are installed on the electric motor and its related components to measure various parameters such as temperature, current, voltage, noise, and vibration. These sensors can be mounted directly on the TEM or added externally.

Data acquisition and transmission. Sensors collect real-time data from the TEM and transmit it to a central server or cloud platform via wired or wireless communication protocols such as Wi-Fi, Bluetooth, Zigbee, or cellular networks. The data includes information about TEM operating conditions, performance indicators, and any abnormalities detected by the sensors.

Data storage and processing. Collected data is stored and processed locally or in the cloud. Advanced analytics techniques such as machine learning algorithms are applied to analyze the data and identify patterns, trends, or abnormalities that may indicate potential TEM problems.

Diagnostic algorithms. Diagnostic algorithms are used to process sensor data and evaluate the condition of TEMs. These algorithms can utilize

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rule-based systems, statistical analysis, or machine learning models to detect faults, predict failures, and calculate the TEM's remaining residual resource.

Alerts and notifications. When an abnormality or potential issue is detected with the TEM, the system generates alerts or notifications to inform maintenance personnel or operators. These alerts can be sent via email, SMS, or specialized applications, allowing for timely intervention to prevent unexpected interruptions or failures.

Predictive maintenance. By continuously monitoring TEM condition and performance, an IoT-based diagnostics system enables predictive maintenance strategies. Maintenance activities can be scheduled based on the actual condition of the TEM. This approach maximizes service life and minimizes downtime.

Integration with motor management systems. In some cases, IoT-based TEM diagnostic systems can be integrated with motor management systems or SCADA systems to provide remote monitoring and control of TEM operations.

This integration allows operators to adjust traction motor parameters and operations as needed in response to detected problems.

An IoT-based TEM diagnostic monitoring system enhances the reliability, efficiency, and safety of TEMs used in transportation. These systems provide deeper insights into the technical condition and performance of the TEM, enabling proactive maintenance and optimization of TEM operations. Figure 6 illustrates the intelligent system designed for monitoring the technical condition of the TEM using the IoT.

Thus, data obtained from TEM through intelligent sensors are collected in real time and archived in a database based on cloud technology. Based on the received data, the traction motor's technical condition parameters are compared with the normal condition parameters, and the output signal is processed. With the output signals, the technical condition of the TEM is assessed in real time and the decision is made to provide maintenance if necessary.

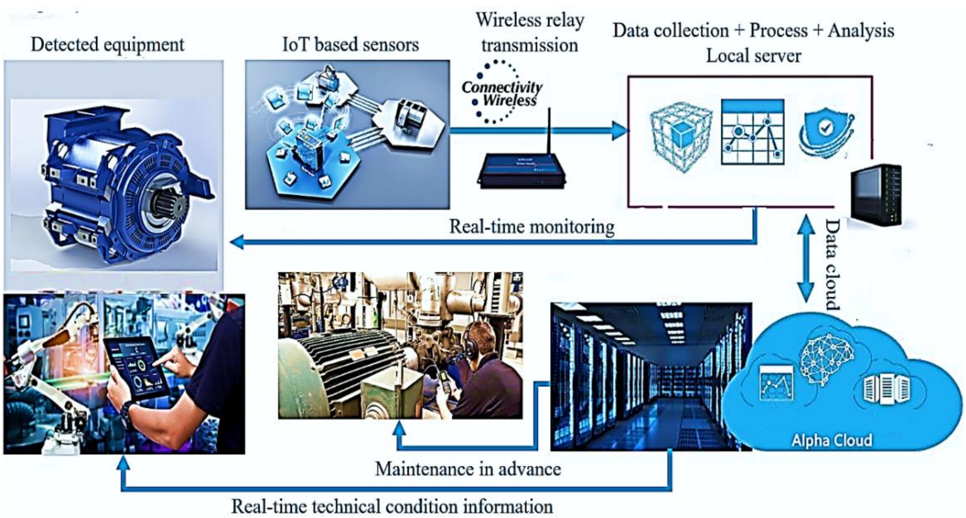

Fig. 6. IoT based traction motor condition monitoring system

Originality and practical value

To diagnose the technical condition of the TEM in real-time, utilizing IoT capabilities within a machine learning-based intelligent monitoring system represents a new area of research. This approach enables dynamic monitoring of the TEM's technical condition. Compared to traditional temperature diagnostic systems, such a multi-parameter system will allow you to determine a specific malfunction. Therefore, it is essential to develop and implement such a monitoring system.

Conclusion

This work discusses the development of a machine learning-based intelligent system designed for real-time monitoring of the technical condition of TEMs. By utilizing two different

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machine learning classifiers, K-means and EML, we compared their advantages in terms of accuracy, sensitivity, specificity, positive predictive value, and negative predictive value. The findings indicate that EML outperforms the K-means classifier, achieving an overall superiority rate of 93%. In contrast, the accuracy and sensitivity of the K-means classifier were found to be 77% and 73%, respectively. These results demonstrate that the EML classifier exhibits superior performance compared to K-means.

Furthermore, the EML classifier can be integrated into the machine learning-based intelligent system for real-time monitoring of electric motors' technical conditions. Additionally, the proposed model can connect to an IoT cloud server, enabling dynamic monitoring of the TEM's technical condition. Using IoT-based sensors, the system analyzes data received from the TEM, makes necessary adjustments, and assesses the motor's technical condition. This decision-making process allows for the prediction and early detection of both the motor's lifespan and potential future failures. Consequently, traditional maintenance practices for TEMs will transition to condition-based maintenance. This approach will enhance the continuity of passenger and cargo transportation, improve the reliability and stability of the overall traction vehicle, and ensure economic viability.

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Оцінка технічного стану тягових двигунів у реальному часі за допомогою технологій машинного навчання та IoT

Мета. Основною метою цього дослідження є аналіз алгоритмів машинного навчання, вибір найбільш точного й ефективного алгоритму діагностики технічного стану асинхронного тягового двигуна на основі таких робочих параметрів, як температура, рівень шуму та вібрації, а також вивчення особливостей застосування технології інтернету речей (IoT) для оцінки технічних умов у реальному часі. **Методика.** За допомогою аналізу та порівняльних методів визначено алгоритм машинного навчання, придатний для діагностики технічного стану асинхронного тягового двигуна. **Результати.** Проаналізовано алгоритми машинного навчання та обрано два різних алгоритми K-means та Extreme Machinearning (EML) для діагностики технічного стану асинхронних двигунів. Алгоритми порівнювали на основі показників ефективності, таких як точність, специфічність, чутливість, позитивне прогностичне значення та негативне прогностичне значення. Результати показали, що алгоритм EML перевершив K-середні за цими показниками, досягнувши загального показника продуктивності 93 %. **Наукова новизна.** Запропоновано нову систему, яка інтегрує модель машинного навчання з технологією IoT для діагностики технічного стану тягових електродвигунів у реальному часі. Цей інноваційний підхід дозволяє динамічно контролювати технічний стан двигуна. **Практична значимість.** Запропонована система на основі моделі машинного навчання оцінює технічний стан тягових двигунів у реальному часі за допомогою IoT. Він містить рекомендації щодо того,

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коли слід виконувати технічне обслуговування з урахуванням фактичного стану двигуна. Система дозволяє планувати технічне обслуговування на основі діагностики в реальному часі, полегшуючи перехід від планового техобслуговування до стратегій прогнозного техобслуговування. Це, у свою чергу, збільшує термін експлуатації та мінімізує незаплановані простої. Використання IoT дає можливість інтегрувати діагностичну систему із системами керування двигуном або системами SCADA, що забезпечує дистанційний моніторинг і контроль роботи двигуна.

Ключові слова: тяговий двигун; моніторинг технічного стану; виявлення несправностей; інтелектуальна діагностика; алгоритми машинного навчання; прогнозне обслуговування

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