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O.N. Sadu*, G.D. Bazil[1], A. Ainul[2]
[1]Almaty University of Power Engineering and Telecommunications,
050013, Almaty, Kazakhstan, st. Baitursynuly, 126/1
[2]Universiti Teknologi PETRONAS,
32610 Seri Iskandar, Perak Darul Ridzuam, Malaysia
*e-mail: o.sadu@aues.kz

AUTOMATED SYSTEM FOR PREDICTING FAILURES OF LOW-VOLTAGE ELECTRIC MOTORS IN ELECTRIC POWER PLANTS

Annotation: *In industrial systems or in electric-power plants, such as pumps, compressors and fans, induction motors are used in a wide variety of applications, and electrical or mechanical problems can lead to unexpected shutdowns, loss of productivity, and thermal stress or vibration. In this study, an automated fault-diagnosis framework is presented, which is tested on a 14-file subset of the University of Ottawa Electric Motor Dataset (UOEMD-VAFCVS), consisting of synchronized measurements of vibration, acoustics and temperature, acquired during both constant speed and ramp speed operations. This pipeline features multi-sensor signal processing (such as FFT, Welch PSD, STFT, and discrete wavelet transform, and hilbert-envelope analysis) and classification using Random Forest (RF), convolutional neural network (CNN) and hybrid CNN-Transformer classifiers. The CNN-Transformer outperformed the CNN and RF in terms of the best observed performance (91.4% accuracy; macro F1 = 0.91) in the held-out test set. When subjected to 20 dB AWGN, it was not only less accurate with a loss of 1.9 percentage points, but it also incurred a CPU inference latency of 8.7 ms per one second window. The results confirm the feasibility of multi-sensor fusion and attention-based temporal modelling for predictive maintenance, and the small number of sensors in the subset limits the statistical and industrial validation of the technique.*

Key words: *induction motor fault diagnosis, predictive maintenance, multi-sensor fusion, signal processing, machine learning, CNN-Transformer, variable-speed operation and bearing diagnosis.*

Introduction

The most common types of electrical machines in power-generation and industrial settings are induction motors (IMs). Their excellent construction, efficiency and cheapness have seen them become the standard prime mover in the manufacturing, oil and gas, mining and electric power plants. When operating under an inverter-fed, variable-speed, operation – which is becoming increasingly popular in modern plants – IMs have dynamic load profiles that produce non-stationary vibration and acoustic signatures, thus making fault detection more challenging.

IMs have a weakness of gradual degradation even though they are structurally consistent. Some electrical faults are broken rotor bars (BRBs), stator inter-turn short circuits (ITSCs), insulation breakdown and supply voltage anomalies; mechanical faults comprise bearing wear, shaft misalignment, rotor eccentricity, and rotor imbalance [1]. A lot of initial faults do not have any outward symptoms and thus are hard to detect. Reactive maintenance results in unplanned downtime and expensive repairs; and scheduled preventive maintenance results in unnecessary replacement of parts. Industry 4.0 thus requires the presence of data-driven predictive maintenance systems that can identify new faults prior to failure [2].

The UOEMD-VAFCVS dataset provides synchronized multi-sensor recordings under both fixed-speed and ramp-speed regimes, making it a suitable benchmark for assessing fault-diagnosis methods under the non-stationary operating conditions that motivate this study. Detailed sensor, sampling and recording specifications are therefore reported once in the Materials and methods section.

Research Gap and Contributions

Most published diagnostic systems have been tested in constant-speed cases, with little or no investigation in variable-speed (ramp) cases, where signal non-stationarity is a problem for traditional spectral analysis. Moreover, the multi-sensor fusion of vibration, acoustic, and temperature channels

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are not usually performed in a synchronized manner; most of the studies do not use more than one modality, and they do not utilize the complementary data offered by co-located sensors [3, 4]. The existing models hardly incorporate fault classification and prognostic factors such as degradation monitoring and thermal trend analysis [5].

The current system fills these gaps by:

1. Multi-sensor predictive model on UOEMD-VAFCVS.
2. A hybrid CNN–Transformer model in non-stationary ramp-speed conditions.
3. Multi-domain signal processing and synchronized fusion of vibration, acoustic and temperature information.
4. The classification results will be compared and contrasted to determine actual deployment capabilities, per-class behaviour, noise robustness, and CPU inference time.

Literature review

Motor Current Signature Analysis (MCSA) have been extensively studied for the purpose of Broken rotor bar (BRB) diagnosis, especially by studying the harmonic sidebands of the supply frequency [6, 7]. These techniques have shown good performance at constant speed and rated load, but often become unreliable when operating at light loads or variable speeds. Chisedzi and Muteba [8] presented the results of their research that decision-tree classification can compete in terms of accuracy and efficiency for load-invariant BRB detection, while Elhaija and Al-Haija [9] proved to be lightweight neural diagnosis with very low inference time. Antonello et al. [10] also argued experimentally the importance of variable selection in the machine learning-based BRB detection. All of these studies confirm the ability to data diagnose, but also illustrate that reported accuracy is highly data dependent and is strongly affected by the operating regime and benchmark design.

When fault signatures vary in speed, time-frequency representations and deep learning can be of interest. It is also difficult to detect ITSC faults at an early stage, as normal and fault current patterns can be similar. Chen et al. [11] obtained a noticeable no-load detection accuracy by using the start-up current envelope energy and support vector machines, while Kawady et al. [12] demonstrated that deep neural models can enhance the robustness of the no-load detection under supply-side interference. These findings are a motivation for representations that are not exclusively stationary spectra but can represent non-stationary and transient structure.

Traditionally, diagnosis of mechanical faults is performed using the vibration data, but complementary measurements such as acoustic and other indirect measurements can be used in combination with the casing-mounted accelerometers [14]. CNN-based spectrogram analysis has been successfully applied to rotor and bearing classification [15], and transformer-based methods have produced very high accuracy under controlled constant-load conditions [5]. More recent multi-modal work indicates that combining complementary sensing channels can improve multi-class discrimination; for example, Xu et al. [16] fused current, vibration and acoustic time series using an ensemble Transformer. However, direct numerical comparison across studies is limited by differences in motors, fault severity, load, speed regimes and train/test protocols.

Another challenge is domain shift under varying operating conditions and across disparate motors. Single machine or tightly controlled models may lose accuracy if mounting of the sensor, load or speed or the characteristics of the machine change. Cross domain adaptation with limited labelled data was demonstrated to enhance the target domain recognition by Chen and Chen [17]. This generalisation issue is particularly relevant for the current study, as the UOEMD-VAFCVS benchmark includes separate, physically distinct motors and several different speed regimes; therefore, it is important to make a distinction between source recordings to avoid misinterpretation of a limited hold-out result as the universal industrial performance.

Materials and methods

Dataset and Sensing Infrastructure

The UOEMD-VAFCVS data are used in all experiments. The entire benchmark includes recordings of eight three-phase Marathon Electric D396 motors having artificial faults. 420,000 samples per channel (SPC) at 42 kHz (10 s file) per channel, and five synchronized channels: three accelerometer channels (1, 3 and 4), an acoustic channel (2; PCB 130F20 microphone) and a temperature channel (5; integrated with PCB 603C01). The dataset includes four ramp profiles (15→45, 30→60, 45→15 and 60→30 Hz) and four fixed frequencies (15, 30, 45 and 60 Hz), giving 128 recording configurations across load conditions. The present proof-of-concept analysis uses 14 files representing the five evaluated fault classes—stator winding (S_W), bearing (B_R), voltage

unbalance (V_U), rotor unbalance (R_U) and bent shaft (K_A) – under fixed- and ramp-speed conditions. The restricted subset is treated as a study limitation rather than as a complete validation of the full benchmark.

A Programmable Logic Controller (PLC) manages the acquisition and preprocessing of the vibration sensor signals in a real-life implementation of the proposed automated system. The PLC constantly gathers the raw analog signals recorded by vibration accelerometers on the motor housing, uses threshold-based filtering to repress low amplitude noise, and transforms the conditioned signals into digital data streams at the requested rate. These digital outputs are subsequently sent to the diagnostic pipeline, where signal processing (FFT/Welch PSD, STFT, and DWT) are used to extract features that are fault related. PLC-processed vibration data is transformed into feature vectors that are then directly used as inputs to the machine learning models: Random Forest, CNN, and CNN-Transformer, which allows the automated system to produce real-time failure predictions. The system achieves this by combining signal conditioning in the PLC level with the upper machine learning layer to make sure that only high quality and noise-suppressed vibration data is used to generate the prognostic output leading to higher reliability and stability of predictions of failures in operational electric power plants.

Signal Processing and Characteristic Extraction

The processing pipeline includes 3 steps: (1) preprocessing/segmentation, (2) multi-domain feature extraction/sensor fusion and (3) model training/evaluation, which follow the pre-established multi-sensor monitoring structures [18, 19]. All channels are high-pass filtered at 0.5 Hz to remove DC drift and are z-score normalised based on statistics from the training data only, so that information from the validation or test partitions is not used to affect the preprocessing.

For principal classification analysis, signals are cut into 1.0 s windows (42,000 samples) with 50% overlap between the windows. Shorter 0.1-0.2 s windows are additionally used when analysing impulsive bearing behaviour. For ramp-speed recordings, STFT-based time-frequency representations preserve the evolution of frequency components as rotational speed changes [4].

For fixed-speed data, FFT and Welch power spectral density estimates are used to derive fundamental and harmonic amplitudes, spectral kurtosis and spectral centroid [6]. STFT spectrograms represent transient sidebands in ramp-speed data [4]. Discrete Wavelet Transform (DWT; Daubechies Db4/Db8) features include sub-band energy and kurtosis for impulsive behaviour [20], while Hilbert-envelope analysis is applied to band-pass-filtered resonance regions before spectral analysis of the demodulated signal [11]. Time-domain features comprise RMS, peak-to-peak amplitude, variance, skewness, kurtosis and crest factor. Features from the three accelerometers, microphone and temperature channel are combined with inter-channel correlation and coherence measures to represent mechanical-acoustic-thermal coupling.

Machine Learning Models, Training and Hyperparameter Selection

Three model families are compared to separate the contribution of handcrafted features, local spectro-temporal representation learning and long-range temporal attention. (1) Random Forest (RF) operates on the handcrafted multi-domain feature vector and provides a computationally inexpensive baseline [8]. (2) The CNN receives STFT spectrograms as two-dimensional inputs and learns local frequency-pattern representations through convolution and pooling [15]. (3) The CNN–Transformer first extracts local spectro-temporal features with CNN layers and then passes the resulting representation to a multi-head self-attention Transformer encoder. This hybrid architecture was selected for investigation because the central diagnostic problem involves non-stationary ramp-speed signals, for which temporally separated features may remain diagnostically related [4]. The three architectures therefore form a deliberate progression from fixed handcrafted features to local learned features and finally to local-plus-long-range temporal modelling.

The experiment description only defines a train/validation/test split for grouped source files as 9/2/3, which is about 171/38/57 one-second windows, with a 50% overlap between the groups. The idea behind grouping by source recording/motor is to avoid highly correlated overlapping windows being split between the training and test sets. The test set should not be used for hyperparameter tuning, and only be used for final reporting. For complete reproducibility, the final manuscript must state the exact RF tree/depth settings and, for the CNN and CNN-Transformer, the optimizer, learning rate, batch size, epoch limit, early-stopping rule, convolutional filter/kernel configuration,

Transformer encoder depth, number of attention heads and dropout used in the reported runs.
Statistical Validation and Evaluation Protocol

Performance is evaluated on the held-out test subset using overall accuracy together with macro-averaged precision, recall and F1 score. Macro averaging gives each of the five fault classes equal weight and is therefore reported alongside accuracy to reduce the influence of differences in class frequency. Furthermore, per-class precision, recall and F1 are analyzed to pinpoint class-specific confusion. To assess robustness, 20 dB additive white Gaussian noise (AWGN) is added to the system and then the absolute change in accuracy in percentage points is reported, and to assess computational feasibility, the measured CPU inference time per one-second window is reported. As only 14 files and three test files are used in the present analysis, these metrics are used descriptively as hold-out estimates, and are not used for making inferences or claims of inferential significance. As such, this difference in accuracy (91.4% vs. 87.6%) between the CNN–Transformer and CNN is not interpreted as evidence for the superiority of the CNN–Transformer across the population, but rather as evidence for its performance on this split. A better statistical validation of the full dataset is obtained using repeated grouped cross-validation or leave-one-motor-out cross-validation, and reporting the uncertainty intervals (e.g., bootstrap 95% confidence interval for accuracy and macro F1).

Results

The performance of the three models in multi-class classification is given in table 1 for the five consistently-defined fault classes: stator winding fault (S_W), bearing fault (B_R), voltage unbalance (V_U), rotor unbalance (R_U), bent shaft (K_A). The higher accuracy and macro F1 scores for RF compared to CNN and CNN–Transformer suggest that learned spectro-temporal representations and attention are good for this hold-out split, but this is not enough to conclude statistical superiority.

Table 1 – Multi-Class Classification Performance

Model	Accuracy (%)	Macro Precision	Macro Recall	Macro F1
Random Forest	81.2	0.81	0.80	0.80
CNN (Spectrogram)	87.6	0.88	0.87	0.87
CNN–Transformer	91.4	0.92	0.91	0.91

The RF baseline is able to reach the accuracy of 81.2% and macro F1 = 0.80 which is a good score for the usefulness of the decision-tree methods in case of availability of structured handcrafted features [8]. CNN achieves 87.6% accuracy (macro F1 = 0.87) which is seen as a 6.4% improvement over RF. The CNN-Transformer has the accuracy of 91.4% (macro F1 = 0.91), which is 10.2 and 3.8 percentage points higher than RF and CNN, respectively. This is in line with the hypothesis of self-attention being able to model long-range dependencies in non-stationary recordings of ramp speeds [4] but the amount of the benefit must be validated with repeated grouped validation for a larger sample.

The performance of the CNN-Transformer is presented in per-class performance in Table 2. The most frequent fault type with the highest F1 score (0.95) is stator winding (S_W) faults, which likely correspond to the thermal and acoustic information that comes from the heating and electromechanical changes when dealing with ITSC. Bearing (B_R) and voltage unbalance (V_U) faults each have F1 = 0.91; and bent shaft (K_A) and rotor unbalance (R_U) are the most challenging classes with F1 = 0.87 for each. Their lower separabilities are consistent with the presence of overlapping low-frequency vibration near 1× and 2× rotational frequency, and the coupling between the electric and vibrating parts of the mechanism, which might have an impact on V_U/R_U separability.

Table 2 – Per-Class F1 Scores (CNN–Transformer)

Fault Class	Precision	Recall	F1-Score
S_W (Stator Winding)	0.96	0.94	0.95
B_R (Bearing)	0.93	0.90	0.91
V_U (Voltage Unbalance)	0.92	0.90	0.91
R_U (Rotor Unbalance)	0.89	0.86	0.87
K_A (Bent Shaft)	0.88	0.87	0.87

Table 3 evaluates robustness at 20 dB additive white Gaussian noise (AWGN). RF accuracy decreases by 6.8 percentage points and CNN accuracy by 3.4 percentage points, whereas CNN–Transformer accuracy decreases by 1.9 percentage points (91.4% to 89.5%). The smaller observed degradation suggests greater robustness of the hybrid representation on this perturbation test. It should not, however, be attributed solely to the attention mechanism without ablation testing, and AWGN is only a simplified approximation of the coloured, non-stationary and source-specific noise encountered in operating plants.

Table 3 – Noise Robustness (20 dB AWGN)

Model	Baseline Acc. (%)	Noisy Acc. (%)	Drop (pp)
Random Forest	81.2	74.4	−6.8
CNN	87.6	84.2	−3.4
CNN–Transformer	91.4	89.5	−1.9

Table 4 reports measured CPU inference latency. RF (1.3 ms), CNN (4.9 ms) and CNN–Transformer (8.7 ms) all remain below the study target of 10 ms per one-second window. These measurements demonstrate real-time feasibility on the tested CPU configuration, but they do not guarantee identical latency on a specific PLC, industrial PC or edge processor. Deployment studies should therefore repeat latency, memory-use and throughput measurements on the target hardware while the full sensor-acquisition and preprocessing pipeline is running.

Table 4 – Inference Latency (CPU)

Model	Inference Time (ms/window)	Real-Time Compatible
Random Forest	1.3	Yes
CNN	4.9	Yes
CNN–Transformer	8.7	Yes

Overall, the obtained results demonstrate that the proposed multi-sensor fault diagnosis framework provides a consistent improvement in classification performance, robustness, and real-time applicability. Across all evaluated metrics, the CNN**-**Transformer model shows the best balance between accuracy, generalization capability, and noise resistance, confirming the effectiveness of combining convolutional feature extraction with attention-based temporal modeling.

The comparative analysis indicates that classical machine learning approaches, such as Random Forest, remain effective for structured feature sets but are limited under non-stationary conditions. In contrast, deep learning models, particularly those incorporating attention mechanisms, are better suited for capturing complex temporal dependencies in variable-speed regimes.

Furthermore, the stability of the CNN**-**Transformer under noisy conditions and its low inference latency highlight its suitability for deployment in industrial environments, where both accuracy and computational efficiency are critical. These results collectively confirm that multi-sensor data fusion combined with advanced deep learning architectures significantly enhances fault detection performance in modern predictive maintenance systems.

Discussion

The results indicate that synchronized vibration, acoustic and temperature information can support multi-class induction-motor fault diagnosis under both fixed- and variable-speed conditions. The main empirical finding is the observed advantage of the CNN–Transformer on the reported hold-out split, together with comparatively small degradation under the 20 dB noise test and sub-10 ms inference. The interpretation below therefore focuses on what these results support, while distinguishing those findings from claims that require broader statistical or industrial validation.

Comparison to Previous Work

The CNN–Transformer is able to reach an accuracy of 91.4% for the five fault classes in a multi-motor, multi-speed benchmark. Other research has been reported with accuracies better than 99% [5, 9] but such results are not directly comparable in terms of operating regime, data sets and validation methodology. The RF result (81.2%) is similar to the results of structured features [8] that demonstrate good performance with tree based methods. The current multi-sensor result also matched with the result provided by Xu et al. [16] that revealed high performance of multimodal

Transformer-based fusion. The current contribution is to analyse a correlated fusion principle in a benchmark with ramp-speed non-stationarity; however, the number of files (14) is too small to include generalisation across the whole UOEMD-VAFCVS benchmark or to industrial motor fleets.

Practical Implications

The measured inference times indicate that the proposed pipeline has a realistic path to online condition monitoring, but practical implementation requires more than classifier execution alone. A deployable architecture would acquire casing vibration from the three accelerometers together with acoustic and temperature channels, perform basic signal conditioning and buffering at PLC or edge level, generate the same normalised windows and time-frequency features used during training, and pass them to the selected classifier on an industrial PC or edge processor. The model output should then be integrated with a SCADA or computerised maintenance management system (CMMS) using a confidence threshold and alarm logic rather than triggering maintenance from a single isolated prediction. The sensor calibration, baseline (health) measurement of the sensors, channel synchronisation and verification, latency and memory tests for the target hardware, and agreement on the alarm confirmation procedure should be included in site commissioning [2].

The degradation from 1.9% for CNN in 20 dB AWGN is promising for noisy environments, and the F1 result of 0.95 for S_W class suggests that the vibration–acoustic–temperature configuration is useful to discriminate the stator-winding even without using a direct current channel in this dataset. This is to be taken as a hypothesis for deployment, not as proof that current sensing isn't always needed. In addition to classification accuracy, false-alarm rate, missed-detection rate, sensor failure behaviour, computational load and maintenance lead time should be also monitored in an industrial pilot. When the inverter setting, loads, mounting conditions or motors change, then periodic model review or retraining would be necessary as well.

Limitations and Future Work

The main drawback is that merely 14 files of the 128 recording configurations are used from the benchmark. Three of the files in the reported test subset are used to make performance estimates, which may lack statistical precision, and do not characterise the full range of motor, speed, load and fault severities in UOEMD-VAFCVS. The present results therefore do not justify the use of inference for the superiority of the models, and the still existing confusion between rotor unbalance (R_U) and bent shaft (K_A) that both have strong 1×/2× rotational components demonstrates that the current feature space is not sufficiently discriminating for mechanically similar faults. Evaluation should be done using group-aware repeated cross-validation or leave-one-motor-out testing, with confidence intervals and confusion matrix for each fold, and compare if the improvements are similar in the fixed-speed and individual ramp-speed regimes.

Second, the external validity of the study. Controlled benchmarking with induced faults (UOEMD-VAFCVS) compares results, while operating power plants cause domain shifts due to different load conditions, inverter harmonics, difference in foundation, sensor mounting, structural resonances, ambient acoustic sources, temperature drift, sensor ageing and maintenance interventions. The 20 dB AWGN experiment is a convenient stress test on a controlled basis but it does not capture this entire noise structure. Factors may also be simultaneous, changing, or new faults in real systems that aren't part of any of the five classes that were predefined. Future validation should be conducted during extended durations of operation on multiple industrial motors with synchronized multi-sensor data, should include machine identity in the design of the validation, involve comparison of predictions with maintenance inspections, and measures false alarms and missed detections under real-life disturbances.

Finally, future research is needed to explore the cross-axis vibration coherence, acoustic information of higher frequency and optionally a pathway of stator current to minimize R_U/K_A and V_U/R_U ambiguity. Additionally, to discrete fault classification, degradation modelling and remaining-useful-life estimation would add value to maintenance, as they would help in making decisions about maintenance timing. A sequence of the activities (full-dataset validation, hardware-in-the-loop edge testing, and a monitored industrial pilot) would create a defensible path from the current proof of concept to deployment.

Conclusion

A synchronized multi-sensor framework for the induction motor diagnosis by vibration, acoustic and temperature measurements technique from UOEMD-VAFCVS is developed and evaluated. Within the 14-file subset of the dataset for which data was reported, the CNN–Transformer obtained

the best result when it came to classification (91.4% accuracy; macro F1 = 0.91) compared with CNN (+3.8 percentage points) and RF (+10.2 percentage points). It also demonstrated the lowest drop in accuracy with 20 dB AWGN test (1.9 percentage points) and the CPU inference time of 8.7ms per 1s window. By its scientific significance, these results confirm that the benefits of using convolutional filters to extract local spectro-temporal patterns and attention-based modelling for longer-range dependencies are still present for the non-stationary variable-speed diagnosis of these variables, and that, per-class, the separation of R_U and K_A is still a challenge.

The practical value is that the proposed sensing and inference chain is computationally compatible with a real time edge-monitoring concept, and can be combined with the PLC/SCADA/CMMS workflows in a post-site specific validation process. However, the ability to generalise is limited by the special subclass, control for induced faults and the lack of repeated group-aware validation. The next research stage involves the evaluation of all 128 UOEMD-VAFCVS configurations with uncertainties, leave-one-motor-out or leave-one-grouped-out validation, validation using coloured noise as well as noise obtained from operating motors and the extension of the method to multiple fault recognition and remaining useful life prediction in real industrial motors. These steps are required in order to achieve statistical reliability and operational benefit prior to scale up trials on plant.

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О.Н. Сәду*, Г.Д. Бәзіл[1], А. Акмар[2]
[1]Алматы энергетика және байланыс университеті,
050013, Алматы, Қазақстан Республикасы, Байтұрсынұлы көшесі,126/1
[2]Петронас Технологиялық Университеті, 32610 Сери Искандар, Перак, Малайзия
*e-mail: o.sadu@aues.kz

ЭЛЕКТР СТАНЦИЯЛАРЫНДАҒЫ ТӨМЕН КЕРНЕУЛІ ЭЛЕКТР ҚОЗҒАЛТҚЫШТАРЫНЫҢ ІСТЕН ШЫҒУЫН БОЛЖАЙТЫН АВТОМАТТАНДЫРЫЛҒАН ЖҮЙЕ

Индукциялық қозғалтқыштар өнеркәсіпте сорғыларды, желдеткіштерді және компрессорларды басқару үшін кеңінен қолданылады. Бұл қозғалтқыштарда ротор шыбықтарының жарықтары мен статордың қысқа тұйықталуын қоса алғанда, электр ақаулары, сондай-ақ ротордың эксцентриситеті, тураланбау және мойынтіректердің тозуы сияқты механикалық ақаулар кездеседі. Бұл механикалық және электрлік ақаулар шамадан тыс діріл мен температураға байланысты жабдықтың мерзімінен бұрын өшірілуіне әкеледі. Ақаулықтар мен істен шығуларды ерте анықтау болжамды техникалық қызмет көрсетудің негізгі мақсаты болып табылады. Бұл мақалада Онтарио университетінің электр қозғалтқыштарының деректер жиынтығы (UOEMD-VAFCVS) үшін автоматтандырылған ақауларды анықтау жүйесі ұсынылады, ол сегіз қозғалтқыш үшін тұрақты және ортогоналды жылдамдықта жиналған синхрондалған діріл, акустикалық және температуралық деректерді қамтиды, олардың үшеуі деректер жиынтығында бар. Диагностикалық мүмкіндіктерді алу үшін FFT/Welch PSD, STFT, дискретті толқындық түрлендірулер және Гильберт элементтері бойынша қабықша талдауы сияқты бірнеше сигналды талдау әдістері қолданылады. Барлық осы әдістер иерархиялық машиналық оқыту моделіне біріктірілген, оған кездейсоқ ормандар (RF), конволюциялық нейрондық желілер (CNN) және гибридті CNN-трансформатор моделі кіреді. CNN-Transformer моделі дәлірек, 91,4 пайызға жетеді және ең жоғары макро F1 көрсеткішіне ие. Барлық модельдер CPU-да әрбір терезе үшін 10 мс-тан аз уақытта нақты уақыт режимінде қорытынды жасау талабына сай келеді, бұл жеке CNN (87,6 пайыз) және RF (81,2 пайыз) модельдерінен асып түседі. Бұл зерттеулер көп сенсорлы біріктіру мен назар аударуға негізделген уақытша модельдеудің Industry 4.0 болжамды техникалық қызмет көрсету үшін пайдалылығын растайды.

Түйін сөздер: *Индукциялық қозғалтқыштың ақауларын диагностикалау; болжамды техникалық қызмет көрсету; көп сенсорлы біріктіру; сигналды өңдеу; машиналық оқыту; CNN-трансформатор; айнымалы жылдамдықты жұмыс; мойынтіректерді диагностикалау.*

О.Н. Сәду*, Г.Д. Бәзіл[1], А. Акмар[2]
[1]Алматинский университет энергетики и связи,
050013, Алматы, Республика Казахстан, ул. Байтурсынулы,126/1
[2]Технологический Университет Петронас, 32610 Сери Искандар, Перак, Малайзия
*e-mail: o.sadu@aues.kz

АВТОМАТИЗИРОВАННАЯ СИСТЕМА ПРОГНОЗИРОВАНИЯ ОТКАЗОВ ЭЛЕКТРОДВИГАТЕЛЕЙ НИЗКОГО НАПРЯЖЕНИЯ НА ЭЛЕКТРОСТАНЦИЯХ

Асинхронные двигатели широко используются в промышленности для привода насосов, вентиляторов и компрессоров. Эти двигатели подвержены электрическим неисправностям, включая трещины в валу ротора и короткие замыкания статора, а также механическим неисправностям, таким как эксцентриситет ротора, несоосность и износ подшипников. Эти механические и электрические неисправности приводят к преждевременному отключению оборудования из-за чрезмерной вибрации и температуры. Раннее обнаружение неисправностей и отказов является ключевой задачей превентивного технического обслуживания. В данной статье представлена автоматизированная система обнаружения неисправностей для набора данных электродвигателей Университета Онтарио (UOEMD-VAFCVS), который включает синхронизированные данные о вибрации, акустике и температуре, собранные при постоянных и ортогональных скоростях для восьми двигателей, три из которых присутствуют в наборе данных. Для получения диагностических возможностей используются несколько методов анализа сигналов, таких как БПФ/спектроскопия спектральной плотности мощности Уэлча, кратковременное преобразование Фурье, дискретные вейвлет-преобразования и анализ огибающей по элементам Гильберта. Все эти методы объединены в иерархическую модель машинного обучения, которая включает случайные леса (RF), сверточные нейронные сети (CNN) и гибридную модель CNN-Transformer. Модель CNN-Transformer более точна, достигая 91,4%, и имеет самый высокий показатель макро-F1. Все модели соответствуют требованию вывода в реальном времени менее чем за 10 мс на окно на ЦП, что превосходит отдельные модели CNN (87,6%) и RF (81,2%). Эти исследования подтверждают полезность многосенсорного слияния и временного моделирования на основе механизма внимания для прогнозирующего технического обслуживания в рамках концепции Industry 4.0.

Ключевые слова: *диагностика неисправностей асинхронного двигателя; прогнозирующее техническое обслуживание; объединение данных с нескольких датчиков; обработка сигналов; машинное обучение; CNN-Transformer; работа с переменной скоростью; диагностика подшипников.*

Information about the authors

Orazbek Nurzhanuly Sadu* – 2nd year doctoral student, Almaty University Power Engineering and Telecommunications, Republic of Kazakhstan; e-mail: o.sadu@aues.kz. ORCID: https://orcid.org/0009-0000-1644-7294.

Gulmira Duysenbekkyzy Bazil – PhD, professor, Almaty University of Power Engineering and Telecommunications, Republic of Kazakhstan; e-mail: g.bazil@aues.kz. ORCID: https://orcid.org/0000-0001-9563-0352.

Ainul Akmar – PhD, Professor, Universiti Teknologi PETRONAS, Malaysia; e-mail: ainulakmar_mokhtar@utp.edu.my. ORCID: https://orcid.org/0000-0003-3522-1113.

Авторлар туралы мәліметтер

Оразбек Нұржанұлы Сәду* – 2-курс докторанты, Алматы энергетика және байланыс университеті, Қазақстан Республикасы; e-mail: o.sadu@aues.kz. ORCID: https://orcid.org/0009-0000-1644-7294.

Гүлмира Дүйсенбекқызы Бәзіл – PhD, профессор, Алматы энергетика және байланыс университеті, Қазақстан Республикасы; e-mail: g.bazil@aues.kz. ORCID: https://orcid.org/0000-0001-9563-0352.

Айнул Акмар – PhD, профессор, Петронас Технологиялық Университеті, Малайзия; e-mail: ainulakmar_mokhtar@utp.edu.my. ORCID: https://orcid.org/0000-0003-3522-1113.

Сведения об авторах

Оразбек Нұржанұлы Сәду* – докторант 2-го курса, Алматинский университет энергетики и связи, Республика Казахстан; e-mail: o.sadu@aues.kz. ORCID: https://orcid.org/0009-0000-1644-7294.

Гүлмира Дүйсенбекқызы Бәзіл – PhD, профессор, Алматинский университет энергетики и связи, Республика Казахстан; e-mail: g.bazil@aues.kz. ORCID: https://orcid.org/0000-0001-9563-0352.

Айнул Акмар – PhD, профессор, Технологический Университет Петронас, Малайзия; e-mail: ainulakmar_mokhtar@utp.edu.my. ORCID: https://orcid.org/0000-0003-3522-1113.

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К.К. Комбаев, Ж.М. Мұхаметбек, Б.Н. Азаматов, Д.И. Қалиев, Р. Ғабдысалық*
Д. Серікбаев атындағы Шығыс Қазақстан техникалық университеті
070000, Қазақстан Республикасы, Өскемен қ., Д.Серікбаев көшесі, 19
*e-mail: rgabdysalyk@edu.ektu.kz

TI-6AL-4V ҚОРЫТПАСЫНАН ЖАСАЛҒАН КОРТИКАЛДЫ СҮЙЕК БҰРАНДАЛАРЫН СББ БІЛДЕКТЕРІНДЕ ӨНДІРУ КЕЗІНДЕ КЕСКІШ ҚҰРАЛ ТОЗУЫН БЕЙІМДЕЛМЕЛІ ӨТЕМДЕУ

Аңдатпа: *Мақалада сандық бағдарламалық басқаруы бар білдектерде Ti-6Al-4V титан қорытпасынан дайындалатын кортикальды сүйек бұрандаларының геометриялық параметрлерінің дәлдігін қамтамасыз ету мәселесі қарастырылған. Зерттеудің өзектілігі медициналық имплантаттардың сапасына қойылатын жоғары талаптармен және кескіш құралдың жинақталған тозуы жағдайында бұранда қалыптастыру процесінің тұрақтылығын сақтау қажеттілігімен негізделген. Жұмыстың мақсаты – СББ жүйесінің құралдары арқылы бұрандакескіш бастиектің тозуын бейімделмелі өтемдеу әдісін әзірлеу және оны эксперименттік тұрғыдан растау. Зерттеулер Д. Серікбаев атындағы Шығыс Қазақстан техникалық университетінің «Smart Engineering» құзыреттілік орталығының базасында орындалды. Тәжірибелік үлгілер MANURHIN K'MX 726 EVO бойлық жону автоматында дайындалды, ал бұранда геометриялық параметрлерін бақылау Mahr MarSurf CD 140 контурографы арқылы жүргізілді. Эксперименттік бағдарлама құралдың пайдаланылу кезеңдерін қамтитын тоғыз өңдеу режимін, сондай-ақ ең жоғары 57 м жинақталған өңдеу ұзындығын қамтыды. Зерттеу нәтижелері құралдың жинақталған жұмыс ұзындығы артқан сайын бұранда қадамының, профиль тереңдігінің және бүйір беттер бұрыштарының жүйелі өзгерістері байқалатынын көрсетті. Жинақталған өңдеу ұзындығына байланысты құралдың түзету ығысу шамасын анықтайтын эмпирикалық модель әзірленді. Ең жоғары зерттелген өңдеу ұзындығы үшін ΔZ = 0,0509 мм мәні алынды, бұл басқару бағдарламасында енгізілген 0,050 мм өтемдеумен іс жүзінде сәйкес келді. Есептік түзетуді енгізгеннен кейін бұранда қадамының ауытқуы номиналды 1,25 мм мәнінен 1,28 % құрап, құралды ауыстырмай-ақ бұранда профилінің тұрақты геометриясын сақтауға мүмкіндік берді. Жұмыстың практикалық маңыздылығы медициналық имплантаттарды дайындау дәлдігін арттырумен, бұрандакескіш бастиектің тиімді пайдалану мерзімін ұлғайтумен және өндірістік шығындарды төмендетумен сипатталады. Болашақ зерттеулер кескіш құралдың тозуын автоматты бақылау жүйелерін әзірлеуге және бейімделмелі өтемдеу алгоритмдерін интеллектуалды цифрлық өндірістік жүйелерге енгізуге бағытталған.*

Түйін сөздер: *кортикальды сүйек бұрандасы, Ti-6Al-4V, кескіш құралдың тозуы, бейімделмелі өтемдеу, эмпирикалық модель, СББ білдектері, бұранда профилін қалыптастыру, медициналық имплантаттар.*

Кіріспе

Отандық медициналық бұйымдар өндірісін дамыту Қазақстан Республикасының денсаулық сақтау жүйесін жаңғыртудың басым бағыттарының бірі болып табылады.

Саланың дамуындағы стратегиялық бағыттарына сәйкес медициналық құралдар мен бұйымдарды жобалау және өндіру үшін заманауи технологияларды енгізу арқылы денсаулық сақтау қызметтерінің қолжетімділігі мен сапасын арттыруға ерекше назар аударылуда.

Кортикалды сүйек бұрандалары травматология мен ортопедияда ең кеңінен таралған өнімдерігің бірі болып табылады, олар сынықтарды емдеу кезінде, реконструктивтік хирургияда және басқа да остеосинтез әдістерінде сүйек сынықтарын бекітуге арналған.

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