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MACHINE LEARNING METHODS USED FOR PROGNOSING FAILURES IN HYBRID ELECTRICITY SUPPLY SOURCES OF TELECOMMUNICATION INFRASTRUCTURE

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Abstract: the continuity of hybrid power supply systems for base stations (solar panel, battery, supercapacitor, diesel generator, power grid) depends on predicting failures in advance. This article systematizes fault types by components, input tokens, and applied machine learning methods (RF, SVM, XGBoost, LSTM/BiLSTM, physics-based neural networks) and compares their advantages and limitations. A three-level architecture and evaluation criteria were proposed, consisting of the edge, cloud, and digital twin. The main obstacle is the lack and disproportion of fault data; the most promising direction is the combination of physical and data-driven approaches.

Keywords: hybrid power supply; fault prediction; machine learning; LSTM; residual useful life; battery; supercapacitor; base station.

I. INTRODUCTION

Uninterrupted power supply for mobile base stations (BS) is a fundamental requirement for network reliability. In areas where the power grid is unreliable, BS are provided with a hybrid power supply system (HESS) consisting of a solar panel (PV), an accumulator (AC), a supercapacitor (SC), a diesel generator (DG), and a local power grid [1, 2]. Failure of components in such a system (decrease in AC capacitance, increase in the equivalent resistance of the SC, breakage of the CP circuits, mechanical failures of the DG) leads to power disconnection. Traditional boundary control records a malfunction only after it occurs, while a predictive approach allows for maintenance planning before an accident occurs. In recent years, artificial intelligence methods have been widely used in fault detection [3], but they are not systematized across HESS components. The purpose of the article is to analyze machine learning (ML) methods used in predicting HESS component failures based on authoritative sources and to substantiate their selection criteria.

II. ANALYSIS OF FAULT FORECASTING METHODS

a. Component methods

Table 1 summarizes the methods of ML recorded in the sources, input signals, and failures for HESS components.

Table 1. HESS component failures and ML methods

Component	Failure	Input symbols	ML methods and outputs
PV	Short circuit, disconnection, grounding, incompatibility	U, I, power, radiation, modulus temperature	SVM, DT, RF, NB, XGBoost - accuracy 97.2–98.0% [4, 5]
AC	Capacity decrease, internal resistance increase, local overheating	U, I, T, charge curve, number of cycles	LSTM/GRU, CNN, Physics-based neural networks (PINN), hybrid models [6-9]
SC	Capacity decrease, ESR increase	U, I, T, capacity, number of cycles	VMD-SSA-BiLSTM: mean RMSE 0.1125, 44.3% lower than BiLSTM [10, 11].
DG	Bearing, winding, and fuel system failures	Vibration, current, temperature	ANN, fuzzy and expert systems, complex ML methods [12]
Monitoring chain	Sensor shift, noise, data quality	Power balance balance, measurement rows	Rules, data, and hybrid-based models; hybrid - 99.96% [3, 13]

Controlled training methods for PV (SVM, decision tree, random forest, XGBoost) distinguished short circuits, interruptions, grounding, and non-compliance failures based on voltage, current, and power fluctuations generated in the MATLAB/Simulink model with an accuracy of 97.2–98.0% [4]. The AI-based PV diagnostics survey recommends hybrid approaches that combine ML, deep learning, and reinforcement learning in future research [14]. The prediction problem for AC and SC is reduced to assessing health status (SoH) and useful life remaining (LRL):

$$SoH = \frac{C_{ac}}{C_{nom}} \times 100\%, \quad (1)$$

$$LRL(t_k) = t_{EOL} - t_k, \quad t_{EOL} = min\{t \mid SoH(t) \leq SoH_{EOL}\}, \quad (2)$$

where C_{ac}, C_{nom} are the actual and nominal capacities; t_{EOL} – resource end time; SoH_{EOL} is the threshold value.

Data-driven methods for AC explore degradation patterns from historical series; the inclusion of physical equations in the loss function (PINN) is considered a promising direction for data-deficient conditions [7, 8], while predicting cyclic lifespan from early cycle data is demonstrated [9]; and the use of artificial intelligence in real-world battery diagnostics is considered [15]. The BiLSTM model, whose hyperparameters are selected by decomposition via VMD and SSA for the SC, achieved an average RMSE of 0.1125 at various temperatures and stresses, which is 44.3% lower than that of a conventional BiLSTM [10]; A review of the mechanisms and models of SC wear [11] can serve as a basis for selecting input characteristics (capacity, equivalent resistance, temperature, voltage). The review of artificial intelligence for the DG highlights fuzzy and expert systems, artificial neural networks, and complex ML methods, as well as implementation challenges - data dependence, computational demand, and model interpretation – and the integration of digital twins, explainable artificial intelligence, and the IoT [12].

b. Data and model selection issues

Liu et al. have divided fault detection models into rule-based, data-based, and hybrid-based: rule-based ones are fast and understandable but limited by predetermined situations; data-based ones learn well in complex conditions but depend on data quality; hybrid models combine flexibility and interpretation, but require more computational resources [3]. The study showed that eliminating class imbalances increased accuracy by 16.2–26.2%, feature separation based on deep learning maintained an accuracy of over 98.5% at SNR = 10 dB, hybrid models achieved 99.96% accuracy, and heuristic optimization of hyperparameters provided an improvement of 6.92–19.375% compared to basic models [3]. From this, two conclusions emerge for HESS: since fault records are few and disproportionate, methods for filling in information and eliminating discrepancies are necessary; sampling frequency affects signal quality – low frequency loses high-frequency details, while high frequency increases noise [3].

III. RECOMMENDED ARCHITECTURE AND EVALUATION CRITERIA

Based on the analysis, a three-level predictive diagnostic architecture for HESS is proposed (Fig. 1). At the extreme level (a device like ESP32 or Raspberry Pi), measurements are filtered, symbols are counted, and a lightweight model (RF or CUSUM) detects a malfunction in real time. The residual power balance [13, 16], SoC, and temperature change rate are used as characteristics; in the author's 24-hour simulation, the residual and CUSUM-based detector detected a 1 A displacement of the AC current sensor within 30 minutes with a 99% probability, whereas the static boundary method failed to detect it. At the cloud level, the LSTM/BiLSTM or PINN models predict the SoH and QU of the AC and SC, while the XGBoost/RF models predict the PV and DG states and are periodically retrained. The digital twin (MATLAB/Simulink) fills the data gap and validates models by introducing synthetic failures [12].

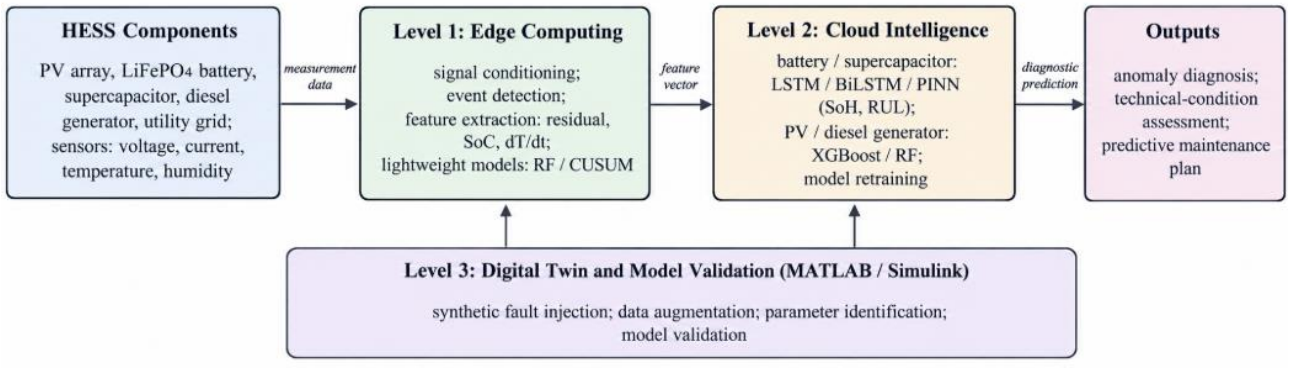


Figure 1. Three-level failure prediction architecture

Model selection criteria: (i) number of fault samples - RF/XGBoost for subtable data, LSTM/BiLSTM for long degradation series, PINN in case of data scarcity; (ii) computational resource and latency - real-time detection at the edge, heavy models in the cloud; (iii) Interpretation - explainable hybrid models for maintenance decisions. Evaluation criteria: recall for classification, F1, and the number of false alarms per day; Mean square error for QFU:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(QFU_i - QFU_{per,i}\right)^2}, \quad (3)$$

where *N* is the number of test samples; $QFU_{per,i}$ is the predicted value. The practical indicator is the prediction horizon, i.e., the time between the warning and the failure.

IV. CONCLUSION

The choice of the component-based ML method depends on the fault type and data volume: RF/SVM/XGBoost for PV, LSTM/BiLSTM and PINN for AC and SC, and ANN and hybrid models for DG. The main obstacles are insufficient and inconsistent fault data, noise, interpretation, and computational resources. The proposed edge-cloud-digital twin architecture combines real-time detection and long-term prediction. In the future, it is necessary to validate the models based on real BS data.

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МЕТОДЫ МАШИННОГО ОБУЧЕНИЯ, ИСПОЛЬЗУЕМЫЕ ДЛЯ ПРОГНОЗИРОВАНИЯ ОТКАЗОВ В ГИБРИДНЫХ ИСТОЧНИКАХ ЭЛЕКТРОСНАБЖЕНИЯ ТЕЛЕКОММУНИКАЦИОННОЙ ИНФРАСТРУКТУРЫ

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Аннотация: непрерывность работы гибридных систем электроснабжения базовых станций (фотоэлектрические панели, аккумулятор, суперконденсатор, дизельный генератор, электросеть) зависит от заблаговременного прогнозирования отказов. В данной статье систематизируются типы неисправностей по компонентам, входные данные и применяемые методы машинного обучения (RF, SVM, XGBoost, LSTM/BiLSTM, физически обоснованные нейронные сети), а также сравниваются их преимущества и ограничения. Предложена трехуровневая архитектура и критерии оценки, состоящие из периферийного уровня, облака и цифрового двойника. Основным препятствием является недостаток и диспропорция данных об отказах; наиболее перспективным направлением является сочетание физических и данных-ориентированных подходов.

Ключевые слова: гибридное электроснабжение; прогнозирование отказов; машинное обучение; LSTM; остаточный полезный ресурс; аккумулятор; суперконденсатор; базовая станция.