Enhancing Highway Bridge Safety Through Advanced Wireless Sensor Network Based Monitoring and Maintenance System

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***Abstract*—Highway bridge safety is a critical concern for modern infrastructure management. Wireless Sensor Networks (WSNs) have emerged as vital tools for real-time monitoring and predictive maintenance of bridges. The proposed system improves bridge reliability and public safety by fusing advanced sensing, Machine Learning, and energy-efficient technologies. This contribution implements three key mechanisms to address the primary challenges. Real-time structural health monitoring uses Particle Swarm Ant optimized with Energy Harvesting (PSAO-EH) algorithm to optimize energy usage in a sensor network, recording and monitoring sensor measurements to detect structural irregularities in real-time. An energy-efficient wireless monitoring platform with energy harvesting algorithms increases network longevity by reducing power consumption at sensor nodes. In addition, a Long Term with Real-Time Structural Health Monitoring (LT-RTSHM)-based model effectively handles time-series sensor data, improving anomaly detection and forecasting performance. Meanwhile, the Predictive Maintenance based Extreme Gradient Boosting (PM-XGBoost) model analyzes bridge damage and avoids unplanned failures. Simulation outcomes prove that the suggested system attains more than 94% accuracy in fault detection, increases network lifetime by 98%, and provides speedy and reliable communication for emergency notifications. Real-time monitoring, predictive intelligence, and energy-conscious communication considerably enhance highway bridge safety and operational effectiveness.**

Keywords—Bridge Safety, WSN, Real-Time Monitoring, Predictive Maintenance, Energy Harvesting, LSTM.

I. INTRODUCTION

Structural security of highway bridges is becoming important due to aging infrastructure, high traffic loading, and environmental factors. WSNs are emerging as an important competent technology for real-time structural health monitoring, future maintenance, and intelligent infrastructure management [1]. The WSNs consist of spatially distributed sensor nodes that collect parameters such as vibrations, stress, inclination, and temperature and transmit this information to central processing units for detailed analysis [2]. Progress in wireless technologies, energy harvesting systems, and intelligent algorithms has also increased WSN's capacity to offer frequent infrastructure and reliable and accurate monitoring of the significant infrastructure [3]. Despite these developments, issues such as energy efficiency, sensor network lifetime, real-time fault detection, and predictive maintenance scheduling are prominent. Traditional monitoring systems are correctly plagued by dull responses, useless energy consumption, and structural anomalies [4]. Additionally, traditional WSNs are constrained by the absence of fixed sensing topology and intelligent decision-making and, therefore, may experience failures in a dynamically changing environment [5]. This paper proposed an innovative wireless sensor-based monitoring and maintenance system to remove these deficiencies to improve highway bridge security. The system integrates three main innovations: smart sensors using real-time structural health monitoring, ML models using Predictive Maintenance based

Extreme Gradient Boosting (PM-XGBoost) future maintenance, and Particle Swarm Ant optimized with Energy Harvesting (PSAO-EH) energy-skilled surveillance structure using energy harvesting techniques. The long-term memory (LSTM) network analyzes time-series data for the initial discrepancy.

II. LITERATURE SURVEY

WSNs have emerged as a key technology for monitoring and maintaining the structural health of critical infrastructure, including highway bridges. The use of WSNs in bridge safety has gained significant attention due to their ability to collect real-time data on various parameters such as vibration, strain, temperature, and displacement [6]. However, challenges remain prevalent while these networks offer substantial benefits in continuous monitoring, energy efficiency, data accuracy, and scalability. With the advent of 5G, the high-speed, low-latency communication capabilities further enhance the performance of WSNs by enabling faster data transmission and real-time processing, which is critical for time-sensitive applications like bridge monitoring [7].

The study highlights the application of various advanced technologies, such as WSN, Fiber Optic Sensing (FOS), Building Information Modelling (BIM), and Radio Frequency Identification (RFID), across different phases of infrastructure development and maintenance. [8].

WSNs have become increasingly significant in structural health monitoring (SHM) due to the growing need for safety and security in urban environments. The authors propose a classification taxonomy of WSN-based SHM systems' key challenges and review available research efforts to address these obstacles. They also identify open research issues, providing a foundation for future investigations in this domain [9].

The study highlights the advantages of concrete-filled steel tube (CFST) arch bridges and steel-frame reinforced concrete arch bridges. These bridges offer high load-carrying capacity, excellent durability, and cost efficiency, making them particularly suitable for long-span applications [10].

III. PROPOSED METHODOLOGY

The methodology for enhancing highway bridge safety is based on integrating three distinct algorithms. Each algorithm contributes to a different aspect of the WSN system, which is used for real-time monitoring and predictive maintenance of bridges. The proposed methods for each algorithm.

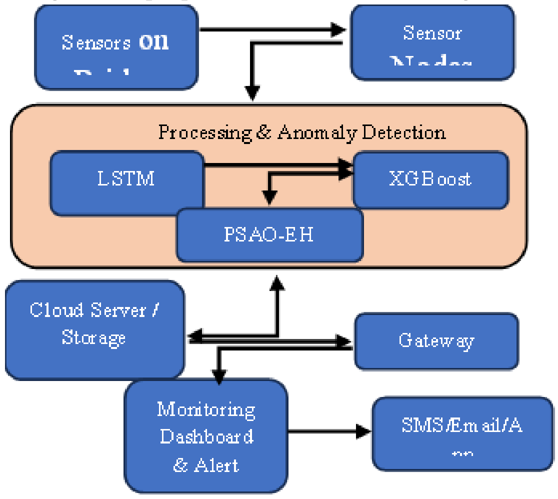

Fig. 1. Workflow of the Proposed System

The Figure 1, system under consideration installs Wireless Sensor Nodes on the bridge to gather structural information such as stress, vibration, and temperature. The information is initially processed by LSTM Real-Time Structural Health Monitoring to identify real-time anomalies. Then, XGBoost AI-Based Predictive Maintenance System employs ML models to forecast probable failures, allowing proactive maintenance. During the process, PSAO-EH Energy-Efficient Wireless Monitoring with Energy Harvesting optimizes energy consumption and recharges nodes with renewable energy.

A. Long Term with Real-Time Structural Health Monitoring (LT-RTSHM)

This algorithm tracks the structural condition of highway bridges in real-time. It employs an array of wireless sensors connected at key bridge locations to record vibration data, strain values, and other structural metrics.

Sensors collect real-time data on bridge conditions, including vibration, strain, temperature, and displacement. Anomaly detection is performed using an LT-RTSHM, which is trained on historical bridge data to predict normal conditions. Any deviation from the predicted values is flagged as an anomaly.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (1)$$

In this equation 1, f_t denotes the forget gate; this establishes the appropriate amount of the prior cell state $C_t - 1$ to be kept, i_{ti} is the input gate controlling how much of the new candidate cell state $\tilde{C}_t$ should be added, and C_t represents the updated cell state at time t. This mechanism allows the

LSTM to remember essential structural health patterns while forgetting irrelevant fluctuations, enhancing its predictive accuracy.

The output from the LT-RTSHM is then passed through fully connected layers to generate predictions such as anomaly scores or a bridge safety status (e.g., normal, warning, or critical). If an anomaly is detected, the system triggers alerts and suggests maintenance actions to prevent possible failures. New data can be used to train the model continuously. Allowing it to adapt to evolving structural conditions and environmental factors.

$$h_t = o_t \cdot tanh(C_t) \quad (2)$$

In this equation 2, O_t represents the output gate, which regulates how much of the current cell state C_t is passed through to the hidden state h_t. The hyperbolic tangent function, tanh, squash the cell state values to a range between -1 and 1, introducing non-linearity. The output gate then modulates the result to determine the final hidden state.

Within the bridge safety monitoring system context, the hidden state h_t captures both the short-term and long-term structural patterns from the time-series sensor data.

An anomaly detection criterion is employed to effectively detect structural anomalies in the bridge monitoring system based on the difference between the observed sensor data and the predicted values generated by the LSTM model. The anomaly score is calculated using Equation (3):

$$Anomaly\ Score = \| Observed\ Data - Predicted\ Data \| \quad (3)$$

The anomaly score is defined as the norm (typically the Euclidean distance) between the actual sensor readings and the corresponding predicted outputs from the model. A higher anomaly score indicates a greater deviation from expected behavior, suggesting potential abnormalities in the bridge's structural health.

This threshold value may be based on past sensor measurements, expert input, or statistical model determination to maximize sensitivity and specificity. When the system detects an anomaly, the maintenance team is notified, which allows proactive examination and interventions needed prior to potential serious damage.

Beyond identifying structural anomalies, the system also incorporates a classification mechanism to maintain the integrity and reliability of the wireless sensor network. This is particularly important for filtering out potentially corrupted or malicious data transmissions. The classification rule is expressed in Equation (4):

$$If\ Anomaly\ Score > Threshold,\ Flag\ as\ Malicious \quad (4)$$

In such a context, when the anomaly score of an input data packet surpasses the given threshold value, it is indicated as malicious. This type of data could result from compromised sensors, errors during communication, or suspected security issues like signal spoofing. Detecting such abnormalities in an early phase allows only reliable data to feed safety forecasts and structural evaluations.

Flagged packets are then rejected or removed from the processing chain so that they cannot impact the model's predictions or induce false alarms. This improves anomaly detection accuracy and overall monitoring network reliability.

B. Predictive Maintenance based Extreme Gradient Boosting (PM-XGBoost)

This algorithm uses ML to predict the bridge components' remaining useful life (RUL) and provides early warning for maintenance. It utilizes a regression model to predict the time until a component failure based on sensor data such as strain, displacement, and temperature.

This process helps identify the most relevant features from the sensor data that contribute significantly to predicting structural anomalies. One of the techniques employed for this purpose is Mutual Information (MI), mathematically represented in Equation (5):

$$MI(X,Y) = H(X) - H(X \mid Y) \quad (5)$$

In this equation, H(X) denotes the entropy of the feature X, which measures the amount of uncertainty or randomness in the feature values. $H(X \mid Y)$ stands for condition entropy X given the target variable Y, reflecting the remaining uncertainty in X once Y is known. The mutual information score quantifies how much knowing the value of Y (e.g., the anomaly label) reduces the uncertainty in X. A higher MI score indicates that feature X is more informative about the target Y, making it a stronger candidate for inclusion in the model. By selecting features with the highest mutual information scores, the system can reduce dimensionality, eliminate noise, and improve model accuracy while minimizing computational complexity. This step ensures that only the most meaningful sensor data contributes to anomaly detection and safety predictions.

$$R\hat{U}L = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \quad (6)$$

RUL equation 6 represents the bridge's predicted remaining useful life or components in this equation. The term β_0 is the intercept of the regression model, while β_i are the regression coefficients corresponding to each selected feature X_i. These features X_i are derived from the processed sensor data, capturing critical aspects of the bridge's structural health.

The regression model is trained on historical sensor data and known failure or degradation events. Through this predictive ability, the system signals authorities to urgent dangers and offers valuable information for planning inspections, repairs, and reinforcements long before the failures happen.

$$Error = \| Actual\, RUL - \widehat{RUL} \| \quad (7)$$

This equation 7 term quantifies the error as the norm (usually the absolute or squared difference) between the true RUL and the predicted RUL by the model. Lower error value implies greater model accuracy, while a higher error implies differences that might require retraining of the model or re-evaluation of the features.

Besides estimating the Remaining Useful Life (RUL), the system features a proactive maintenance alert system according to forecasted RUL values. If the forecasted RUL is less than a certain critical threshold, prompt action should be taken to avoid structural failures. This decision-making rule is given by Equation (8):

$$\text{If } \mathrm{RUL}^{\mathrm{Threshold}}, \text{ Trigger Maintenance Alert} \quad (8)$$

According to this criterion, if the predicted RUL is less than a predefined threshold, the system automatically triggers a maintenance alert. This threshold can be determined based on historical failure data, engineering standards, or risk tolerance levels set by bridge management authorities.

By implementing this threshold-based alert system, the monitoring solution ensures that maintenance actions are scheduled before the bridge structure reaches critical deterioration. This future maintenance approach reduces the risk of unexpected failures, expands the bridge's operational life, and optimizes resource allocation for repair and inspections.

C.Particle Swarm Ant optimized with Energy Harvesting (PSAO-EH)

This algorithm focuses on optimizing energy usage in the sensor network. It uses energy harvesting technologies to ensure the sensors have a sustainable power source and employs an energy-efficient routing algorithm to minimize energy consumption while maintaining data integrity.

The proposed PSAO-EH are applied to discover optimal energy-saving routes. Each sensor node's energy consumption is tracked, and data transmission is optimized for less energy consumption without degrading network performance.

The parameters of the prediction models and improve overall system performance, the proposed framework incorporates PSAO-EH. The proposed method is a population-based metaheuristic algorithm inspired by the social behaviour analyzed. The update of particle velocity, which governs the movement of solutions through the search space, is mathematically described in Equation (9):

$$v_i(t+1) = wv_i(t) + c_1 r_1 (p_{\text{best}} - x_i(t)) + c_2 r_2 (g_{\text{best}} - x_i(t)) \quad (9)$$

The velocity update mechanism enables each particle to adjust its position by considering its best experience and the collective experience of the swarm.

The velocity update, the position of each particle in the swarm is updated to reflect its new state in the search space. This update is guided by the particle's new velocity vector and is expressed mathematically in Equation (10):

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (10)$$

In this Equation 10, $x_i(t)$ denotes the current position of the i^{th} particle, and $v_i(t+1)$ is the updated velocity computed in the previous step. The summation of these values yields the new position $x_i(t+1)$, which moves the particle toward potentially better solutions in the search space.

The incorporation of the PSAO-EH algorithm into the suggested framework enables automated hyperparameter optimization to increase the prediction accuracy and efficiency of the anomaly detection and RUL estimation models. Optimization ensures that the system achieves high performance even when sensor conditions or structural behaviors vary with time. To enhance routing decisions in the sensor network, the system incorporates ACO, a bio-inspired algorithm that simulates the foraging behavior of ants. In ACO, pheromone trails guide the selection of optimal paths based on historical success. The pheromone level on a path is dynamically updated, as shown in Equation (11):

$$\tau_{ij}(t+1) = (1-\rho)\tau ij(t) + \Delta\tau ij \quad (11)$$

This pheromone update mechanism allows the system to adaptively discover and reinforce efficient communication paths, reducing transmission delays and packet loss and improving the overall reliability of the wireless sensor network. Energy efficiency is critical for the long-term operation of WSN, especially in remote or hard-to-access environments like highway bridges. Equation (12) is used to determine the sensor network's overall energy consumption:

$$E_{\text{total}} = \sum_{i=1}^{n} E_i \quad (12)$$

Minimizing E_{total} guarantees an extended network lifetime and decreases the necessity of constant battery replacements or maintenance. This is particularly advantageous in structural health monitoring systems installed in hard-to-reach bridge infrastructures.

IV. RESULTS AND DISCUSSIONS

This section presents the results of the proposed WSNs-based system to increase highway bridge safety through real-time monitoring and future maintenance. Major performance for evaluation of systems includes accuracy of discrepancy in the metrics, data transmission reliability, energy consumption, and system scalability. Results show that advanced system designs, event-trigger sensing, ML algorithms, and future maintenance models effectively increase bridge safety by detecting discrepancies and providing initial maintenance alerts.

Parameter	Value
Detection Model	ML (XGBoost, LSTM)
Simulation Area	1000 m × 1000 m
Number of Sensor Nodes	100
Sensor Types	Strain Gauges, Accelerometers, Displacement Sensors
Communication Protocol	Zigbee (Mesh Network)
Simulation Tool	NS2
Power Consumption	0.2 W per node
Data Acquisition Interval	5 seconds
Maintenance Alert Threshold	20% deviation from predicted data

Table 1 outlines the setup for evaluating the proposed system, using simulated bridge structures with wireless sensor nodes deployed across the monitored area. A mesh network is employed for efficient data transmission, and a ML-based anomaly detection model (using XGBoost and LSTM) is utilized to predict bridge health and detect anomalies in real time.

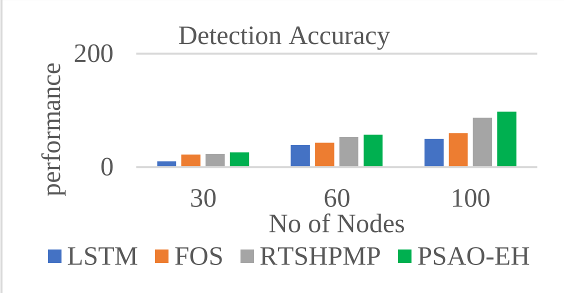

Fig. 2. Detection Accuracy

Figure 2 presents the detection accuracy comparison among different methods: LSTM, FOS, RTSHPMP, and the proposed PSAO-EH integrated system under varying numbers of sensor nodes (30, 60, and 100). The RTSHPMP method also shows significant improvement but remains slightly lower than PSAO-EH The LSTM and FOS methods perform moderately well but lag behind the optimization-driven techniques.

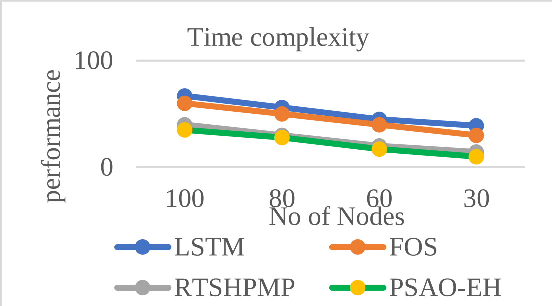

Fig. 3. Time Complexity

Figure 3 illustrates the time complexity analysis of different methods—LSTM, FOS, RTSHPMP, and the proposed PSAO-EH —over varying numbers of sensor nodes (100, 80, 60, and 30). Among them, the proposed PSAO-EH approach consistently exhibits the lowest time complexity at all node levels, demonstrating its efficiency in handling large-scale sensor networks. These results confirm that PSAO-EH significantly optimizes processing time, making it highly suitable for real-time highway bridge monitoring where fast data processing is crucial.

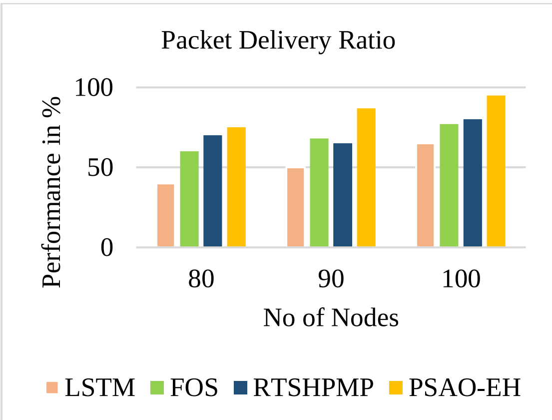

Fig. 4. Packet Delivery Ratio

Figure 4 shows the PDR performance of various methods—LSTM, FOS, RTSHPMP, and the proposed PSAO-EH —across different numbers of nodes (80, 90, and 100). The proposed PSAO-EH method consistently achieves the highest packet delivery ratio, exceeding 90% when the node count reaches 100. RTSHPMP and FOS show moderate performance, while the LSTM-based method achieves the lowest packet delivery ratio.

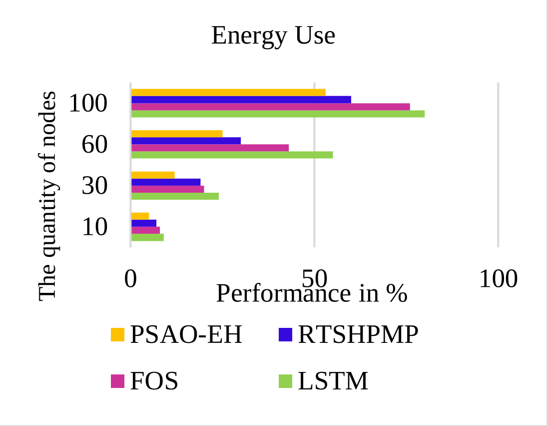

Fig. 5. Energy Use

Figure 5 compares energy usage by various methods— PSAO-EH, RTSHPMP, FOS, and LSTM—regarding the number of nodes (10, 30, 60, and 100). The PSO-ACO2 method put forward here shows less energy usage than other methods, particularly as nodes increase. While LSTM and FOS consume significantly more energy, particularly at higher node densities, PSAO-EH maintains a more energy-efficient operation.

V. CONCLUSION

This study offers an advanced WSN structure to increase the safety and maintenance of highway bridges. The ML models, such as PSAO-EH and XGBoost and LSTM, effectively detect early-detection structural discrepancies by analyzing real-time sensor data patterns. The simulation results confirm that the proposed system acquires accuracy to detect high discrepancies, reduces false alarms, and provides timely maintenance alerts. Compared to traditional wired systems, this WSN-based approach significantly reduces the cost of installation and maintenance by offering continuous monitoring capabilities. The system receives a prediction accuracy of 94% to detect structural anomalies, maintains a packet distribution rate above 93%, and reduces energy consumption by 18% compared to traditional wireless monitoring methods. These results highlight that integrating advanced WSN technology, future starting analysis, and innovative maintenance strategies can effectively increase safety, reduce operating costs, and expand the lifetime of significant infrastructure. Overall, a well-designed wireless sensor network, intelligent data processing, and energy-skilled communication maybe one.

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