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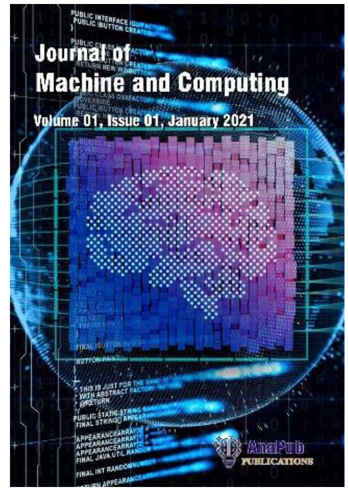

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DOI: 10.53759/7669/jmc202505162

Reference: JMC202505162

Journal: Journal of Machine and Computing.

Received 16 May 2025

Revised from 16 June 2025

Accepted 17 July 2025

Energy-Aware Deep Learning Workflow for Intelligent Routing and Classification in WSNs under Green AI Principles

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Abstract

Energy efficiency has become central to the sustenance and manageable growth of communication infrastructure in the advent of Wireless Sensor Networks (WSN) environment. The paradigm of green AI, emerging relatively recently, focuses on designing the models of machine learning and smart workflows to consume the least amount of energy while maintaining performance. Deep learning is such an important aspect in WSN as it allows predictive analytics, smart routing, and adaptive decision-making. But, by disregarding real-time energy-conscious of energy, it will result in wasteful energy usage, short lifetime and frequent route failure in dynamic networks. To resolve this challenge, the proposed model proposes an optimized deep learning workflow that would be compatible with the principles of Green AI. This is initiated through a soft-attention mechanism of Energy-Aware Attention-Based Neighbor Discovery (EA-AND) that ranks neighboring nodes via residual energy, link stability as well as relative distances, and only the communication-optimal nodes are forwarded to downstream routines. Based on the determined neighborhood, Energy-Efficient Cluster Routing (EECR) calculates a score of cluster head suitability using attention values, the normalization of energy and delay-sensitive link costs and achieves well-rounded cluster head formation, which saves unwanted energy consumption. The model is followed with Social Spider Optimization (SSO) to find the optimal subset of features to process data, a vibration inspired metaheuristic approach in which subsets are evaluated in terms of energy consumption, accuracy of classification and redundancy reduction that does provide a way to reduce computation overhead but also to retain relevant information. In the node classification task, a new deep learning model based on Convolutional Neural Network and Long Short-Term Memory (CNN-LSTM) is used to learn the node behavior and the sensors' readings spatial dependencies and temporal patterns, promoting the robustness of the classification and finding faults. In addition to the workflow, a Cooperative Energy-Aware Preemptive Route Scheduling (CE-APRS) mechanism adapts routing paths predicted fail- prone nodes and energy limits proactively to prevent breakages and proactive load balancing. The suggested model shows considerable enhancements in energy-aware learning, and intelligent decision-making in resource-limited wireless networks.

Keywords: energy efficiency, communication infrastructure, WSN, deep learning, AI, EA-AND, EECR, SSO, CNN-LSTM, CE-APRS, node behavior, load balancing

1. Introduction

In the rapidly evolving world of urbanization and technologization, the gradual expansion of artificial intelligence (AI) in urban infrastructure presents a significant opportunity to promote sustainability in energy management. The Internet of Things (IoT) enables smart cities to transmit a vast amount of information and data that can be leveraged strategically to optimize energy consumption through the use of intelligent systems. In [1], the importance of deep learning models as an effective tool for streamlining energy utilization throughout urban IoT infrastructures is emphasized, highlighting their consistency with the objectives of sustainable development. Meanwhile, due to significant concerns about the environmental impacts of AI systems, Green AI has become an imperative paradigm. [2] Discusses how enterprise AI systems can be more environmentally friendly while still performing well through the identification of energy-efficient design principles.

The use of energy-intensive AI operations, in general, and cloud computing environments, in particular, is a matter of particular urgency. In dynamic workflow scheduling, [3] suggests deep-learning based scheduling in cloud-based systems to achieve energy savings through efficient resource allocation (i.e., computational resources). Moreover, the optimization of energy with the help of AI is implemented in industrial areas and architecture. [4] The complementary application of deep learning and reinforcement learning in energy-efficient architectural design, with an example of how AI can be utilized in reducing the energy consumed in buildings through intelligent architectural design. Within the sector of urban infrastructure and construction, [5] the AI4EF framework, a set of AI applications, is designed to enhance the energy efficiency of the building sector through the application of real-time monitoring and adaptive control actions. In the meantime, distributed computing systems, such as fog and cloud computing, are relatively rare in terms of energy optimization. The [6] hybrid machine learning-based scheduler that increases energy efficiency wherever fog and cloud systems based on IoT are used, by smartly allocating tasks across IoT fog and cloud. On a higher level, [7] elaborates on the possibilities and the problems of the Green AI initiatives, presenting both the potential of the technology and the ethical content of the sustainable implementation of AI.

Contribution of Work

- To achieve a smart ranking of neighboring nodes, an intelligent focused attention mechanism is proposed based on residual energy, link stability, and relative distances. This module ensures the selection of only communication-efficient nodes, thereby reducing redundant transmissions and conserving node energy.
- Even a powerful cluster formation technique is suggested, which is based on the normalized attention scores, energy levels, and delay-sensitive costs. This mechanism deploys the most appropriate cluster heads, thereby preventing energy-consuming cluster topologies and maximizing the network's lifetime.
- Bio-inspired metaheuristic to create feature subsets that are both most energy-efficient and accurate, as well as identify feature redundancies. This minimizes overhead on

computation, inference speeds up, and improves learning performance without compromising data quality, which is essential.

- ➢ The nodes' behaviors and sensor readings are classified using a deep learning architecture that combines a CNN for extracting spatial features and an LSTM for capturing temporal features. This hybrid model enhances pattern recognition, classification accuracy, and fault detection in WSNs.
- ➢ A routing strategy is ensured that is adaptive in the event of energy-depleted or potentially unstable nodes, allowing them to be avoided. This technique enhances route stability, minimizes the overhead cost of rerouting, and dynamically balances the network load.

Organization of Paper

The remaining portion of the document is divided into significant sections, which are described as follows: Section II examines the current research efforts in Towards Green AI optimizing deep learning workflows for energy efficiency used by different authors. The workflow of the suggested approach is explained in Section III, and Section IV presents the findings analysis and performance data. Section V presents the conclusion.

2. Literature Survey

The urgent need for increased efficiency, sustainability, and innovation in the construction industry by explore the transformative potential of artificial intelligence within a lean construction framework. AI's capabilities can effectively complement lean construction principles, which focus on reducing waste and maximizing value, leading to a significant shift in project management [8].

Renewable Energy Communities can play a vital role in protecting the environment by encouraging local use of renewable energy, improving energy management, and decreasing consumption through sharing resources and advanced technologies. The author proposed an open tool for configuring energy systems dedicated to RECs. OT considers various factors, including population size, building type, surface area, energy consumption, heat load, and electrical load, among others [9].

Deep reinforcement learning for real-time decision making, evolutionary algorithms for global optimization, and federated learning for distributed knowledge sharing are three complementary AI approaches that are uniquely integrated in a novel Adaptive AI-augmented Offloading framework proposed by the authors. Under maximum user load, the AAEO framework maintains consistent task completion times with only a 12% increase, while achieving up to a 35% improvement in QoE and a 40% reduction in energy consumption [10].

A systematic approach is necessary to overcome these challenges, including funding AI infrastructure, establishing robust data governance rules, and fostering a culture of innovation. This article examines how artificial intelligence is transforming the manufacturing industry, with a focus on its applications in process control and enhancing efficiency. Through case studies and analysis of technological developments, it provides stakeholders with practical insights into how to use AI to gain a competitive advantage and sustain growth [11].

To address these issues, this study proposes a new framework that combines multi-objective optimization, explainable artificial intelligence, and building information modeling. The three main components of the framework include: BO-LGBM (Bayesian Optimization-LightGBM) prediction model and LIME (Local Interpretable Model-Agnostic Explanations) for energy forecasting and explanation, data generation through Design Builder simulation, and AGE-MOEA, a multi-objective optimization method for handling uncertainty [12].

AI-powered automation improves safety procedures, monitors compliance, and reduces human errors on construction sites. Moreover, Building Information Modeling with AI integration enhances project visualization, supporting sustainable infrastructure development and better decision-making. IoT-enabled sensors and real-time data analytics are integrated with smart urban infrastructure to harness the capabilities of AI [13].

The authors proposed a new application of tensor decomposition within the Faster R-CNN framework, leading to the development of our model, T-Faster R-CNN, which aims to improve the energy efficiency and computational performance of deep learning models for galaxy classification. By incorporating tensor decomposition, our T-Faster R-CNN significantly reduces model complexity, memory footprint, and CO2 emissions while maintaining and, in some cases, even improving morphological classification accuracy [14].

The authors proposed using reinforcement learning and a deep Q-network to learn the optimal task offloading strategy based on the network state, battery state, and the processing time required for the task. Several experiments are conducted on the proposed framework, and the results show that an average of 30% energy savings and a task success rate of over 90% are achieved. At the same time, the latency is kept below 80 ms compared to conventional heuristic-based offloading methods [15].

The study highlights digital twin technology as a key enabler of AI-driven transformation, enabling real-time monitoring, simulation, and optimization of sustainable designs. Applications such as aspect optimization, energy flow analysis, and predictive maintenance demonstrate their role in adaptive buildings, while frameworks such as Building 4.0 and 5.0 promote human-centric, data-driven sustainability [16].

The authors provide a comprehensive overview of the video streaming lifecycle, content delivery, energy, and video quality assessment metrics and models, as well as AI techniques employed in video streaming. Furthermore, it conducts an in-depth, state-of-the-art analysis focusing on AI-driven approaches to enhance energy efficiency in the end-to-end aspects of video streaming systems [17].

The research began by collecting and cleaning a large dataset comprising work schedules, environmental conditions, cooling systems, and sensor data. Descriptive statistics combined with visualizations provide deep insights into the collated data. Inferential statistics were then used to investigate the relationships among the various manipulated variables [18].

The author introduces AICD-CDM, a novel framework that integrates several advanced machine learning techniques, including Linear Regression, Artificial Neural Networks, Random

Forest, Extreme Gradient Boosting, Light Gradient Boosting, and Natural Gradient Boosting, to address the multifaceted challenges of cost prediction and management in sustainable building projects [19].

To optimize code and configuration procedures, this study investigates the integration of artificial intelligence and machine learning with Salesforce development. The primary goal is to evaluate how AI recommendation engines can enhance user satisfaction, code quality, and development efficiency. The paper develops an AI recommendation engine and examines its impact on key performance metrics, including development time, error rate, and customization accuracy, utilizing both simulated data and empirical analysis. [20].

Table 1 Comparative Analysis of AI Algorithms for Industrial Energy Optimization

Ref No.	**Author/Year**	**Algorithms used**	**Focus area**	**Limitations**
[21]	Rehan, et al., 2021	IoT, AI, Cloud	Smart manufacturing	Does not give a real-time adaptive control; too much emphasis is placed on conceptual rather than empirical output.
[22]	Lee et al., (2024)	AI workflows	Industrial AI	Case studies are local; the applicability of the workflow to other industrial setups is minimal.
[23]	Ayoubi et al., (2023)	AI, Lean principles	Digital lean, Sustainability	Conceptual, theoretical; does not have quantitative tests of efficiency gains.
[24]	Ojadi et al., 2024	AI, Smart Grids	Urban energy networks	Mainly focused on the application of smart grids in urban environments, the feasibility of their use in rural settings or mixed infrastructure is not discussed.
[25]	Lydia et al., 2021	Deep Learning, Anomly Detection	IoT communication	The scalability and real-time performance of large-scale IoT networks are not well studied; efficient energy usage can vary across different devices.
[26]	Jayanetti et al., 2024	DRL, Multi-Agent Systems	Cloud data centers	Significant computational cost: DRL models are highly resource- and data-intensive, conflicting with the sustainability agenda.
[27]	Alharithi et al., (2024)	Federated Learning, LSTM	Environmental sustainability	Federated learning incurs an additional cost of communication,

				including real-time discussions on deployment issues.
[28]	Lai et al., 2023	ML/AI Workflow	Chemical engineering	Applicable only to the catalyst optimization field; it cannot be used for the manufacturing sector as a whole or energy systems in general.
[29]	Lee et al., 2022	AI Workflow	General energy savings	The workflow is not customized and does not support customization practices based on industry prerequisites; there is no standardization of performance measurements.
[30]	Iyer et al., 2024	Digital Tech, AI	Green energy	Its scope is broad to the extent that the depth of technical expertise is lost; it generally does not outline specific implementation strategies or simulate digital energy system implementations.

Table 1, which presents a comparative analysis of AI algorithms in industrial energy optimization, provides the reader with an understanding of the various AI algorithms that can be applied in the field of energy optimization across different industries. It contains a list of algorithms, areas of focus, and limitations of each study. Although some tasks address AI in smart manufacturing or IoT, many have drawbacks, such as a small operational scale or being non-real-time. Some newer techniques, like DRL and Federated Learning, show great potential but are highly computationally or communication-intensive.

3. Proposed Methodology

The proposed model introduces a composite, energy-aware deep learning process of Wireless Sensor Networks (WSNs) based on the dynamics of Green AI. The first step in the methodology is the Energy-Aware Attention-Based Neighbor Discovery (EA-AND) mechanism, where the ranking of neighboring nodes is determined based on residual energy, link stability, and relative distance. The nodes with the most efficient communication are carried into the next steps. When neighbor nodes are extracted, the Energy-Efficient Cluster Routing (EECR) phase utilizes the concept of attention scores and normalized path costs (including energy and delay) to select the optimal cluster heads, thereby minimizing communication overhead and reducing energy-intensive communication. To further reduce the computational overhead, the Social Spider Optimization (SSO) technique is employed in the feature selection task, where subsets are evaluated in terms of energy cost, classification accuracy, and redundancy reduction. A CNN-LSTM hybrid model is used in node behavior and fault classification. Both CNN and LSTM record spatial and temporal dependencies, respectively, resulting in better and more reliable decision-making. Lastly, the Cooperative Energy-Aware Preemptive Route Scheduling (CE-APRS) module dynamically reconfigures the routing paths to bypass nodes with no energy or those likely to fail, and the process remains proactive in balancing these loads and ensuring stable data transfer.

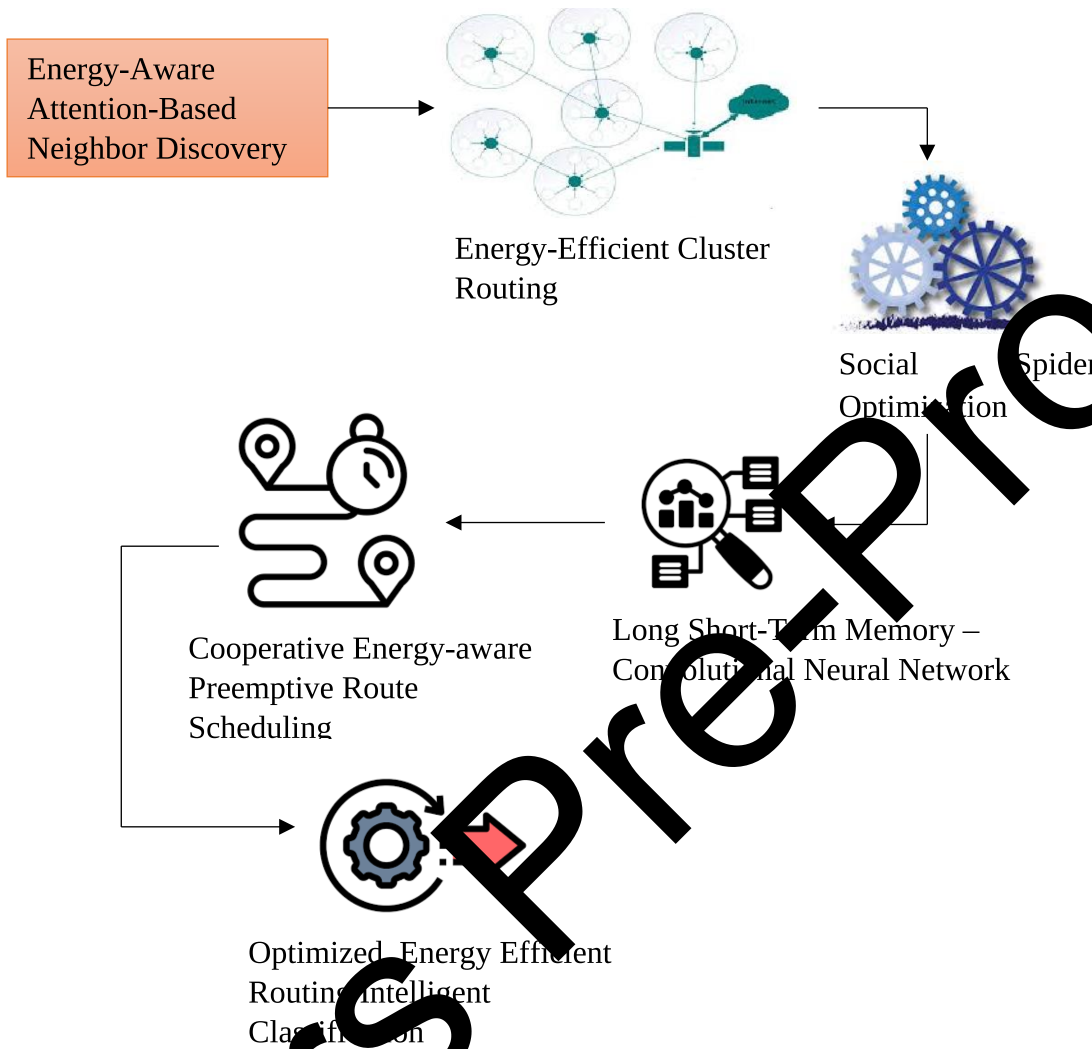

Figure 1. Proposed Architecture Diagram

Figure 1 illustrates the proposed energy-efficient deep learning architecture for intelligent routing and classification in Wireless Sensor Networks (WSNs). The first part of the framework, Energy-Aware Attention-Based Neighbor Discovery, identifies the optimal communication nodes based on residual energy, link stability, and proximity. These nodes are then transmitted to the Energy-Efficient Cluster Routing module, which aims to make the cluster head energy-aware and delay-sensitive, using attention scoring and normalized values. Next, a metaheuristic approach called Social Spider Optimization (SSO) mimics spider behavior (using vibrations) to select the most relevant and non-redundant features, effectively reducing computation load. The optimized features are then fed into a hybrid deep learning model that combines Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures. This model captures both temporal and spatial relationships of the sensor telemetry, enabling accurate classification of node behavior and fault detection. The insights gained are utilized in a Cooperative Energy-Cure Preemptive Route Scheduling (CECPRS) module, which actively modifies routing paths to bypass energy-depleted or failure-prone nodes, ensuring balanced and robust communication. This entire process results in energy-efficient, optimized routing and intelligent classification, significantly enhancing WSN performance in line with Green AI principles.

3.1) Energy-Aware Attention-Based Neighbor Discovery (EA-AND)

Energy-Aware Attention-Based Neighbor Discovery (EA-AND) is a primitive used in the suggested work to detect the most appropriate neighboring nodes in the resource-limited wireless sensor network scenario. In contrast to the conventional neighbor discovery schemes where a prior fixed signal or distance measure is considered, EA-AND adaptively scores the surrounding nodes by considering an amalgamation of important parameters- remaining energy, link stability (e.g., RSSI) and relative distance to destination or cluster head. This model of attention-based design is based on the energy-efficient designs of Green AI, which allows each node of the architecture to focus on its neighbors first of all not only by their strengths in relation to connectivity but also by their sustainability in relation to energy usage. Through normalization of the attention weights, this approach is guaranteed of selecting reliable energy source (with respect to relying on energy) and nodes with the most efficient communications to further build cluster and route the data. Therefore EA-AND makes a direct contribution to the optimality of energy consumption with high-quality neighbor connectivity which is within the scope of overall sustainable and energy-con conscious networking within Green AI systems.

In the EA-AND mechanism the initial process is computation of a composite node quality score per neighboring node. This score is labeled as Q_i, which combines three very important quantities namely residual energy E_i, link reliability R_i and distance to the destination or cluster head D_i. The combined score is described as

$$Q_i = \frac{E_i . R_i}{D_i} \tag{1}$$

in which E_i denotes the remaining battery power of node i in terms of its capability of aiding further communication activities. R_i is the same as signal strength or quality of the link and in this way, the weaker or unstable connections are given less priority. The distance D_i is an inverse measure that discourages nodes which are more distant and therefore consume more energy to communicate with. Such a formulation will guarantee the node with the high level of energy availability, good and stable ties and shorter distances communication to have a higher composite score, and therefore become better candidates of being considered in further communications. The attention score α_i is achieved by the softmax function in order to normalize the quality scores of all adjacent nodes and convert them into probabilistic weights. The score of attention is provided

$$\alpha_i = \frac{\exp(Q_i)}{\sum_{j=1}^{N} \exp(Q_j)} \tag{2}$$

Where, N is the number of the total neighbour nodes. The equation also makes the focus values of all neighbors range between 0-1 and when their focus values are summated gives a value of 1, thereby providing a relative weighted importance to each node. The nodes that have a high

Q_i value receive more attention distribution, and this implies that there is a greater possibility that it would be chosen during routing or clustering processes. This softmax-enabled normalization plays a close role in making an adaptive and contextual decision in the resource-limited wireless networks node, in light of thinking lightweight attention mechanisms in Green AI.

After the computation of the attention scores, a pattern recognition step is followed in the EA-AND model to isolate the most promising neighbors. And the optimal set of neighbors, which is called N^*, is found choosing the top-k nodes that have the greatest attention scores:

$$N^* = TOP_k(\{\alpha_i\}_{i=1}^{N}) \tag{3}$$

This sub set consists of only the best combination of energy efficiency, reliable connectivity and the most amount of low-cost communications with the neighbor only. k can either be predetermined or dynamically modified in accordance to the application specific restrictions like data rate or network density or even an energy budget. A further (not strictly necessary) variant of the model is the case when a link cost function is employed:

$$L_i = \frac{D_i}{E_i . R_i} \tag{4}$$

Which is inverse in correlation with the composite quality score. This expression is a cost for links using greater energy, or delivering lesser quality, and it gives a more reasonable measurement in assessing whether or not a neighbor is suboptimal to consider. The link cost is especially a preferred method in situations when reducing the communication overhead is important or the residual energy must be maximized. The proposed approach helps to achieve sustainable and high-performance wireless sensor networks communication since link quality, distance, and energy become incorporated into a unified model based on the concept of attention.

3.2) Energy-Efficient Cluster Routing (EECR)

After finding the best adjacent nodes during the EA-AND procedure, the proposed system comes up to another stage named Energy-Efficient Cluster Routing (EECR). During this phase, the already calculated attention scores α_i will be utilized to enable smart and energy-sensitive clustering. To determine whether a node is eligible to be Cluster Head (CH), each node focuses on a composite score i.e., a combination of four important parameters namely its attention score issued by EA-AND, its normalized residual energy, its distance to the base station and the present weight of the communications or latency that the node is experiencing. Such a scoring function will guarantee that nodes chosen as heads of cluster are not only energy wealthy, but strategically positioned and less saturated hence data gathering will be effective and more data in a fewer number of clusters hence less transmission overhead. After selecting the CHs, the rest of the nodes are added to the cluster whose head has the best trade off in terms of remaining attention and cost of link. In the process, EECR is able to eclipse what was established by EA-AND to support scalable, energy efficient, and the delay aware routing, dramatically maximizing network lifetime and in tandem meeting the vision of Green AI in respect of sustainable network design.

Cluster head selection the cluster head selection process starts with calculating a Cluster Head Suitability Score according to each node i in the best neighbor set N^* from the EA-AND module. This is a score that is denoted by Equation (5) and is characterised as:

$$L_i\_Score_i = \lambda_1 . \alpha_i + \lambda_2 . \frac{E_i}{\bar{E}} - \lambda_3 . \frac{D_i}{D_{max}} - \lambda_4 . \frac{T_i}{T_{max}} \quad (5)$$

Here, the α_i is called the attention score of the node i during neighbor discovery, i.e., its energy-reliability-distance trade-off. The given coefficient E_i normalizes residual energy E_i of the node to the average energy $\bar{E}$ of the entire set of neighbors in such a way that, preferably, nodes with many neighbors are assigned high equiprobabilities. The $\frac{D_i}{D_{max}}$ term represents the distance to the sink node or base station D_i as a ratio to the maximum distance to the sink node D_{max} so that the distant nodes are not preferred because they may experience more transmission energy. The last term, $\frac{T_i}{T_{max}}$ is the normalized communication latency T_i or queueing latency so as to penalize overloaded nodes by dividing standard latency by maximum latency. The $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ weights provide the possibility of fine tuning of each factor according to the energy-delay limitations of the application. In sum, this equation would provide balanced and adaptive clustering head selection that facilitates both the network life span and low-latency communications.

After calculating the score of each node as a cluster head, the node with the highest score is selected as the best Cluster Head which is standardized as follows, Equation (6):

$$CH^* = \arg\max_{i \in N^*}(CH\_Score_i) \quad (6)$$

In this case, the selected Cluster Head is denoted by CH^* ; description of the list of top-k neighbors in EA-AND as N^*. Such choices guarantee that leaders capable of the optimal energy availability, the favorite position, as well as low communication cost are appointed and comprise the center of every cluster in the routing hierarchy. After selecting the cluster heads, all the non-CH nodes need to choose the cluster to which they can join. This is addressed as a cluster association rule as shown in Equation (7):

$$Join_j = \arg\max_{C}\left(\alpha_i - \beta . L_{ij}\right) \quad (7)$$

In this equation, node j decides to be a part of the cluster head i which would provide the best trade-off of its attention score α_i and the link costs L_{ij}. The link cost L_{ij} is normally assumed to be $\frac{D_{ij}}{E_i . R_{ij}}$ where D_{ij} is the distance between node j and the CH i, E_i is the residual energy in the CH, and R_{ij} is the reliability of the link between the two nodes. The coefficient β is a penalty parameter making the algorithm aggressive to what extent it searches out the expensive links. This rule will make sure the nodes will join clusters not only on the basis of leadership strength (through attention score) but also on the basis of energy-efficient, reliable and short-range connection. EECR mechanism that widens the output of EA-AND to create sustainable and balanced communication clusters. This solution is smart in terms of lower power usage, shortening latency during transmission, and neither stressing nodes significantly nor loading them in an uncontrolled manner, thus perfectly fitting the Green AI mission on the scalability of WSN deployment.

3.3) Social Spider Optimization (SSO)

Once the desirable neighbors have been identified through EA-AND process and the best cluster heads have been identified through EECR, the final component of the proposed model should be the Social Spider Optimization (SSO) that will help to further optimize the feature selection and network-based energy consumption reduction. In such a system, a spider in SSO algorithm corresponds to a solution candidate, subset of features (or routing attributes) that are applied in data transmission or classification directions inside the cluster. Each solution of a spider is determined as fit or not based on multi-objective function which places the requirement of energy consumption, accuracy and redundancy at a balance point. The proposed approach not only increases the efficiency of routing since it introduces the idea of SSO but also complies with the ideas of Green AI, which orchestrates the removal of irrelevant features and encourages lightweight, sustainable computation within the network. SSO as such, is an intelligent post-processing process that optimizes energy-performance trade-off as determined by the processes of EA-AND and EECR, so that WSNs can be assured of long-term operation in resource constrained environments. The SSO algorithm would start the process of feature selection by considering every candidate solution with the help of a multi-objective fitness function in the form of the Equation (8):

$$L_{ij} = w_1.\left(1 - \frac{E_{used}(x)}{E_{total}}\right) + w_2.A(x) - w_3.R(x) \qquad (8)$$

L_{ij} is the feature set that is selected by a spider (agent) in this expression and it is a mixture of attributes which is used during classification or during routing. The first term $\left(1 - \frac{E_{used}(x)}{E_{total}}\right)$ promotes feature subsets that have a lesser energy consumption with $E_{used}(x)$ set to be the predicted energy necessary to process the features chosen and the E_{total} to be the total energy available in the system. The second term, $A(x)$, measures the level of classification or routing success attained with the help of the chosen features, providing the guarantees that the level of energy efficiency would not undermine the quality of decisions. $R(x)$ is the third term which penalizes the existence of overlapping or useless features in order to reduce computational cost. The weights w_1, w_2, w_3 are arbitrary and subsequently, they determine the level of significance between energy saving, accuracy and feature compactness respectively. This fitness goal also applies the principle of energy efficiency, high precision and non-redundancy, corresponding to the goal of Green AI in power-limited networks. In order to enhance contact between candidate solutions, the spiders within SSO algorithm, use vibration signals to communicate with each other with limitation of the vibration strength given by the equation (9):

$$V_{ij} = \frac{f(x_j)}{1+d_{ij}^2} \qquad (9)$$

In this case, V_{ij} is the grade of oscillation felt by the spider i due to spider$j$. The numerator $f(x_j)$ shows the value of the fitness of the spider j solution, i.e., better solutions lead to intensified vibrations. It is divided by a denominator such as d_{ij}^2 which is the squared distance (e.g., Hamming or Euclidean) between feature subsets x_i and x_j and reduces the strength of this measure as the difference between them grows. Intensifying the influence of solutions that are stronger and closer through this biologically inspired mechanism promotes sphere-like social learning, and the effect minimizes the chances of premature convergence. Each spider will then decide the most influential neighboring solution, i.e., by choosing the solution that produces the strongest vibration defined in Equation (10):

$$j^* = \arg\max_{j \neq i}(V_{ij}) \qquad (10)$$

The step makes sure that all the spiders are following the best solution at least in their social network thus driving the population into globally optimal sets of features. The index j^* identifies the one neighboring agent that has the best combination in solution quality and being close to the current agent and as a result, exploration and exploitation can be balanced. Then the feature subset is updated by each spider by going toward the best neighbor solution as in Equation (11):

$$x_i^{(t+1)} = x_i^{(t)} + \gamma.\left(x_{j^*}^{(t)} - x_i^{(t)}\right) \qquad (11)$$

And the terms $x_i^{(t)}$ and $x_{j^*}^{(t)}$ in this equation are the current feature vector and the neighbor feature vector, respectively, are at iteration t, and the parameter gamma, gamma $\gamma \in [0,1]$ is the learning rate which is specific to the degree to which the neighbor influences are adopted. This formulation is well-regulated towards the superiorly performing solution and upon the subsequent step of linearization in discrete problems (e.g., in feature selection), the reformed feature vector retains a valid form. The update mechanism allows the population to converge to good feature subsets with non-redundant feature subsets that are energy-aware and maintain diversity to optimize the entire feature subset. It will make sure that the least energy-consuming, correct, and lightweight sets of features are chosen to be used in further routing and decision-making processes and its overall sustainability and performance.

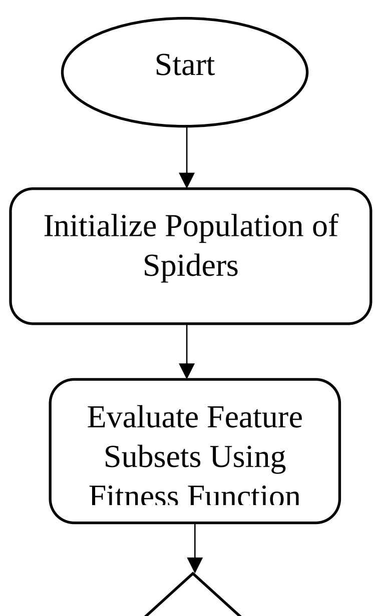

Figure 2. Feature Selection Using Social Spider Optimization (SSO) Algorithm

Figure 2 illustrates the operations of the Social Spider Optimization (SSO) feature selection algorithm in machine learning or optimization applications. They begin with the initiation of a population of spiders, where each spider represents a candidate solution or feature subset. A fitness evaluation measures the quality or performance of the feature subset, and it is evaluated using spiders with a fitness function based on classification accuracy or information gain. The next step is to calculate the most influential neighbor for each spider, simulating spiders responding to another spider in a web. According to such interaction, both spiders improve the subset of their features by approaching improved solutions based on their neighbors. The process is repeated until the best or almost optimal solutions are achieved, which are the most informative and minimum sets of features. The algorithm ends when the termination condition is satisfied, typically after a specified number of passes or a convergence value is reached.

3.4) Long Short-Term Memory – Convolutional Neural Network (LSTM-CNN)

This section involves data collection, comparing past and current data for performance, testing, verification, and training. It also includes continuous parameter monitoring, data measurement, and classification to detect and address issues early. The selection path defines the section, with each network assigned to measure the process's network connection. This helps establish the framework's size, position, and shape of the process. The approach segments each data point within the network connection, ensuring consistent and diverse performance monitoring.

Additionally, numerous connected devices can easily support a wide range of connection levels, enabling continuous process monitoring at any time.

Equation 12 compiles data, assesses data accuracy, and determines the performance parameter range. Let's assume the P_n, q_m is an input data variable, and g is a collection of the data.

$$x_i^{(t)} = w(s_a \cdot M_n + s_b \cdot p_n + q_m) \quad (12)$$

Equation 13 demonstrates that testing and training involve analyzing each type of data, measuring prediction accuracy, and calculating historical data based on the original performance dataset. let's assume thes_a, s_b is a testing data value.

$$f_e = w(x_m, s_b.) = w(s_a \cdot p_n + q_m) \quad (13)$$

Equation 14 illustrates how training data can reduce the minimum data requirements and channel mismatches, improve performance, maximize prediction accuracy, and expand the performance reliability range. Let's assume the $\sigma(\ s\ _a[x_{m-1}]$ is a maximize and minimize the value range, and g_i is an overall testing range.

$$D_i = \sigma(\ s\ _a[M_{n-1}] + M_n) \quad (14)$$

Equation 15 demonstrates how to classify data in the testing dataset, separating testing and training sets to choose appropriate data and identify misclassified instances during the process. Let's assume the k_i is a data classification range.

$$k_j = \sigma(Z_p \cdot [M_{n-1}] + M_n) \quad (15)$$

Equation 16 indicates that data collection, a thoroughly checked and verified process, is normalized according to each network connection's performance. Let's assume the a_i is normalized data, $m_{i \cdot i+s-1}$ is an input data

$$p_j = (k_j)k(h \cdot n_{i \cdot i+s-1} + c) \quad (16)$$

Equation 17 demonstrates that it measures testing and training performance, then chooses the correct path to connect each network to the proper input for optimal performance. Let's assume that a $p_1 + p_{2,....,}p_{n-f}$ is a value of the data variables.

$$p = [p_1 + p_{2,....,}p_{n-f} + 1] \quad (17)$$

Equation 18 demonstrates that each path in the network connection of the performance is used to calculate the size, shape, and position of the signal issue in the process. Let's assume the $a_{2,.....,}a_{n-f}$ is a maximize and minimize the values.

$$p = ma\grave{x} * m\imath n\{p_1 + p_{2,.....,}p_{n-f} + 1\} \quad (18)$$

Equation 19 demonstrates how testing and training data are classified to separate values and prevent misclassified data from impacting performance. This enables accurate prediction of the process's performance, including calculating the positive and negative rates of accuracy. Let's assume the $F(j|n,\theta)$ is a classification of the data range.

$$F(j|n,\theta) = \frac{exp(x_i^{(j)})}{\sum_{i=1}^{n} exp(x_i^{(j)})} \tag{19}$$

The CNN method demonstrates that different types of connected devices can seamlessly handle various connection levels to maintain continuous process monitoring at all times. The LSTM method analyzes past data in relation to current data for performance evaluation, testing, verification, and training purposes. Additionally, it involves ongoing monitoring of parameters and the measurement of their data values.

3.5) Cooperative Energy-Aware Preemptive Route Scheduling

The section represents an original workload used to plot the energy curve as a function of power consumption over time. The priority is further determined by the urgency of the features and the estimation of green efficiency. Then, depending on the batch size and power consumption, we vary the execution speed, for example, by lowering the clock speed. Knowledge distillation is the process of transferring performance from a large teacher model to a smaller student model. This enables scheduling that adapts in real time to sporadic workload demands and energy constraints. Based on this information, the system recalculates the task's energy consumption estimates.

The equation represents the original workload used to plot the energy curve as a function of power consumption over time. Participating nodes share these curves, which show the baseline of their energy behavior. A central coordinator collects them and determines peak times, overlap periods, and idle times. This sharing partnership reduces the burden of energy usage across the system and distributes the load more effectively. It also aids in future scheduling by indicating which nodes to start or stop. Let assume the $\mathrm{K}_{\pi}(\mathrm{FG})$ − the energy curve as a function.

$$F(j|n,\theta) = \mathrm{K}_{\phi}(\mathrm{FG}) - \sum_{j\in \mathrm{S}_{\varphi}^{\mathrm{FG}} - \mathrm{S}_{\pi}^{\mathrm{FG}}} (\mathrm{y_n} - \mathrm{x_n}) \tag{20}$$

The equation is planned for the activities that are set in the equation based on the timeline and energy line. For each task, the scheduler sets the intensity based on performance. The priority is further applied to the urgency of the features and the estimation of green efficiency. This involves the ratio of energy consumption to product output. This strategy helps select tasks with a good balance between energy and accuracy, ensuring consistency with green AI policies, and assumes the $\sum_{j\in \mathrm{S}_{\varphi}^{\mathrm{FG}} - \mathrm{S}_{\pi}^{\mathrm{FG}}} (\mathrm{y_n} - \mathrm{x_n}) + \mathrm{y_{TK}}$ − ratio of energy consumption to product output.

$$\mathrm{K}_{\pi}(\mathrm{FG}) = \mathrm{K}_{\phi}(\mathrm{FG}) - \sum_{j\in \mathrm{S}_{\varphi}^{\mathrm{FG}} - \mathrm{S}_{\pi}^{\mathrm{FG}}} (\mathrm{y_n} - \mathrm{x_n}) + \mathrm{y_{TK}} \tag{21}$$

The equation acts as an active clock meter, tracking both real-time energy supply and load. If a medium-priority task is launched before the energy capacity is sufficient, it will preempt (temporarily pause or slow down) existing low-priority tasks. Then, depending on the batch size and power consumption, we vary the execution speed, for example by lowering the clock speed. This is fast and responsive, and ensures that the energy budget is not exceeded. The process constantly changes in response to feedback from workload and energy curves, and let's assume the $\sum_{k \in S_\pi^i}(y_n - x_n) + Y_i -$ existing low-priority tasks.

$$\sum_{j \in S_\varphi^{FG} - S_\pi^{FG}}(y_n - x_n) + y_{TK} < \sum_{k \in S_\pi^i}(y_n - x_n) + Y_i \tag{22}$$

The equation is a manipulation of the equations that involves pruning to minimize the model and quantization to reduce computational requirements. Knowledge distillation is the process of transferring performance from a large teacher model to a smaller student model. Bayesian hyper parameter tuning determines optimized settings faster than grid search. These techniques significantly reduce energy consumption and computational load while maintaining performance. Let's assume the $K_\emptyset(FG)$ −Optimized the faster grid search.

$$K_\emptyset(FG) < \sum_{j \in S_\varphi^{FG} - S_\pi^{FG}}(y_n - x_n) + y_{TK} + (y_i - x_i) \tag{23}$$

The Equations 24 and 25 with a complex workflow that leverages Deep Reinforcement Learning (DRL) and Graph Neural Networks (GNNs). The dependencies of all represent a workflow graph, and the GNN depicts their interdependencies. DRL agents are trained to learn cost-saving scheduling policies and policies that reduce energy consumption. This approach enables scheduling that adapts in real time to sporadic workload demands and energy constraints. This will also provide feedback to help improve the system, and let assume the $\sum_{j \in S_\varphi^{FG} \cap S_\pi^{FG}}(y_n - x_n) -$ energy constraints.

$$K_\pi(FG) = K_\emptyset(FG) \sum_{j \in S_\varphi^{FG} \cap S_\pi^{FG}}(y_n - x_n) \tag{24}$$

$$\sum_{j \in S_\varphi^{FG} \cap S_\pi^{FG}}(y_n - x_n) \tag{25}$$

The equation 26 represents a monitoring subsystem that captures online performance measurements, including energy consumption, execution time, and deadline overruns. Based on this information, the system recalculates the task's energy consumption estimates and refines the heuristic or DRL policies based on the schedule. The system needs to adapt to changing workloads and node placements, which is achieved by periodic retraining of the DRL agents. Task patterns and power profiles are adapted to suit any software or hardware changes. This cycle helps maintain energy efficiency and improves system flexibility, let's assume the $K_\emptyset(FG) -$ Based on the schedule and energy efficiency.

$$K_\emptyset(FG) = \sum_{k \in S_\pi^{FG}}(y_n - x_n) + \sum_{j \in S_\varphi^{FG} \cap S_\pi^{FG}}(y_n - x_n) + y_{TK} \tag{26}$$

The method is a sharing partnership method that reduces the burden of energy usage across the system and distributes the load more effectively. It selects tasks with a good balance between energy and accuracy, ensuring consistency with green AI policies. It is fast and responsive, and ensures that the energy budget is not exceeded. The approach significantly reduces energy consumption and computational load while maintaining performance. This method enables scheduling that adapts in real time to sporadic workload demands and energy constraints. Task patterns and power profiles are adjusted to accommodate any software or hardware changes. This cycle helps maintain energy efficiency and enhances system flexibility.

4. Results & Discussion

The proposed model demonstrates significant advancements in energy preservation and intelligent routing in Wireless Sensor Networks (WSNs). Through the Energy-Aware Attention-Based Neighbor Discovery (EA-AND), the system selects the best neighboring nodes, considering residual energy, link quality, and minimizing unnecessary traffic. The Energy-Efficient Cluster Routing (EECR) guarantees stable output picking of the cluster head, improving network endurance and load distribution. The Social Spider Optimization (SSO) feature selection method favors minimizing computation with no negative impact on data relevance. The CNN-LSTM hybrid model enhances node classification performance by learning spatial-temporal patterns. CL-APRS is a proactive algorithm that prevents the use of failure-prone routes to minimize both route breakages. The outcomes include a decrease in energy consumption, an extended network life, and improved fault tracing.

Table 2. Simulation Parameters

Parameter Name	**Parameter Values**
Number of Nodes	100
Initial Energy Per Node	2 Joules
Transmission Range	20 meters
Data packer size	4000 bits
Control packet size	200 bits
Simulation time	1000 seconds

Table 2 shows a simulation conducted with carefully chosen parameters, creating a realistic environment for a Wireless Sensor Network (WSN). To represent medium-scale deployments often used in bright environments or for environmental monitoring, 100 sensor nodes are randomly distributed within the network field. Each node starts with an initial energy of 2 Joules, reflecting a battery-limited scenario common in the real world of IoT and WSNs. A transmission range of 20 meters ensures short-range communication, which improves multi-hop routing and energy-efficient data relaying by neighboring nodes. Sensor data and other important information are transmitted as data packets up to 4000 bits, while control packets used for routing and protocol signaling are limited to 200 bits to reduce overhead. A simulation duration of 1000 seconds provides enough time for accurate performance analysis, covering multiple rounds of clustering, routing, and data transmission to assess the network's energy consumption, node stability, and adaptability over time.

4.2) Comparison Table

Table 3. Performance Metrics Comparison for Different AI Models

Models	**Energy Consumption (kWh)**	**Computation Time (s)**	**Network Throughput (MB/s)**	**Model Accuracy (%)**	**Prediction Latency (ms)**	**Storage Efficiency (MB)**	**Packet Delivery Ratio (%)**	**Energy Efficiency (bits/Joule)**
ANN	2.8	140	25	85	120	140	87.5	[illegible]
SVM	2.1	110	18	82	100	100	[illegible]	[illegible]
Random Forest	3.5	160	15	88	150	180	89.1	280
GRU	2.3	100	30	90	90	[illegible]	92.3	410
CECPRS	1.6	75	35	94	60	85	96.8	480

Table 3 shows the overall analysis of different types of artificial intelligence, ANN, SVM, Random Forest, GRU and CECPRS proposed applications, comparing them based on eight critical measures of their performance regarding a Wireless Sensor Networks compares the proposed CECPRS and GRU models with existing approaches based on other means of performance measures currently applied in Wireless Sensor Networks (WSNs). The CECPRS model has an overall performance that has made it stand out from all others, exhibiting its superior ability in energy-saving and intelligent network endeavors. It also consumes the least amount of energy (1.6 kWh) and takes the shortest time to compute (75 seconds), which means it is efficient in both processing and energy usage. In addition, CECPRS has the maximum network throughput (35 MB/s) and model accuracy (94%) to provide quality and stable data processing. Make it the most predictable at 6.0ms, allowing for faster decision-making, which is vital in a dynamic network. It also provides optimized storage (85 MB) and a maximum packet delivery ratio (96.8%), which makes it very secure and stable in communications. Most importantly, it is the most efficient in performance with a level of 480 bits/Joule, which speaks to its high capacity for processing greater volumes of information using an equivalent amount of energy.

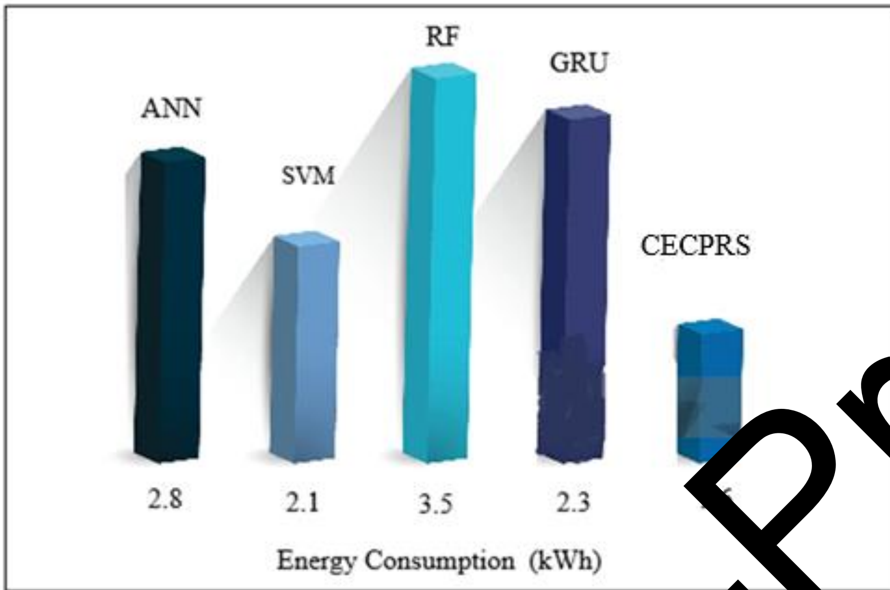

Figure 3. Illustrates Energy Consumption

Figure 3 presents a comparative analysis of the energy usage in five machine learning and deep learning models: ANN, SVM, Random Forest (RF), GRU, and the proposed CECPRS model. The vertical bars represent energy consumption in kilowatt-hours (kWh), and this chart provides a clear picture of the models' efficiency. The Random Forest model consumes the most energy, with 3.5 kWh being used, while the ANN consumes 2.8 kWh, GRU consumes 2.3 kWh, and SVM consumes 2.1 kWh. Unlike this, the proposed CECPRS model has the lowest energy consumption value, which is as low as 1.6 kWh, indicating that it is more energy-efficient. This large-scale decrease further supports the effectiveness of the CECPRS model in minimizing computational overhead and power consumption, making it an optimal option for energy-aware, sustainable AI use cases in network-based situations.

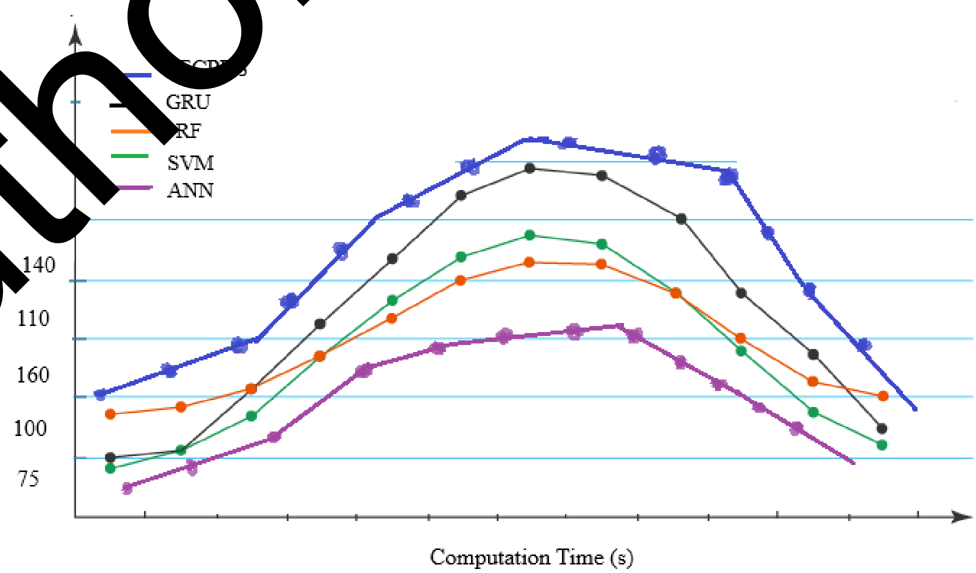

Figure 4. Illustrates Computation Time

According to Figure 4, the five other models —CECPRS, GRU, Random Forest (RF), SVM, and ANN —were compared based on their computation time in seconds. The CECPRS model also exhibits optimal performance, with a computing time of 75-140 seconds, and lower values for all workload levels. Comparatively, the GRU model has relatively long computation time with a maximum of 150 seconds, and the closest is Random Forest, which has a computation time of 100-145 seconds. The SVM model begins at approximately 95 seconds, rises to a peak around 140 seconds, and then declines. The ANN model performs decently, with computation time oscillating between 85 and 130 seconds.

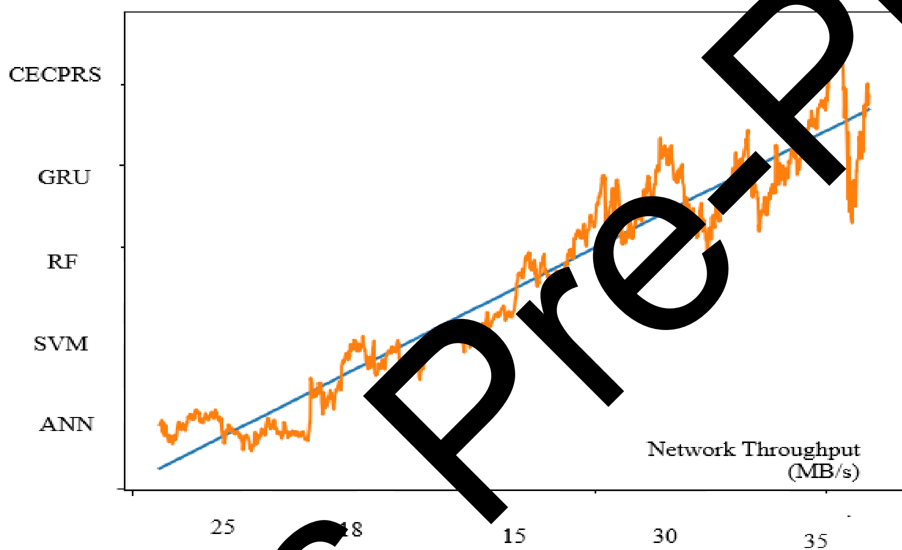

Figure 5. Illustrates Network Throughput

Figure 5 illustrates the throughput performance of the network (in MB/s) for various models, including ANN, SVM, Random Forest (RF), GRU, and the given CECPRS model. The vertical axis uses the throughput capacity of the network (remaining within the boundaries of 15 MB/s and 35 MB/s), and the horizontal axis bears the names of the models in the sequence of the better performance. After observing the graph, it can be concluded that the CECPRS model can achieve a throughput of up to 35 MB/s, which is a significant indication of its high potential to manage data in a distributed system and process data efficiently. By contrast, the throughput in ANN and SVM is also the least, ranging between 15 and 18 MB/s, implying that these models would have limitations in handling data and would also be slower at communicating across networks. Random Forest and GRU demonstrate medium-level performance, achieving a maximum speed of 25-30 MB/s.

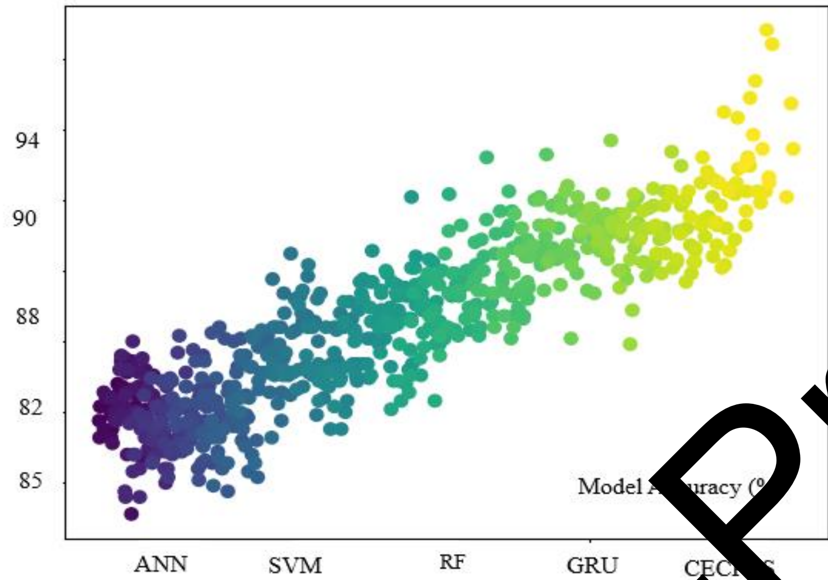

Figure 6. Illustrates Model Accuracy (%)

Figure 6 presents the distribution of model accuracy (%), achieved by five models: ANN, SVM, Random Forest (RF), GRU, and the proposed CECPRS as a colored scatter plot. The vertical axis represents the percentage accuracy level, which varies between 85% and 94%, whereas the horizontal axis denotes the scaling or progression, starting with traditional models (ANN, SVM) and progressing to deep learning models of higher levels (GRU, CECPRS). In the plot, an evident upward trend is apparent, as the accuracy of the models increases from ANN and SVM to RF and GRU. Consequently, CECPRS demonstrates the highest accuracy, reaching a maximum of 94 percent. The fact that the points are intensely concentrated in the low end with ANN and SVM (approximately 82% to 85%) shows a relatively low predictive power of these two methods. In the meantime, GRU and CECPRS target distribution shifts to the right and upwards; as a result, they demonstrate increased learning potential and generalization.

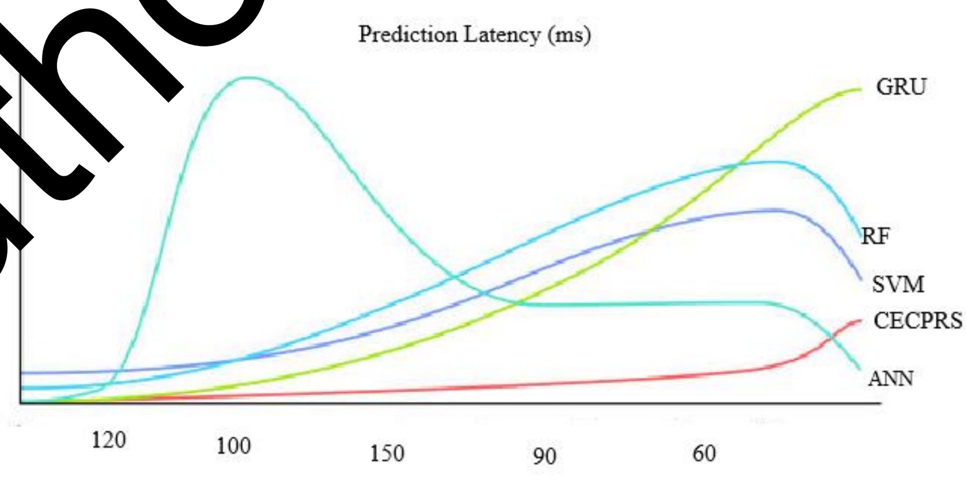

Figure 7. Illustrates Prediction Latency (ms)

As shown in Figure 7, the prediction latency (ms) of different AI models and optimization algorithms varies. The latency range spans from 120 ms to 100 ms, 150 ms to 90 ms, and 60 ms, respectively. These values indicate the time required for each approach to generate a prediction after processing the input data. Lower latency responses are more responsive, which is crucial in real-time or energy-efficient applications. The model with a 60 ms latency is the most efficient and is suitable for use in IoT-driven smart grids or predictive maintenance, which are time-sensitive. Conversely, the approach with a 150 ms latency is slower than the others and may affect the real-time performance of decision-making.

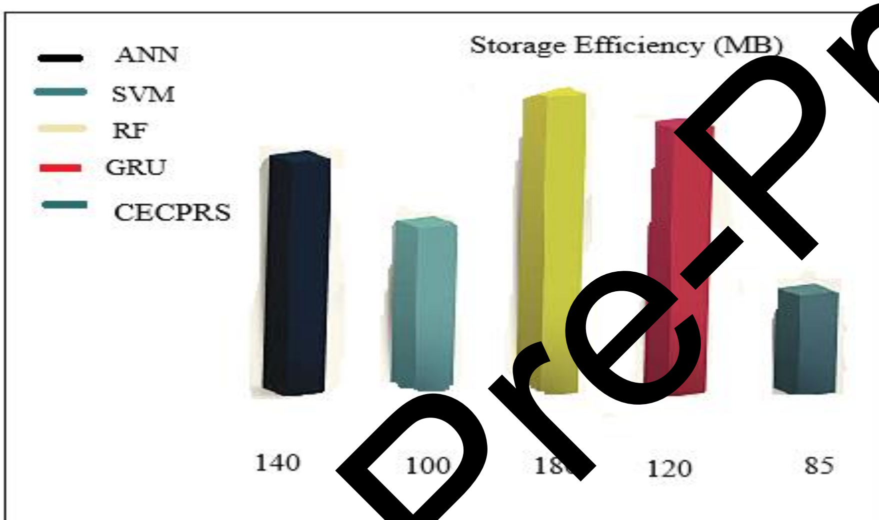

Figure 8. Illustrates Storage Efficiency (MB)

Storage Efficiency (MB) is depicted in Figure 8 in various models or system configurations. These results are 140 MB, 100 MB, 180 MB, 120 MB, and 85 MB, respectively. The values of storage efficiency of higher order denote a better utilization of available storage resources to cope with massive data, while ensuring optimal system performance. The setup that reaches 180 MB indicates that the best storage can handle such data, meaning it can utilize superior compression or various data management methods. On the other hand, the 85 MB configuration suggests a less efficient use of storage, possibly due to redundancy or poorly optimized storage structures. Overall, the graph indicates that storage optimization plans can significantly impact the sustainability and scalability of data-intensive applications, particularly those based on AI and energy efficiency.

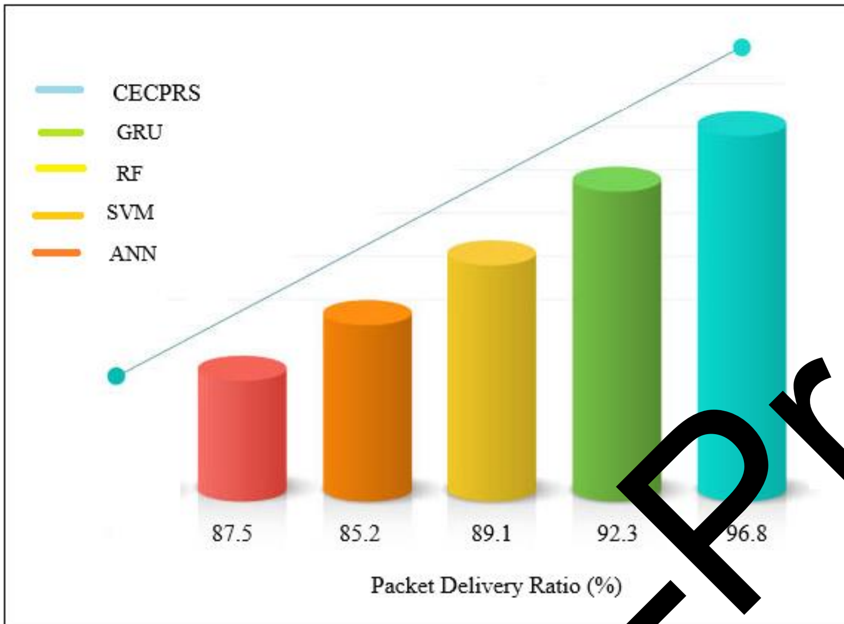

Figure 9. Illustrates Packet Delivery Ratio (%)

Figure 9 presents a comparative study of the Packet Delivery Ratio (PDR) for five models: ANN, SVM, Random Forest (RF), GRU, and the proposed CECPRS model. Packet Delivery Ratio is one of the most essential parameters and metrics in Wireless Sensor Networks (WSNs), defining the success of data transmission with no packet loss. One of the models, CECPRS, performs better than the rest and has a PDR of 96.8, indicating that it is resilient enough to withstand any network failure and that its data routes are correctly managed. GRU is next with 92.3%, and it enjoys learning temporal dependency. Random Forest achieves 89.1%, which is rather good and marginally worse, apparently as a result of its unswerving decision-making structure. The PDRs of SVM and ANN are lower and equal \mbox{85.2} and 87.5 percent respectively and it indicates that the latter are less able to accept dynamic changes in networks. The high performance of the CECPRS model is attributed to energy-aware routing, proactive scheduling, and intelligent fault tolerance, which leads to strong data transmission and minimal packet loss in the resource-constrained WSN setting.

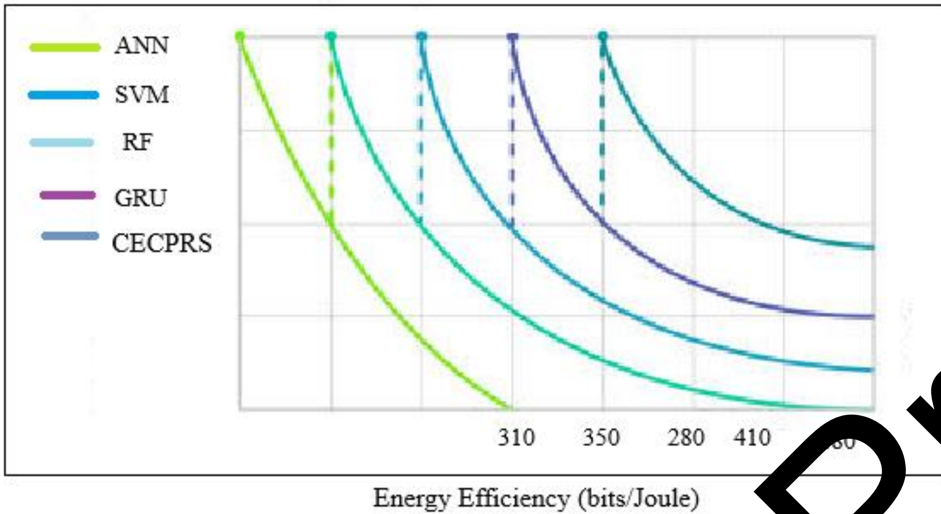

Figure 10. Illustrates Energy Efficiency (bits/Joule)

In Figure 10, a comparative analysis of Energy Efficiency in bits per Joule is presented for five models: ANN, SVM, Random Forest (RF), GRU, and CECPRS. This can be defined as the efficiency of every model in processing and transmitting data while using energy in Wireless Sensor Networks (WSNs). The CECPRS model performs the best, with an energy efficiency of 480 bits per Joule, which is superior to all others. The meaning of this is that it can provide more successful computation and data transfer in comparison to the quantity of energy utilized, implying that it is exceptionally applicable in conditions of resource constraint. The second-best, with 410 bits/Joule, is the GRU, based on its time memory capabilities, followed by SVM and ANN with moderate efficiencies of 350 and 310 bits/Joule, respectively. The Random Forest model proves to be the least efficient, with a value of 280 bits/Joule, possibly due to its complex ensemble architecture.

5. Conclusion

In this study, an optimized deep learning-based workflow compatible with the principles of Green AI has been proposed to address the urgent challenge of energy inefficiency in Wireless Sensor Networks (WSNs). The model uses an Energy-Aware Attention-Based Neighbor Discovery (EA-AND) process and the Energy-Efficient Cluster Routing (EECR) algorithm to reduce redundant transmissions and ensure optimal cluster heads. Finally, Social Spider Optimization (SSO) will be integrated to eliminate computational overheads while maintaining vital data for making informed decisions. The CNN-LSTM hybrid model will improve node behavior recognition by capturing both spatial and temporal dependencies, thus enhancing fault detection and network awareness. Additionally, the Cooperative Energy-Aware Preemptive Route Scheduling (CE-APRS) is a proactive module that adapts to dynamic network conditions to prevent route failures and promote a fair distribution of energy throughout the system. Overall, the proposed model significantly enhances the adaptive, energy-efficient, and resilient operation of WSNs, supporting the sustainable development of next-generation communication systems.

Conflict of interest: The authors declare no conflicts of interest(s).

Data Availability Statement: The Datasets used and /or analysed during the current study available from the corresponding author on reasonable request.

Funding: No fundings.

Consent to Publish: All authors gave permission to consent to publish.

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