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Deep Recurrent Neural Network (DRNN) Based Model for Energy Prediction in Wireless Sensor Network

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ABSTRACT

The short battery life of sensor nodes makes energy utilisation a crucial aspect of wireless sensor networks (WSNs), which are utilised in a range of applications. Energy consumption continues to be a limiting problem despite current research concentrating extensively on energy-conscious apps and operating systems. once the sensor nodes have been set up. Battery replacement and recharging can be difficult or even impossible, which can lead to inaccurate lifespan predictions for sensor networks that might cost a lot of money and put the network's intended purpose at danger. The models exhibit great accuracy in estimating energy usage, allowing for the creation of WSNs that are more effective and sustainable. This method's relevance is broadened to include IoT and cyber-physical systems, providing precise energy prediction.

Keywords : Sensor Nodes, Deep Learning, Feed-Forward Neural Network, Energy Prediction

I. INTRODUCTION

WSNs consist of small, cost-effective, and low-power sensor nodes that can collect and transmit data wirelessly. These networks have gained significant popularity due to their versatile applications in various fields, including environmental monitoring, healthcare, industrial automation, and smart homes.

Given that sensor nodes in WSNs are often powered by batteries, energy efficiency is a critical consideration for the successful deployment and maintenance of these networks. Maximizing the battery life of sensor nodes is essential for ensuring their prolonged operation.

Accurate prediction of energy consumption is crucial for optimizing the performance of sensor nodes and extending their battery life. Knowing how much energy a sensor node will use helps in planning maintenance and energy-saving strategies.

researchers have increasingly turned to deep learning models to forecast the energy consumption of sensor nodes in WSNs. Deep learning, a subset of machine learning, is known for its ability to handle complex patterns and large datasets, making it a suitable choice for energy consumption prediction in sensor networks.The study shows that when deep learning techniques are used instead of traditional machine learning approaches, the accuracy of energy prediction is significantly increased. This strategy can help scientists and engineers create WSNs that are energy-efficient, assuring their sustainability. Furthermore, the suggested approach has a wide range of applications, including adaptive power control in WSNs and energy-efficient routing. The study brings up new opportunities for creating efficient and sustainable WSNs and offers insightful information on the power use of sensor nodes.

The available information suggests that among these models, artificial neural networks (ANN) have been considered to produce the best results for energy consumption prediction. Additionally, the use of Deep Learning (DL) models, such as Long Short-Term Memory (LSTM) with Auto-Encoders (AE), has been explored for forecasting solar energy use based on meteorological data. These advanced techniques leverage the power of deep learning to improve the accuracy of energy consumption predictions.

The same dataset, which contains data for around a month and every 30 seconds, was utilised in this study. Deep learning models have demonstrated considerable promise in properly forecasting the energy consumption of sensor nodes, which can help them function more effectively and last longer on batteries. We want to draw attention to the major advancements, problems, and possible benefits of deep learning models for improving energy efficiency in WSNs. For people interested in the confluence of deep learning and energy efficiency, as well as for researchers and practitioners working in the field of WSNs, this survey will be helpful.

II. MOTIVATION

Most of the current approaches have taken into account factors such as power consumption, energy consumption, etc. to enhance the lifetime and performance of the WSN. Nevertheless, there are several difficulties when dealing with a large network. For example, many intelligent routing protocols claim to be energy-efficient, but many are not. Therefore, the aim of this work is to propose a prediction model based on deep recurrent neural networks (DRNNs) to predict the amount of energy remaining in the node prior to the actual routing.

1.2 Energy Consumption Balancing (ECB): This is one of the crucial features to attain the maximum network lifetime where all the sensor nodes must consume only sufficient energy required to operate in their lifespan. In HWSNs, multi-hop communication is broadly employed to maintain energy efficiency providing communication over a short range. Mean while, such communication mode can cause power imbalance issue in the network, as multi-hop transmission routes lead to communication load on sensors, and the load becomes larger on those sensors those are nearer to the sink nodes. Thus, to enhance a WSN's lifetime, apart from reducing the communication ranges using multi-hop communication paths, it also necessitates balancing the energy consumption in the WSN. Hence, techniques ensuring an A wireless sensor network must maintain a consistent level of energy dissipation in order to provide optimal performance for extended periods of time. [7].

III. LITERATURE REVIEW

This section discusses a survey of available articals on existing techniques on the basis of energy consumption and energy prediction. These existing methods and techniques were reviewed and studied with the intension to get insights of the energy consumption and energy harvesting.

[1] Evaluating the Power Consumption of Wireless Sensor Network Applications Using ModelsAntonio Damaso, Davi Freitas, Nelson Rosa, Bruno Silva, and Paulo Maciel

the authors conducted a comprehensive study to develop analytical models for predicting power consumption in WSNs. Their research likely revealed the strengths and weaknesses of different methods for measuring power consumption, and they aimed to provide more accurate and application-specific insights into the behavior of sensor nodes in these networks.

This information can be invaluable for optimizing the design and deployment of WSNs in real-world scenarios.

[2] Power consumption Assessment in Wireless Sensor Networks by Antonio Moschitta and Igor Neri

the paper is concerned with assessing the energy efficiency of wireless sensor networks and provides a comparative analysis of routing protocols. It highlights the importance of considering whether the network is homogeneous or heterogeneous and suggests that the choice of routing protocol should be tailored to the specific application and network requirements. This research is valuable for designing and optimizing WSNs in various real-world scenarios. The core of the paper focuses on a detailed analysis of power consumption within WSNs. The authors investigate how the different routing protocols impact power usage and network lifetime. This analysis likely involves simulations and data collection to draw conclusions.

The paper describes the experimental setup used for the analysis. This setup may include simulation models of both homogeneous and heterogeneous WSNs to evaluate and compare power consumption, network lifetime, and other relevant metrics across the routing protocols.

[3] "Prediction and Management in Energy Harvested Wireless Sensor Nodes" by Joaquín Recas Piorno, Carlo Bergonzini, David Atienza, and Tajana Simunic Rosing, the paper provides an overview of energy conservation technologies, energy management challenges, and prediction techniques within WSNs. These technologies could include solar energy harvesting, kinetic energy recovery. It emphasizes the importance of efficient energy management due to the limited power resources of sensor nodes and discusses specific methods like WCMA for improving energy prediction accuracy. This research can be valuable for designing and optimizing WSNs to enhance their energy efficiency and overall performance in real-world applications.

The paper discusses techniques for predicting and managing energy within WSNs. It mentions the "weather-conditioned moving average (WCMA)" as a solar prediction algorithm. This algorithm may be designed to forecast solar energy availability based on current and historical weather conditions. It's suggested that WCMA is more efficient than the "Exponential weighted average (EWMA)" method, with a comparative average error of only 10%.

[4] Accurate Prediction of Power Consumption in Sensor Networks by Olaf Landsiedel, Klaus Wehrle, Stefan Gotz

his paper introduces an innovative model-based approach for predicting power consumption in sensor nodes. It demonstrates its accuracy through practical experiments and highlights its superior performance compared to existing methods. The approach has the potential to be applied in various contexts, particularly for optimizing energy consumption and predicting battery life in sensor networks. However, it's important to be aware of its limitations, especially when dealing with dynamic network conditions and the need for precise environmental data.

The paper also acknowledges certain limitations of the proposed approach. These limitations include the need for precise models of sensors and environmental parameters. Additionally, the approach assumes a static network topology, which might not always hold in dynamic environments. The paper describes experiments conducted on an actual sensor network with different node configurations and operational scenarios. The goal of these experiments is to validate the accuracy of the proposed model. According to the paper, the model's predictions have an average error of less than 10%. The paper compares the newly proposed method with existing methods for predicting power consumption within sensor nodes. It provides evidence that the proposed model outperforms these existing methods, highlighting its superiority in terms of accuracy.

[5] An Efficient Data Model for Energy Prediction using Wireless Sensors Michel Chammas, Abdallah Makhoul, and Jacques Demerjian:

this research paper presents a data model for predicting energy consumption in buildings. The model encompasses weather, occupancy, and appliance modules and is tested using real-world data. It proves to be a valuable tool for building energy management, offering accurate predictions of energy consumption, which can lead to more efficient energy use and cost savings.

The paper reports the results of the evaluation and demonstrates that the proposed data model can accurately predict energy consumption. It mentions that the model achieves an average error rate of less than 5%, indicating its effectiveness in forecasting energy usage in buildings.

The author validate the data model using real-world data collected from a building in Lebanon. This validation process is crucial for assessing the model's accuracy and effectiveness in a practical setting.

[6] Energy Efficient-based Sensor Data Prediction using Deep Concatenate MLP Made Adi Paramartha Putra, Ade Pitra Hermawan,

the research article from the Networked Systems Lab at Kumoh National Institute of Technology in Korea addresses the challenges of developing energy-efficient models for sensor data prediction. It proposes a deep learning-based solution, specifically a deep concatenate model, and provides experimental evidence to support the efficiency and accuracy of their approach compared to existing models. This work contributes to improving energy efficiency in sensor data prediction, which has applications in various fields, including the Internet of Things (IoT) and sensor networks.

The article likely elaborates on the various components of their deep concatenate model, including the architecture of the neural network, the types of input data, and how the model processes and predicts sensor data.

The authors present experimental results to demonstrate the efficiency and precision of their proposed model.

These results are likely based on real-world or simulated data and could include comparisons with existing models. The goal is to show that their approach is superior in terms of both energy efficiency and prediction accuracy.

IV. Proposed Energy Model

For the effective transferring of data packets in the network, it is important to evaluate the energy consumption of each node. The energy consumption comprises the energy involved to transmit, and forward the data. The energy consumed by a node ‘ p ’ that belongs to the link $l(p,q) \in L$ is formulated as,

$$E_p^C = E_p^l + E_p^t + E_p^r + E_p^s \tag{1}$$

where, E_p^l, E_p^t, E_p^r, E_p^s denote the energy consumption of p^{th} node during listening, transmitting, receiving, and sleeping. Assuming $E_p^r = 0$, with ‘ p ’ as the source node and $E_p^t = 0$, with ‘ q ’ as the destination node, the energy consumed by the p^{th} node is,

$$E_p^C = \begin{cases} \left(s_p^l C^l + C^t \dfrac{n}{d} + s_p^s C^s\right) V \; ; \; if\ p\ is\ a\ Tx \\ \left(s_p^l C^l + C^r \dfrac{n}{d} + s_p^s C^s\right) V \; ; \; if\ \ p\ \ is\ a\ Rx \end{cases} \tag{2}$$

where, C^l, C^t, C^r, C^s represent current drawn while the node is in listening, transmitting, receiving, and sleeping modes, n is the packet length in bits, d is the data rate in kbps, and V is the battery voltage.

$$s_p^s = B^I - S^D = 2^{bo} - 2^{so} \tag{3}$$

$$s_p^l = B^I - \left(s_p^t + s_p^r + s_p^s + s_{CCA}\right) \tag{4}$$

In beacon-enabled mode, super frame structure of IEEE 802.15.4 has the Beacon Interval (B^I) and Superframe duration (S^D), which are defined by the values of beacon order (bo) and superframe order (so).

Then, the energy harvested at node p is computed based on two levels, level 2 and level 3 [23] as,

$$E_p^h = \begin{cases} s_p^s \eta_p^h \;; & if\ level3 \le E_p^R \le level2 \\ \left(s_p^{bo} + s_p^s\right)\eta_p^h \;; & if\ 0 < E_p^R < level3 \end{cases} \tag{5}$$

where, η_p^h and s_p^{bo} indicate the p^{th} node energy harvesting rate and the time consumed during the 'extra backoff' process, defined in [23]. Thus, the residual energy at the p^{th} node is finally computed as,

$$E_p^R = E_p^I - E_p^C + E_p^h \tag{6}$$

where, E_p^I is the initial energy at the p^{th} node.

1. Energy prediction using Deep Recurrent Neural Network:

This section details the energy prediction carried out using the deep learning technique. The technique employed in the work is DRNN [9] [31], which functions depending on the input observations and internal states. The input to the DRNN is the residual energy computed in equation (6), while the output is the predicted energy of the nodes, denoted as $P^{E_p^R}$ .DRNN possesses a dynamic network that learns sequential dependencies at any time period.The advantage of using DRNN is that the network works on its current input and weights without the information known a-priori, as it maintains the previous data for limited time. Let i_κ^p , h_κ^p , and o_κ^p represent the input, hidden state, and output vector, each of dimension $B\times1$, $U\times1$, and $Y\times1$, respectively. For a given sequence, $\left(i_1^p, i_2^p, \ldots, i_K^p\right)$, the output at $\left(h_1^p, h_2^p, \ldots, h_K^p\right)$, and $\left(o_1^p, o_2^p, \ldots, o_K^p\right)$ of the DRNN is given as,

$$h_\kappa^p = f\left(e_{ih} i_\kappa^p + e_{hh} h_{\kappa-1}^p + M_h\right) \tag{7}$$

$$y_\kappa^p = e_{ho} h_\kappa^p + M_o \tag{8}$$

where, e_{ih} , e_{hh} ,and e_{ho} are the weight matrices, while M_h , M_o , and f are the biases and the sigmoid function. Here, the input of a layer depends on the output of previous identical layers. Hence, the hidden states of ℓ^{th} layer, for 'Q 'number of hidden layers can be re-written as,

$$h_\kappa^{p^\ell} = f\left(e_{h^{\ell-1}h^\ell} h_\kappa^{p^{\ell-1}} + e_{h^\ell h^\ell} h_{\kappa-1}^{p^\ell} + M_h\right) \tag{9}$$

$$y_\kappa^p = e_{h^Q o} h_\kappa^Q + M_o \tag{10}$$

where, $h_\kappa^{p^\ell}$ indicates the hidden state of ℓ^{th} layer. The architecture of DRNN is interpreted in Figure 1.

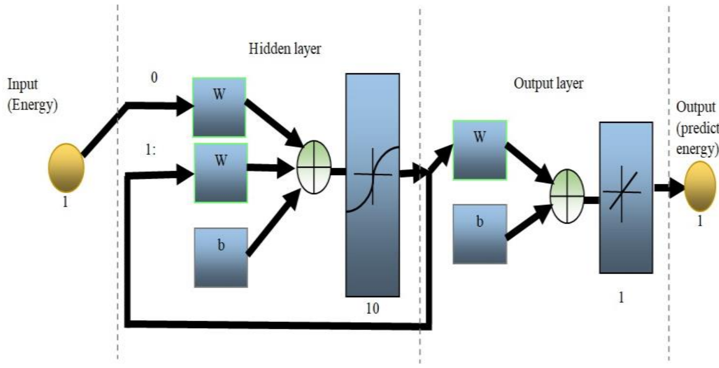

Figure 1.Deep RNN architecture

Hidden Layer is the intermediate layers between the input and output layer and process the data by applying complex non-linear functions to them. These layers are the key component that enables a neural network to learn complex tasks and achieve excellent performance. we represents the weight and b is the bias. the input to the sigmoid is a value between –∞ and + ∞, while its output can only be between 0 and 1. In the above architecture, 10 represents the input to the sigmoid, and 1 represents the input to the Relu activation function. 1:2 represents 1 input which is given to both hidden layer and output layer. 0 is the input to the hidden layer.

V. Conclusion

Wireless sensor networks has numerous applications in variety of fields, but the constraint of limited battery life of sensor nodes is a big challenge which further opens up a way of further research. In this paper we research about various energy prediction approached in Wireless Sensor Nodes. Although there are various methods to predict the energy consumption in a sensor node, this parameter needs a more accurate way of prediction of energy.The proposed deep learning model proves to be a optimistic solution for accurate prediction of energy utilization of sensor nodes. the proposed prediction model's potential to be applied in practical, real-world settings for energy optimization and cost reduction underscores its importance and relevance in the field of Wireless Sensor Networks.

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