Deep Learning-Based Receiver Energy Prediction in Energy Harvesting Wireless Sensor Network

El-hadi Zazoua
Department of Computer Science
University of Quebec at Montreal, Canada
zazoua.el_hadi@courrier.uqam.ca

Wessam Ajib
Department of Computer Science
University of Quebec at Montreal, Canada
ajib.wessam@uqam.ca

Mounir Boukadoum
Department of Computer Science
University of Quebec at Montreal, Canada
boukadoum.mounir@uqam.ca

***Abstract*— Predicting the available energy at a receiver node in energy-harvesting wireless sensor networks may substantially improve data transmission and routing performances. In this work, we survey the state-of-the-art to predict the next node's energy in a communication path using probability and older machine learning techniques and propose and evaluate three deep learning alternatives. Our simulations with real-world energy harvesting data show that our approach provides better prediction accuracy and considerably improves the network performance for data packet loss and transmission delay.**

Keywords—wireless sensor networks, energy harvesting, deep learning, LSTM, Transformer, N-BEATS.

I. Introduction

The random nature of harvested renewable energy considerably affects the performance of wireless sensor networks with energy harvesting (WSN-EH) nodes. When a transmitter (Tx) node does not take into consideration the amount of available energy at the next receiver (Rx) node, the transmitted data may be lost due to receiver battery depletion. On a larger scale, this may lead to network reliability issues and energy misuse. To address the problem, predicting the available energy at Rx has been considered. However, the traditional approaches using probability and older machine learning (ML) techniques appear to have reached their limits. In this work, we investigate three prediction models based on deep learning, a recent subset of ML, as potential alternatives to the state-of-the-art in terms of prediction error, and we assess through simulation the performance improvement brought by these models on WSN-EH performance.

II. Recent Work on Energy Prediction in WSN-EH

The energy prediction models that have been already proposed for WSN-EH systems can be categorized as follows.

A. Stochastic prediction models

They are mainly based on Markovian modeling. A first-order Markov chain is given in [1] to consider the state of the EH process, the amount of stored energy in a node and the data traffic to determine the node state. The authors in [2] present the Maker, a Markov-based model for multi-source EH nodes in corporal WSNs. They highlight the requirements for WSN with multiple EH cards, such as battery capacity. In [3], the Accurate Solar Irradiance Prediction Model (ASIM) incorporates high-order Markov chains to predict the solar irradiance through time and use it for energy allowance in WSN-EH. The authors show an increasing model accuracy with the order of the Markov chain until a plateau is reached.

B. Statistical prediction models

In [4], the Exponentially Weighted Moving Average model (EWMA) is used to predict the solar energy in a WSN-EH. It offers advantageous computational complexity and memory usage but loses effectiveness when abrupt weather changes occur. In [5], the Weather Conditioned Moving Average (WCMA) prediction model incorporates weather conditions in EWMA to improve its prediction accuracy, but this incurs significantly higher computational and memory needs. In [5], the Accurate Solar Energy Allocation (ASEA) model, also based on EWMA, improves accuracy by introducing a parameter that reflects the current solar conditions. In [6], the Profile-Energy model (Pro-Energy) memorizes the energy profiles of different weather conditions and uses them to determine which one best corresponds to the prediction to make. Improvements were brought to this model in [7] and [8]. In [9], a linear adaptive filter is the harvested energy predictor, with its coefficients updated by the Normalized Least Mean Square (NLMS) algorithm after each prediction. Simulations show it is more efficient than EWMA but less efficient than WCMA, and it requires less memory and calculations. In [10], the Weather Forecast Based Prediction (WFBP) model is proposed for 35% more WSN-EH efficiency compared to a network using EWMA or WCMA. The authors in [11] propose the Solar Energy Prediction using Additive Decomposition (SEPAD) model to outperform WCMA and EWMA in changing weather conditions, but all the model's weight coefficients must be manually determined, and it requires an important storage memory. In [12], the Real Forecast Weather Moving Average model (RWMA), based on WCMA, introduces the notion of real time to surpass both the WCMA and EWMA models in precision. However, it must be parameterized experimentally and incurs a heavier computational and memory load. In [13], the authors propose the Wind Energy Predictor model (WEP), dedicated to the prediction of wind energy for WSN-EH. They show that WEP provides better precision than Pro-Energy and EWMA, while being frugal in its memory needs. The authors in [14] use the Kalman filter to outperform EWMA and NLMS in terms of average absolute error. It also has the advantage of adaptiveness to overcome the problem of static weight coefficients, a major problem in existing prediction models.

C. Machine Learning (ML) Models

In [5], reinforcement learning is used in the Q-Learning model for Solar Energy Prediction (QL-SEP). The model is founded on EWMA with an added parameter to represent the current trend of available solar energy. Simulations show that QL-SEP offers better prediction than EWMA but also has its disadvantages and increases the computational load. In [15], a feedforward artificial neural network (ANN) is used to predict the harvested energy at the WSN-EH nodes, offering a better prediction than EWMA, WCMA and Pro-Energy. In [16], a fuzzy logic-based prediction model is used to propose a routing protocol for WSN-EH with a low rate of packet loss.

In the preceding, the statistics and stochastic approaches

2023 IEEE 14th Latin America Symposium on Circuits and Systems (LASCAS) | 978-1-6654-5705-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/LASCAS56464.2023.10108110

can only make accurate predictions at the population level, since they use means as variables. On the other hand, ML techniques usually target individual predictions. In this respect, recurrent ANNs are particularly efficient for time-series prediction, thanks to anz internal variable that memorizes the network states as context to predict the successive elements. Yet, this capability is limited by the vanishing gradient phenomenon, which makes the prediction less accurate as the processed elements are older. The long short-term memory (LSTM, [17]) neural model partially solves this problem but is limited by the memory capacity of the network. The more recent Transformer model [18] replaces the context memory with the concept of attention, hence eliminating the vanishing gradient problem, but at the price of a substantial increase in computational complexity. The authors of [19] propose N-beats, a deep neural network based on a sequence of stacks, each one made of a sequence of blocks, and each block made of a fully connected neural network with bidirectional predictions. Each block makes its predictions based on the residual error from the previous one, hence only focusing on the local characteristic of the input sequence that reach it. Then, the partial forecasts of the blocks of all stacks are aggregated to form a global forecast. N-beats makes a compromise, aiming to offer better precision than the LSTM and lower computation load than the Transformer.

III. System Model

A. Network model

As Fig. 1 shows, the considered network model consists of N wireless sensor nodes with EH capabilities. The first node captures and transmits the sensed information whereas the last node role is restricted to a receiving function like a sink. The intermediate nodes serve as relays.

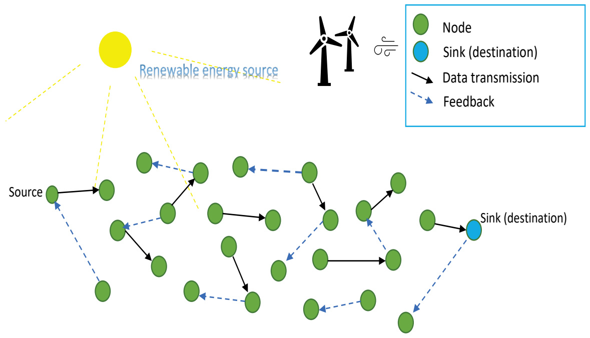

Fig. 1. Renewable energy wireless sensor network

This work only considers the energy consumed by the radio module and ignores the one consumed elsewhere as it is usually comparatively negligible in embedded WSNs. At the end of time slot (TS) n, each node feeds back to the precedent nodes the state of charge of its battery, the amount of energy harvested during the TS n, the channel quality and its state: Tx or Rx. If a node receives a packet during TS n, its state will be Tx at n+1; otherwise, it will be Rx. This feedback allows each recipient node (possibly Tx) to predict which forward node(s) can receive data. Then, a Tx can select the Rx among the next forward nodes based on availability, estimated energy level and channel quality.

When a node is in Tx state, the corresponding time slot is divided into three phases as shown in Fig. 2. In phase 1, the node predicts the energy available at the next forward nodes and checks the transmission conditions. During phase 2, the node sends a data packet if the conditions are met, and in phase 3, each node sends feedback to the preceding ones. As mentioned, we assume that the energy expenditures of phases 1 and 3 can be neglected in comparison to phase 2, as are also their durations. When the node is in a Rx state, the TS has only two phases: a reception phase and a feedback phase.

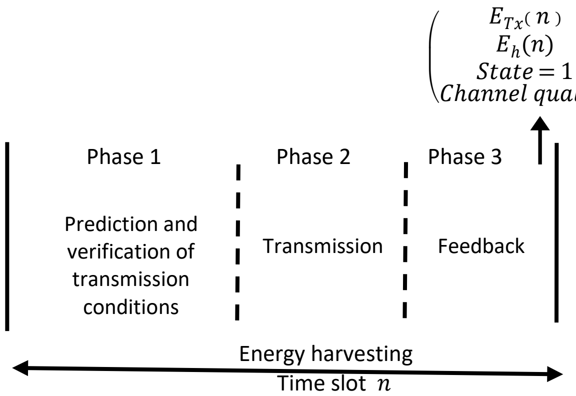

Fig. 2 Timing sequence of a Tx node's operation

B. The communication process

The communication during TS n proceeds as follows: at the end of TS $n-1$, a Tx receives feedback from its forward neighbors in the direction of the sink. Based on this feedback, the Tx begins its 1st phase by estimating the amount of energy available at each of these nodes:

$$\hat{E}_{Rx}(n) = \max\{E_{Rx}^{max}, E_{Rx}(n-1) + \hat{E}_h(n)\} \qquad (1)$$

where $\hat{E}_{Rx}(n)$ is the estimated energy available at Rx, E_{Rx}^{max} is the capacity of its battery and $\hat{E}_h(n)$ is the estimated $E_h(n)$, the energy harvested during TS n. Then, the Tx sends data in the 2nd phase if the following two conditions are met:

$$\begin{cases} E_{Tx}(n) \geq E_t(n) \\ \hat{E}_{Rx}(n) \geq E_t(n) \end{cases} \qquad (2)$$

where $E_{Tx}(n)$ is the energy state of the Tx node's battery at the beginning of TS n and $E_t(n)$ is the required energy for transmission during TS n. $E_t(n)$ is calculated by considering the maximum rate at which data can be transmitted, according to Shannon's law:

$$C = B \times log_2\left(1 + \frac{|h|^2 \times E_t(n)}{\delta^2 \times B \times T_s \times \mathrm{Gap}}\right) \qquad (3)$$

where C is the data packet size, $|h|^2$ the channel gain, δ^2 is the channel noise's spectral density, B the channel bandwidth, T_s the TS duration and Gap a compensation term to adapt the theoretical equation to channel errors. The channel gain is measured by Rx and is assumed to be perfectly fed back to the Tx. It is assumed to be Rayleigh-distributed with an average of $d^{-\alpha}$ and a standard deviation of 1, where d is the distance between Tx and Rx and α is the path loss coefficient.

Based on the predicted energy levels, the channel gain, and the state (Tx or Rx), Tx selects between the next nodes the one to send the packet to. After transmission, it receives feedback from it about the amount of stored energy, the channel gain, and state at TS $n+1$. This allows to evaluate the impact of the prediction models on network performance.

IV. Simulations and Results

A. Parameters of the deep neural network models

For the Transformer, the query, key and value matrix size are set to [12×1] for a trade-off between precision and computation time, and the number of attention heads is set to 12. As varying the number of encoder layers from 3 to 6 yielded similar prediction accuracy, three layers are used for reduced computational complexity. We also use a simple regression layer instead of the decoder stack since the latter is unnecessary for time series prediction [20].

The number of layers of the LSTM is fixed to get the same number of trainable parameters as the Transformer. For N-Beats, the hyperparameter values are the ones that led to the highest prediction accuracy through simulations. Hence, the ratio of the lengths of input sequence to predicted sequence is set to 3, the basic block number is set to 2 and the size of matrices θ^f and θ^b is 4×4. The number of layers is set to ensure an equal number of parameters with the Transformer and the LSTM.

B. Data and metrics

To compare the prediction models, we used solar energy data captured every thirty minutes from Jan. 1, 1998, to Dec. 31, 2019, in Montreal [21]. These data are normalized to a solar panel of $10 \times 10\ cm^2$ and we assume an average panel conversion efficiency of 14%. 70% of the data are used for training the models and 30% for testing. The Adam optimizer was used for training, using a batch size of 32. The comparison metric for predictions is the root-mean-square-error (RMSE) of the test data. Two other metrics are used to evaluate the impact on network performance: the packed success rate defined as the ratio between the number of received packets and the number of transmitted packets, and the transmission delay defined as the number of TSs required for transmitting a data packet from the source to the sink. In the " without prediction" case, Tx sends a packet during each time slot where it has sufficient transmit energy, regardless of the energy at Rx. Unless mentioned otherwise, we consider $B = 1\ MHz$, $T_s = 10\ ms$, $\delta^2 = -50$ dbm and Gap $= 1\ db$, $B_{max} = 3\ E_t$, where E_t is the time-average energy necessary to transmit a packet, the packet size is set to 50 kbit and the distance between nodes is $d = 100\ m$ and $a = 3$.

C. Comparison of prediction models

First, we implement and compare the prediction accuracy of the Transformer, LSTM and N-Beat sequence-oriented deep neural networks, and of five state-of-the-art prediction models, EWMA, NLMS, ASEA, ANN and QL-SEP. The same computational environment and same data are used for training and testing all the models. Fig. 3 presents the RMSE prediction error of each one, showing a clear superiority of the deep learning models. Since the prediction accuracy affect WSN-EH performance through its link to packet loss, losses, we focused on the better performing deep learning models to evaluate the impact on network performance.

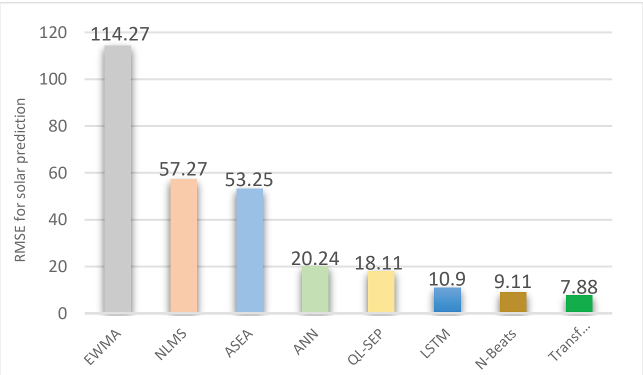

Fig. 3 RMSE error of the different predictors

Fig. 4 shows the effect of the number of nodes on the success rate, showing a negative impact as the number of nodes increases, but using prediction leads to nearly flat curve with about 98% success rate for the Transformer, which slightly outperforms the LSTM and N-BEATS networks. On the other hand, not using prediction results in a decaying curve.

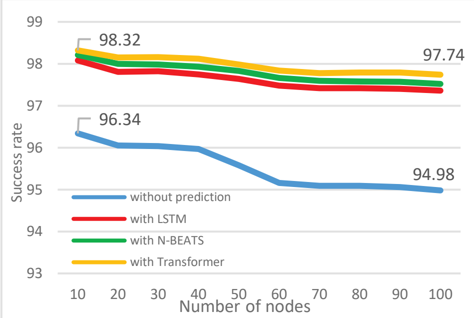

Fig. 4 Success rate versus the number of nodes ($50kbit$ packets)

Fig. 5 shows the effect of the packet size on the success rate for a network of 100 nodes. Here again, the Transformer shows the best performance, followed by N-BEAT and LSTM. Without prediction, a drastic decrease from 99.88% to 67.17% success rate occurs as the packet size increases from 10 kbit to 100 kbit. On the other hand, a convex curve is observed with prediction, possibly because beyond a minimum value (about 70 kbit), the needed transmission energy starts limiting the number of transmitted packets, thus decreasing the chance of losses.

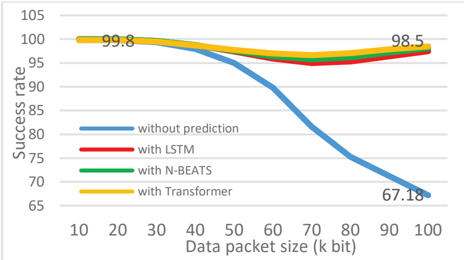

Fig. 5 Success rate versus the data packet size (100 nodes)

Fig. 6 shows the impact of node distance on the success rate. It reveals a decreasing success rate as expected, since increasing the distance increases the energy required for transmission and the number of relay nodes. Still, a substantial and increasing gap exists between using and not using prediction.

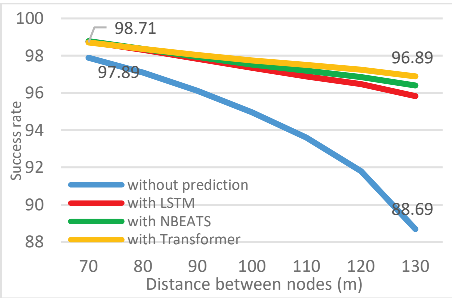

Fig. 6 Success rate versus the distance (packets)

Fig. 7 shows the effect of maximum battery capacity on the success rate, where maximum battery capacity is defined as $E^{max} = j \times E_t$, where j is an integer between 2 and 10. It shows that larger battery capacities decrease the success rate by up to 6% for the network without prediction and 1.5% on average for the networks with. This may be explained by the fact that larger batteries allow to increase the packet rate and hence the probability of transmission failure.

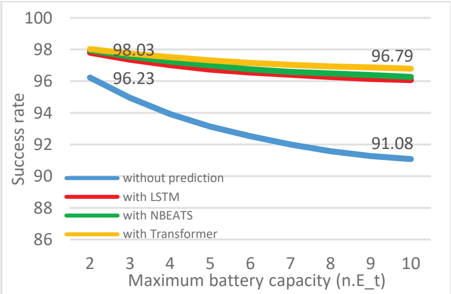

Fig. 7 Success rate versus the maximum battery capacity

Fig. 8 considers a network with 100 nodes, showing an increasing delay with packet size because of more required transmission energy. Similar behavior is observed with and without prediction up to 50 kbit packet sizes, with the networks with prediction performing better afterward.

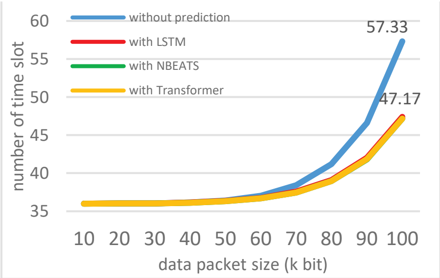

Fig. 8 Delay versus the data packet size (100 nodes)

Fig. 9 and Fig. 10 show respectively the impact of the number of nodes and of node distance on the transmission delay. As shown, the delay increases in both cases, which is expected since the transmission energy increases, with the possibility of energy depletion at the receivers. Both figures show that using prediction leads to lower delays.

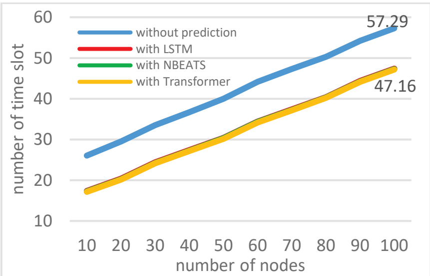

Fig. 9 Delay versus the number of nodes (100$kbit$ packets)

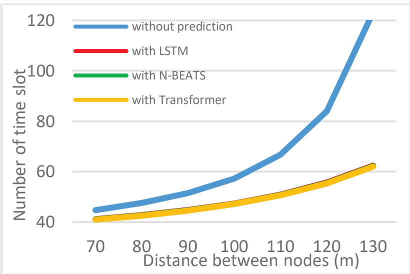

Fig. 5 Delay versus distance (100 $kbit$ packets, 100 nodes)

Fig. 11 shows the impact of maximum battery capacity on the delay in a network with 100 nodes using a packet size of 50 kbit or . The results for the size still show the superiority of using prediction, with 16% to 20% less delay. Moreover, a nearly flat curve is obtained instead of an increasing one. In both cases, the delay increase may be explained by the network's rate being too high to allow the batteries to recharge fast enough for the packet transmissions, but this effect is insignificant when using prediction. For the 50 kbit packet size, the difference in performance with and without prediction is very small (~0.6%) since the required energy for transmission is not large enough. We also observe that the delay decreases when maximum battery capacity increase using prediction. Thus, larger battery capacities store enough energy to ensure transmissions if the solar energy harvest can meet the transmission rate of the 50 kbit packets.

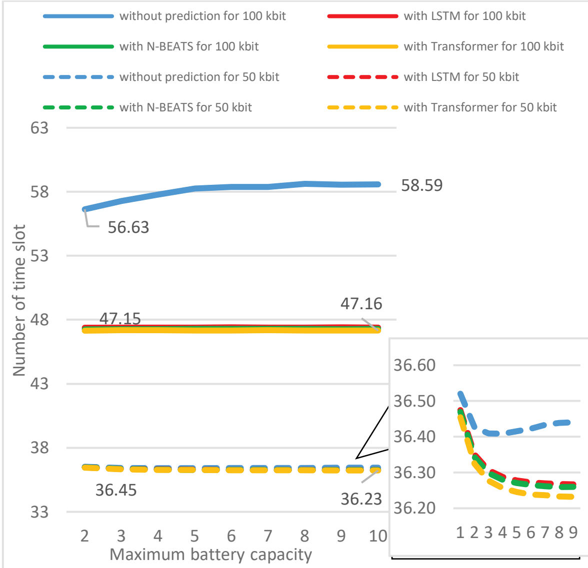

Fig 11. Delay to transmit and packets versus maximum battery capacity for 100 nodes network

V. Conclusion

In this work, we proposed and evaluated the use of three ML-based, deep learning prediction models for the available energy at the receiving nodes in a WSN-EH. The prediction is used to define the energy allocation and routing strategy in the network. We proposed a transmission model based on the predicted energy at the next node and studied the effect of prediction on network performance. Our simulations show that the deep-learning models provide better prediction accuracy than the state-of-the-art, and that using prediction yields better performance in terms of transmission reliability, energy saving and time saving.

References

[1] A. Seyedi and B. Sikdar, "Modeling and analysis of energy harvesting nodes in wireless sensor networks", in Proc. of Annual Allerton Conf. on Commun., Control, and Computing, 2008, pp. 67-71.

[2] J. Ventura and K. Chowdhury, "Markov modeling of energy harvesting Body Sensor Networks," in Proc. of IEEE Int. Symp. on Personal, Indoor and Mobile Radio Commun. (IEEE PIMRC), 2011, pp. 2168-2172.

[3] M. F. Ghuman, A. Iqbal, H. K. Qureshi, and M. Lestas, "Solar energy availability model for wireless sensor networks," in Proc. of Int. Workshop on Energy Harvesting Energy Neutral Sensing Systems, 2015. pp. 21–26.

[4] S. Koşunalp , "A Performance Evaluation of Solar Energy Prediction Approaches for Energy-Harvesting Wireless Sensor Networks", Int. J. of Applied Mathematics Electronics and Computers, no. Special Issue-1, pp. 424-427, Dec. 2016.

[5] S. Kosunalp, "A New Energy Prediction Algorithm for Energy-Harvesting Wireless Sensor Networks With Q-Learning," IEEE Access, vol. 4, pp. 5755-5763, 2016.

[6] A. Cammarano, C. Petrioli and D. Spenza, "Pro-Energy: A novel energy prediction model for solar and wind energy-harvesting wireless sensor networks," in Proc. of IEEE MASS 2012, pp. 75-83.

[7] A. Cammarano, C. Petrioli, and D. Spenza, “Improving energy predictions in EH-WSNs with pro-energy-VLT,” in Proc. of ACM Con. on Embedded Networked Sensor Systems (SenSys'13). Nov. 2013.

[8] M. Mughal, H. Qureshi, U. Saleem, M. Saleem, A. Pitsillides and M. Lestas, “Harvested Energy Prediction Schemes for Wireless Sensor Networks: Performance Evaluation and Enhancements,” Wireless Communications and Mobile Computing. 2017.

[9] T. N. Le, O. Sentieys, O. Berder, A. Pegatoquet and C. Belleudy, “Adaptive Filter for Energy Predictor in Energy Harvesting Wireless Sensor Networks,” in Proc. of Int. Conf. on Architecture of Computing Systems, 2013, pp. 1-4. Prague, Czech Republic.

[10] Y. Li, Z. Jia and X. Li, “Task Scheduling Based on Weather Forecast in Energy Harvesting Sensor Systems,” IEEE Sensors J., vol. 14, no. 11, pp. 3763-3765, Nov. 2014.

[11] M. Hassan and A. Bermak, “Solar Harvested energy prediction algorithm for wireless sensors,” in Proc. of Asia Symp. on Quality Electronic Design (ASQED), 2012, pp. 178-181.

[12] H. Ren, J. Guo, L. Sun and C. Han, “Prediction Algorithm Based on Weather Forecast for Energy-Harvesting Wireless Sensor Networks,” in Proc. of IEEE TrustCom/BigDataSE 2018, pp. 1785-1790.

[13] S. Kosunalp, "An Energy Prediction Algorithm for Wind-Powered Wireless Sensor Networks with Energy Harvesting". 2017.

[14] K. Saidi, W. Ajib and M. Boukadoum, “Adaptive transmitter load size using receiver harvested energy prediction by Kalman filter,” in Proc. of IEEE Int. Sym. Commun. Systems, Networks and Digital Signal Processing (CSNDSP), Prague, Czech Republic, 2016, pp. 1-5.

[15] M. Al-Omari, K. Hassini, A. Fakhfakh and O. Kanoun, "Prediction of Energy in Solar Powered Wireless Sensors Using Artificial Neural Network," 2019 In Proc. of Int. Multi-Conference on Systems, Signals & Devices (SSD), Istanbul, Turkey, 2019, pp. 288-293.

[16] P. S. Katkar and V. R. Ghorpade, "Fuzzy approach to predict mobility and energy to prolong the life of Wireless sensor network," in Proc. of IEEE Int. WIE Conf. on Electrical and Computer Engineering (WIECON-ECE), Pune, 2016, pp. 12-15.

[17] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory, in Neural Computation", vol. 9, no. 8, pp. 1735-1780, 15 Nov. 1997. doi: 10.1162/neco.1997.9.8.1735.

[18] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, Llion Jones, Aidan N. Gomez, L. Kaiser, I. Polosukhin. "Attention Is All You Need". In Proc. of Int. Conf. on Neural Information Processing Systems (NIPS'17). Curran Associates Inc., Red Hook, NY, USA, 6000–6010. 2017

[19] B. Oreshkin, D. Carpo, N. Chapados and Y. Bengio, "N-BEATS: Neural basis expansion analysis for interpretable time series forecasting", In Proc. of Int. Conf. on Learning Representations, 2020.

[20] J. Schmidt, “Stock predictions with state-of-the-art Transformer and Time Embeddings”, Juillet 2020.

[21] https://nsrdb.nrel.gov/