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DUTY CYCLE MAXIMIZATION OF ENERGY HARVESTED WIRELESS SENSOR NETWORK(EHWSN) FOR MISSION CRITICAL APPLICATIONS USING FORECASTED ENERGY

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Abstract – Energy Harvesting is an approach to boost throughput and extend the lifespan of a wireless sensor network used for mission-critical applications like safety, control and monitoring applications in oil and gas industries, where exceeding the delay limit can cause serious hazards and even threats to human life. This study proposed an adaptive duty algorithm that can decrease delay time by modifying its duty cycle based on predicted and residual energy. A Python framework-based Holt-Winter technique with the additive trend and additive seasonality was used to predict the solar forecast and pre-estimate duty cycle for future slots. The model's performance for the month of January was evaluated using prediction horizons of one hour, six hours, twelve hours, and twenty-four hours and Data from the National Renewal Energy Laboratory (NREL) were used to validate the suggested work. Comparing the suggested method to the prior work, average duty cycles and residual battery levels increase by 6% and 20%, respectively. Furthermore, the suggested strategy also ensures that the residual energy level will always be higher than 60%.

Keywords – Wireless sensor network, Mission critical applications, Energy Harvesting, Prediction Techniques, oil and gas industries

1. INTRODUCTION

The Wireless sensor network is a collection of nodes deployed in Remote areas to gather information and send it to Gateways or servers. These sensor nodes are made up of microcontrollers, batteries, and transceivers, and major sources of power consumption are sensing, data aggregation, transmission, and reception of data, of which transmission and reception account for most of it. In Initial applications, WSNs were battery-powered and used primarily for environmental monitoring and military applications[1]where energy efficiency was the main criterion to enhance the lifetime of sensor nodes[2][3][4]. So to communicate efficiently, Medium Access Control (MAC) protocol is used, which increases energy efficiency by properly scheduling the ON-OFF time of each sensor node, which refers to the duty cycle[5][6][7] of the sensor node. The Reduce Duty cycle increases the Energy Efficiency of traditional WSNs, but it also increases the time delay which is not acceptable in mission-critical applications[8][9].Recently, to power sensor nodes, researchers started using an ambient source of energy due to the development of small Solar modules, piezoelectric modules, RF Energy harvesters, and Thermal Energy harvesters, which opened the way for WSNs use in mission-critical applications[10][9][11] which decrease network Latency through Harvested Energy along with Energy efficiency. These applications include safety, control and monitoring application in oil and gas Industries, Health monitoring, flood monitoring, and volcanic eruptions requiring low Delay or High throughput with power management. To find the best ambient source of energy with high energy density and availability, scientists examined a variety of energy sources[12], including thermal, solar, and radiofrequency energy, and found that Solar energy was the most abundant and had the best energy density. Another advantage of solar energy is that we can predict the duty cycle of the next slots with the help of predicted forecast energy which also helps in the proper design of protocols based on it, but solar radiation varies with time and place[13], so proper Forecasting techniques are required to achieve this.

The motivation of the research was to optimize the Duty cycle of the sensor node with respect to Predicted harvested energy and Available battery Power. The literature survey on related works was divided into three categories: (1) Type of storage (2) Prediction Techniques (3) Energy management based on duty cycling. In this article, the Harvest-Store-Use paradigm was used to power the node and charge the batteries. Several Energy storage technologies are available to implement the energy buffer like Supercapacitors[14], NiCd[15] and NiMH batteries[16].Among all storage technologies NiMH comes out to be a strong contender with High Energy density but suffers from limited Charge-discharge cycle problems, Which can be increased by either increasing the Battery capacity or by decreasing the range of charge and discharge limit.

Initially Solar Energy forecasting techniques was based on exponentially weighted moving average[17][18],but due to non-linearity, trends, and seasonality Prediction accuracy was poor. To increase the Forecasting Accuracy, later on, Researcher also used machine learning and time series methods. However, for univariate models, the time series method can provide a comparable result while being many times quicker than ML techniques[19]. Many statistical time series forecasting methods have been utilized in WSN, with Auto Regressive Moving Average (ARMA)[20], Auto Regressive Integrated Moving Average(ARIMA), and Seasonal Auto-Regressive Integrated Moving Average (SARIMA)[21][22], Holt winter method[[23], and Facebook Prophet model[24]. It was discovered, that to add seasonability into ARIMA, one needs to get p, d, and q parameters as well as P, D, Q, and M parameters. This is a laborious process, but one can also use the "pdarima" package in Python to automatically extract these parameters, albeit occasionally this method is also inaccurate. In this paper, the Holt winter technique with the damped additive trend and seasonability or triple Exponential approach was employed because it delivers quick and exact findings with minimal data irregularities and takes into account level, trend, and seasonality when forecasting data.Low-duty cycle is not permitted in mission-critical applications or event-driven systems where a transmission packet loss has hampered the entire operation. It was discovered that increasing the duty cycle can reduce delays or improve throughput, where its maximum value is determined by the Electrically Neutral condition (ENO[17][25]), which is the condition in which power consumption at any given time must be less than the harvested energy, and its minimum value is determined by the routing or MAC layer protocol's minimum delay requirement. Various research was conducted, to optimize the Duty cycle which was either battery-centric[26] only or battery centric along with Predicted Harvested Energy[27]. In the most recent study[28], the authors used machine learning to forecast and modify Duty cycles based on the data priorities in

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mission-critical applications, where average duty for all types of data was achieved at 57 %.In the above survey, it was evident that an average duty cycle of less than 70% was achieved till date.

This article presented three solutions for reducing wait time or increasing the duty cycle of future slots. The first and second algorithms forecasted energy and used it to maximize the duty cycle for future slots until maximum assignment for further slots was no longer attainable; the third method employed Residual energy for remaining slots until it hit the Threshold value. Solar energy forecasting, duty cycle maximization utilizing forecasted energy and residual energy, and duty cycle adaptation based on actual energy are all aspects of the proposed work. The experimental results demonstrate different benefits in terms of (1) better and faster forecasting technique (2) maximizing average duty cycle (3) increasing prediction horizon (4) increased battery life when compared to comparable studies.

2. METHODOLOGY

The major goal of this research was to minimize delay by maximizing the duty cycle of the sensor node using forecasted energy transmitted by the gateway and its available residual energy, as indicated in Figure 1 with future research scope. Three algorithms were implemented in the suggested study. One was for prediction, while the other two were for maximizing duty cycle parameters in terms of expected energy and residual energy. As explained below, the proposed work is implemented in many phases that occur one after the other to achieve the intended result, and Table 1 displays all of the symbols used in the system along with their descriptions.

2.1 Solar Energy Prediction

In the first Phase to compare with previous research, Historical data were taken from the NREL Solar Radiation Research laboratory, and The year 2010 to 2015 data was taken as training, and the Year 2016 data was for testing and validating the model.It was trained and validated for the January month data of six years to check the effectiveness of the model in low irradiance. This study employed the exponential method, in which a recent observation was given a higher weight than an older one, and the weight decays exponentially. Holt winter method with a damped additive trend and additive seasonality was used in this paper. It is an algorithm that combines smoothing equations for the label, trend, and season ability with the exponential equation, and the equation of each one was shown below[29].

$$\hat{O}_{t+j/t} = L_t + \phi_j B_t + S_{t+j-m(k+1)} \quad (1)$$

$$L_t = \alpha_1 (O_t - S_{t-m}) + (1-\alpha_1)(L_{t-1} + \phi_4 B_{t-1}) \quad (2)$$

$$B_t = \alpha_2^* (L_t - L_{t-1}) + (1-\alpha_2^*)\phi_4 B_{t-1} \quad (3)$$

$$S_t = \alpha_3 (O_t - L_{t-1} - \phi_4 B_{t-1}) + (1-\alpha_3) S_{t-m} \quad (4)$$

Where $\hat{O}_{t+j}$ =Predicted outputs after time t, L_t =level estimates, B_t =trend estimates, S_t =seasonal estimates and m Denotes number of season and $\alpha_1, \alpha_2^*, \alpha_3, \phi_4$ are smoothing parameters.

When acquiring solar data over a long period, seasonal fluctuation is nearly constant, therefore the additive technique is preferred over the multiplicative method[29], which produces poor forecasts. Data was collected from 7:00 a.m. to 5:30 p.m. with night data being removed.

2.2 Initial Duty Assignment

In this Phase, The initial Assignment of the duty cycle of each slot was made based on Harvested energy. If $P(i)_{Harvested} < P(i)_{Slot}$ then such slot termed as Dark slot D_{Dark} and if $P(i)_{Harvested} > P(i)_{Slot}$ then such slots termed as Sun slots D_{Sun} which were specified (5) & (6) and adapted according kansal et al.[17], the value of these Duty cycles was estimated using Equations (5) and (6).

$$D_{Dark} = \left[\frac{P(i)_{Harvested}}{P(i)_{Slot} + P(i)_{Harvested}\left(\frac{1}{\eta} - 1\right)}\right] \quad (5)$$

$$D_{Sun} = \left[\frac{P(i)_{Harvested}}{P(i)_{Slot}}\right] \quad (6)$$

2.3 Maximum Duty Cycle Assignment Using Total Harvested Energy E_{Total}

This phase was critical; first, the total Forecasted Harvested Energy for future slots was calculated. Next, the maximum Duty Cycle $D(i) = D_{\max}$ was assigned to those slots that had an Initial Duty Cycle greater than the Maximum Duty Cycle or Remaining Total Harvested Energy E_{Total} greater than the maximum Energy $E_{D\max}$

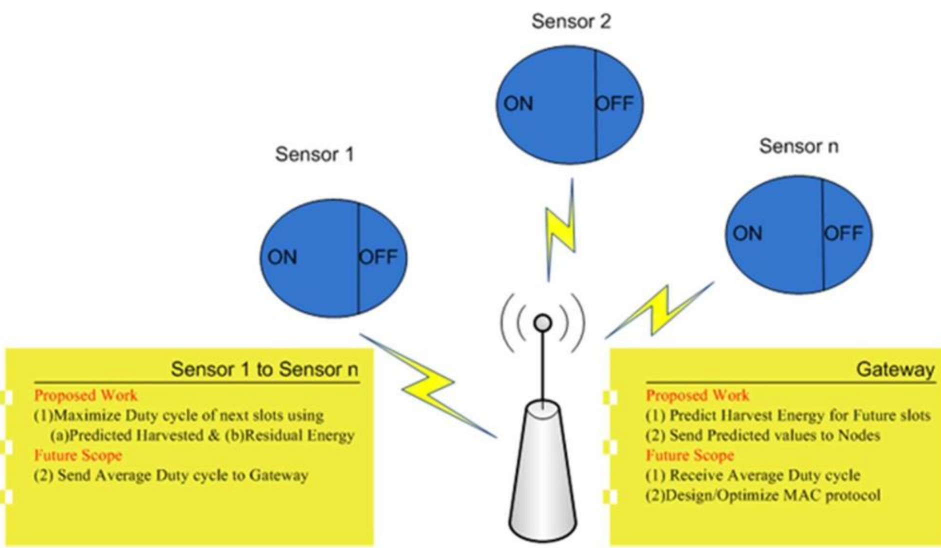

Figure 1 Proposed System

Consumed by Sensor node. When there was insufficient energy to give the Maximum duty cycle to additional slots, the slots retain their prior value of Duty cycle i.e. $D(i)_{initial}$ .Total Harvested and maximum consumed Energy by sensor node were calculated according to Equation (7) and (8).

$$E_{Total} = \sum_{i}^{N} P(i)_{Harvested} \; (i \in N) \quad (7)$$

$$E_{D\max} = D_{\max} \times P_{Active} + (1 - D_{\max}) \times P_{Sleep} \quad (8)$$

Table1.Symbols and their description

Variable	Description
$P(i)_{slot}$	Power consumption in ith Slot
$D(i)$	Duty cycle in ith Slot
D_{sun}	Initial Duty cycle when $P(i)_{Harvested} > P(i)_{slot}$
D_{Dark}	Initial Duty cycle when $P(i)_{Harvested} < P(i)_{Consumed}$
$D(i)_{\max}$	Maximum Duty cycle
$D(i)_{\min}$	Minimum Duty cycle
$E_{D\max}$	Power consumption when $D(i) = D_{\max}$
$\square_1, \square_2$	Upper and lower Thresold of battery
$\square_1, \square_1, \square_2$	Values depends upon $P(i)_{Harvested}$
$B_{Thresold}$	Threshold level of battery
$\square_1$	Average Harvesting Power

2.4 Maximum Duty Cycle Assignment Using Residual Battery Level

This phase used the battery's remaining energy to increase

The duty cycle of slots with a duty cycle lower than the

maximum Duty cycle $D_{\max}$. If the Harvested Energy was greater than the Consumed Energy of the ith slot, the Maximum duty cycle $D_{\max}$ assigned and the Residual battery for the next slot increased by $\square_1$, where $\square_1$ was computed using equation (9). If the aforementioned was not the case, the battery's residual energy was consumed to boost the Duty cycle until its value did not fall below the threshold level, which was 60% of the maximum value. To work on the Safer side concerning stored Energy constants $\square_1$ and $\square_2$ were chosen according to equations (10) and (11).The selected Duty will be either Maximum, Minimum, or Zero, depending on the Residual Energy of the ith slot; the final case did not occur because the Residual Energy was always larger than 60%. The duty cycle will be the maximum if Battery's Energy is greater than the Threshold value by an amount of $\square_1$, and In this case, the Residual battery Energy for the next slot decrease by value $\square_1$ .The duty cycle will be minimum $D_{\min}$ if the Residual Energy of the ith slot was greater than the Threshold value $B_{Thresold}$ by $\square_2$ but less than the threshold value $B_{Thresold}$ by $\square_1$, and in this case, the Residual Energy of the next slot decrease by an amount of $\square_2$.The values of $\square_1$ and $\square_2$ were calculated according to equations (12) and (13).

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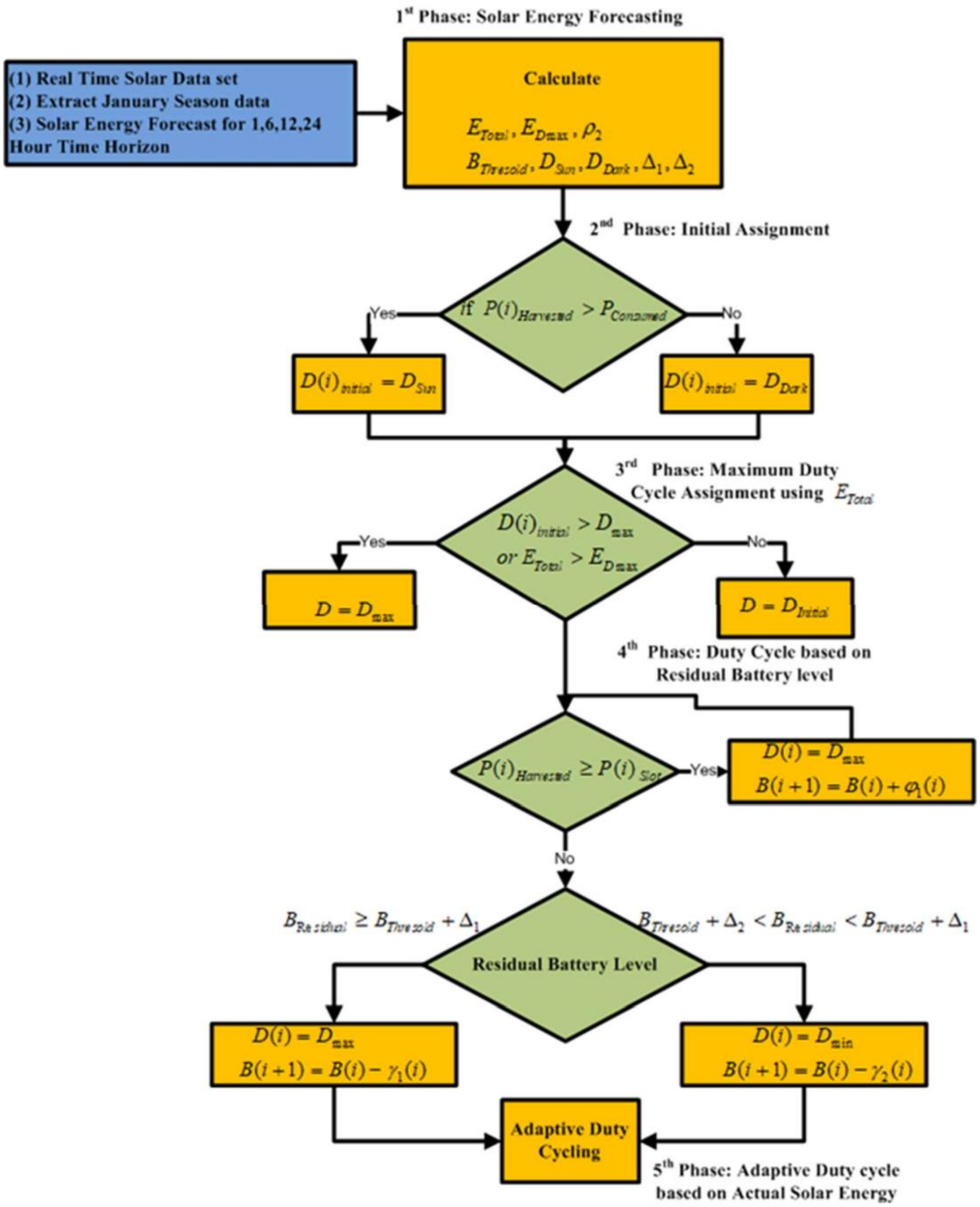
$$\square_1 = \begin{bmatrix} \square\, \square\, (1 \square D_{\max}) \square P(i)_{Harevested} \\ + \square\, \square\, (P(i)_{Harvested} \;\square\; P(i)_{Slot}) \end{bmatrix} \quad (9)$$

$$\square_1 = D_{\max} \square P_{Active} + (1 \square D_{\max}) \square P_{Sleep} \quad (10)$$

Figure 2.Proposed Methodology



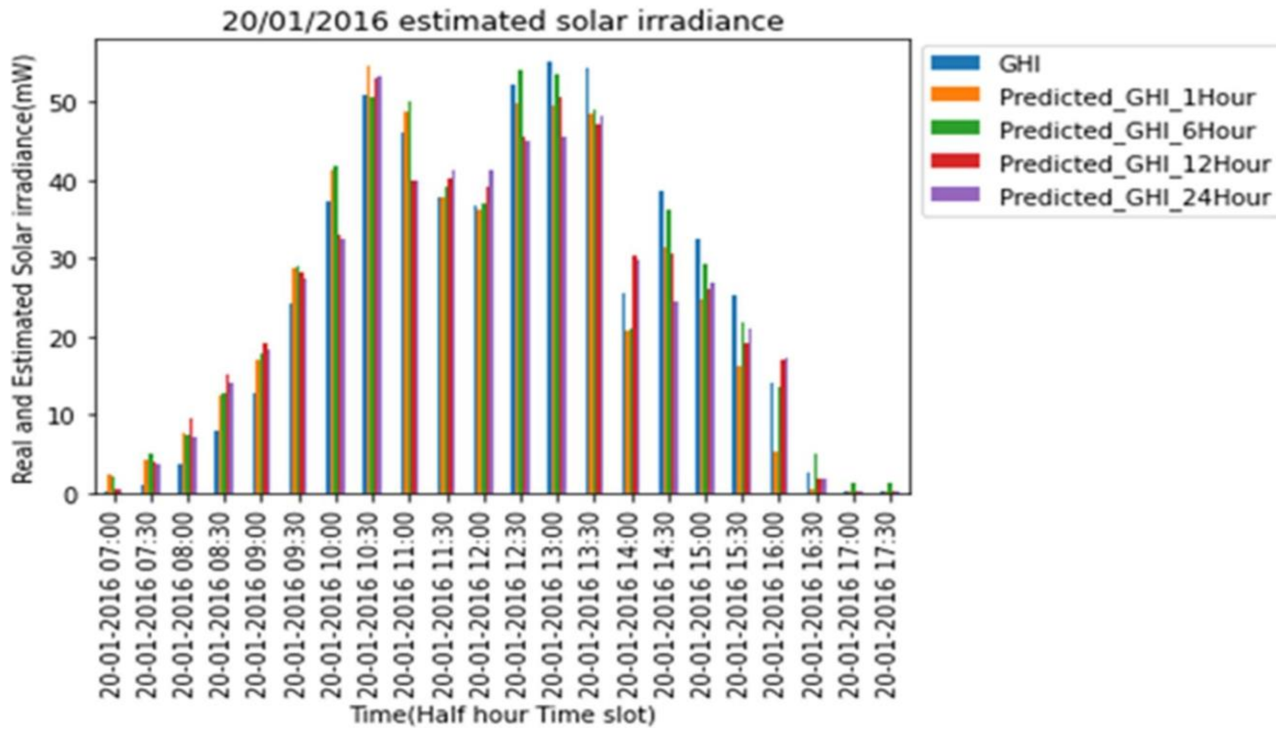


Figure3. Solar Energy Prediction for various Forecasting Horizons

$$E_2 = D_{min} \times P_{Active} + (1 - D_{min}) \times P_{Sleep} \tag{11}$$

$$E_1 = \left[(1 - D_{max}) \times P(i)_{Harevested} + D_{max} \times (P(i)_{Slot} - P(i)_{Harvested}) \right] \tag{12}$$

$$E_2 = \left[(1 - D_{min}) \times P(i)_{Harevested} + D_{min} \times (P(i)_{Slot} - P(i)_{Harvested}) \right] \tag{13}$$

In Equation (9), (12) and (13) first part represent Harvested Energy stored during sleep period, but in Equation (12), (13) second part denotes the extra energy taken from Residual battery to increase the Duty cycle from $D(i)$ to D_{max}, and $D(i)$ to D_{min} in active mode, and in Equation (9),second part denote the extra harvested energy stored during active mode when harvested energy greater than consumed Energy.

2.5 Adaptive Duty cycle based on Actual Harvested Energy

The duty cycle assigned in this phase or algorithm was based on Actual harvested energy $p(i)_{Actual}$, if it was higher than consumed energy and also higher than anticipated energy $P(i)_{Harvested}$ for an i^{th} slot, then the maximum duty cycle D_{max} was assigned from the current slot to the subsequent slots until enough energy was left. If the above requirement does not meet, the minimum Duty

Cycle $D_{\min}$ will be assigned from the current slots to the following slots until enough energy was left. Proposed methodology in the form of flow chart as shown in figure 2.

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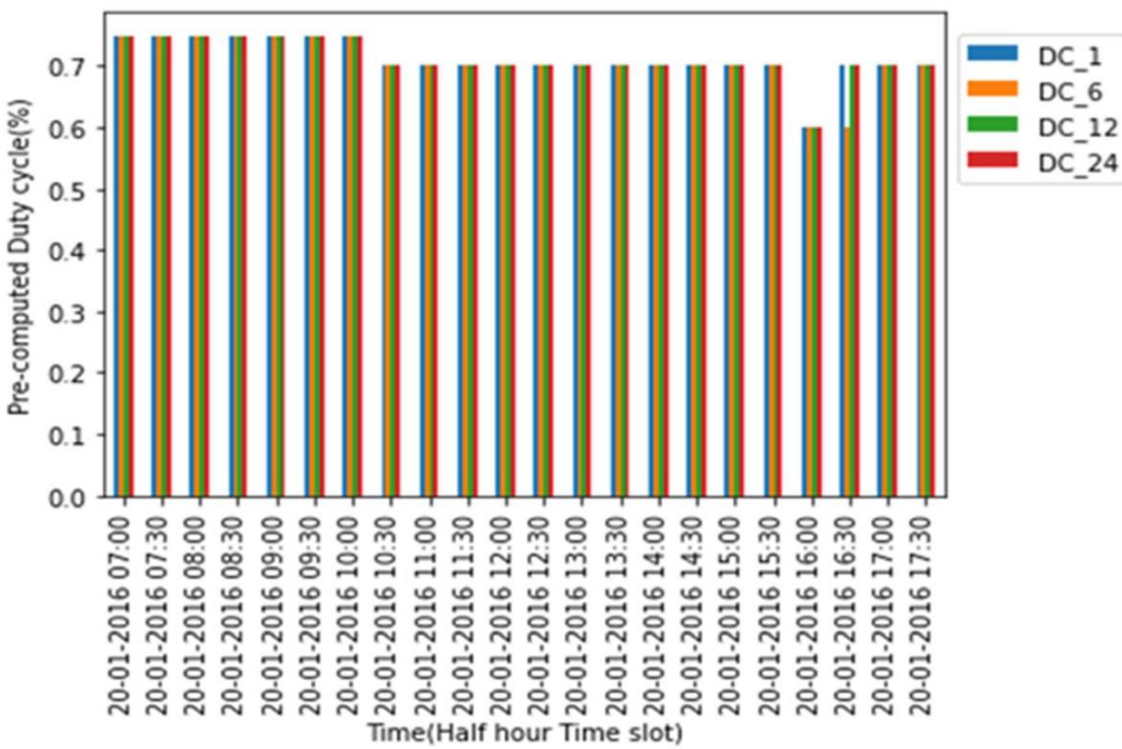

Figure 4 .Pre-computed Duty cycle for various Forecasting Horizons

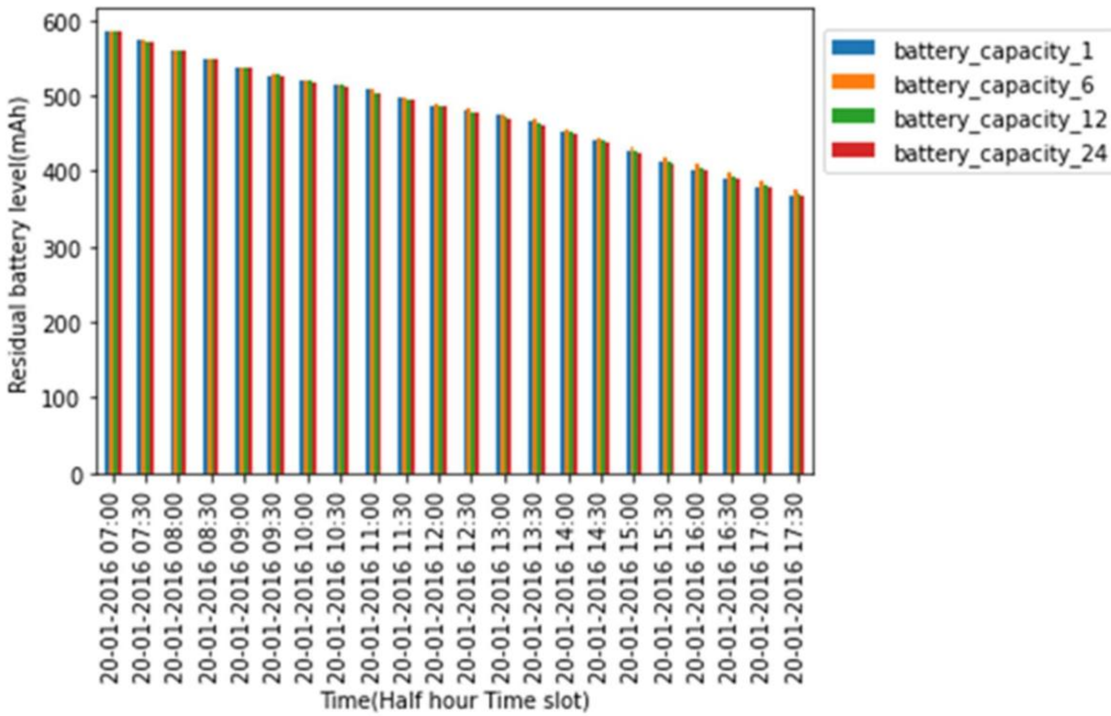

Figure 5.Residual Battery level for various Forecasting Horizons

Table 2: Comparison of Performance parameters with previous work

Prediction Horizon			**Accuracy (%)**	**Accuracy**[16] **(%)**		**D_{Avg}**[16] **(%)**		**B_{last}**[16] **(mAh)**
1 Hour	3.98	9.89	88.28	87.27	71.136	66.85	366.25	293
6 Hour	2.82	9.87	89.39	89.09	70.68	66.22	375.54	292
12 Hour	4.17	13.06	79.31	78.18	71.14	67.4	368.8	293
24 Hour	4.47	7.09	69.48	89.09	71.14	64.7	366.45	294

4. CONCLUSION

The mission-critical application requires less delay latency with Energy efficiency, achieved by supplying extra Energy through Energy Harvesting and residual battery energy. However, the stochastic nature of Weather conditions leads to uncertainty in the correct Harvesting rate. This paper proposed Holt's winter method with a damped additive trend, and additive seasonality to predict Forecasted energy. After that, the Duty cycle of the next slots was pre-estimated and maximized using Predicted harvested energy and Residual Battery. The proposed work increased the average Duty cycle by 6% and the Residual battery level by 20% compared to previous work. This approach also improves the Residual battery's lifetime by decreasing the length of the Charge and discharge cycle by operating the battery above 60% level. The Python framework was used to validate the above results. In the future, proposed methodologies will be expanded from sensor node to network study by properly developing and optimizing MAC layer design for Energy Harvesting wireless sensor networks to boost network throughput.

REFERENCES

[1] K. W. Al-ani, A. S. Abdalkafor, and A. M. Nassar, "An overview of wireless sensor network and its applications," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 17, no. 3, p. 1480, 2020, doi: 10.11591/ijeecs.v17.i3.pp1480-1486.

[2] I. Dietrich and F. Dressler, "On the lifetime of wireless sensor networks," *ACM Trans. Sens. Networks*, vol. 5, no. 1, pp. 1–39, 2009.

[3] S. M. Chowdhury and A. Hossain, "Different energy saving schemes in wireless sensor networks: A survey," *Wirel. Pers. Commun.*, vol. 114, no. 3, pp. 2043–2062, 2020.

[4] S. Hadi, H. Rahm Dakheel, and A. Jarullah Yaseen, "Energy efficient with prolonging

lifetime in homogeneous wireless sensor networks," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 28, no. 2, p. 801, 2022, doi: 10.11591/ijeecs.v28.i2.pp801-809.

[5] S. Galmés and S. Escolar, "Analytical Model for the Duty Cycle in Solar-Based EH-WSN for Environmental Monitoring," *Sensors*, vol. 18, no. 8, 2018, doi: 10.3390/s18082499.

[6] V. K. Verma and V. Kumar, "Review of MAC Protocols for Energy Harvesting Wireless Sensor Network (EH-WSN)," *Internet Things Big Data Appl. Recent Adv. Challenges*, pp. 141–149, 2020.

[7] I. J. Habeeb, H. A. Jasim, and M. H. Hashim, "Balance energy based on duty cycle method for extending wireless sensor network lifetime," *Bull. Electr. Eng. Informatics*, vol. 12, no. 5, pp. 3105–3114, 2023.

[8] A. Javadpour *et al.*, "Toward a secure industrial wireless body area network focusing MAC layer protocols: an analytical review," *IEEE Trans. Ind. Informatics*, 2022.

[9] H. Farag, M. Gidlund, and P. Österberg, "A delay-bounded MAC protocol for mission-and time-critical applications in industrial wireless sensor networks," *IEEE Sens. J.*, vol. 18, no. 6, pp. 2607–2616, 2018.

[10] M. reza Akhondi, A. Talevski, S. Carlsen, and S. Petersen, "Applications of wireless sensor networks in the oil, gas and resources industries," in *2010 24th IEEE International Conference on Advanced Information Networking and Applications*, 2010, pp. 941–948.

[11] S. Ali *et al.*, "SimpliMote: A Wireless Sensor Network Monitoring Platform for Oil and Gas Pipelines," *IEEE Syst. J.*, vol. 12, no. 1, pp. 778–789, 2018, doi: 10.1109/JSYST.2016.2597171.

[12] M. Gholikhani, H. Roshani, S. Dessouky, and A. T. Papagiannakis, "A critical review of roadway energy harvesting technologies," *Appl. Energy*, vol. 261, p. 114388, 2020.

[13] V. Raghunathan, A. Kansal, J. Hsu, J. Friedman, and M. Srivastava, "Design considerations for solar energy harvesting wireless embedded systems," *2005 4th Int. Symp. Inf. Process. Sens. Networks, IPSN 2005*, vol. 2005, pp. 457–462, 2005, doi: 10.1109/IPSN.2005.1440973.

[14] A. S. Weddell, G. V. Merrett, T. J. Kazmierski, and B. M. Al-Hashimi, "Accurate supercapacitor modeling for energy harvesting wireless sensor nodes," *IEEE Trans. Circuits Syst. II Express Briefs*, vol. 58, no. 12, pp. 911–915, 2011, doi: 10.1109/TCSII.2011.2172712.

[15] K. Chan, H. Phoon, C. Ooi, W. Pang, and S. Wong, "Power management of a wireless sensor node with solar energy harvesting technology," *Microelectron. Int.*, vol. 29, no. 2, pp. 76–82, Jan. 2012, doi: 10.1108/13565361211237662.

[16] A. Sharma and A. Kakkar, "Machine learning based optimal renewable energy allocation in sustained wireless sensor networks," *Wirel. Networks*, vol. 0123456789, 2019, doi: 10.1007/s11276-018-01929-w.

[17] A. Kansal, J. Hsu, S. Zahedi, and M. B. Srivastava, "Power management in energy harvesting sensor networks," *ACM Trans. Embed. Comput. Syst.*, vol. 6, no. 4, pp. 32-es, 2007, doi: 10.1145/1274858.1274870.

[18] C. Bergonzini, D. Atienza, and T. S. Rosing, "Prediction and Management in Energy Harvested Wireless Sensor Nodes," pp. 6–10, 2009.

[19] G. Reikard and C. Hansen, "Forecasting solar irradiance at short horizons: Frequency and time domain models," *Renew. Energy*, pp. 1270–1290, 2019, doi: 10.1016/j.renene.2018.08.081.

[20] M. Jaihuni *et al.*, "A partially amended hybrid Bi-Gru—ARIMA model (PAHM) for predicting solar irradiance in short and very-short terms," *Energies*, vol. 13, no. 2, 2020, doi: 10.3390/en13020435.

[21] M. H. Alsharif, M. K. Younes, and J. Kim, "Time series ARIMA model for prediction of daily and monthly average global solar radiation: The case study of Seoul, South Korea," *Symmetry (Basel).*, vol. 11, no. 2, pp. 1–17, 2019, doi: 10.3390/sym11020240.

[22] A. Shadab, S. Said, and S. Ahmad, "Box–Jenkins multiplicative ARIMA modeling for prediction of solar radiation: a case study," *Int. J. Energy Water Resour.*, vol. 3, no. 4, pp. 305–318, 2019, doi: 10.1007/s42108-019-00037-5.

[23] M. Heydari, H. Benisi Ghadim, M. Rashidi, and M. Noori, "Application of Holt-Winters Time Series Models for Predicting Climatic Parameters (Case Study: Robat Garah-Bil Station, Iran)," *Polish J. Environ. Stud.*, vol. 29, no. 1, pp. 617–627, 2020, doi: 10.15244/pjoes/100496.

[24] V. K. Verma and S. S. Srikant, "Hample filter based Short term Solar Forecasting using Facebook Prophet Library in Energy Harvested Wireless Sensor Network (EHWSN)," *IEIE Trans. Smart Process. Comput.*, vol. 11, no. 5, pp. 368–375, 2022.

[25] A. Kansal, J. Hsu, M. Srivastava, and V. Raghunathan, "Harvesting aware power management for sensor networks," *Proc. - Des. Autom. Conf.*, pp. 651–656, 2006, doi: 10.1145/1146909.1147075.

[26] S. K. Mothku and R. R. Rout, "Fuzzy logic based adaptive duty cycling for sustainability in energy harvesting sensor actor networks," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 34, no. 1, pp. 1489–1497, 2022, doi: https://doi.org/10.1016/j.jksuci.2018.09.023.

[27] A. Cinco-Solis, J. J. Camacho-Escoto, L. Orozco-Barbosa, and J. Gomez, "PPAASS: Practical Power-Aware Duty Cycle Algorithm for Solar Energy Harvesting Sensors," *IEEE Access*, vol. 10, pp. 117855–117870, 2022.

[28] S. Sarang, G. M. Stojanović, M. Drieberg, S. Stankovski, K. Bingi, and V. Jeoti, "Machine Learning Prediction Based Adaptive Duty Cycle MAC Protocol for Solar Energy Harvesting Wireless Sensor Networks," *IEEE Access*, vol. 11, pp. 17536–17554, 2023, doi: 10.1109/ACCESS.2023.3246108.

[29] R. Hyndman, A. B. Koehler, J. K. Ord, and R. D. Snyder, *Forecasting with exponential smoothing: the state space approach*. Springer Science & Business Media, 2008.