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Prediction-based Duty cycle Optimization of Energy Harvested Wireless Sensor Networks (EHWSN) in Mission Critical Applications

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Energy Harvesting is an approach to boost throughput and extend the lifespan of a wireless sensor network used for mission-critical applications where Exceeding the delay limit can cause serious hazards and even threats to human life. These applications include health monitoring, industrial processes, forest fire detection, etc.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.The model's performance for January was evaluated using prediction horizons of one hour, six hours, twelve hours, and twenty-four hours, and Data from the NREL Solar Radiation Research Laboratory 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 ensures that the residual energy level will always be higher than 60%.

Keywords: Energy Harvesting, Wireless sensor network, Mission critical applications, Solar forecast, Adaptive Duty cycle.

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].The transceiver in WSN is a Major source of power consumption, so whenever sensor nodes try to communicate with each other in a channel, there will be power consumption due to idle listening, packet reception, transmission, overhearing, and even due to collision of data. So to communicate efficiently, 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. 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 which decrease network Latency through Harvested Energy along with Energy efficiency.These applications include Industrial process monitoring, Health monitoring, flood monitoring, and volcanic eruptions requiring low Delay or High throughput with power management.

In an Energy Harvesting Wireless sensor network(EHWSN) Energy efficiency is achieved by operating sensor nodes in Electrically Neutral Operation (ENO)[8] condition, which can be accomplished by operating sensor nodes in such a manner so that energy consumption is always lower than energy harvesting. To find the best ambient source of energy with high energy density and availability, scientists examined a variety of energy sources[9], 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[10], so proper Forecasting techniques are required to achieve this. The major contributions of this paper are (1) Better and Fast Forecasting Technique (2)Maximize Average Duty cycle (3) Increased Prediction Horizon (4) Increased Battery life.

2. Background and Related Work

In mission-critical applications[11][12], delay Time is reduced by increasing the Duty cycle, but in energy-harvesting wireless sensor nodes (EHWSN), Harvested energy is stochastic in nature and shows temporal and spatial variation, so it is very difficult to make the constant duty cycle for all sensor nodes. As a result, extensive prediction algorithms are necessary, which involve numerous criteria such as trend, season ability, and past data labeling to Forecast available energy in the next Time slots and predictthe Duty cycle based on it.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.

2.1. Type of Storage

It's vital to know which storage technology to employ because, 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,NiCd,and NiMH batteries. According to the survey it’s come to know supercapacitor[13] has high efficiency but suffers from leakage current problems and has low energy density. NiCd[14] suffers from memory effect problems and is made from toxic chemicals. Lithium-ion batteries have high energy density but need complex charging circuits and limited charge and Recharge cycles. In this survey NiMH[15] 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.

2.2. Prediction Techniques

Initial solar energy prediction for wireless sensor node was made exponentially weighted moving average[8][16],but due to non-linearity, trends, and seasonality Prediction accuracy was poor.To increase the Forecasting Accuracy, later on, the 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[17].Many statistical time series forecasting methods have been utilized in WSN, with Auto Regressive Moving Average(ARMA)[18], Auto Regressive Integrated Moving Average(ARIMA), and Seasonal Auto-Regressive Integrated Moving Average (SARIMA)[19][20] and Holt's winter method[21].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.

2.3.Energy Management based on Duty Cycle Approach

To save power, the microcontroller switches between sleep and active mode which is known as the Duty cycle of the Sensor Node. However, owing to the extended sleep time, there will be a decrease in received data packets or in other words, the quality of service. Because each node in an EHWSN wakes up or sleeps at a different time or has a variable duty cycle depending on the ENO situation, the major emphasis of researchers is to improve the average duty cycle of each node or to optimize the throughput. Low-duty cycles are not permitted in mission-critical applications or event-driven systems where the loss of a transmission packet has caused the entire operation to be impeded.Kansal et al.[8]Was the first to develop the term "Electrically Neutral Operation(ENO)" For an energy-harvested wireless sensor network, the power consumption at any one moment must be less than the harvested energy, and the WSN can have an indefinite lifetime as a result. The connection between the rate at which energy is gathered, consumed, and stored in the battery was given by Kansal et at.[22]. As a consequence, duty cycle optimization based on harvested energy prediction converges to duty cycle optimization based on actual energy. Finally, rather than the lifespan problem, which was the only subject of research in battery power WSN, now this topic has centered on throughputoptimization. It was discovered that raising the duty cycle can reduce delays or improve throughput, and the minimum duty cycle value is set 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 only or battery centric along with Predicted Harvested Energy[23][24].In the most recent study[25], the authors used machine learning to forecast and modify Duty cycles based on the data priorities in 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.

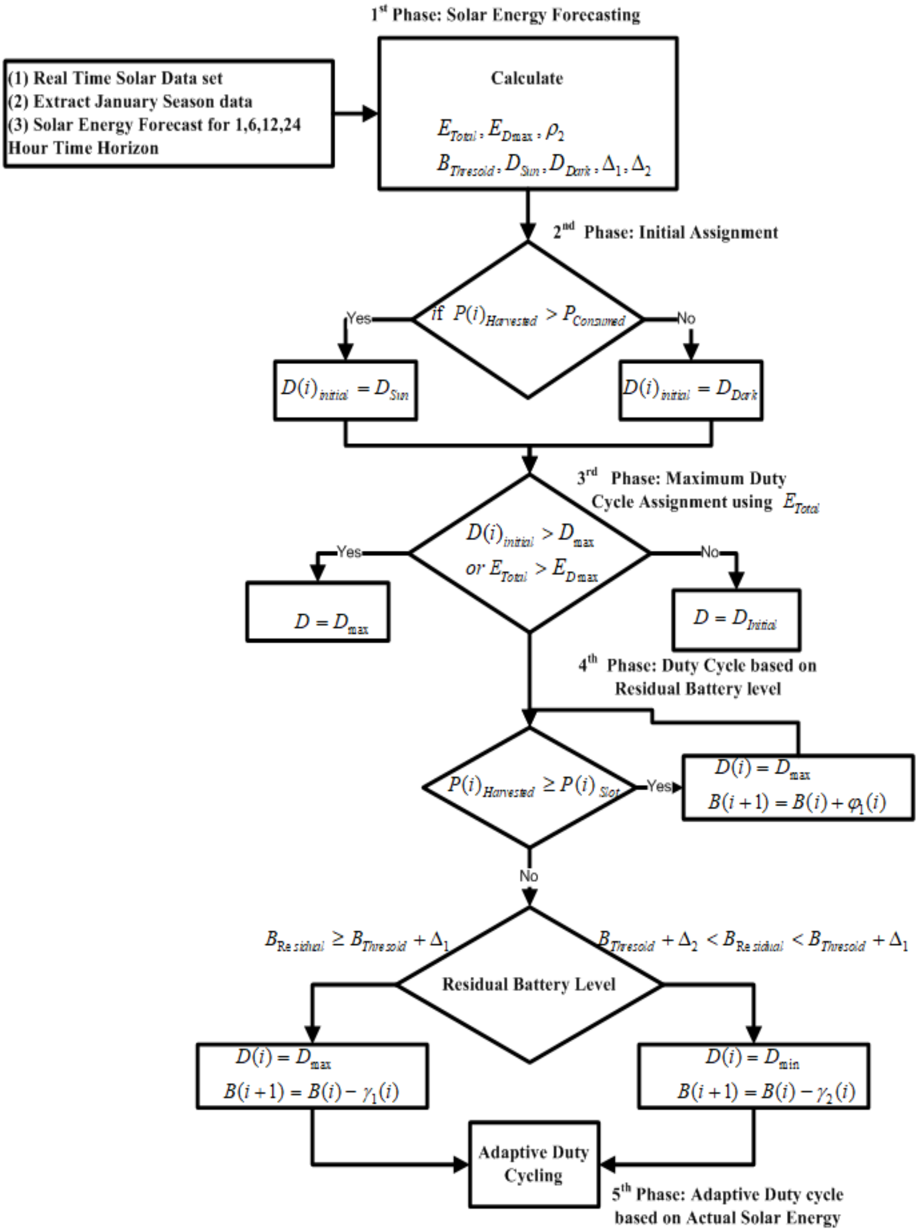


Figure 1. Proposed Model

Table 1. Symbols and their description

Variable	Description
$P(i)_{slot}$	Power consumption in i^{th} Slot
$D(i)$	Duty cycle in ithSlot
D_{sun}	Initial Duty cycle when $P(i)_{Harvested} > P(i)_{Consumed}$
D_{Dark}	Initial Duty cycle when $P(i)_{Harvested} < P(i)_{Consumed}$
$D_{\max}$	Maximum Duty cycle

$D_{\min}$	Minimum Duty cycle
$E_{D\max}$	Power consumption when $D(i) = D_{\max}$
Δ_1, Δ_2	Upper and lower Thresold of battery
$\phi_1, \gamma_1, \gamma_2$	Values depends upon $P(i)_{Harvested}$
$B_{Thresold}$	Thresold level of battery
ρ_1	Average Harvesting Power

3. Proposed work

To Maximize the Average, maximum, and minimum Duty cycle formission-critical applications of the sensor nodeconcerning predicted Harvested energy and available Residual Battery, Three algorithms were proposed. One For Prediction and two for maximizing Duty cycle parameters with respect to predicted Energy and Residual Battery.The proposed system's flow chart is shown in Figure 1 with various Phases occurring one after the other to accomplish the desired result, andTable 1 lists all of the symbols used in the system along with their descriptions.

3.1. Solar Energy Forecasting

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 seasonability with the exponential equation, and the equation of each one is shown below[26].

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

$$L_t = \phi_1 (O_t - S_{t-m}) + (1-\phi_1)(L_{t-1} + \phi_4 B_{t-1}) \tag{2}$$

$$B_t = \phi_2^* (L_t - L_{t-1}) + (1-\phi_2^*)\phi_4 B_{t-1} \tag{3}$$

$$S_t = \phi_3 (O_t - L_{t-1} - \phi_4 B_{t-1}) + (1-\phi_3) S_{t-m} \tag{4}$$

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 the number of seasonsand ϕ_1, ϕ_2^*, ϕ_3, ϕ_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[26], which produces poor forecasts. Data was collected from 7:00 a.m. to 5:30 p.m. with night data being removed.

3.2. Initial Duty Assignemnt

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} andif $P(i)_{Harvested} > P(i)_{Slot}$ then such slots termed as Sun slots D_{Sun} whichwere specified in (5) & (6)

and adapted according toKansal et al.[8]

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

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

3.3. Maximum Duty Cycle Assignment Using Total Harvested Energy E_{Total} :

This phase was very crucial, in this first total Forceated harvested Energyfor N slots and Power consumption $E_{D\max}$ were calculated when $D(i) = D_{\max}$,and these values were calculated according to Equations (7) and (8).

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

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

After that start assigning $D_{\max}$ from the First slot till the condition $D(i)_{Initial} > D_{\max}$ met or $E_{Total} > E_{D\max}$ .When there was no sufficient energy to assign $D_{\max}$ then $D(i) = D(i)_{Initial}$ for all slots which may take value either D_{Sun} or D_{Dark} .

3.4. Maximum duty cycleassignment using residual battery level

This phase employed the battery's leftover energy to boost the duty cycle of those slots having duty cycles lower than $D_{\max}$ .If $P(i)_{Harvested} \geq P(i)_{Slot}$ then $D(i) = D_{\max}$ and $B_{\text{Re}\,sidual}(i+1) = B_{\text{Re}\,sidual}(i) + \phi_1$;else if $B(i)_{\text{Re}\,sidual} \geq B_{Thresold} + \Delta_1$,the Maximum Duty cycle $D_{\max}$ will be allocated and the Battery level will be $B_{\text{Re}\,sidual}(i+1) = B_{\text{Re}\,sidual}(i) - \gamma_1$;else if $B_{Thresold} + \Delta_2 < B(i)_{\text{Re}\,sidual} < B_{Thresold} + \Delta_1$,the Minimum Duty cycle $D_{\min}$ will be assigned and the Battery level will be $B_{\text{Re}\,sidual}(i+1) = B_{\text{Re}\,sidual}(i) - \gamma_2$;else $B(i)_{\text{Re}\,sidual} < B_{Thresold} + \Delta_2$,Duty cycle will be zero.The last occurrencewill never occur since the Residual Battery level was always greater than the Threshold value in our method.The values of $\phi_1, \Delta_1, \Delta_2, \gamma_1$ and γ_2 calculated from Equations (9),(10),(11),(12) & (13)

$$\phi_1 = \eta \times (1 - D_{\max}) \times P(i)_{Harevested} + \eta \times (P(i)_{Harvested} - P(i)_{Slot}) \quad (9)$$

$$\Delta_1 = D_{\max} \times P_{Active} + (1 - D_{\max}) \times P_{Sleep} \quad (10)$$

$$\Delta_2 = D_{\min} \times P_{Active} + (1 - D_{\min}) \times P_{Sleep} \quad (11)$$

$$\gamma_1 = \eta \times (1 - D_{\max}) \times P(i)_{Harevested} - \eta \times D_{\max} \times (P(i)_{Slot} - P(i)_{Harvested}) \quad (12)$$

$$\gamma_2 = \eta \times (1 - D_{\min}) \times P(i)_{Harevested} - \eta \times D_{\min} \times (P(i)_{Slot} - P(i)_{Harvested}) \quad (13)$$

In Equations (9),(12) & (13) first part represents Harvested Energy stored during the sleep period,but in Equations (12),and (13), the second part denotes the extra energy taken from the

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), the second part denotes the extra harvested energy stored during active mode when harvested energy is greater than consumed Energy.

3.5. Adaptive Duty cycle based on Actual Harvested Energy

In this Phase or algorithm, the Duty cycle is assigned based on Actual Harvested energy,if $P(i)_{Actual} > P(i)_{Slot}$ and also if $P(i)Actual > P(i)Harvested$ then $D_{\max}$ will be assigned from the current slot to the further slots, until enough energy is left. If the former condition isn't satisfied then $D_{\min}$ will be assigned from the current slots to the further slots, until enough energy is left.

4. Simulation and Results

The simulation was carried out in a Python environment to maximize the Average Duty cycle of the Sensor Node with theHelp of predicted Harvested energy and available Residual Battery for mission applications. For simulation, we assume a 100 mW solar panel, a value of 75% and 60% for $D_{\max}$ and $D_{\min}$, a battery with a capacity of 600mAh,and a Threshold value of 360mAh for Battery. The sensor node consumes 100 mW in the active state and 3 mW in the sleep state and sends packets every second.

4.1. Result Analysis

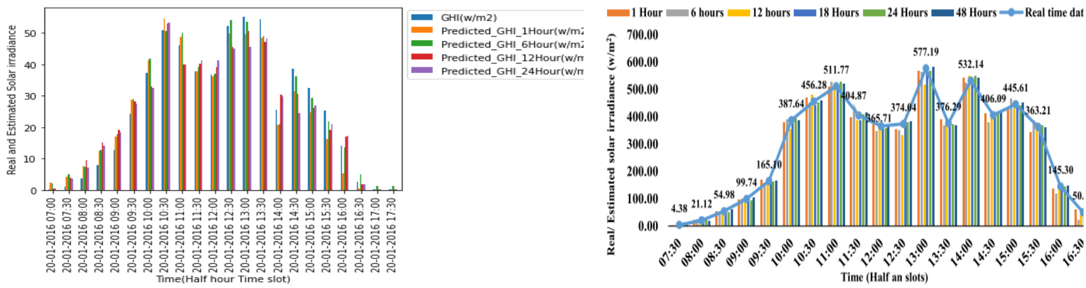
To check the effectiveness of the proposed model, we compared the previous model's duty cycle[15][25][15] and found that among them Amandeep et al.[15]Achieved the highest value of duty cycles(66.29%) so far. So proposed work compared the proposed model with Amandeep's work in terms of Predicted Energy, average Duty cycle, and Residual energy, and presented in Table 2

Table 2.The performance comparison with Amandeep et al.[15]

Prediction Horizon	RMSE	RMSE[15]	Accuracy	Accuracy[15]	D_{Avg}	D_{Avg}[15]	B_{last} (mAh)	B_{last}[15] (mAh)
1Hour	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	76.38	78.18	71.14	67.40	368.80	293
24 Hour	4.47	7.09	69.48	89.09	71.14	64.70	366.45	294

4.2. Result Analysis of Solar Prediction

As shown in Table 2, the proposed model performs better in terms of RMSE and Accuracy over a 1 to 12-hour prediction horizon, but Accuracy deteriorates after that. Figure 2depicts the proposed work's and previous work's prediction results. The proposed forecast is based on a 100mW solar panel with an average harvesting power of 62.04 mW in January, and the labels "Predicted_GHI_1Hour" to "Predicted_GHI_24Hour" reflect prediction results for 1 to 24-hour Forecasting. The proposed work prediction was from 7:00 a.m. to 5:30 p.m., whereas the previous one was from 7:30 a.m. to 4:30 p.m., so the forecasting horizon increased by 1:30 hour in our situation.

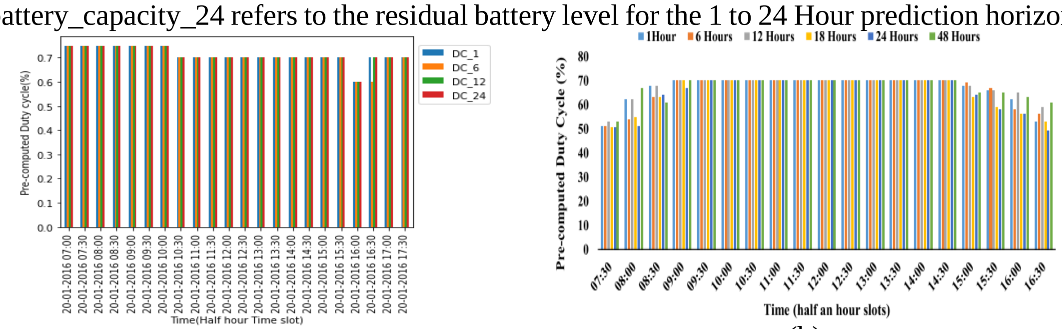


(a) (b)

Figure 2. Predicted solar Energy for different horizons (a) Proposed work (b)Aamandeep's work

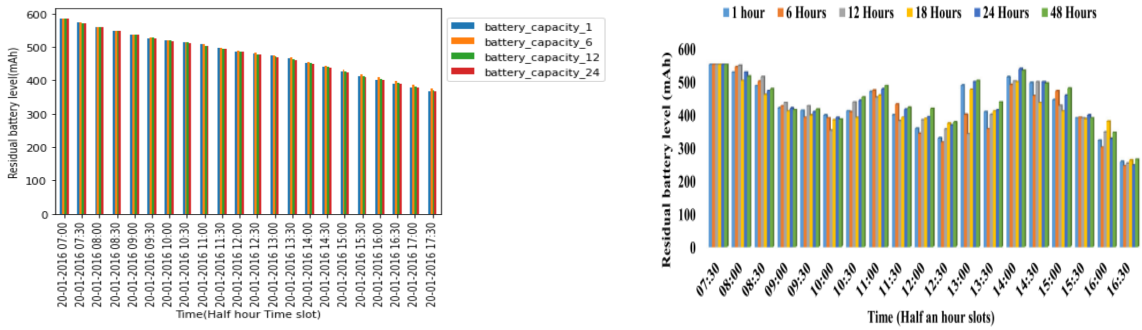
4.3. Result analysis of sensor nodeduty cycle and residual battery energy

The duty cycle was determined by the amount of energy collected as well as the available Residual Battery Energy. First, we attempted to assign a maximum duty cycle using Harvested Energy, and in the absence of solar energy, we used Residual Energy to keep the duty cycle between 75% and 60%, respectively. Average duty cycles of 71.136%, 70.68%, 71.14%, and 71.14% were determined and displayed in Table 2 for 1,6,12, and 24 ahead predictions, and as shown in Figure 3 results were better than Amandeep's 66.85%,66.22%,67.40%, and 64.70% for the same prediction horizon, and also maintain the values between the predefined maximum and minimum values. It was also observed from Figure 4 that average residual energy of 366.25mAh, 375.54mAh, 368.80mAh, and 366.45mAh remained in the battery for all prediction horizons and were better than the previous works value 293mAh, 292mAh, 293mAh and 294mAh,and thesewere also above the predefine 60% Thresholdvalue.In Figure 3, DC_1 to DC_24 refers Duty cycle, and in Figure 4 battery_capacity_1 to battery_capacity_24 refers to the residual battery level for the 1 to 24 Hour prediction horizon.



(a) (b)

Figure 3. Predicted Duty cycle comparisons for 20/01/16 (a) proposed work (b) Aamandeep's work



(a) (b)

Figure 4. Residual Battery level comparison for 20/01/16 (a) proposed work (b) Aamandeep's work

5. Conclusion

The proposed work increased the average Duty cycle by 6% and the Residual battery level by 20% as compared to previous works. To achieve this, solar Energy was predicted for different prediction horizons using the Holt winter method with a damped additive trend and additive seasonality, after this Duty cycle of the next slots was pre-estimated and maximized using Predicted harvested energy and Residual Battery. This approach improves the lifetime and Throughput of mission-critical applications by optimizing the minimum, maximum, and average duty cycle. The Adaptive Duty Cycle Approach re-adjusts these pre-estimated Duty cycles depending on Actual Solar measurements in each slot. 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.

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