<u>RCC INSTITUTE OF INFORMATION TECHNOLOGY</u>

DEPARTMENT OF INFORMATION TECHNOLOGY

Presents

<u>ENERGY PREDICTION USING USING PRO-ENERGY-Q MODEL</u>

Under the supervision of

Prof. Moumita Deb

by

ZAHIRAH AHMAD (IT2014/076)
ZEESHAN HUSSAIN (IT2014/072)
SUDIPTA KUMARI (IT2014/065)

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Place: RCCIIT, Kolkata

Date:

……………………………

ZAHIRAH AHMAD

……………………………

ZEESHAN HUSSAIN

……………………………

SUDIPTA KUMARI

Department of Information Technology

RCCIIT, Beliaghata,

Kolkata – 700 015,

West Bengal, India

APPROVAL

This is to certify that the project report entitled "***ENERGY PREDICTION USING PRO-ENERGY-Q MODEL***" prepared under my supervision by ZAHIRAH AHMAD (11700214086), SUDIPTA KUMARI(11700214075), ZEESHAN HUSSAIN(11700214087) be accepted in partial fulfillment for the degree of Bachelor of Technology in Information Technology.

It is to be understood that by this approval, the undersigned does not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn thereof, but approves the report only for the purpose for which it has been submitted.

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MR. DIPANKAR MAJUMDAR, MOUMITA DEB,

HOD OF IT DEPT ASSISTANT PROFESSOR OF IT DEPT

ABSTRACT

It is believed that an accurate estimation of future energy level should be integrated in the design of MAC protocols. With accurate energy prediction, nodes can save some parts of current energy for future use. This avoids facing temporary energy shortages when the energy falls below a critical level necessary to transmit important information. Therefore, careful prediction of future energy levels at specific time durations opens a new perspective.

In this approach, a new solar energy prediction algorithm which considers the current weather conditions to accurately predict the available energy is proposed. The Q-learning method is employed to determine the accuracy of current weather conditions [9]. We therefore call the algorithm `Pro – Energy approach with Q-learning based on solar energy prediction' (Pro-Energy Q).In order to demonstrate the performance of QL-SEP, we evaluated it using real measurements obtained from National Renewable Energy Laboratory (NREL) in 2017 [10]. The performance results show that Pro-Energy Q makes more accurate prediction than other state-of- art approaches.

CONTENTS

INTRODUCTION

An accurate and reliable energy prediction scheme combined with an automated energy data collection system can help building managers identify maintenance problems and determine the best energy control strategies. An automated energy prediction system can be built on top of a mathematical prediction model consisting of several parameters. The model parameters are estimated using existing data that typically include energy demand or consumption and temperature measurements recorded in the past. A variety of prediction models have been proposed in the literature that include time-series models, Fourier series models, regression models, Artificial Neural Network (ANN) models, and Fuzzy logic models[5].

Each model type has its own features, advantages and disadvantages, and in addition, its performance varies from one application to another. With the exception of a few ANN models, most of the surveyed literature focus on static prediction, a prediction scheme that involves single prediction model that does not evolve over **va**rying weather conditions. The majority of the proposed prediction algorithms have attempted to predict solar energy because of its advantages over other forms of environmental energy [8]. Solar energy is the most effective energy source for EH-WSNs because it has the highest power intensity. Another key distinction of solar energy is that it has a periodic cycle which makes its prediction possible, subject to prediction errors. Fig. 1 presents an example architecture of an EH sensor node with the sun as the energy source, a solar panel to produce energy from the sun, and a super-capacitor to store the harvested energy.

A popular way of predicting solar energy is to exploit the historical summary of an energy harvesting profile. Energy generation patterns from past days are observed to predict the current energy generation rate. Not only the past days' energy generation pattern but also the current weather condition are vital to minimizing prediction errors in particular in frequently changing weather conditions. The Q-learning method is employed to determine the accuracy of current weather conditions [9]. We therefore call the algorithm `Pro- Energy with Q-learning based solar energy prediction' Pro-Energy Q.

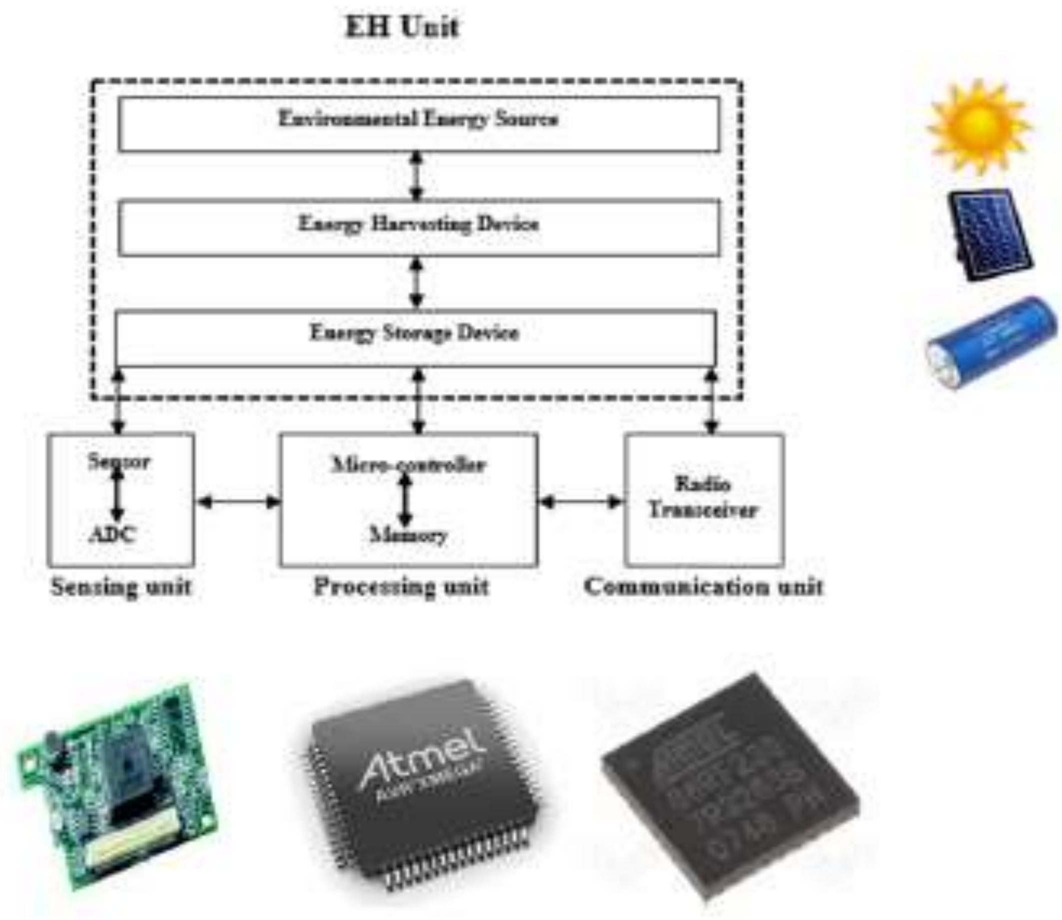


Fig 1:Structure of an EH Node harvesting solar energy

LITERATURE SURVEY

Traditional wireless sensor networks (WSNs) face the problem of a limited-energy source, typically batteries, resulting in the need for careful and effective utilization of the energy source. However, inevitable energy depletion will eventually disturb the operation of a WSN. Energy harvesting (EH) technology is acquiring particular interest, because it has the potential to provide a continuous energy supply in battery-powered WSNs. Therefore, the prediction of future energy availability is a critical issue, as the amount of the harvestable energy may vary over time.

In a WSN's domain, accurate prediction of short-term energy, from a few minutes to a few hours, is particularly important for avoiding short-term energy shortages as sensor nodes are required to operate whenever an environmental feature is sensed. Therefore, current prediction algorithms for EH-WSNs focus mainly on the estimation of the near future energy availability with as small a prediction error as possible. Solar energy, because of the rotation of the earth, has a diurnal cycle in which consecutive days are likely to exhibit similar weather conditions. Existing approaches exploit the diurnal cycle of solar energy by dividing a complete day into equal-length time slots as depicted in Fig. 2. The prediction of energy for each slot is derived at the onset of the associated slot. The length of a time slot depends on the application requirements and resources. It is typically set to one hour, so that each day is composed of 24 slots of one-hour duration. The purpose of splitting a day into slots is to observe the energy generation profile of past days in each slot and to record it in order to predict the current energy level accurately.

RELATED WORK

Energy prediction models usually rely on available datasets, patterns, and samples to increase the prediction accuracy and a number of parameters are involved with which the prediction error rate can be controlled. This section describes the fundamental concepts behind the WCMA,EWMA, Pro-Energy, and Pro-Energy Q prediction models. The WCMA and Pro-Energy models are considered as landmark solutions which have been shown in the literature to outperform previous proposals and we thus use them as reference solutions against which we compare our recently proposed ASIM scheme and the Pro-Energy Q scheme which is first presented in this documentation.

<u>EWMA</u>: The Exponentially Weighted Moving-Average (EWMA) algorithm is a widely used solar energy prediction scheme proposed by Kansal et al. in [12], which is based on an exponentially weighted moving-average filter [13]. EWMA relies on the assumption that the energy available at a given time of the day is similar to the energy generation observed at the same time on the previous days. The amount of energy available during the past days is maintained as a weighted average, in which the contribution of older data is exponentially decaying.Therefore, EWMA considers the historical information of an energy generation profile combining the energy estimated and the energy harvested as presented in Equation 1.

$$E(d, n) = \alpha E(d-1, n) + (1-\alpha) H(d-1, n) \quad \text{……………………(1)}$$

Where d represents the current day and n is the slot number. EWMA sums the last amount of harvested energy (H) and estimated energy (E) with a weighting factor, $0 < a < 1$, arranging the importance of the R and E. The main drawback of EWMA is its vulnerability in frequently changing weather conditions. In particular, EWMA produces signi_cant prediction errors when there is a mix of sunny and cloudy days.

WCMA:In order to address this problem, a new estimation method, the Weather-Conditioned Moving Average (WCMA), has been proposed by Piorno el at. in [9]. The WCMA prediction algorithm avoids this effect by taking into account, when computing the prediction for a given timeslot, the average energy availability experienced in that slot in the previous days. Such average value is then scaled according to a weighting factor indicating how the weather conditions of the current day changed with respect to the previous days. In case of frequently changing weather conditions, WCMA is shown to obtain average prediction errors almost 20% smaller than EWMA. The average of a number of energy values also contributes to the prediction equation. The prediction equation for a particular slot is therefore related to the energy in the previous slot, and the mean value of the corresponding slot for a number of days and current solar conditions is given in Equation 2

$$E(d, n) = \alpha H + (1 - \alpha) M(d, n) \mathrm{GAP}(d, n, K) \quad \text{………………….(2)}$$

Each element in the P vector is actually inversely proportional to the distance from the current value $p_{\mathbf{k}}$. Therefore, GAP value is finally calculated as:

$$\mathrm{GAP} = \frac{V \cdot P}{\sum P}. \quad \text{……………………(3)}$$

PRO-ENERGY: Pro-Energy also exploits past days' energy harvesting profile in order to forecast future energy intake. Pro-Energy considers the amount of energy harvested in the previous slot as in WCMA. Similarly, a matrix, E(i, j), maintaining the energy harvested in the past of D days is derived. The distinctive feature of Pro-Energy is that the most similar day to the current day in terms of energy generation is obtained from the E matrix. Therefore, a combination of energy observed in the previous slot and the energy from the most similar day contribute to predicting the current energy as presented in Equation 4

Where H represents the amount of the energy harvested in the previous slot and E_{MS} is the energy observed in slot n in the most similar day. In order to determine the similarity level of D previous days to the current day, the mean absolute error (MAE) in each stored day for K previous slots up to current slot is computed. The day with the lowest MAE is selected as the most similar day. Pro-Energy keeps track of a pool of D typical previous profiles, each of which represents a different solar condition. The stored profile is dynamically updated for the adaptation of predictions against changing seasonal patterns.A weighted profile (WP) is then computed toreplace the E_{MS}in Equation 8

$$WP = \frac{\sum_{j=0}^{P} w_j \cdot E_{sj}}{P-1}$$

$$w_j = 1 - \frac{MAE\left(E_{sj}, C\right)}{\sum_{j=1}^{P} MAE\left(E_{sj}, C\right)}$$

Therefore, the final energy prediction equation with the multiple profile is:

$$\hat{\mathrm{E}}(d, n) = \alpha \mathrm{H} + (1-\alpha)\mathrm{WP}.$$

PROBLEM ANALYSIS

The principle aim of this work is to review recently proposed harvested energy prediction schemes and provide a comparative study against landmark solutions which appear in the literature in order to investigate the relative advantages of each policy. To this end, the most prominent existing prediction policies are considered, enhancements are proposed, and the resulting prediction schemes are compared in a number of scenarios to identify which policies perform better.

In particular, we propose enhancements to the Pro-Energy model, the so-called Profile-Energy using Q-Learning (IPro-Energy Q). We then compare its performance with the Pro-Energy and WCMA model as both short and long term predictors .The latter is a good measure of the implementation complexity of the algorithm whereas the achieved throughput is a good measure of the effectiveness of the prediction policy when integrated in an actual sensor network.

Our contributions can be summarized as follows.

(1)We propose enhancements to Pro-Energy model to which we refer as Pro-Energy Q model.

(2) We have merged the concept of Pro-Energy and Q-Leaning in order to increase the reliability factor of the prediction model.

(3) We are calculating the error rate at each stage between the current energy and the previous rate and then assigning a reward(using Q-Learning)if the error rate is low.

(4) We perform simulations to evaluate the performance of the three considered models using the prediction accuracy, the execution time, and the throughput as the performance metrics.

PROPOSED MODEL

In this section, we outline the main features of the Pro-Energy model indicating proposed enhancements which lead to the Pro-Energy Q model. Pro-Energy is also a statistical energy prediction model, designed to predict the energy over short and medium term horizons. It considers the dataset of previously recorded days as an input for the prediction of the future energy intake. It divides a particular day into N equally sized timeslots. N is usually chosen to be 24. At each particular interval, it predicts the energy to be available in the next timeslot. In this model, a vector is used to store the predicted energy during the current day.This vector stores the 24 values corresponding to the equally sized timeslots[3].

In this documentation, a Pro-Energy Q model is proposed which is also a statistical energy prediction model and an enhancement of the Pro-Energy model. It is an enhanced version of Pro-Energy that is proposed to improve the prediction accuracy by changing the implementation technique instead of revising the basic components and modules of the Pro-Energy scheme. It uses the previously observed harvested energy for the prediction over short and medium term horizons. It has two main distinguishing features.

- First, it does not classify typical days with respect to their characteristics.More specifically, unlike Pro-Energy, it does not store a day's data based on the fact that it is pure sunny, cloudy, rainy, or mixed. This design choice is based on a series of trace driven experiments which show that this is one of the main limitations of Pro-Energy resulting in prediction errors. To compensate for weather variations, Pro-Energy Q uses the weighted profile (WP) technique, also used in [2] through the Q-learning approach.

- Secondly, it minimizes the control overhead in terms of both storage and execution time. This is achieved by minimizing the size of the stored Energy profiles to a particular profile that is most similar to the current day trend. In the implementation and design of Pro-Energy, it considers and combines just the two most similar previously recorded days (i.e., $P = 2$). Combining more number of days can make an impact by increasing the prediction error.
- Thirdly, a new solar energy prediction algorithm which considers the current weather conditions to accurately predict the available energy is proposed. The Q-learning method is employed to determine the accuracy of current weather conditions [9]. We therefore call the algorithm `Pro-Enery model with Q-learning based solar energy prediction' Pro-Energy Q

In order to demonstrate the performance of Pro-Energy Q, we panel in 2017 [10]. The performance results show the enhancements compared to the other Pro-Energy Q makes more accurate prediction than other state-of- approaches. The performance outputs

are presented in the later Section .

PRO-ENERGY Q MODEL DESIGN

In this section, a new solar energy prediction approach is introduced for EH-WSNs which exploits the historical information of past-days' energy generation and the most recent weather conditions in the present day. The pro-posed approach, a solar energy prediction algorithm with Pro-Energy Q, relies on the assumption that solar energy exhibits a cycle as a periodic energy source in which the time domain is split into equal-length slots repeated daily[4].

This motivates the performance of energy predictions at the onset of each slot. It is believed that EWMA is an efficient way of observing long-term seasonal conditions with no mechanism for adapting to relatively short-term (hourly or daily) variations Pro-Energy Q takes advantage of the properties of EWMA in that a feature acquiring the status of the current solar condition is employed. To do this, Pro-Energy Q updates Equation 1 with a new parameter, called the daily ratio (DR), as presented in Equation

$$\text{Pro-Energy Q} = \text{Pro-Energy}(1+Q)$$

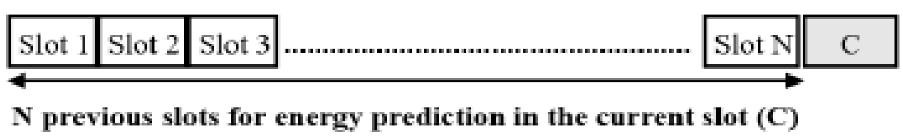


Fig 2

THE Q-LEARNING APPROACH

When forecasting energy in a particular slot, the prediction accuracy in the previous slots is important information. The question of how accurate a prediction is in a previous slot ideally gives us a direction not to only consider the equal contribution of previous slots (the increase/decrease ratio) in relation to the prediction of the current slot. Therefore, each slot in maintains a level of prediction accuracy which represents the reliability of prediction in the slot.

This leads to combining the increase/decrease ratios and the reliability of prediction in order to significantly endow the predictions with high reliability. This is achieved by Equation 5

$$\mathrm{DR} = \frac{\sum_{i=1}^{N} P_e(i) \cdot R(i)}{N} \qquad \ldots\ldots\ldots\ldots\ldots\ldots(5)$$

Where P_e indicates the prediction error and R is the reliability level.

In order to give greater importance to the closer time slots as the most recent slots would carry the most recent information, this multiplication, similar to WCMA, is weighted by the increasing index (i).

Eventually, the daily ratio, DR, is computed as:

$$\mathrm{DR} = \frac{\sum_{i=1}^{N} P_e(i) \cdot R(i) \cdot i}{\sum i} \qquad \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Here R is the reward factor and a robust level of R is maintained in this approach. We assign either a value of 1 or 0 to this Reward variable. The value 1 is assigned whenever the Prediction

Error i.e., Pe(i) is less than or equal to 0.5.If Pe(i) is greater than 0.5 we assign to it.In this approach we have renamed this DR as Q indicating it as the Q-value for the Pro-Energy Q model. Pro-Energy Q employs a Q-learning approach in which each slot is initiated with a Q-value independently to denote the reliability level of this slot. We introduced a new dynamic modification of the learning rate value. The main motivation behind this modification was to reduce the Q-value more aggressively when the PER is high. In this strategy, the modified learning rate is obtained by multiplying the initial learning rate by the PER, if r has taken the negative value. For example, let it be 0.1 and the PER be 0.5: the modified learning rate will be 0.05 (0.1-0.05)[1]. Another example with a of 1 results in a modified learning rate of 0.1. Therefore, increasing the PER will produce more rapid reduction of the Q-value. The PER for a single slot is calculated as:

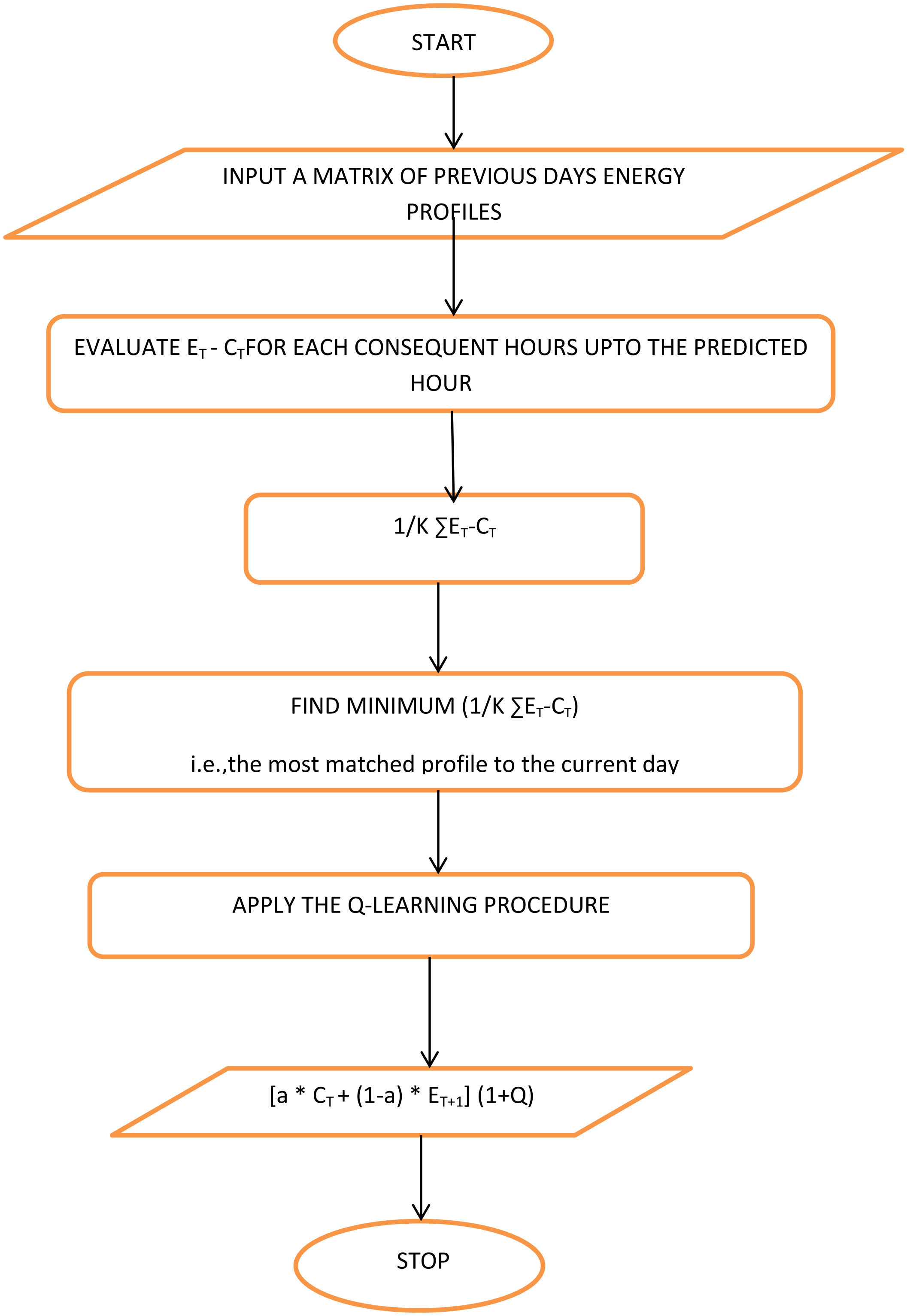
$$\mathrm{PER} = \left|\frac{H-P}{P}\right| \quad \text{…………………..(7)}$$

Where H is the actual harvested energy in the slot and P is the predicted energy value from Pro-Energy Q. Finally, the DR can be calculated as:

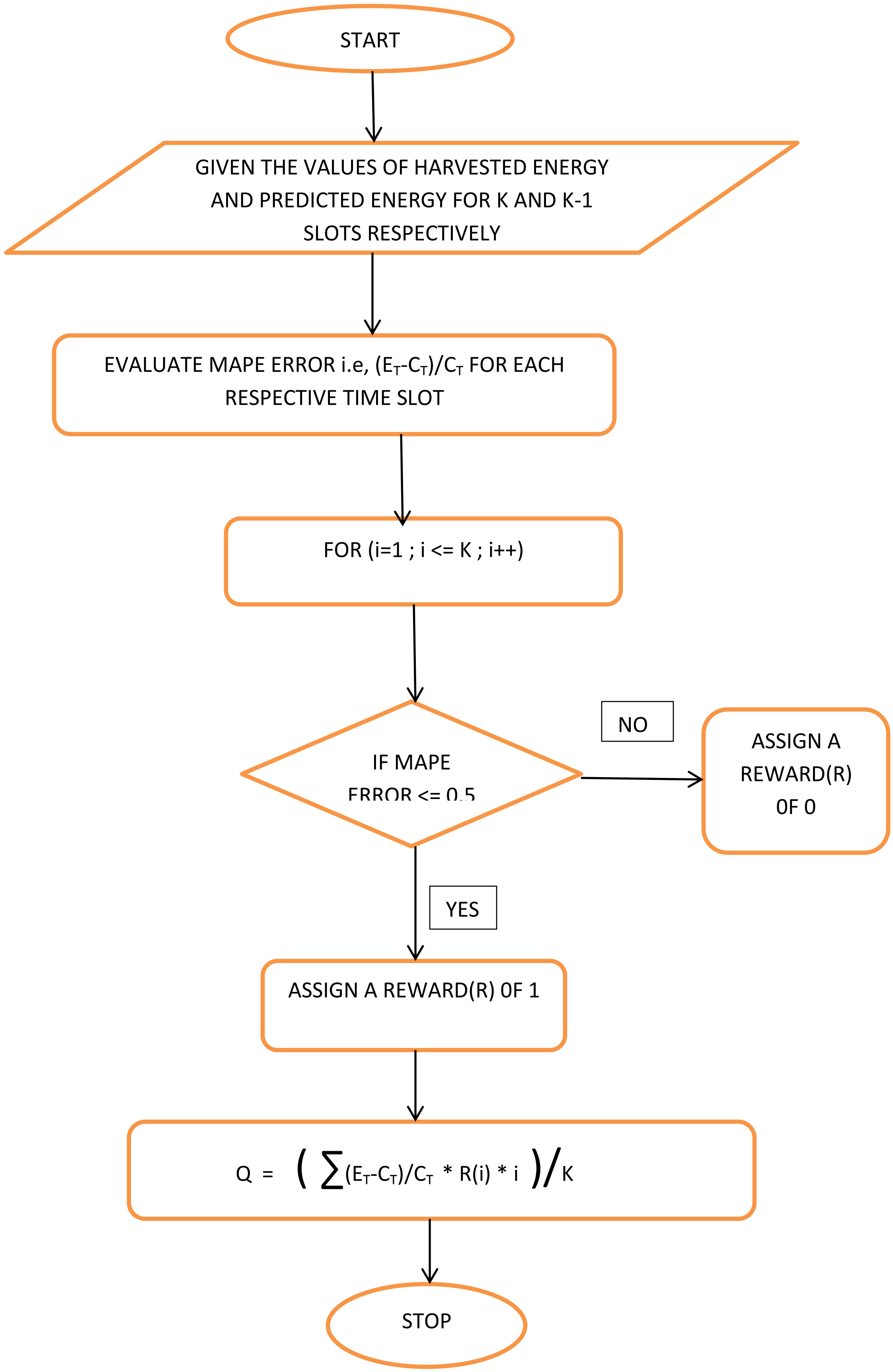
$$\mathrm{DR} = \frac{\sum_{i=1}^{N}\left(\frac{H-P}{P}\right)\cdot Q(i)\cdot i}{\sum i}. \quad \text{…………………….(8)}$$

In this approach we have renamed this DR as Q indicating it as the Q-value for the Pro-Energy Q model.

FLOWCHART REPRESENTATION



In order to understand the Q-Learning process better here we present the basic design of the Q-learning implementation


START
GIVEN THE VALUES OF HARVESTED ENERGY AND PREDICTED ENERGY FOR K AND K-1 SLOTS RESPECTIVELY
EVALUATE MAPE ERROR i.e, $(E_T-C_T)/C_T$ FOR EACH RESPECTIVE TIME SLOT
FOR (i=1 ; i <= K ; i++)
IF MAPE ERROR <= 0.5
NO
ASSIGN A REWARD(R) 0F 0
YES
ASSIGN A REWARD(R) 0F 1
$Q = \left(\sum (E_T-C_T)/C_T * R(i) * i \right)/K$
STOP

In the flowcharts defined above, these are the following notations:

E_T: THE HARVESTED ENERGY (OR THE STORED ENERGY PROFILE)

C_T: THE CURRENT DAY ENERGY PROFILE

K: THE TOTAL NO OF SLOTS THE WHOLE DAY IS DIVIDED INTO

α: THE LEARNING FACTOR

Q: THE Q- LEARNING VALUE OBTAINED

R: THE REWARD FACTOR THAT IS EITHER 1 OR

CODING

```
function p = pro(n)          % function definition in matlab %



% Creating an array to store all the previous day Energy Profiles i.e the Harvested Energy %

arr = [47.0593 41.7533 34.3555 29.9865 27.5987 28.3685 23.0988 22.0873 19.5520
18.2315 19.0787 18.9820 20.8480 23.8643 27.1207;
36.3438 35.2670 27.8192 27.9255 25.2737 23.0403 20.5002 17.1440 16.1975 15.1798 15.4510
16.0703 18.1398 21.0097 24.5013;
20.6983 20.0348 17.9523 14.9673 11.9083 9.7980 9.2447 8.3682 7.7249 7.5815 8.3183 8.6850
10.0757 12.9845 13.8268;
23.0130 21.6870 18.9720 15.2345 16.8532 13.2052 9.8205 8.7831 21.2290 15.8138 18.0677
21.4725 25.2750 30.5960 37.8968;
58.7083 58.2947 57.1245 55.7847 53.1267 48.5495 45.4565 43.8613 41.6892 40.0263 39.5872
41.0005 44.2713 48.4243 50.9260;
61.4122 59.4338 50.8180 46.0187 42.2093 37.9850 35.0912 31.1672 27.0485 25.7635 25.8483
24.4435 26.3178 29.9700 27.8278;
41.1218 41.6702 39.3537 33.8938 29.0292 24.0858 21.3672 19.7328 17.0572 15.6953 17.2447
19.0225 18.8332 20.9708 24.9082;
```

40.3908 41.2292 37.1808 33.6977 32.9737 29.5542 31.5553 26.5598 23.9195 22.9692 21.5752 20.3367 21.7898 27.8793 30.4770;

27.9485 26.8412 24.0822 21.9355 19.3068 17.0473 17.3795 19.0572 21.6077 21.6338 24.6580 23.3245 24.3458 26.1030 28.8110;

32.6840 31.6590 27.1555 24.7233 22.4578 21.6197 19.3910 16.9775 17.6075 26.2592 26.0892 30.5600 33.5045 32.2957 32.4020;

40.2467 39.4380 36.5772 33.5852 29.7757 25.5402 26.9855 25.4082 24.9853 26.8913 34.5695 34.5943 33.4133 36.9673 45.9168;

35.7930 33.9565 31.1547 26.6548 23.3213 22.1550 19.2212 17.3012 16.0665 16.0025 17.3040 19.6132 19.9508 28.1882 32.9738;

26.9102 26.0963 22.9598 18.6517 18.7643 20.9900 17.6678 32.5042 24.8635 22.4888 19.0658 21.4953 27.4037 29.5562 32.8863;

29.3877 28.9217 25.7993 20.7368 17.5960 16.2922 13.9940 15.2807 16.3607 19.4847 22.9673 23.0038 26.1027 28.9747 32.5802;

48.8120 44.8733 39.2230 34.1068 23.7675 17.8822 15.6042 14.5340 13.2240 12.2932 13.4398 15.9973 17.3313 19.4077 21.1507;

97.8417 99.7833 99.2583 93.7600 74.8832 61.3833 60.9550 62.7223 58.8255 55.5977 50.1385 47.3575 50.0927 61.0258 69.4052;

77.7852 66.5435 58.9543 58.0987 53.5447 49.7275 49.3715 44.4737 54.4053 68.3668 49.2762 47.0333 56.3972 62.4783 60.6977;

45.5550 42.6657 34.1518 25.8010 20.5547 19.8632 18.7580 16.9492 14.8770 14.6643 15.2625 15.8628 19.2773 21.3843 23.0163;

```
19.8892 18.8623 17.7088 17.1308 11.5410 7.3668 6.8891 6.3527 6.6997 6.9169 7.5378 8.1167
20.6212 35.8505 39.2817;
61.9505 57.9728 47.6380 45.6617 42.0127 37.1097 33.1285 27.9092 24.8500 23.0985 21.7700
21.9335 23.3340 28.1295 30.5672;]

ai = [];       %function declaration %
for r = 1:n
ai(r) = input('Enter value for n+1 or 100 to stop :');
if ai(r) == 100    % user input to find the Current day Energy trend upto the predicted hour %

break
else
ai(end+1) = ai(r)
end
end
s=0;
loc = 0;

arrn = [];
for v = 1:15
for u = 1:n
```

```
s = s+abs(arr(v,u)-ai(u))          % finding the difference between the current day and the
end;                               stored profile trend %

arrn(v) = s/n
   s=0
end;

arrn = arrn.'
[M,I] = min(arrn)                  % selecting the most matched energy profile to the
                               current day's trend %
loc = I

profile = [];
profile = arr(loc, : )

%Applying the Q-Learning approach %
s1 = 0;
di = [];
for t = 1:n
di(t) = (profile(t) - ai(t))/ai(t)
if di(t) <= 0.5
      s1 = s1 + (di(t))
```

```
end


end


Q = s1/n


a = 0.87;

for y =1:n

   f = ai(n) * a + (1-a) * profile(n)            % the Pro-Energy Q formula %

end


p = f*(1+Q)                                      % the final Pro-Energy Q formula %
```

COMPARATIVE GRAPH STUDY

A comparative graph is drawn in order to evaluate the performance of three different models using MATLAB.

The three different prediction models are ;

1. The proposed Pro – Energy Q model
2. The Pro – Energy Q
3. The WCMA model

% the data obtained from Pro-Energy Q model %

x = [12, 11 ,10 , 9 , 8 , 7, 6, 5, 4, 3, 2, 1];

y = [25.1660 , 24.5880 , 23.3050 , 21.6832 , 19.9880 , 18.2400 , 14.9042 , 13.2162 , 14.6838 , 14.5013 , 15.4082 , 17.7688];

plot(x,y,'b-');

% the data obtained from Pro-Energy model %

z = [27.0121 , 26.5769 , 25.5031 , 25.7469 , 20.9987 , 21.3270 , 17.0412 , 15.3121 , 16.2431 , 16.5410 , 18.0132 , 19.6709];

plot(x,z,'r--');

```
% the data obtained from WCMA model %

w = [ 28.5342 , 28.3471 , 28.3019 , 26.9497 , 23.5769 , 22.4869 , 19.3214 , 16.8432 , 18.7466 ,
19.0148 , 19.9987 , 21.5472];

h=plot(x,y,':b*',x,z,':rO',x, w,'g--*');


set([h],'LineWidth',2)                     % changing the plotline width %


xlabel('Time(hrs)');              % labelling the x-axis %

ylabel('Energy');                 % labelling the y-axis %
```

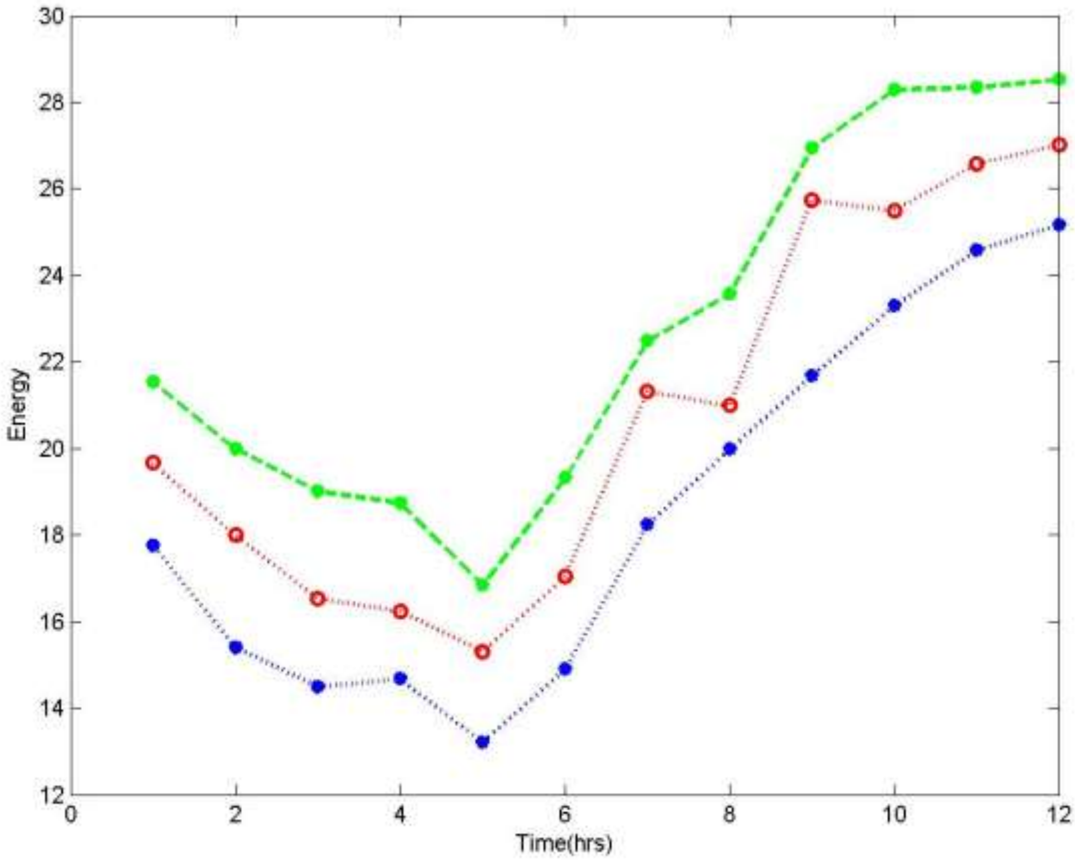
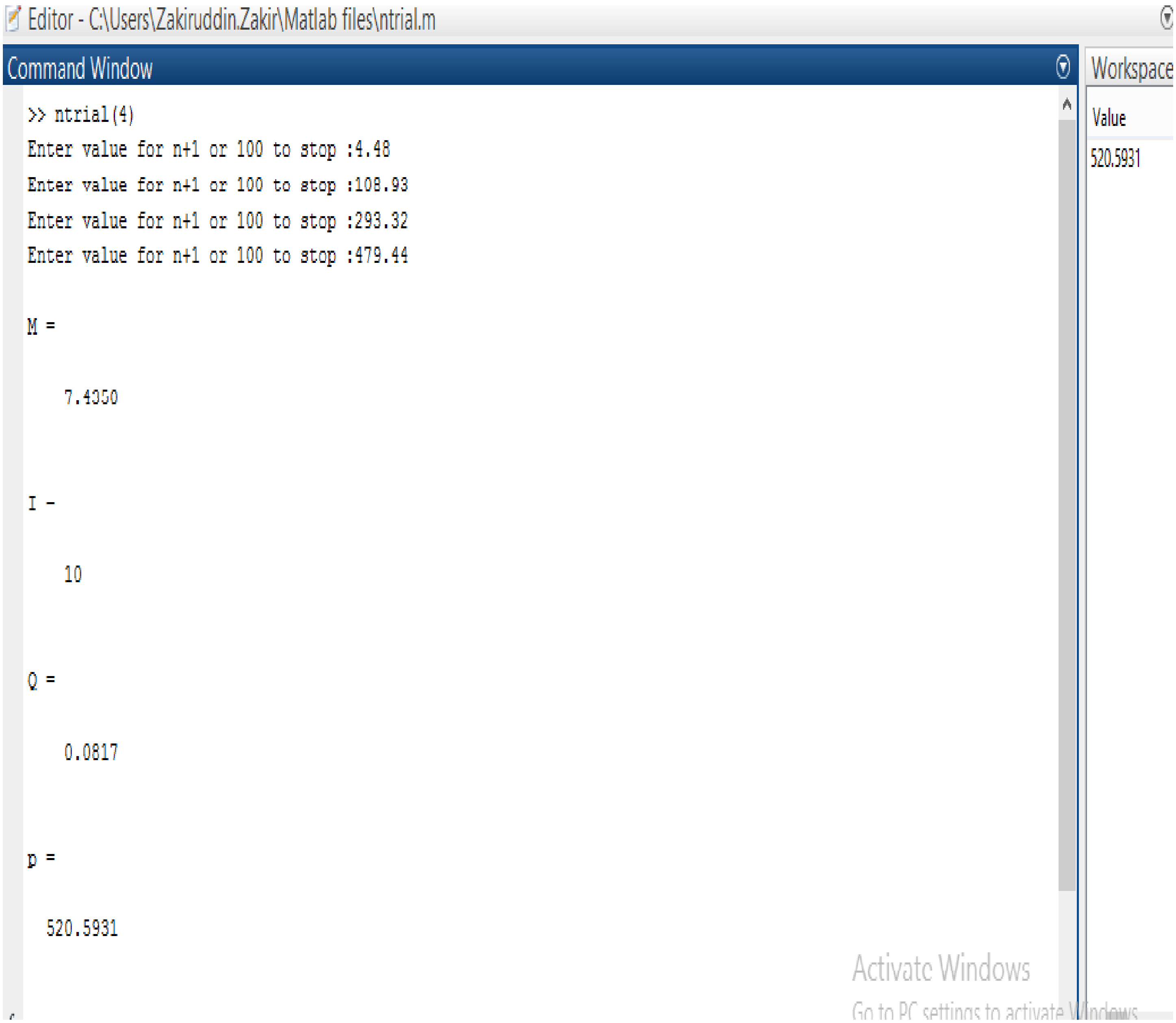


Fig 3: A plotline graph for performance evaluation of the models using MATLAB

OUTPUT SCREEN



PROPOSED ENHANCEMENTS

We propose the Pro-Energy Q scheme and compare its performance against Pro-Energy, which we have recently proposed and two landmark solutions, namely, EWMA and WCMA.Our results indicate that the proposed Pro-Energy Q scheme outperforms the other candidate models in terms of the prediction accuracy achieved by up to 78% for short term predictions and 50% for medium term prediction horizons. For long term predictions, its prediction accuracy is comparable to the Pro-Energy model but outperforms the other models by up to 64%.

However there is a scope of improvement in every prediction model and our model is no different. Further we could see the proposed enhancements in our proposed model they can be summoned as follows:

1.Robustness : The Q-value of an action is usually set at 0 as a default. The results tell us that it takes longer to converge to C1 whereas the Q-value reduces to 0 more quickly. This property, the rapid decline of the Q-value, enables a fast response to long-term change. However, this issue may degrade the level of robustness against infrequent changes. Hence more robust profile storage can be constructed for better prediction.

2.Size of the stored energy profile and its execution time : The execution time is a parameter associated with the implementation complexity of a model and in this study we use it as an evaluation metric. Simulation experiments are conducted on MATLAB and the average execution time is evaluated by means of the *cputime* and *tic-toc* function. The simulation scenario involves prediction over a single timeslot and the results are thus independent of the prediction horizon. The *tic-toc* function is the recommended function to measure the model performance [37] but *cputime* is taken

into account as well. In Table 2, the measured execution time is presented for each candidate prediction model using both time-measuring functions. The WCMA model reports

smaller execution time compared to the other three models but it varies for different datasets. Therefore by decreasing the size of the stored energy profile the execution time could increase upto 30% of the overall cpu time.

3.Adaptability to frequently changing weather condition : by making this model adjust to varying weather condition could be of great help.It could work well in areas where the climatic conditions keeps varying from day to day.

PERFORMANCE ANALYSIS

The performance of Pro-Energy Q in comparison with that of WCMA and Pro-Energy was evaluated using real-life solar data obtained over a one-year period in order to establish

the ideal performances of the schemes [10]. EWMA was not considered in the performance comparisons as Pro-Energy already outperforms it. It was important to set appropriate experiment settings to allow all schemes to achieve their optimum performance. The total number of time slots in a day was set at 24 so that whole day was represented by 24 time slots each of which corresponded to a one-hour duration. In Pro-Energy, D (the number of previous energy profiles stored), K (the number of previous slots for comparing the stored energy profiles) and P (the number of combined profiles) were set at 10, 7 and 5 respectively, as suggested in the original paper. In N (the number of previous slots up to the current slot) and (the learning rate in Q-learning) were set at 20 and 0.87 respectively.

We have drawn a graph fot the three models and the results show us that high of α in EWMA, Pro-Energy and provide inaccurate predictions, whereas medium and high values of α 0:4 < α < 0:9, in Pro-Energy Q ensure more accurate predictions. In EWMA and Pro-Energy , therefore, the estimated average energy (E) and the harvested energy (H) should contribute closely to achieving accurate predictions.

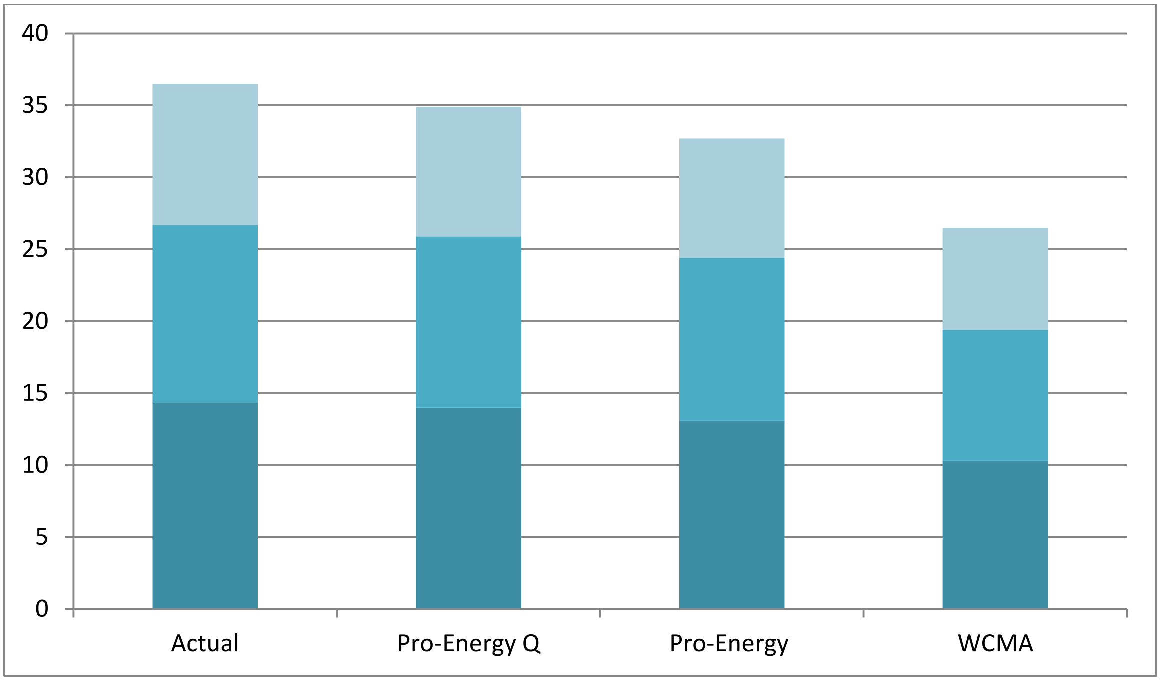


Fig 4: The enrgy prediction accuracy of the three models

In general, Pro-Energy Q had a superior performance because it carefully observes the current solar conditions. Pro-Energy had opposite performance results as it relies on the energy harvested in the previous slot and the energy trends observed in previous days. Small values of α ensure performance enhancements meaning that low values of α mean a low contribution of energy in the previous slot. Increasing α leads to performance degradations as Pro-Energy does not adapt to current weather conditions, with a reduced contribution of the typical previous profiles in such settings. Therefore, one of the main conclusions of this study in terms of highly accurate energy prediction is to reconcile the past energy generation profile with the current energy pattern.

CONCLUSION

The energy harvesting (EH) process has the potential to supplement energy to power sensor nodes and allow them to operate perpetually. However, solar energy has an uncertainty about the availability of future energy which makes the optimum use of solar energy a difficult task in sensor nodes. In order to allocate the optimal energy among the sensor nodes in a WSN, energy-prediction algorithms are designed with the aim of maximizing the performance of EH-WSNs.

This documentation has presented the design and implementation of perform all the current state-of-art algorithms. The proposed scheme carefully checks the current solar conditions to adapt to variations in the present day. The performances of the proposed scheme and of the state-of-art approaches have been tested using real-life traces of the harvested energy obtained from the US National Renewable Energy Laboratory. The performance results validate that our algorithm has better performance in long-term evaluations. The proposed algorithm can be incorporated into the development of the current and future MAC protocols in order to forecast the amount of the energy to be harvested within a particular time slot, thereby improving the performance of WSNs through managing the energy level of the sensor nodes intelligently.

LIST OF FIGURES

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