Solar energy prediction and task scheduling for wireless sensor nodes based on long short term memory

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Abstract. Traditional wireless sensor networks (WSNs) with limited energy capacity suffer from bounded lifetimes, which have become a major restriction on the development of WSNs. As a common renewable energy, solar energy instead of ordinary batteries can solve energy supply problem in wireless sensor nodes by transferring ambient energy to usable electrical power. In the process of solar energy harvesting, energy prediction is an essential precondition to ensure the reasonable task scheduling of wireless sensor nodes. As the uncertainty of solar energy, we present a long short term memory recurrent neural network (LSTM-RNN) solar energy prediction method, to predict solar energy in the next three days based on historical solar energy collection data and environmental data. Based on energy prediction results, the predictive task scheduling strategy is put forward to improve the performance of wireless sensor nodes. Experimental results show that the proposed LSTM-RNN solar energy prediction method has higher precision and better convergence than other conventional methods. The predictive strategy significantly increases the task completion rate of the wireless sensor node by using the prediction energy information while maintaining an approximate survival time.

1. Introduction
In recent years, wireless sensor networks (WSNs) have been deployed in a wide range of measurement applications [1], such as environmental monitoring, human health detection, and public safety. However, the traditional battery-powered wireless sensor nodes with limited energy capacity suffer from bounded lifetimes, which have become a major restriction on the development of WSNs [2]. Energy harvesting technologies can use energy from the ambient sources (such as solar power, wind, and mechanical vibration) to power WSNs nodes and devices [3]. As a result, environmentally wireless sensor networks can be self-powered, and significantly increase their typical lifetimes.

However, energy harvested from the ambient environment is not always available or reliable [4]. Energy supply stability of energy harvesting wireless sensor nodes is affected by both natural and artificial factors, which have the characteristics of uncertainty [5]. For example, solar energy changes over the diurnal cycle, and significantly influenced by weather conditions and seasonal patterns. Energy harvesting prediction allows to estimate energy intake in the near future, so that the wireless sensor node can adjust its task schedule to balance energy consumption [6].

The energy prediction problem of solar wireless sensor nodes was first proposed by Aman Kansal of the University of California, Los Angeles in 2007. He used the exponentially weighted moving-average (EWMA) method to predict energy changes in solar wireless sensor nodes [7]. The disadvantage of the EWMA method is that the predict performance is significantly reduced when weather conditions change frequently. In 2016, Qiang Liu of Imperial College put forward a
knowledge-based neural network (KBNN) solar energy harvesting prediction method to solve the energy management problem of solar-powered embedded systems. The advantage of the KBNN method is that it does not require a large number of training samples. However, it has low prediction accuracy and low robustness [8]. In addition, there are many researchers using fuzzy sequence prediction, support vector regression and other methods for energy prediction of solar wireless sensor nodes. However, these methods have a lot of problems such as insufficient prediction period and single applicable environments [9-10].

This paper presents a long short term memory recurrent neural network (LSTM-RNN) solar energy prediction method for solar-powered wireless sensor nodes. According to the predicted energy information, the predictive task scheduling strategy is put forward to improve the performance of wireless sensor nodes. Then we set up a solar-powered wireless sensor nodes experimental platform to measure the solar cell voltage and various environmental signals to establish an experimental database. Next, the LSTM-RNN prediction method is compared with two current commonly used prediction methods. Experimental results demonstrate that the proposed LSTM-RNN solar energy prediction method has higher precision and better convergence than other conventional methods. LSTM-RNN method can use long-term historical data to provide accurate prediction results to improve the lifetime and measurement reliability of wireless sensor nodes. By using the prediction energy information, the predictive task scheduling strategy significantly increases the task completion rate of the node while maintaining the survival time as much as possible. The predictive strategy increases the survival time from 3.7 hours to 6.9 hours under 50 lx, and improves the task completion rate from $1.6 \times 10^{-3}$ Hz to $2.8 \times 10^{-3}$ Hz under 250 lx.

This paper is organized as follows. In Section 2, the long short term memory recurrent neural network solar energy prediction method is presented. In Section 3, a predictive task scheduling strategy is proposed. The experimental results of prediction method evaluation and scheduling strategy evaluation are presented in Section 4. Section 5 is the conclusion.

2. Long short term memory solar energy prediction method

2.1. Solar energy harvesting wireless sensor nodes model

To analyze solar energy harvesting intake characteristic, it is necessary to build a mathematical model for solar cell on wireless sensor node. Considering a wireless sensor node for indoor environment monitoring. The wireless sensor node is powered by a lithium battery, which is charged by solar cells. Solar cell converts the energy into electricity through the photovoltaic effect. Solar energy can be affected by many environmental factors, such as weather, season, shadow, and so on. Furthermore, the Maximum Power Point Tracking problem should be considered to optimize the solar energy harvesting system’s efficiency [11-12]. In this paper, the solar cell and wireless sensor node are placed at fixed indoor positions.

Then we present the solar energy harvesting model. We define the subscript $k$ in this section denotes the measured value of the $k_{th}$ time interval. Timestamp $t_k$ is a label of measurement data at $k_{th}$ time interval. Every time interval is constantly equal to 5 minutes. Solar cell voltage $u_k$ reflects the characteristic of energy intake, and influenced by radiation, temperature, humidity, and so on. $S_k$ is a vector composed of these environmental parameters, where $t_k$, $u_k$, $\text{TEMP}_k$, and $\text{HR}_k$ represent timestamp, solar cell voltage, temperature, and humidity, respectively. The data in $S_k$ are actually measured by the solar wireless sensor nodes experimental platform. Next, feature extraction is performed to obtain the average value $ar{x}$, peak value $x_{\text{max}}$, a valley value $x_{\text{min}}$, and standard deviation $x_{\text{std}}$ of the data. The feature vector $F_k$ consists of these parameters, and constitutes the vector $X_k$ with vector $S_k$. $X_k$ is the input data vector composed by these environmental data, and $Y_k$ is the output data vector of energy prediction results.

This model is proposed to establish a mapping relationship between solar energy prediction results $Y_k$ and input data vector $X_k$. 
2.2. Long short term memory recurrent neural network prediction method

Recurrent neural networks are time-correlated and are suitable for solving energy prediction problems of solar wireless sensor nodes. In addition, long short term memory units can use more historical information to improve the accuracy of prediction results.

2.2.1. Recurrent Neural Networks Prediction Method. Recurrent Neural Networks (RNN) are time-correlated artificial neural networks, and are suitable for processing time series data. The structure of RNN after expansion on time series includes input vector sequence $x_t$ of solar cell parameters, hidden layer vector sequence $h_t$, and output layer vector sequence $y_t$. The hidden layer sequence $h_t$ and the output layer sequence $y_t$ are respectively obtained through the corresponding nonlinear transformation. The formula is as follows.

\[ h_t = g(W_x x_t + H h_{t-1} + b) \]  
\[ y_t = softmax(W_h h_t + b_y) \]  

In the above two formulas, $W, H, b, W_y, b_y$ are parameters obtained through network training and learning. The symbol $g$ represents a nonlinear function. The symbol softmax is a nonlinear multi-classification function, which represents the mapping of $N$-dimensional vector $\beta$ to the $(0, 1)$ interval.

\[ softmax(\beta)_i = \frac{e^{\beta_i}}{\sum_{j=1}^{N} e^{\beta_j}}, i = 1, ..., N \]  

The traditional recurrent neural network prediction method has the problem of gradient disappearance. With the increase number of iterations, the network’s perception of nodes with long time steps will drop. Therefore, RNN prediction method’s ability to use long-term information is reduced, resulting in prediction accuracy decline.

2.2.2. Long Short Term Memory. The long short term memory unit can solve the gradient disappearance problem in the above-mentioned RNN prediction method, and use long-term information to improve the accuracy of prediction result. Long short term memory (LSTM) is based on the traditional RNN, replacing each hidden layer neuron with a memory cell and adding a forgetting mechanism. The status information of the memory unit does not change with time, but is updated by the forgetting mechanism to retain useful information for the prediction results. Compared with traditional RNN, LSTM can store long-term information. The LSTM cell structure is shown in figure 1.

The input parameters of LSTM unit are $x_t$ and $h_{t-1}$, where $x_t$ denotes the current input layer vector and $h_{t-1}$ denotes the hidden layer vector at the previous moment. The solid arrow in the figure indicates the value at the current time $t$, and the dashed arrow indicates the value at time $t - 1$. The memory cell’s writing, forgetting, and outputting operations are determined by three gates: input gate $i$, output gate $o$, forget gate $f$. At the beginning of each time $t$, the unit first calculates the activation function $[i_t, f_t]$ of the input gate and the forget gate, and updates the memory cell from $c_{t-1}$ to $c_t$.  

\[ S_k = \{t_k, u_k, TEMP_k, HR_k\} \]  
\[ F^*_k = \{\bar{x}^*_k, x_{max}^*, x_{min}^*, x_{std}^*\} \]  
\[ F_k = \{f_k^*, r_{TEMP}^*, r_{H}^*\} \]  
\[ X_k = \{S_k, F_k\} \]  
\[ Y_k = \{\hat{t}_k, \hat{u}_k\} \]
Then the unit calculates the output gate activation function $o_t$, and the hidden layer outputs $h_t$. The specific formulas are as follows:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + V_i c_{t-1} + b_i)$$  \hspace{1cm} (9)

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + V_c c_{t-1} + b_f)$$  \hspace{1cm} (10)

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c x_t + U_c h_{t-1} + b_c)$$  \hspace{1cm} (11)

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + V_o c_t + b_o)$$  \hspace{1cm} (12)

$$h_t = o_t \odot \tanh(c_t)$$  \hspace{1cm} (13)

In the above formulas, $\sigma$ represents a sigmoid function, $\odot$ represents vector multiplication, and $\tanh$ represents a hyperbolic tangent function. $W_{i,f,o}, U_{i,f,o},$ and $V_{i,f,o}$ represent the parameter matrixes of input gate, forget gate, and output gate, respectively. The input gate calculates and writes a new state value based on the current input $x_t$ and the previously hidden layer output $h_{t-1}$. The forget gate controls the memory unit to discard part of memory information through the feedback of $f_t \odot c_{t-1}$. The output gate finally calculates the hidden layer output $h_t$ according to the current input $x_t$, the previous hidden layer output $h_{t-1}$, and the current state $c_t$ of the memory unit.

**Figure 1.** Illustration of long short term memory cell.

2.2.3. Long Short Term Memory Prediction Method Implementation. The proposed LSTM prediction method has three parts: data pre-processing, model training, and model prediction. First, resample the collected data (including solar cell voltage $u_k$, temperature $\text{TEMP}_k$ and humidity $\text{HR}_k$) to match the time stamps, and calculate the feature vectors of each type of data. The subscript $k$ in this section denotes the measured value of the $k$th time interval. By training the LSTM recurrent neural network, the error between output $Y_k$ and real value $\{t_k, u_k\}$ is continuously reduced. Eventually the error reaches the acceptance range $\varepsilon$. For any $t_k, u_k = \hat{u}_k + \varepsilon$. Then use the time related properties of the recurrent neural network to predict data in future periods. In addition, the LSTM unit can store long-term information and is suitable for long-term span training.

Figure 2 shows the network structure of the long short term memory prediction method including an input layer, a LSTM layer, a fusion layer, and an output layer. The input layer is the solar cell voltage and the environmental data feature vector, and the output layer is the solar cell voltage prediction results vector. The pseudocode of LSTM prediction method is shown in table 1.
Figure 2. The network structure of LSTM solar energy prediction method.

Table 1. Pseudocode of LSTM Prediction Method.

| LSTM Solar Energy Prediction Method Pseudocode |
|-----------------------------------------------|
| **Step 1: Data pre-processing**               |
| A) Resample the original data of the solar cell to match the time stamp. |
| B) Calculate the feature vectors of each type of data. |
| **Step 2: Predictive model training**        |
| A) Input historical data as training set for the LSTM prediction model. |
| B) Calculate the hidden layer vector $H_k$ by input layer vector $X_k$. |
| C) Calculate the output layer vector $Y_k$ by $softmax$ function and vector $H_k$. |
| D) Adjust the parameter matrixes of the LSTM cell by error back-propagation. |
| E) Repeat the above step, until reach the limit of accuracy or iterations. |
| **Step 3: Model prediction and error analysis** |
| A) Input prediction tags to the trained LSTM prediction model. |
| B) Calculate the prediction results. |
| C) Calculate the error between prediction results and real data. |

3. Predictive task scheduling strategy based on energy prediction

Based on the results of solar energy prediction model, a predictive task scheduling strategy can be established. The wireless sensor node in this paper has two kinds of tasks in this paper: sensing task and communication task. The sensing task includes measuring battery voltage, temperature, and humidity. The communication task is sending wireless data every 5 minutes. There are two indicators for evaluating node performance: survival time and task completion rate. Survival time is the total time when the node is active. Task completion rate is the number of tasks completed in a unit time. However, these two indicators are in conflict with each other in the energy limited situation. Once the node's energy is not enough to support its active state, it will stop all tasks including the energy harvesting process. Our purpose is to maximize the task completion rate while ensuring the survival of the node.

The predictive Strategy takes into account current energy cache and the energy that may be harvested in the future, to schedule the energy use of wireless sensor nodes. In addition, there are two basic task scheduling strategies: conservative strategy and greedy strategy. The definitions of these strategies are as follows:

A) Conservative strategy: the tasks will be performed only if the current energy cache is sufficient.
B) Greed strategy: perform tasks directly regardless of current energy status.
C) Predictive strategy: the tasks will be performed when the current cache energy plus the next period collected energy meets the task’s energy requirement. It means that the battery voltage should not fall below the node’s starting voltage after this task is performed.

The pseudocode of these task scheduling strategies are shown in table 2. $E_{\text{cost}}$ represents the energy consumed by each single task. $E_{\text{collect}}$ denotes the energy that may be collected during future task period. $E_{\text{buffer}}$ is the battery’s current cache energy.

| Table 2. Pseudocode of Task Scheduling Strategy. |
|-----------------------------------------------|
| Conservative Strategy | Greedy Strategy | Predictive Strategy |
| **Step 1:** while (node is alive); | **Step 1:** while (node is alive); | **Step 1:** while (node is alive); |
| **Step 2:** if $E_{\text{buffer}} \geq E_{\text{cost}}$; | **Step 2:** do perform the task; | **Step 2:** if $E_{\text{buffer}} + E_{\text{collect}} \geq E_{\text{cost}}$; |
| **Step 3:** then perform the task; | **Step 3:** then perform the task; | **Step 3:** then perform the task; |
| **Step 4:** else go to step 2; | **Step 4:** else go to step 2; | **Step 4:** else go to step 2; |

4. Experiments

4.1. Experimental platform and conditions

The solar energy harvesting WSNs experimental platform is implemented indoors (close to a panoramic window) on the Crossbow eKo Pro Series wireless sensor node. The reason for performing the experiment indoor is to study the energy harvesting characteristics under different light conditions through an adjustable lamp. The wireless sensor node is composed of solar cell, lithium battery, energy management circuit, environmental monitoring sensors, and transmitter module. These sensors can monitor solar cell voltage, solar radiation, temperature, and humidity. The sensor node is powered by a lithium battery, which is charged by a solar cell. The measurement data of sensors (including solar cell voltage, temperature and humidity) are transmitted to the computer through a router every 5 minutes wirelessly. This router has capability to run 802.15.4 PHY low-data-rate WPAN, and 802.3 Ethernet. Finally, data processing and prediction tasks are completed in the computer through LabVIEW and MATLAB. In future research, the proposed method will run directly on the wireless sensor node.

The size of the solar cell used in the experiment is 13×25cm, and the output voltage is 0~5 V. The type of voltage sensor is MEP410CB, which has a measuring range of ±12 V, an accuracy of 0.1%, and a resolution of 0.01 V. The temperature sensor is eS1101, which has a measuring range of -40 °C ~ +70 °C, a precision of ± 1 °C, and a resolution of 0.1 °C. The humidity sensor is SHT75, which has a measuring range of 0% to 100% RH, an accuracy of ±3% RH, and a resolution 0.05% RH. Wireless communication module: frequency 2.405~2.480 GHz, IEEE 802.15.4 protocol. The schematic of the solar energy wireless sensor nodes experimental platform is shown in figure 3.

Figure 3. Solar energy harvesting wireless sensor nodes experimental platform.
4.2. Solar energy prediction algorithms evaluation
First, solar battery voltage and environmental data from September 1 to September 30, 2017 are collected through the solar energy harvesting wireless sensor nodes experimental platform. Then, using rising edge detection method to divide the original signal into multiple segments, and calculate the average value $\bar{x}$, peak value $x_{\text{max}}$, valley value $x_{\text{min}}$, and the standard deviation $x_{\text{std}}$ in each data segment as the feature vector $F_k$. Next, input feature vector $F_k$ into the LSTM prediction model, and adjust the parameter matrixes of the memory unit to train the model. Finally, the trained model is used to predict the solar voltage data in the next 3 days, and compared with real data to analyse the prediction error. The relevant parameters of the LSTM-RNN prediction method used in this paper are as follows: the input layer contains 16 nodes; the LSTM layer contains 32 nodes; the softmax fusion layer; the output layer contains 2 nodes; RMSprop is used as the training method.

To evaluate the performance of proposed LSTM-RNN energy prediction algorithm, the following two common prediction methods are compared under the same training set and test set:

A) Knowledge-Based Neural Network (KBNN) [8]. Based on the traditional artificial neural network, KBNN adds a knowledge neuron paralleling to the original output layer. KBNN experiment-related parameters: input layer of 3 nodes, output layer of 2 nodes, a 3-layer Perceptron, and a 3-parameter knowledge neuron.

B) Support Vector Regression (SVR) [10]. SVR is an extension of the support vector machine. It is a regression analysis method that maps data to high-order space. SVR experiment related parameters: radial basis kernel function $e^{-\gamma |u-v|^2}$, loss function parameter $\epsilon = 1e^{-6}$.

The comparison experiment uses two error metrics to evaluate the prediction results: mean relative error (MRE), and root mean square error (RMSE). The definitions of these metrics are as follows:

$$MRE = \frac{\sum_{k=1}^{N}|U_k - \hat{U}_k|}{\sum_{k=1}^{N}U_k}$$  \hspace{1cm} (14)

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^{N}(U_k - \hat{U}_k)^2}$$ \hspace{1cm} (15)

Figure 4 shows the time-domain waveform comparison results for the three prediction methods. It can be obviously seen that the prediction results of LSTM method are the most consistent with the actual data. Figure 5 shows the average relative error comparison of the three prediction methods. It can be observed that as the number of training iterations increases, the prediction errors of the three methods gradually decrease, and the error of LSTM method are always the smallest. Table 3 and table 4 lists the average relative errors and root mean squared errors for the three prediction methods at different iterations. The experimental results show that the proposed LSTM-RNN solar energy prediction method has higher precision and better convergence than other conventional methods. Moreover, the LSTM-RNN prediction method can make better use of long-term historical information and further improve the accuracy of prediction results.

| Table 3. Mean Relative Error of different algorithms. |
|-----------------------------------------------|
| Iterations | KBNN  | SVR   | LSTM |
|------------|-------|-------|------|
| MRE (%)    |       |       |      |
| 200        | 27.26 | 19.56 | 11.98|
| 600        | 22.41 | 17.35 | 9.81 |
| 1000       | 19.84 | 16.21 | 8.75 |

| Table 4. Root Mean Square Error of different algorithms. |
|-----------------------------------------------|
| Iterations | KBNN  | SVR   | LSTM |
|------------|-------|-------|------|
| RMSE (V)   |       |       |      |
| 200        | 0.91  | 0.58  | 0.38 |
| 600        | 0.71  | 0.49  | 0.27 |
| 1000       | 0.45  | 0.38  | 0.23 |
4.3. Task scheduling strategy evaluation

Wireless sensor nodes follow different task scheduling strategies affecting their survival time and task completion rates, which directly determine the overall performance of the nodes. Survival time: when the energy buffer voltage is higher than the node start-up voltage, the node is considered to be active. Otherwise, the node is considered to be inactive. Task completion rate: it is calculated by the average number of tasks completed in a unit time (its unit is Hz or cycle per hour, cph). The purpose of task scheduling strategy is to maximize the task completion rate while ensuring the survival of the node.

As showed in figure 6, under different lighting conditions and different task scheduling strategies, the node's survival time and task completion rate are distinct. The three curves show the change of node's survival time with different light intensities under the three strategies. The three kinds of histograms represent the task completion rates vary with different light intensities under the three strategies.

Under the conservative strategy, the node has the longest survival time, but the lowest task completion rate. Under the greedy strategy, the node’s task completion rate is high, but its survival time is the shortest. The predictive strategy takes into account both the survival time and the task completion rate. Compared with the greedy strategy, the predictive strategy can greatly improve the survival time of the node, especially in low light conditions. For example, the predictive strategy increases the survival time from 3.7 hours to 6.9 hours under 50 lx. Compared with the conservative strategy, the predictive strategy can nearly double the task completion rate while keeping the approximate survival time. For example, the predictive strategy increases the task completion rate from $1.6 \times 10^{-3}$ Hz to $2.8 \times 10^{-3}$ Hz under 250 lx. In short, the predictive strategy can maximize the task completion rate by using the energy information of the future time period while maintaining the survival time of the node as much as possible.
5. Conclusions
This paper presents a long short term memory recurrent neural network solar energy prediction method for solar-powered wireless sensor nodes. According to the energy prediction results, the predictive task scheduling strategy is put forward to improve the performance of wireless sensor nodes. Then we set up a solar wireless sensor nodes experimental platform to measure the voltage of solar cells and various environmental signals to establish an experimental database. Next, the prediction evaluation experiment and the task scheduling strategy evaluation experiment are proposed. Experimental results demonstrate that the proposed LSTM-RNN solar energy prediction method has higher precision and better convergence than other conventional methods. LSTM-RNN method can use long-term historical data to provide accurate prediction results to improve the lifetime and measurement reliability of wireless sensor nodes. The predictive strategy significantly increases the task completion rate by using the energy information of the future time period while maintaining the survival time of the wireless sensor node as much as possible. In a word, the proposed LSTM-RNN solar energy prediction method and predictive task scheduling strategy improve the energy supply stability and measurement reliability of the wireless sensor nodes.

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References
[1] Li Y, Jia Z, Li X 2014 Task Scheduling Based on Weather Forecast in Energy Harvesting Sensor Systems IEEE Sensors Journal 14(11): 3763-3765
[2] Dionisi A, Marioli D, Sardini E, et al. 2016 Autonomous Wearable System for Vital Signs Measurement With Energy-Harvesting Module IEEE Transactions on Instrumentation and Measurement 65(6): 1423-1434
[3] Wang X, Ma J, Wang S, et al. 2010 Distributed energy optimization for target tracking in wireless sensor networks IEEE Transactions on Mobile Computing 9(1): 73-86
[4] Liu Q, Mak T, Zhang T, et al. 2015 Power-Adaptive Computing System Design for Solar-Energy-Powered Embedded Systems IEEE Transactions on Very Large Scale Integration (VLSI) Systems 23(8): 1402-1414
[5] Cammarano A, Petrioli C, Spenza D 2016 Online Energy Harvesting Prediction in Environmentally Powered Wireless Sensor Networks IEEE Sensors Journal 16(17): 6793-6804
[6] Basagni S, Naderi M Y, Petrioli C, et al. 2013 Wireless sensor networks with energy harvesting Mobile Ad Hoc Networking: The Cutting Edge Directions 701-736
[7] Kansal A, Hsu J, Zahedi S, et al. 2007 Power management in energy harvesting sensor networks ACM Transactions on Embedded Computing Systems (TECS) 6(4): 32
[8] Liu Q and Zhang Q J 2016 Accuracy Improvement of Energy Prediction for Solar-Energy-Powered Embedded Systems IEEE Transactions on Very Large Scale Integration Systems 24(6):2062-2074
[9] Saez D, Avila F, Olivares D, et al. 2015 Fuzzy Prediction Interval Models for Forecasting Renewable Resources and Loads in Microgrids IEEE Transactions on Smart Grid 6(2): 548-556
[10] Yang H T, Huang C M, Huang Y C, et al. 2014 A Weather-Based Hybrid Method for 1-Day Ahead Hourly Forecasting of PV Power Output IEEE Transactions on Sustainable Energy 5(3):917-926
[11] Belkaid A, Colak I, Isik O 2016 Photovoltaic maximum power point tracking under fast varying of solar radiation Applied Energy 179:523-530
[12] Balato M, Costanzo L and Vitelli M 2015 Series–Parallel PV array re-configuration: Maximization of the extraction of energy and much more Applied Energy 159(1):145-160