A Novel Second Order Radial Basis Function Neural Network Technique for Enhanced Load Forecasting of Photovoltaic Power Systems

Arwa Ben Farhat [1†], Shyam.Singh Chandel [2††], Wai Lok Woo [3††], Cherif Adnene[4††],

University of Carthage,Tunisia, Shoolini University, India, Northumbria University, Faculty of sciences of Tunisia

Summary
In this study, a novel improved second order Radial Basis Function Neural Network based method with excellent scheduling capabilities is used for the dynamic prediction of short and long-term energy required applications. The effectiveness and the reliability of the algorithm are evaluated using training operations with New England-ISO database. The dynamic prediction algorithm is implemented in Matlab and the computation of mean absolute error and mean absolute percent error, and training time for the forecasted load, are determined. The results show the impact of temperature and other input parameters on the accuracy of solar Photovoltaic load forecasting. The mean absolute percent error is found to be between 1% to 3% and the training time is evaluated from 3s to 10s. The results are also compared with the previous studies, which show that this new method predicts short and long-term load better than sigmoidal neural network and bagged regression trees. The forecasted energy is found to be the nearest to the correct values as given by England ISO database, which shows that the method can be used reliably for short and long-term load forecasting of any electrical system.

Key words:
Artificial Neural Network (ANN); Radial Basis Function Neural Network (RBFNN); Load forecasting; Electrical systems, Photovoltaic systems.

1. Introduction

The smart electric meters for remote energy measurements are still not available in a number of developing countries, despite its considerable progress in developed countries [1,2], as a result, the dynamic prediction algorithms are used for short-term and long-term load forecasting in energy measurements and electrical distribution applications. However, the forecasted data from the electrical service companies are found to be inaccurate according to 90% of the subscribers of these companies in Africa [3,4]. Therefore, the main objective of the present study is to improve the accuracy of the forecasted electrical load and the effectiveness of the forecasting algorithms for solar PV systems. –The New England ISO database is used as input load data for training, forecasting, and testing of the short and long-term load data along with other input parameters for MAPE and training time calculation, for each number of epoch and RBF units.

The use of ANN based load forecasting algorithm is widely investigated in the recent years [5, 6], as they demonstrate excellent scheduling capabilities and strong effectiveness for the classification, clustering, management as well as prediction [7, 8, 9], RBFNN is one of the newly designed neural network algorithms, which uses RBF for classification and forecasting [10, 11, 12]. RBFNN is used in the present work as it has, demonstrated strong effectiveness, especially in short and long term load prediction for solar PV systems, with good generalization abilities [13,14, 15,16], which do not influence the overall structure of the network, as compared to sigmoïdal neural network [17,18].

The RBFNN uses RBF as activation functions, which are modeled by the combination of the RBF and the output parameters and are used for short and long-term load forecasting in the present research for both training and validation to forecast and test the accuracy of load in solar PV systems. The choice is referred to the effectiveness, performance, robustness, reliability, accuracy as well as the low business cost of RBFNN as compared to sigmoïdal neural networks, bagged regression trees, and feed-forward back propagation neural network. The litterature survey shows RBFNN is widely used for data prediction accuracy in performance evaluation analysis of PV systems.

1.2 Novelty and research contribution

The identified research gaps based in the literature survey are considered in the present study by including the three main criteria of the performance evaluation of the load forecasting algorithms namely: load data accuracy, the training time and the low cost business as well as the use of two RBFNN methods merged in one protocol called corrected-ISO.
The main problems that have been overcomed in this research using enhanced-ISO based RBFNN, are the curse and the overfitting of sigmoïdal neural networks based ANN methods such as neuron by neuron method for the training, load forecasting and the performance testing, which limited the accuracy of the used time series load prediction techniques.
The England ISO data sets are used in this research as it is the biggest and the most reliable data base that deals with the short and long term load forecasting in PV systems as compared to other online data bases and also contribute to the MAE and MAPE results enhancement. The enhanced-ISO method based RBFNN, predicts load using temperature and seasonability as well as ISO New England Data set input parameters which are used for the comparison between the forecasted data with the same time series.

Manuscript received February 5, 2021
Manuscript revised February 20, 2021
https://doi.org/10.22937/IJCSNS.2021.21.2.9

Enhanced-ISO selects the most relevant clusters according to the corrected data of England ISO database of the same time series and removes the extra-clusters, which reduce the curse and overfitting of sigmoïdal neural network and improve the MAPE accuracy evaluator with more generalization of the overall structure of the ANN.
The value of MAPE that reflects the data accuracy in load forecasting which is evaluated between 2% to 20%. The data accuracy is adressed in this research to be enhanced using a novel RBFNN method based on the combinaison of ISO and ErrCor methods for load forecasting and MAPE accuracy evaluator enhancement.
The paper is organized as follows: Overview of the relevant research studies is presented in section 2. The required tools and the used RBFNN methods-based ISO and ErrCor for short and long-term load forecasting in PV systems are detailed in section 3. The obtained results with the used methods are presented, discussed and compared with the existing research studies in section 4; the conclusion summarizes the contribution of this work and discusses some perspectives for the demand side management in solar PV systems.

2. Overview of relevant research studies and identified research gaps

In this section a brief overview of most relevant researches related to present study are provided in order to identify the highlights and research gaps.
Hernandez et al. [13] discussed the most relevant studies related to load forecasting in PV systems in smart grids environment over the last 40 years and presented different used models. The authors have analyzed the load needs in the future smart grid. The limitation of this study is the lack of experimental tests to prove the reliability of the existing methods.
Yadav and Chandel [14] have reviewed ANN based different algorithms as multi-layer feed forward neural network, back propagation training algorithms, scaled conjugate gradient, Lavenberg-Marquardt algorithms and wavelet recurrent neural networks and have identified the suitable methods for solar radiation prediction in PV systems and focused on the forecasted data accuracy of ANN. The study considered the accuracy as the only criteria for the prediction algorithms performance evaluation and not considered other aspects like complexity, response time, and low business cost criteria.
Teo et.al. [15] studied the PV power forecasting using ELM based ANN and have based on the RMSE calculation for the evaluation of PV power data accuracy using 5 input parameters and 3 simulations for each step of training and sets. The limitations of this work are the limitation on the use of ELM as the only method for PV power forecasting and the lack of comparative analysis with the existing results available in the literature.

Hernández et.al. [16] studied short-term load forecasting based micro-grid environment using 2 different input parameters, namely electricity consumption and solar radiation data and discussed different STLF models and studied the effects of each variable, to identify the best method for load forecasting. This study can be improved by a comparative analysis with results obtained from other methods.
Bodgam et.al. [17] have used RBFNN methods for the dynamic prediction based on training and validation and calculated training time and MAPE for used RBFNN according to three inputs and have used different number of RBFs and activation function parameters for testing the training time. This research has studied the performance and the accuracy of different RBFNN methods for PV load forecasting. This work can be improved by integrating high-speed pre-processing methods to filter the errors.
Xingu et.al. [18] have implemented a performance algorithm-based ANN model for the global solar radiation forecasting. The authors have calculated MAE and RMSE for the training, testing and the validation of errors. The research has used only conventional artificial neural network based back-propagation and not considered other newest and more effective algorithms like RBFNN and Levenberg–Marquardt for load and PV power forecasting [21, 22, 24]. This research has also not used detailed comparative analysis with the results available in the literature.
Gabriel Trierweiler Ribeiro et.al. [25], have proposed a novel Framework of wavenet ensemble for short-term load forecasting, where data sets are normalized, optimal time interval is calculated, and feature subsets are extracted. Cross validation, constructive selection, simple mean, stocked generalization algorithms, are used for wavenet aggregation for the hour-ahead load forecasting. The proposed framework is compared with similar forecasting techniques like sigmoïdal activation function, single wavenet, and regression trees and cross validation results using 10 folds and demonstrated the effectiveness of the proposed load forecasting framework based on wavenet ensemble in overcoming the performance of the compared models.
Yang Zhang et.al.[26] have proposed a synthetic prediction approach considering the load and price signals in PV systems and based in multi-input multi-output model. It is based on least square support vector regression machine forecast engine. The authors have used multi mutual information to forecast the best source of input and novel gravitational search algorithm for model learning considering MAPE and error variance to compare the output and evaluate the efficiency of the proposed algorithms for the load forecasting of solar PV systems.
Chao-Ming Huang et.al. [27] have proposed an intelligent method-based classification, training, forecasting and forecasting updating stages for the prediction of one-day-hourly PV power generation, They have used 5 training models based on RBFNN and fuzzy inference to select the

adequate fuzzy model from the training models. The proposed method is tested on an actual PV power generation system. The performance of the proposed method is compared with the existing methods using one-year testing data.

Weibiao, Qiao et.al. [28], have proposed an hybrid prediction model using Improved whale warm algorithm and relevance vector machine, as well as an empirical mode decomposition and approximate antropy to aïd the calculation. The results of the proposed model show the accuracy and the convergence speed of the new algorithm are higher than other algorithms indicating the best optimization abilities.

Yuxin Wen et.al. [29], have presented two probabilistic approches based on bootsrap method and quantile regression method to forecast the uncertainty associated with solar PV power point forecasting, The proposed hybrid intelligent model is composed of wavelet transform, soft computing model, and RBFNN for data filtering and optimization. The point forecast capacity of the proposed hybrid intelligent model is compared with hybrid models and the results demonstrated the efficiency of hybrid intelligent model in PV power uncertainty quantification.

Only a single criterion is mostly used in the load forecasting algorithms whereas load data accuracy, the training time and low cost business, are important to be considered for the accurate performance evaluation [30, 31, 32, 34]. Different ANN methods [33, 35, 36] are used for electricity load forecasting but no comparative analysis of results obtained, is done.

3. The improved RBFNN model and methodology

3.1The RBFNN model

The ANN techniques have shown strong capabilities in multi-purpose approaches like recognition, classification, clustering and prediction [21, 22] and RBFNN are the ANN based RBF and are the benchmarked centered functions, presented as the interconnected neurons in shallow architecture and strong generalisation. The RBF core is used in various algorithms for learning and clustering. RBFNN have simple configuration, faster training procedure used for prediction, strong potential of approximation, regularization and generalization [23] compared to feed-forward neural network. They use smaller entities of input patterns and have minimal RBF input units and then better generalization as compared to traditional sigmoidal neural networks, they tolerate the overtraining and the vanishing of the learning gradient phenomenon more effectively than sigmoidal neural networks and other newest algorithms like deep learning and feed-forward back propagation neural network [22].

RBFNN architecture is generally composed of three layers linked together by the interconnected nodes that integrate the network as shown in figure 1. The first layer is used to receive input data in order to enter them into the model, the inputs xi in the first layer are rescaled by the input weights $U_{i,h}$.. The second layer known by the hidden layer is composed of a number of scaled vector **Vp,h** mapped in *H*-dimension, and transferred by the output weight $\mathbf{W_h}$ into the output layer. The third layer presents the obtained output data.

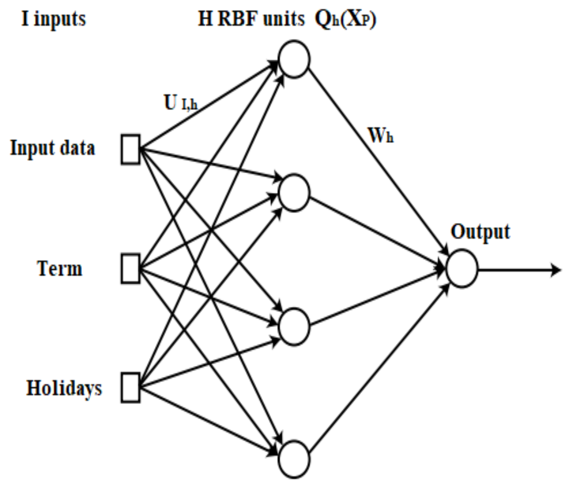

Fig1. RBFNN model for the short/long-term load forecasting

The RBF unit is the center of the specific data in input layer within RBF compents included support vector, RBF weight and RBF center to obtain the location of the output neuron, the advantage of RBF use is the lower mutual interaction between RBF units than the traditional sigmoïdal neural networks and that leads to much better generalization properties of RBFNN. The RBF units have smaller portions of input patterns and a single output in general cases. The RBF units are trained in the hidden layer and activated in linear operations by the following Gaussian activation function:

$$\alpha_i(x) = \exp\left[\frac{-\| X - C_i \|^2}{2\sigma_i^2}\right] \quad i = 1,2,\cdots m \tag{1}$$

where :

$a_i(x)$ is the Gaussian function for the i-th hidden node

c_i is the coordinate values of the centroids of the i-th RBF unit,

σ_i is the radius of the i-th RBF unit.

For an input pattern, the output of RBFNN is the connection between hidden unit and the output data specified by the following equation:

$$y_k = \sum_{i=1}^{m} \omega_{ik}\alpha_i(x) \quad k = 1,2,\cdots,p \tag{2}$$

Whereas the k value is equal to 1 for the regression problems. The RBF parameters are adjusted in RBFNN in the figure 1. RBF parameters are:

- input weights*:* they present the weight connection between the i-th input and RBF unit.
- gamma parameter σ_i,,
- output weights wi_k *(i=1,2, ……m and k=1).*

3.1.1 Implementation of input parameters in RBFNN model :

RBFNN are affected by the input parameters, which are the dataset array of both historical weather and load information, the term expressed by the horizon of the forecasting, it can be (long/short) term load forecasting, and the holiday data, which are presented by create Holiday Dates () or the holiday indicator, expressed by the boolean (0/1). The RBFNN receive the input parameters from the input layer, they train, and test the input parameters in the hidden layer to forecast the (short/long) term load and evaluate the predicted load data accuracy. The RBFNN have simple configuration and faster training procedure. It executes accurate interpolation on a group of data features in a multidimensional space. The hidden layer of RBFNN uses Radial Basis Function ($\phi()$) as a nonlinear activation function to activate the input parameters and executes nonlinear transformation of input parameters. The output layer receives the trained load data by the linear activation function modeled the nonlinearity into new space [23, 36, 37]. Several operations are performed by the RBFNN, starting from the input data activation by the activation functions, going through the training and the test of input parameters in the hidden layer for the load data prediction and ending by the obtention of the forecasted load data as the output results. The load data are tested by RBFNN and returned the errors evaluated by MAE and MAPE.

3.2 The RBFNN based methods for load forecasting:

The majority of RBFNN algorithms are adjusting only output weights, because, the adjustment of all RBF input and output parameters is more sophisticated, more time consuming and needs more costly-operational process than sigmoïdal neural networks. The RBF input parameters using ELM are selected randomly. However, all RBF parameters in ErrCor are processed and selected in the learning process, witch, returned more accurate load forecasting results.

Decay radial basis function neural networks [17] : DRBF are the training algorithms based on the adjustment of output weights through the interconnexion of all RBF units, they have the same radiuses between all the RBF units during all training process, they are based on the equality between the number of output weights and the number of training patterns, it has a fast training process, However, it returned a high MAPE because, it did not train all the patterns.

Support Vector Regression [21]: SVR is based on SVM algorithms for the fusion of groups of data according to the closest euclidien distance to build the support vectors based on the weight input and the locations of RBF using the adjustment of input parameters. The input weights and the radiuses, for all RBF units are the same during patterns training, as a result, the training process is reduced to linear regression to fasten the SVR technique. The limitation of SVR that the support vectors are chosen only from the data set, and can not have other locations, and the use of the same radius for all RBF units, than the poor covering of all data training and the unability of generalization, which impact the data accuracy and increase the MAPE.

Extream Learning Machine [15]: ELM use algorithms based on orthogonal least squares, the output parameters in ELM are selected randomly and only output weights if RBF units are adjusted. The random selection of the input parameters returns often better results than the results that are obtained with DRBFNN and SVR algorithms. The main advantage of ELM that is a faster training process and the drawbacks are the use of both RBF and SVR inputs, which complicate the training process and the data accuracy that are impacted by the use of high weight value, that may cause high MAPE.

3.3. Corrected-ISO proposed method based RBFNN for the short/long term load forecasting :

The corrected-ISO method is proposed for the forecasting error correction, it is inspired from Improved Second Order and error correction methods based on RBFNN for the short and long-term load forecasting. The ISO and ErrCor methods are combined together in one proposed paradigm called corrected-ISO. ISO and ErrCor are chosen in this proposed research because they are the most reliable and effective algorithms, since they return better-forecasted data and shorter training and testing time than SVR and ELM.

Improved Second Order [20]: ISO is the learning algorithm, uses the iteration process based training and testing errors using inverse Hessian matrix expressed by this function:

$$W_{k+1} = W_k + H_k^{-1} g \tag{3}$$

To replace the time-consuming of this complex computational process related to the accumulation of the sub-matrix with the gradient vectors, The quasi-Hessian matrix is replaced by the jacobian J. The ISO adjusted all the parameters of RBF units with more generalization abilities, it is able to return more accurate data than Levenberg-Marquardt developed by sigmoïdal networks. The main drawback of ISO that it has a complex computational and time-consuming process.

Error Correction ErrCor [17]: ErrCor algorithm is the modification of ISO algorithm; it starts with the point with the largest error to obtain the optimal solution with minimum error. His advantages are the highest error validation during the training process, and the fastest time during the error correction process.

A comparative advantages and limitations of the methods are given in Table 2.

Table.2. Summary of the used RBFNN methods for the training and testing input data in short/long term-forecasting algorithms

Method	Concept	Advantages	Drawbacks
Improved Second Order ISO [20]	-Iteration algorithms based on the reduction of errors expressed by Wk+1 = WK –ag in the first order and the quasi-Hessian matrix in the 2nd order. -Adjustment of all input and output parameters related to RBF units.	-Reachs lower training/testing errors with much less number of RBF units. -Generates 10 times better accurate data than LM algorithms developed by sigmoïdal neural-networks.	-The complex computational process ; -Needs a long execution time.

Error Correction ErrCor [17]	Starts with the point of the largest error. characterized by a single analysis to obtain the optimal solution.	-Reducing the training process complexity. -Error validation is more accurate as compared to ELM and SVR. -Error correction execution time is faster than SVR and ELM.	-It can modify the overall structure of the ANN during the error correction and incoherent data suppression process.

The proposed corrected-ISO method uses ANN algorithms for the short/long term load forecasting. The corrected- ISO is integrated in load forecasting algorithms, in where, the input parameters {previous load measurements matrix, Temperature, holiday information} are trained and the performance of the short and long term load forecasting algorithms is evaluated by the calculation of relief accuracy evaluator MAPE.
3.4. The load forecasting paradigm with RBFNN

The proposed corrected-ISO method is used in load forecasting algorithm to train RBF units with input parameters. RBFNN algorithms based corrected-ISO method receive input parameters {load data, temperature, holiday information} from input layer and train them in the hidden layer. The trained hidden radial basis function units are tested in the same layer by the corrected-ISO method, using ANN algorithms, and then, the load data are forecasted, the MAPE and training time are calculated. The outputs are scaled by the output weights and returned into the output layer.

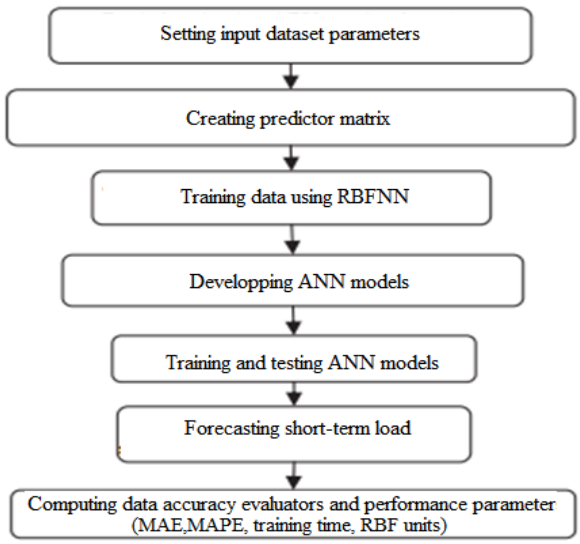

Fig.2. Load forecasting used RBFNN

3.4.1. **Algorithm for short-term load data forecasting**:

The steps of load-forecasting algorithm based RBFNN including training, forecasting, and error testing are shown in the flow chart in Figure.3. The flow-chart shows that, if the forecasted load value is superior to 0, then the algorithm will be validated and the MAE will be incremented, else the algorithm returned to the prediction process.

The load forecasting algorithm performs the short-term load data using pre-trained neural network with radial basis functions, which are used for the activation of neurons in ANN model.
function y = load forecast (date, temperature, is Holiday)
y = load forecast (model, date, hour, temperature, is Working Day)
This function shows the predictors generation as a matrix of predictor for the load forecasting model :
function [X, dates, labels] = genPredictors(data, term, holidays)
[X, dates, labels] = gen Predictors (data, term, holidays)

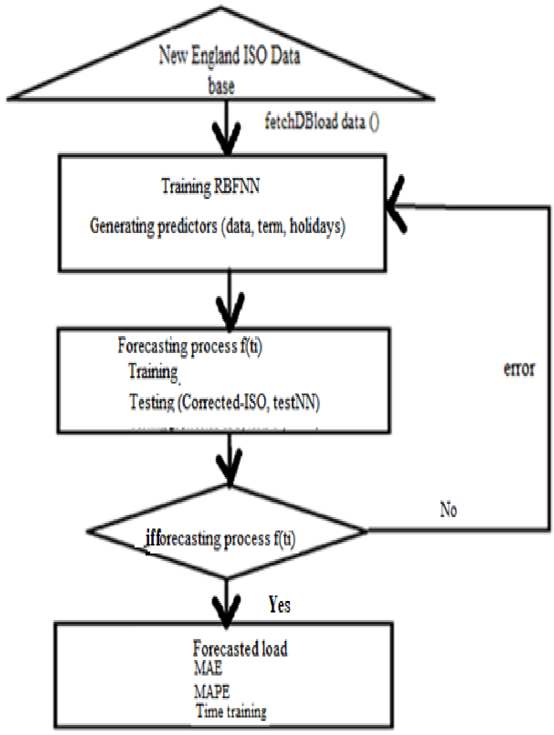

Fig.3. Short-term load forecasting algorithm

3.4.2. **The existing solar radiation-forecasting algorithm**

The short- and long-term load forecasting is inspired from the solar radiation forecasting aim covered in [18,22,24], which used ANN model and weather input parameters (Temperature, Humidity etc.) to forecast solar radiation. The load forecasting was used temperature information sorted by the forecasted solar radiation, the England load data set, and the holiday's information are the used input parameters to forecast the short/long term load use and calculate the training time and MAPE.

The most important difference between the existing algorithms that solar radiation forecasting algorithms have used sigmoidal NN, while the load forecasting algorithm have used corrected-ISO based RBFNN for training, forecasting and testing errors.

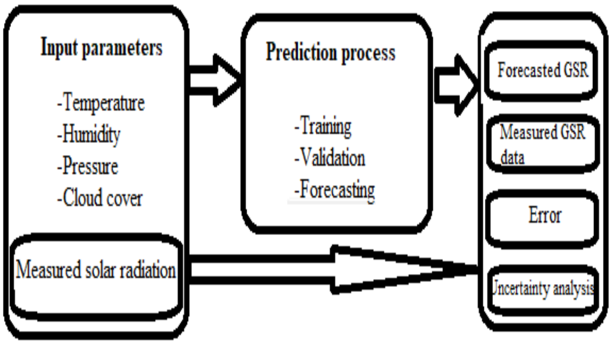

Figure 4. Algorithm of the solar radiation forecasting [18]

4. Results and discussion

The dynamic prediction algorithms use training and testing processes with different number of RBF units depending on the size of the network during the short/ long term load forecasting. The short-term load data are forecasted, the time training is computed and the accuracy feature evaluator MAPE is calculated. This section presents the results obtained by corrected-ISO method based RBFNN that are between 1,4 % and 2,7 % for MAPE and 3,9 s and 10 s for training time.

4.1. England ISO Data Set

England ISO Data set considering daily and weekly load intervals in the order of GW is investigated for this study, and presented in the scenarios of figure 5:

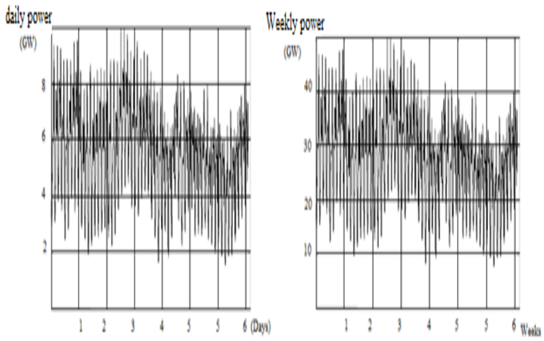

Fig.5. Daily and weekly England ISO used data set for load forecasting and performance evaluation

4.2. Dynamic prediction results

The forecasted data have used New England ISO data set and has presented the scenarios of short and long-term load forecasting. The dynamic prediction algorithms were implemented in Matlab tool, using the input parameters of previous measurements, weather, holiday information to forecast load, validate models, and calculate training time and MAPE according to the selected epoch and RBF number as presented in Table 3.

Table 3: Best results with corrected-ISO based RBFNN in function of epoch and RBF units

Number of RBFs	Epochs	Training time (s)	MAPE %
5000	**4**	**3.9**	**2.7**
3800	5	4.0	2.37
3500	6	5.0	2.25
3000	7	5.8	2.2
2500	8	7.0	1.85
2000	9	8.0	1.6
1000	**10**	10	**1.4**

The Table 3 presents the MAPE and training time during load forecasting process, the best MAPE is 1,4 with 10 epochs and 1000 RBF units and the lowest training time is 3,9 s with 4 epochs and 5000 RBF units, the results show a correlation between MAPE, epoch and RBF number and other correlation between epoch and training time. The lowest selected epoch number, the lowest obtained training time, the lowest trained RBF units, and the highest selected number of epoch, the best MAPE obtained.

4.2.1. The scenarios of the short and long-term load forecasting:

The short and long-term load has composed of England ISO Dataset and has considered temperature and seasonability as input parameters. Temperature data are extracted from solar radiation database, seasonability is determinated by a Boolean or by the predefined function fetch. The scenarios 6.a and 6.b show England ISO data sets and short and long-term forecasted load with proposed ISO-RBFNN. The scenarios show a similarity between the England ISO database and the forecasted data using the proposed method:

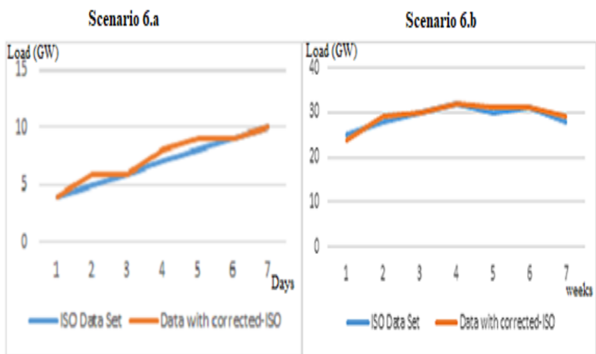

Fig.6. Daily and weekly energy forecasting based corrected-ISO with England ISO Data sets in the same time series

The scenarios 7.a and 7.b in figure 7 show the MAPE with and without proposed ISO based RBFNN for both short and long-term load forecasting considering daily and weekly intervals. The scenarios 7.a and 7.b show that RBFNN algorithms forecast daily and weekly load with the same efficiency for daily and weekly intervals with MAPE is between 0% and 2% for both daily and weekly load forecasting.

Figure.7. MAPE with and without corrected-ISO in daily and weekly load forecasting

The scenarios 8.a et 8.b show the training time with and without proposed corrected ISO method based RBFNN for both short and long-term load forecasting considering daily and weekly intervals. The Scenarios 8.a and 8.b in figure 8 show that load forecasting based corrected-ISO-RBFNN is lower than load forecasting without proposed ISO-RBFNN, with 5s with corrected ISO and 250s without in daily load forecasting, and with 50s for weekly load forecasting with corrected ISO and 2000s without ISO-RBFNN. Then the high impact of the proposed method in the time training reduction.

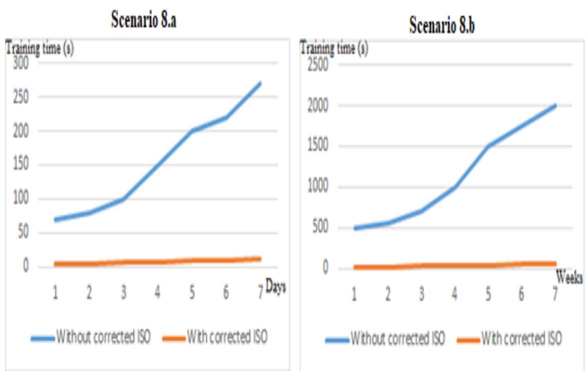

Fig.8. Time training with and without corrected-ISO during daily and weekly load forecasting

The scenarios 9.a, 9.b, 9.c and 9.d in figure 9 show the MAPE and the training time using the proposed-corrected-ISO- RBFNN with SVR and ELM. The MAPE and training time are lower with proposed ISO-RBFNN than SVR and ELM for both short and long-term load forecasting scenarios. There are with 1% and 2% with ISO-RBFNN versus 5% and 8% in ELM and SVR in weekly forecasting and 50s of weekly time training by the proposed ISO-RBFNN method versus 1500 s and 2000s by ELM and SVR. Then, the proposed corrected-ISO based RBFNN is more effective than SVR and ELM for energy prediction and can be used to forecast energy.

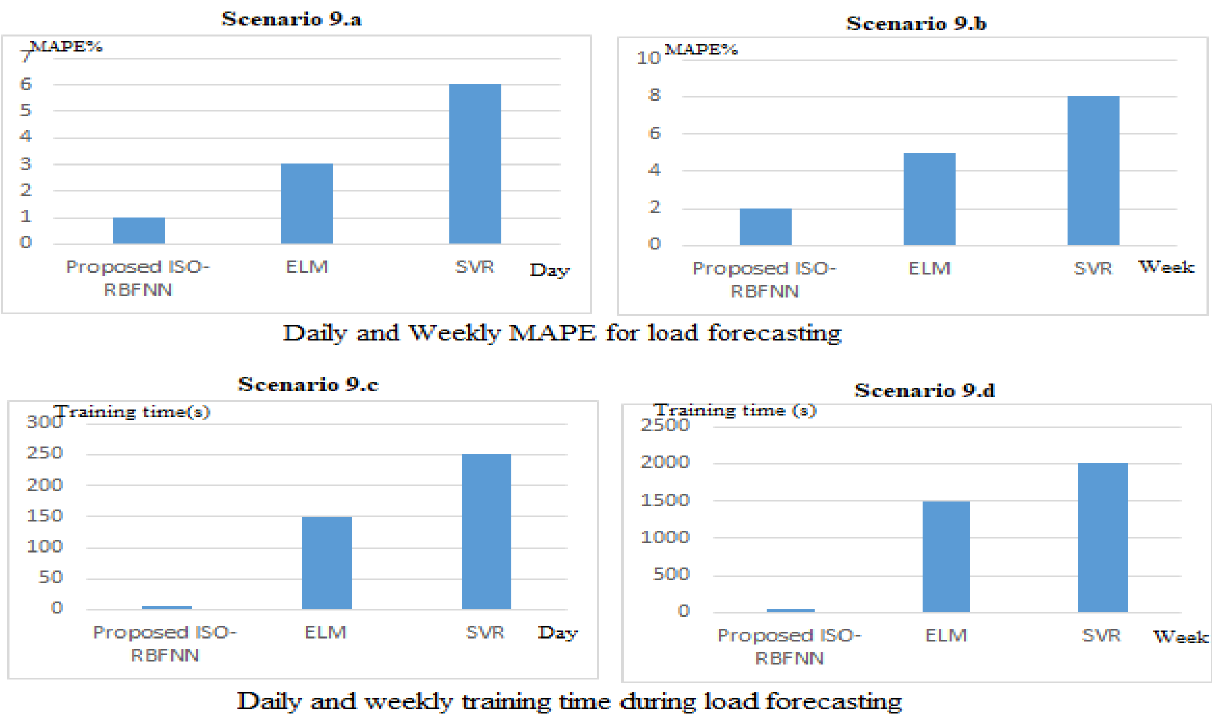

Fig.9. Comparison of the suggested method with the two existed methods and using the daily and weekly MAPE and time training during load forecasting

Table 4 summarizes the results of the corrected-ISO proposed method based RBFNN in load forecasting and compares the obtained results from the proposed corrected-ISO method with the results of the litterature used ANN and sigmoidal neural network for solar radiation forecasting in ref [17, 18, 19, 24]:

Table. 4. The evaluation of the obtained MAPE results with respect to the litterature study

Proposed Method	**Results**	**Discussion**
Corrected-ISO based RBFNN for Load forecasting	$$\mathrm{MAPE} = \left(\frac{1}{n} \sum_{i=1}^{n} \left| \frac{\mathrm{Load}_{i(ANN)} - \mathrm{load}_{i(actual)}}{\mathrm{load}_{i(actual)}} \right| \right) \times 100$$ 1.4% <MAPE of load data using _corrected-ISO<2,7% depending on the epochs and RBF units 2,17% <MAPE during short term load forecasting using ELM based RBFNN using the same data-base <2,75% [ref.17] 2,2% <MAPE during short term load forecasting using ISO based RBFNN using the same data-base <2,73% [ref.17] 1.4% <MAPE during solar radiation forecasting using sigmoidal NN <6.6% [ref.18] 6,98% <MAPE during solar radiation forecasting using the most relevant input parameters obtained by WEKA software and trained by ANN <16.96% [ref.24]	The MAPE of the short-term load-forecasting algorithm is lower than the MAPE using ELM with the same database [17] and using ISO method with the same database in [17]. The MAPE of the load forecasting algorithm in all tests is lower than the MAPE of solar radiation forecasting which is between 1,4 and 6,6 in [ref 18] and between 6,98 and 16,96 in [24]. Then: The obtained MAPE accuracy evaluator by corrected-ISO based RBFNN is better than that it was obtained by sigmoidal NN and ANN in ref.[18, 24, 30] for solar radiation forecasting. The corrected-ISO based RBFNN can be used to reduce MAPE in short-term load forecasting and can be used for all forecasting algorithms.

Table.5. The comparison of the obtained training time results with the litterature study

Proposed Method	**Results**	**Discussion**
Corrected-ISO based RBFNN for Load forecasting	3.9s <Training time during load forecasting using _corrected-ISO < 10 s 0.027 h <training time during short term load forecasting with ELM using the same data-base with 200 to 5000 RBF units < 2.174 h [ref.17] 1.29 h <MAPE during short term load forecasting using ISO based RBFNN using the same data-base with 100 RBF units and 200 epochs < 48 h [ref.17]	The training time during short-term load forecasting algorithms is between 3.9 s and 10 s using 10 to 5000 RBF units and 4 to 10 epochs. The obtained training time is lower than it was obtained with ELM using the same database with 200 to 500 RBF units [ref.17]. It is too lower compared to training time using ISO method with the same database with 100 RBF units and 200 epochs in [ref 17]. The corrected-ISO based RBFNN has reduced training time in short-term load forecasting, it can be used for all forecasting algorithms that needed to train big data.

Table 6 presents the used training algorithms using ANN model and compare the results of each training algorithm with the results of the enhanced-ISO based RBFNN model to evaluate the performance of the Shifted-ISO for the dynamic load forecasting,

Table.6. The evaluation of the performance of Training algorithms-based ANN model with the proposed shifted-ISO based RBFNN model

Model and training algorithm	Concept with used epochs and RBF units	Results of ANN prediction accuracy	Results of Shifted-ISO based RBFNN model
Decay Radial Basis Function Neural Network DRBFNN [21]	-Based on the equality between the number of inputs and the number of output that is equal to the number of model training. -Based on the adjustment of weights through the interconnexion of all RBFNNs. -Used RBF units= 52608 -Epochs= 1000	-Fast training time = 0.19h with RBFNN using 1000 epochs and 52608 RBF units. -High MAPE= 74.74 compared to RBFNN model	-training time = 10s with 1000 RBF and 10 epochs -Low MAPE =1.4 compared to DRBFNN training algorithm
Support Vector Regression SVR [21]	-Based on the fusion of groups of data according to the nearest euclidien distance to build the support vectors based on the input weight and the locations of RBF by adjusting input parameters -Used RBF units = 9040 -epochs= 1000	-high training time= 11 .92 h -MAPE = 2.07 % with 9040 RBF units and 1000 epochs	-3.9<training time < 10s with 1000 to 5000 RBF units and 4 to 10 epochs -1.4 %< MAPE <2.7% with the same parameters.
Extream Learning Machine ELM [8,15]	Algorithms based on the use of orthogonal least squares to find the output weights and the locations of the RBF centers. -Used RBF units = 2500 -epochs=1000	-Reasonable results of MAPE which is equal to 2.19% and training time= 0.24 h -Faster than other training algorithms based ANN despite the use of 2500 RBF units and SVR inputs. -The use of both RBF and SVR inputs complicate the training.	-3.9<training time < 10s with 1000 to 5000 RBF units and 4 to 10 epochs -1.4% <MAPE <2.7% with the same parameters.
Improved Second Order ISO [20]	Iteration algorithms based on the minimization of errors expressed in 1st order by Wk + 1 = WK –a g and in 2nd order by the identity matrix. Adjustment of all parameters related to RBF. -Used RBF units = 70 -epochs=1000	-Generates results 10 times more accurate than SVR. -High computational time. -MAPE = 2.2% -Training time=25 h .	-3.9<training time < 10 s with 1000 to 5000 RBF units and 4 to 10 epochs -1.4 %< MAPE <2.7% with the same parameters.
Error Correction ErrCor [21]	characterized by a single analysis to obtain the optimal solution. -Used RBF units = 100 -epochs=1000	-Results are more accurate compared to ELM and SVR with MAPE= 2.02% And training time= 22h. -Error correction execution time is faster compared to ISO. -The drawbacks of ErrCor are the reduction of the generalization of ANN model and the modification of the overall structure of the network.	-3.9<training time < 10 s with 1000 to 5000 RBF units and 4 to 10 epochs -1.4% <MAPE <2.7% with the same parameters.

5. Conclusions

In this study a novel corrected-ISO method based RBFNN is used for short and long-term photovoltaic load forecasting and performance enhancement and validation. The impact of temperature and load parameters on the accuracy of the forecasted PV load are also investigated. The training time and MAPE are calculated which is found to be more effective than sigmoidal neural network. The training time is found from 3.9s to 10s with corrected ISO method using 1000 to 5000 RBF units and 4 to 10 epochs, which is lower than as obtained by ELM and ISO, which generated 0.027 hours with 200 RBF units and 1.29 h with 100 RBF units and 200 epochs.

RBFNN model demonstrates the forecasted data accuracy, which shows a good agreement in comparison to the targets of England solar PV database. Both MAPE and training time results show the reliability of the present forecasting algorithm based on RBFNN, as compared to sigmoidal neural network and ANN that generate 1.4% to 6.6% and 6.98 % to 16.96% of MAPE in solar radiation forecasting and 3.9 s to 10 s for training time as compared to 2 to 48 h with sigmoidal neural network.
This work can further be extended in a follow up research to deal with the demand side management by using demand-response programs in the context of enhancing the quality of the supply and balancing the offers and the demands.

References

[1] Kukuča Peter et.al. From Smart Metering to Smart Grid, Measurement Science Review, Vol16, N3, 2016. DOI: https://doi.org/10.1515/msr-2016-0017.

[2] A. Abdul Khadar, et.al. Research Advancements Towards in Existing Smart Metering over Smart Grid, International Journal of Advanced Computer Science and Applications, Vol8 ,N5, , 2017. DOI: 10.14569 / IJACSA.2017.080511 .

[3] Zheng J., Gao D., and Lin L., "Smart Meters in Smart Grid: An Overview," presented at the 2013 IEEE Green Technologies Conference, Denver, CO, 2013, DOI: 10.1109 / GreenTech.2013.17.

[4] Etuahene Samual et.al., Artificial Neural Network based Artificial Intelligent Algorithms for Accurate Monthly Load Forecasting of Power Consumption, London Journal of Research in Science, Vol19, N°2, P°1-15, 2019.

[5] Gams Nalcaci et.al., Long-term load forecasting: Models based on MARS, ANN and LR methods, Central European Journal of Operations Research,Vol27, P°1033-1049, 2018.

[6] Hamed H.H.Aly.,A Proposed Hybrid Load Forecasting Models of ANN,WNN and KF based on clustering Techniques for Smart Grids, Electric Power Systems Research, Vol182, N106191, 2020.

[7] Hernandez Luis et.al. Artificial neural network for short-term load forecasting in distribution systems, Energies, Vol7, N 1576-1598, 2014.

[8] A.S Kahweja et.al. Joint Bagged-Boosted ANN: Using ensemble Machine Learning to improve short-term electricity Load Forecasting, Electric Power Systems Research, Vol179, N 106080, 2019.

[9] E. Juan Zarate Perez, Performance Analysis of Bagging Feed-Forward Neural Network for Forecasting Building Energy Demand, Current Journal of Applied Science and Technology Vol 30, N2, P1-12, 2018.

[10] Ravil Bikmetov et.al. "Dynamic prediction capabilities of Smart Metering Infrastructure", Conference Paper, October 2015, DOI: 10.1109 / NAPS.2015.7335235 .

[11] Seung-Mook Baek, Mid Term Load Pattern Forecasting with recurrent Artificial Neural Network, IEEE Access, Vol7, P 172830 à 172838, 2017.

[12] New England ISO Database, available at this link: https://www.iso-ne.com/.

[13] Hernandez Luis, et al., A Survey on Electric power demand forecasting: future trends in smart grids, micro-grids and smart buildings. IEEE Communication Survey Tutorial, Vol16, N3, 2014.

[14] Amit Kumar Yadav, S.S. Chandel, Solar radiation prediction using Artificial Neural Network techniques: A review, Renewable and Sustainable Energy Reviews,Vol 33,N 772-781, 2017.

[15] T. T. Teo, T. Logenthiran and W. L. Woo, "Forecasting of photovoltaic power using extreme learning machine," IEEE Innovative Smart Grid Technologies - Asia (ISGT ASIA), Bangkok, pp. 1-6, 2015. DOI: 10.1109/ISGT-Asia.2015.7387113.

[16] Hernández Luis, Artificial Neural Network for Short-Term Load Forecasting in Distribution Systems, Energies,Vol°7,N° 1576-1598, 2014.

[17]Bodgan M. et.al., A Novel RBF Training Algorithm for Short-Term Electric Load Forecasting and Comparative Studies, IEEE Transactions on Indistrual Electronics, Vol.62, P. 6519 à 6529, 2015.

[18]Xingyu Yan et.al. Solar radiation forecasting causing Artificial Neuronal Network for local power reserve, CISTEM, Vol 106,N 288-297, 2014.

[19] Guillaume Prez et.al. "Impact of the power consumption in the buildings in Central School of Lille", P°1-30, 2018.

[20] Tiantian Xie, Fast and Efficient Second-Order Method for Training Radial Basis Function Networks, IEEE Transactions on Neural Networks and Learning Systems, Vol. 23, N4, 2012.

[21] Haoyan Yang et.al., Short-term forecasting of Micro-grid based on grey correletion analysis and neural networ optimized by mind evolutionary algorithm, IEEE PES Innovative Smart Grid Technologies Asia, P° 2738-2742, 2019.

[22] Amit Kumar Yadav, SS Chandel, Artificial Neural Network based Prediction of Solar Radiation for Indian Stations, International Journal of Computer Applications, Vol50 – No.9, 2012.

[23] Amit Kumar Yadav, Vikrant Sharma, Hasmat Malik, SS Chandel ,Daily array yeild of grid-interactive photovoltaic plant using relief attribute evaluator based Radial Basis Function Neural Network, Renewable and Sustainable Energy Reviews, Vol81, N2, P° 2115-2127, 2017.

[24] Amit Kumar Yadav, Hasmat Malik, SS Chandel, Selection of most relevant input parameters using WEKA for artificial neural network based solar radiation prediction models ; Renewable and Sustainable Energy Reviews, Vol31, N31, P° 509-519, 2014.

[25] Gabriel Trierweiler Ribeiro et.al., Enhanced ensemble structures using wavelet neural networks applied to short-term load forecasting, Engineering Applications of Artificial Intelligence, Vol95, P°103852, 2020.

[26] Yang Zhang et.al., A novel integrated price and load forecasting method in smart grid environment based on multi-level structure, Vol95, N103852, 2019.
[27] Chao-Ming Huang et.al., One-day-ahead hourly forecasting for photovoltaic power generation using an intelligent method with weather-based forecasting models, IET Generation, Transmission & Distribution, Vol. 9, Iss. 14, pp. 1874–1882, 2015.
[28] Weibiao Qiao et.al., A Novel Hybrid Prediction Model for Hourly Gas Consumption in Supply Side Based on Improved Whale Optimization Algorithm and Relevance Vector Machine, IEEE Access, 2019.
[29] Yuxin Wen et.al., Performance Evaluation of Probabilistic Methods Based on Bootstrap and Quantile Regression to Quantify PV Power Point Forecast Uncertainty, IEEE Transactions On Neural Networks And Learning Systems, Vol.,31, N4, 2020[30]Florin Dragomir, Forecasting of Photovoltaic Power Generation by RBF Neural Networks, Advanced Materials Research, ISSN: 1662-8985, Vol. 918, pp 200-205, 2017.
[31] Amit Kumar Yadav , S.S. Chandel, Artificial Neural Network based Prediction of Solar Radiation for Indian Stations, International Journal of Computer Applications, Vol50 – No.9, July 2012.
[32] Samuel Atuahene, et.al. Artificial Neural Network based Artificial Intelligent Algorithms for Accurate Monthly Load Forecasting of Power Consumption, London Journal of Research in Science, Natural and Formal, Vol 19, Issue2, 2019
[33] Muhammed Wasseem et.al. Data-Driven Load Forecasting of Air Conditioners for Demand Response Using Levenberg–Marquardt Algorithm-Based ANN, Big data and Cognitive Computing,Vol3,N36, 2019.
[34] E. Juan Zarate Perez, Performance Analysis of Bagging Feed-Forward Neural Network for Forecasting Building Energy Demand, Current Journal of Applied Science and Technology
Vol 30, N2, P1-12, 2018.
[35] Farshid Keynia, A new feature selection algorithm and composite neural network for electricity price forecasting, Engineering Applications of Artificial Intelligence, Vol25, P1687–1697, 2012.
[36] Ramesh KumarV et.aL, Daily peak load forecast using artificial neural network, International Journal of Electrical and Computer Engineering, Vol 9, N4, P. 2256~2263, 2019
[37] Jingwen Tian, Meijuan Gao, Fan Zhang, Network intrution detection method based on radial basis function neural network, IEEE Natural Computation workshop, 2009.
[38] Liu, J. (2013). Radial Basis Function (RBF) neural network control for mechanical systems: design, analysis and Matlab simulation. Springer Science & Business Media.

Ben Farhat Arwa received the B.E. and M.E. degrees, from university of Tunis El manar 2012 and 2015, respectively. She started the Ph.D in 2017 in university of carthage. After working as a temporary assistant professor in the Dept. of computer sciences, in ESSEC BUSINESS school, Her research interest includes the use of Machine Learning methods for the short and long term load forecasting.