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Deep Neural Network Using New Training Strategy Based Forecasting Method for Wind Speed and Solar Irradiance Forecast

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Abstract: In line to meet the energy exigency, renewable energies like wind and solar receive remarkable popularity, expeditious enlargement of power generation from wind and solar energy entails acute forecasting of wind speed and solar irradiation therefore, it has been an intensive research field in recent and past years. This paper endeavor prediction of wind speed and solar irradiance concern to various time horizons with the help of the new training strategy based deep neural network, which aimed to enable furtherance power system working and management. The deep neural network initial model is developed by means of the generative model (unsupervised pre training) thereafter the development framework is trained (fine tuned) using self regulated particle swarm optimization (SPSO) algorithm. Thus, the optimal parameters of deep neural network (DNN) achieved, which lead to further reduce the error index and advance the forecasting accuracy for both applications like wind speed and solar irradiance forecasting. This paper also covered to identify the best framework of proposed new strategy based deep neural network concern to hidden layer and hidden neurons. Evaluation outcomes convey that the difference between the forecast output and the original target value is very low.

Key words: Renewable energy system · Forecasting · Artificial intelligence · Deep Learning · Optimization

INTRODUCTION

In the light of changing and intermitted of renewable energy generation from wind and solar energy, the power system operator and vendor are feeling the essentiality for more intelligent and flexible forecasting method. As in smart grid, virtual power plant, micro grid and so on the forecast of wind speed and solar irradiance led to a key aspects of successful optimized operation and management of the power system. Numerous researchers are actively suggested lots of forecasting techniques. Along with the development as applied to the research area of wind speed and solar irradiance forecasting. Existing techniques had not enough to produce the best outcomes, stability and generalization ability for multi-time horizon forecasting. This ignites new ideas to improve the forecasting accuracy in the field of wind speed and solar irradiance forecasting for multi horizon range. An artificial neural network is a computer system which replicates the human brain behavior. In the field of machine learning deep learning is a new concept which is emerged by Hinton *et al*. [1-3]. Special attention to be paid on deep neural network due to its extend generalization, problem solving ability with good solutions and convergence. The deep neural network is very appealing thus, provides a pathway for many improvements, in recent research deep neural network parameter optimizations are performed concern to harmony search [4], PSO [5] and GA [6].

For many hidden layers comprised network learning algorithm only back propagation not able to provide a feasible outcome, it took much time to converge and entrapped into local optima or minima in order to get rid of these limitations pre training followed training is performed using self regulated particle swarm optimization.

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Problem Background and Earlier Published Research: Renewable energies fulfill the energy dependency in which solar and wind energy plays an imperative role due to eco-friendly and availability but these resources depends on the meteorological aspects thus possess the uncertainty and haphazardness nature. This creates power quality, integration, reserve capacity related issues in distributed generation and micro grid system. Solar and wind farms optimal working strategies are determined by wind speed and solar irradiance forecasting. With respect to wind energy very high wind speed cause breakdown while low wind speed not enough to produce productive outcomes, similarly for solar energy, low or null and high solar irradiance cause issue related to battery charger life time and effective productive outcomes. In addition to this the uncertainty also led critical issue with respect to feasible working of the power system. The aforementioned problems are alleviated by means of the various time horizon forecasting of wind speed and solar irradiance. Henceforth, acute forecasting of wind speed and solar irradiance is one of the emerging research topics.

Lots difficult real-time applications are not solved precisely by the shallow neural network. Thus, neural network with one or more hidden layers, i.e deep neural network possess the ability to dealt such a complexities to a great extent. The problem associated with many hidden layer based neural network (i.e. Deep neural network) are as follows:

- Over fitting and under fitting.
- Fails to escape from local minima.
- Poor generalization error.

The deep neural network tends to vanish gradient with respect to small initial weight initialization similarly deep neural network attains unsatisfied convergence with regard to high initial weight. Thus, choosing the best initial weights is a tough task, which can be overcome by pre training. High value parameter leads to over fitting (training error is good while testing error is bad); regularization is used to avoid over fitting. Hence, aforementioned problem related to deep neural network is eliminated by means of the proposed new training strategy based deep neural network, regularization is done with the help of pre training based on stacked restricted Boltzmann machine and training is done by means of self regulated particle swarm optimization. This paper bids SPSO based training of deep neural network (topology based on deep belief network) to forecast acute wind speed and solar irradiance.

Relevant Works for Considering Application Are Reported as Below: Madhiarasan, M & Deepa, S. N 2016 [7] studied wind speed forecasting performance with respect to various time scale range regards to six artificial neural network including novel networks (RRBFN and IBPN) and popular well known networks (MLP, BPN, RBFN, Elman). The novel network based forecasting shown better quality of forecasting concern to wind speed forecasting on Coimbatore region three data sets. Madhiarasan, M & Deepa, S. N 2016 [8] carried out work to forecast the wind speed using multilayer perceptron neural network, in which appropriate hidden neuron is estimated with the help of certain criteria. Remarks: Compared with other criterion suggested criterion lead to good outcome concern to wind speed forecasting application. Zhi Li *et al*. 2016 [9] presented a combinational prediction model for ultra short term wind power forecasting which is modeled by means of the extreme learning machine and error correction approach. Madhiarasan, M & Deepa, S. N 2016 [10] suggested four absolute networks based ensemble neural network in order to forecast wind speed with regard to different time horizons. Validity confirmed with the help k-fold cross validation. Madhiarasan, M & Deepa, S. N 2016 [11] performed hybrid technique based on (IMGWOA) improved modified grey wolf optimization algorithm and improved spike prop adopted spiking neural network. Applicability is tested with regards to wind speed forecasting in long term horizons. Tiago Pinto *et al*. 2014 [12] pointed out eRBF (exponential radial basis function) and RBF (radial basis function) kernels associated support vector machine for short term wind speed forecasting. Remark: compared to ANN based methods eRBF kernel based SVM made good forecasting outcomes. Madhiarasan, M & Deepa, S. N 2016 [13] presented wind speed forecasting method based on improved back propagation networks and better framework concern to hidden neurons in the hidden layer is pointed out by means of the novel criterion. Madhiarasan, M & Deepa, S. N 2016 [14] novel MGWO (modified grey wolf optimizer) associated Elman neural network is established for wind speed forecasting. An optimal hidden unit is determined by new criteria. Remarks: The validity of the proposed method is proved based on comparative analysis. Madhiarasan, M., Deepa, S.N. 2016 [15] recommended recursive radial basis function network based wind speed forecasting model in which appropriate hidden neuron number is estimated with the help of the new criterion, meanwhile performed result analyze concern to training

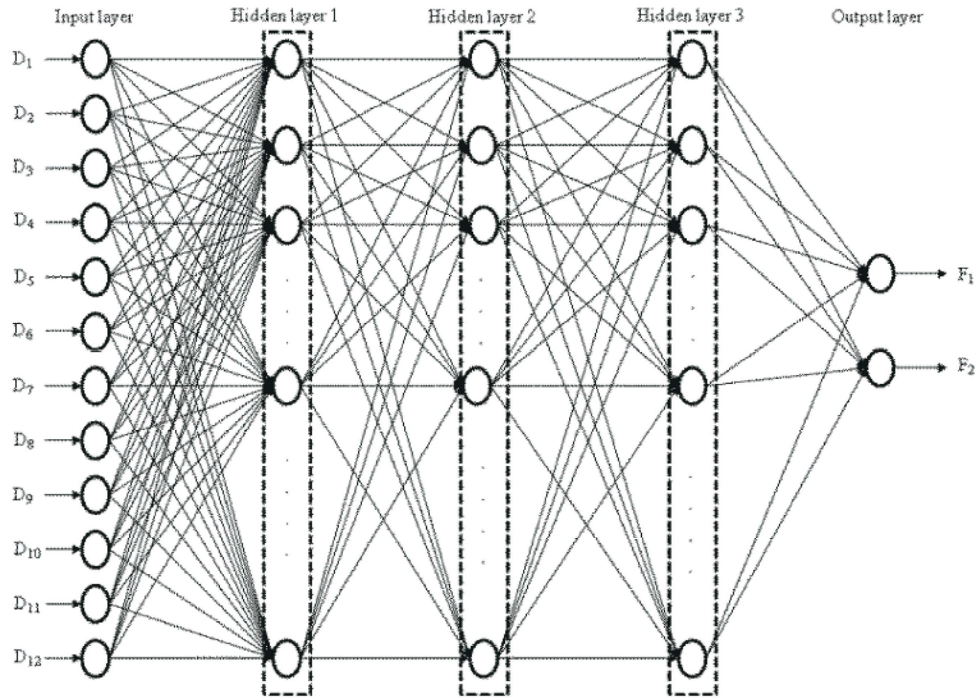

Fig. 1: Deep neural network framework

and testing data classification and the best percent of training and testing data set is determined. Thus, pointed out model results superior performance in terms of accuracy, convergence, generalization and stability.

C. S. Ioakimidis *et al*. 2013 [16] reported multilayer perceptron neural networks based 24 hours ahead solar irradiance forecasting, with the help of the predicted solar irradiance PV power output also estimated. Remarks: Size of the input data are minimized by statistical feature parameters. Madhiarasan, M & Deepa, S. N 2016 [17] bid to develop the solar irradiance estimation model with the help of innovative neural network in which apt hidden neurons are identified concern to the proposed novel deciding standard. T. Burianek and S. Misak 2016 [18] suggested extreme learning machine based forecasting model in order to forecast solar irradiance, validity is confirmed with 5 fold cross validation. Testing error RMSE mean±STD for solar irradiance forecasting is 0.2857±0.0368. K. A. Baharin *et al*. 2014 [19] pointed out the support vector machine based solar irradiance forecasting model, which is performing well than that of persistence and conventional MLP for hourly solar irradiance forecasting.

Based on the analysis of previous work, it can be noted that some of them focused to contribute towards the furtherance of power system working, control and management, but pervious published works are not able to fulfill the above requirement to the extent thus leave a room for research. This paper proposes a new state of the art method for wind speed and solar irradiance forecasting using a deep neural network trained by the SPSO.

Baseline of Proposed Method

Model Construction: Multilayer feed-forward neural network with more than one hidden layer is describing a deep neural network. Deep neural network framework with three hidden layers, one input layer and one output layer is illustrated in Figure 1. Unsupervised pre training endorses to promote better convergence without sticking into local optima. During pre training process, the contrastive divergence based stacked RBM (Restricted Boltzmann Machine) is performed. The normalized data are given as inputs (visible) for the first RBM; thereafter output of the first RBM is used as the hidden activation for second or immediate RBM. In this manner all stacked RBMs are extracting the significant feature concern to the inputs RBM. This process performed iteratively up to the most right side of RBM. This type of layer-by-layer pre training improves the deep neural network performance by means of better initialization. For proposed deep neural network SPSO based training is incorporated followed by unsupervised pre training, which result the better forecasting performance.

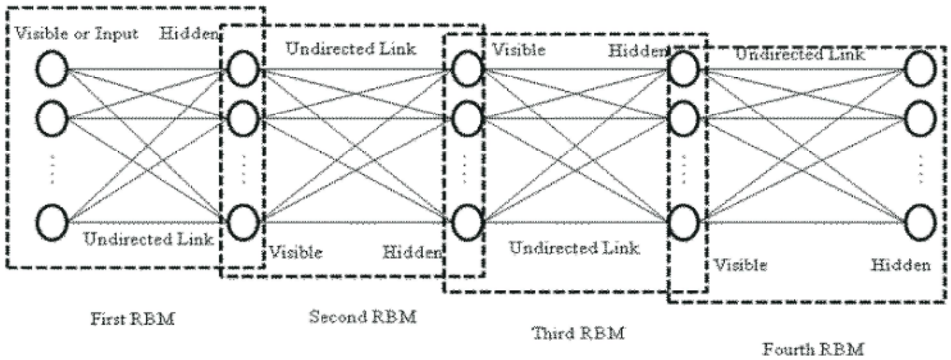

Fig. 2: Structure of stacked RBM

Table 1: Input variables & output variable description with units

	Variables	Description	Units
Input	D_1	Solar Irradiance	W/m^2
	D_2	Maximum Temperature	Degree Celsius
	D_3	Minimum Temperature	Degree Celsius
	D_4	Sun Shine Hours	Hours
	D_5	Pressure	mbar
	D_6	Cloud Cover	Okta
	D_7	Dew Point	Degree Celsius
	D_8	Direct Normal Irradiance	W/m^2
	D_9	Wind Direction	Degree
	D_{10}	Precipitation of Water Content	%
	D_{11}	Wind Speed	m/s
	D_{12}	Relative Humidity	%
Output	F_1	Forecast Wind Speed	m/s
	F_2	Forecast Solar Irradiance	W/m^2

Reason for Considering Input Variables: The output power generation from wind and solar energy possess a stochastic behavior because it directly depends on wind speed and solar irradiance which is influenced by atmospheric weather conditions like temperature, cloud cover, wind direction, pressure, precipitation of water content, relative humidity, dew points and so on. By taking into account of the environmental real-value variables like wind speed, wind direction, solar irradiance, minimum temperature, maximum temperature, sunshine hours, relative humidity, dew point, precipitation of water content, pressure, cloud cover, as a inputs, which provides the furtherance ability to forecast the wind speed and solar irradiance because these variables are highly related to wind speed and solar irradiance. Hence, it is easy to forecast the unseen testing data samples with precise results. The proposed framework input and output variable descriptions with units are clearly pointed out in Table 1.

Role of Stacked RBM for Deep Neural Network and Mathematical Foundation: The deep neural network better weight initialization obtains by adopting stacked restricted Boltzmann machine (SRBM), in which the left side RBM aid for computation of the right side RBMs. Most right hidden layer meaningful and effective representation of the input data is achieved by stacked restricted Boltzmann machine. The structure of SRBM is shown in Figure 2.

Energy functions of RBM

$$E(d,h) = -\sum_m b_m d_m - \sum_n c_n h_n - \sum_m \sum_n d_m s_{mn} h_n \tag{1}$$

Matrix Form

$$E(d,h) = -b^T d - c^T h - d^T sh \tag{2}$$

where, d – visible or input vector, h – hidden vector, b – bias term related to input or visible layer, c – bias term related to the hidden layer, s – synaptic connections.

With respect to energy function the probability distribution over the connecting link is expressed as follows:

$$P(d,h) = \frac{1}{Z} e^{-E(d,h)} \tag{3}$$

$$Z = \sum_{d,h} e^{-E(d,h)} \tag{4}$$

Z- Normalizer or partition function i.e. sum of all links or connections.

Visible or input vector probability or marginal probability.

$$P(d) = \frac{1}{Z} \sum_h e^{-E(d,h)} \tag{5}$$

Probability of hidden neurons with respect to given input for providing h=1

$$P\left(h_n = 1 \middle| d\right) = \sigma\left(c_n + \sum_m d_m s_{mn}\right) \tag{6}$$

σ – Tangent hyperbolic activation function.

Similar for probability of input neurons with respect to hidden vectors h for providing d=1.

$$P\left(d = 1 \middle| h\right) = \sigma\left(b_m + \sum_n b_n s_{mn}\right) \tag{7}$$

Stochastic gradient descent constructive divergence.

$$\Delta s_{mn} = \alpha\left(\langle dh\rangle_{data} - \langle dh\rangle_{model}\right) + \eta\left(\langle dh\rangle_{data} - \langle dh\rangle_{model}\right) \tag{8}$$

Constructive divergence is a form of regularization. The constructive divergence is akin to Gibbs sampling with k=1. Sparse auto encoder is very costly compared to SRBM.

Synaptic or Weight matrix updating formulation.

$$s^{t+1} = s^t + \alpha\left(E\left[hd\right]^{data} - E\left[hd\right]^{model}\right) + \eta\left(E\left[hd\right]^{data} - E\left[hd\right]^{model}\right) \tag{9}$$

$$E\left[hd\right]^{model} = P\left(\tilde{h}\middle|\tilde{d}\right) \tag{10}$$

Bias vise and hidden neurons are modified using the following formula.

$$s^{t+1} = s^t + \alpha\left(P\left(h\middle|d\right)d^T - P\left(h\middle|\tilde{d}\right)d^T\right) - \gamma s^t + \eta\Delta s^{t-1} \tag{11}$$

$$c^{t+1} = c^t + \alpha\left(d - \tilde{d}\right) + \eta\Delta c^{t-1} \tag{12}$$

$$b^{t+1} = b^t + \alpha\left(P\left(h\middle|d\right) - P\left(\tilde{h}\middle|\tilde{d}\right)\right) + \eta\Delta b^{t-1} \tag{13}$$

Expectation under the distribution data are denoted by angle brackets.

where, γ- Synapses or weight decay variable.
α- Learning rate.
η- Momentum factor.

The low energy is obtained by changing the weights, which is the process takes place in optimization phase. During the pre training stage the use of stacked restricted Boltzmann machine leverage the low energy with good weight and bias initialization. The parameters are learned locally using unsupervised way for single hidden layer, with the same training set identified parameter for first hidden layer is fixed, then the second hidden layer is added to identify the parameters for second hidden layer similar manner subsequent hidden layer parameters are identified for the given input representation. Finally, output layer is added and as a whole the pertained hidden layer linked output layer are trained by the SPSO.

Role of SPSO for Deep Neural Network and Mathematical Model: PSO is more powerful population based optimization algorithm and it has the ability to solve any optimization problem with promising solution, which is developed by Kennedy, J & Eberhart, R. in the year of 1995 [20] and new version of PSO is known as NPSO (new particle swarm optimization) proposed by Immanuel Selvakumar, A & Thanushkodi, K [21]. Thus, possess outperform capability than GA and make competitive result compared to a novel optimization algorithm. In this paper search agent (particle) searching ability is effectively improved by self regulating behavior that is search agent worst and good positions are taken into consideration in the velocity modification formulation. Thus, search agent regulates them self based on the best and worst experience regards to position, the best experience cognitive calculation acceleration factor assists for the search agent to attain the best position while the worst experience cognitive calculation acceleration factor aid search agent away from the bad position. Incorporation of the search agent worst experience into the velocity updates equation aid for effective exploration.

The neural network initialization process is performed with the help of the unsupervised stacked restricted Boltzmann machine based pre training; thereafter the self regulated particle swarm optimization algorithm is adapted

Table 2: Proposed deep neural network set values.

Proposed Neural Network	Variables	Set Values
Proposed Deep Neural Network	Number of input neurons	12
	Number of hidden layers	$H_l \in$ {1, 2, 3, 4 &5}
	Number of hidden neurons	$N_h \in$ {25, 50, 75, 100, 125, 150, 175& 200}
	Number of Output neurons	2
	Epochs	50
	Threshold	1
	Learning rate	0.01
	Momentum factor	0.9

Table 3: Self regulated particle swarm optimization algorithm set values

Algorithm	Variables	Set Values
SPSO	Number of particles	60
	Number of generations	100
	w	Random values
	r_1, r_2 & r_3	Random values
	c_{cb}' & c_{cw}'	2
	c_s'	2

for fine tuning i.e search the exact optimal value to lead a great extent outcome. Weight space region is created by pre training process from this weight space region the optimal weights are determined with the help of self regulated particle swarm optimization algorithm. This paper, polishing up the deep neural network by means of the self regulated particle swarm optimization (SPSO) during fine tuning process, this might furtherance network stability, generalization and accuracy.

Velocity and position modification formulation are expressed as follows:

$$\begin{aligned}\omega_i^k(n+1) = w \cdot \omega_i^k(n) + c_{cb}' \cdot r_1 \cdot \left(P_{besti}^{\;k}(n) - \phi_i^k(n)\right) + \\ c_{cw}' \cdot r_2 \cdot \left(\phi_i^k(n) - P_{worsti}^{\;k}(n)\right) + \\ c_s' \cdot r_3 \cdot \left(G_{besti}^{\;k}(n) - \phi_i^k(n)\right)\end{aligned} \quad (14)$$

$$\phi_i^k(n+1) = \phi_i^k(n) + \omega_i^k(n+1) \quad (15)$$

where, w- Inertia weight, c_{cb}'- best experience cognitive calculation acceleration factor, c_{cw}'-worst experience cognitive calculation acceleration factor c_s'-social calculation acceleration factor, r_1, r_2 & r_3 -random variables, $\phi_i^k(n)$ -current position of search agent i in dimension k at iteration n, $P_{best_i}^{\;k}(n)$ -best position of search agent i in dimension k at iteration n, $P_{worst_i}^{\;k}(n)$ -worst position of search agent i in dimension k at iteration n $G_{best_i}^{\;k}(n)$- among the group of search agent the global best position, $\omega_i^k(n)$ -velocity of search agent i in dimension k at iteration n.

Model Evaluation: The suggested method is programmed in MATLAB and experimental set values for deep neural network and self regulated particle swarm optimization algorithm are presented in Table 2 and 3 respectively. An average of 10 runs taken in order confirms the stability. The proportions of training and testing data set are classified as 70% and 30% respectively, which were acquired from the National Oceanic and Atmospheric Administration, United States with respect to all input variables correspond to the periods of 10 years from 2005 to 2015. The research work carried out here proposed new training strategy associated deep neural network. Furthermore, the adequate number of hidden layers is identified by evaluation with $H_l \in$ {1, 2, 3, 4 &5} and adequate amount of hidden neurons is identified by evaluation with $N_h \in$ {25, 50, 75, 100, 125, 150, 175, 200}.

Procedures Involved in the Proposed Strategy: The execution procedure of the proposed method is elucidated as follows, for better ease of understanding the proposed method flowchart is portrayed in Figure 3.

Procedure 1: Acquire the input data samples for the chosen application.

Procedure 2: Input the considered input variables (acquired data samples) and perform normalization process.

Acquired data's normalized with the help of MinMax technique and formulation is expressed as

$$d_{acquired}' = \left(\frac{d_{acquired} - d_{acquired\_\min}}{d_{acquired\_\max} - d_{acquired\_\min}}\right) \left(d_{t\arg et\_\max}' - d_{t\arg et\_\min}'\right) + d_{t\arg et\_\min}' \quad (16)$$

Let, $d_{acquired}$ -acquired input data, $d_{acquired\_\min}$-minimum of the acquired input data, $d_{acquired\_\max}$-maximum of the acquired input data, $d_{t\arg et\_\min}'$ -minimum of the original target, $d_{t\arg et\_\max}'$ -maximum of the original target.

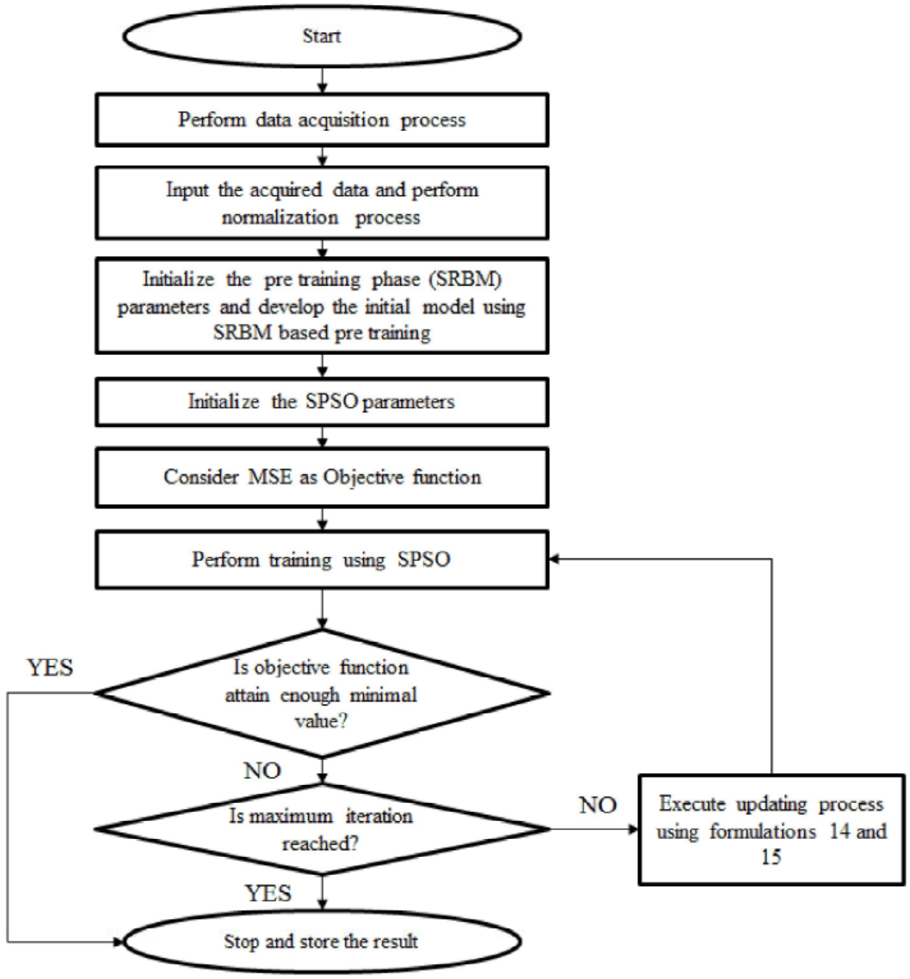

Fig. 3: Proposed method flow charts

Procedure 3: Initialize the network parameters and develop the deep neural network initial model using stacked restricted Boltzmann machine (SRBM) based pre training.

Procedure 4: Initialize the self regulated particle swarm optimization algorithm parameters and chosen the objective functions as a minimization of mean square error.

Objective Function:

Objective function = minimization of mean square error (MSE) (17)

$$\text{Mean square error (MSE)} = \frac{1}{T}\sum_{a=1}^{T}(F_a^{'} - F_a)^2 \qquad (18)$$

Let, T- total amount of acquired data samples, $F_a^{'}$ -Original target, F_a -Forecast output.

Procedure 5: Perform training using self regulated particle swarm optimization algorithm, check whether the objective function attain the enough minimal value if yes, stop and store the outcome else check whether the maximum iteration is reached or not if no means execute the updating process using formulation 14 and 15 until the maximum iteration otherwise end the process and store outcome.

Results Concern to a Framework Assessment of the Proposed Method for Considering Applications: The proposed strategy adopted deep neural network performance with regards to the aspects of hidden neurons and hidden layers for the considered applications such as wind speed forecasting and solar irradiance forecasting are reported in Table 4 and 5 respectively. Evaluation of the proposed method concern to the framework assessment is performed taken mean squared error as an evaluation error index; the hidden layers are varied from 1 to 5 similarly hidden neuron are also varied from 25 to 200 for each hidden layer. The outcomes of each combination with respect to the taken evaluation error index are tabulated in Table 4 and 5 as the best, mean and standard deviation (STD) for wind speed forecasting and solar irradiance forecasting respectively. According to the least evaluation error index (mean square error) the adequate number of hidden layers and adequate number of hidden neurons respect to that hidden layer is identified.

Framework Based Assessment for Wind Speed Forecasting: Wind speed forecasting is performed using the proposed method and carried out analysis regards to the framework.

According to the results in Table 4 the best framework of the proposed method is determined as 3 hidden layers and 125 hidden neurons. The plots with respect to the best framework for wind speed forecasting are presented in Figures 4-8. Figure 4 shows the number of datum vs. input samples of wind speed. Forecasts wind speed obtained by the proposed method compared with the original data respect to the number of data samples is represented in Figure 5, for better understanding log plot is also shown in Figure 6. Evaluation error index with respect to number of datum is depicted in Figure 7 and a plot of outputs vs. targets for wind speed forecasting is showcased in Figure 8. Proposed method produces acute forecasts of wind speed due to this highest accuracy the forecast wind speed akin to the original target which is perceived from Figure 5 & 6, thus the error index is very minimal and R (regression) =1 which are noted from the Figures 7 & 8 respectively.

Table 4: Proposed method framework based assessment for wind speed forecasting

Proposed Strategy Associated Deep Neural Network Framework						
Amount of hidden neurons in each hidden layer		Evaluation Error Index (MSE)				
		1 Hidden layer	2 Hidden layers	3 Hidden layers	4 Hidden layers	5 Hidden layers
25	BEST	9.2974e-12	2.3605e-13	5.2373e-19	4.6045e-19	4.3174e-19
	MEAN	9.8050e-12	2.9628e-13	6.1706e-19	4.9128e-19	4.7778e-19
	STD	7.7663e-06	8.5170e-08	4.6011e-10	4.4728e-10	4.2041e-10
50	BEST	5.2939e-13	6.6265e-14	4.0654e-19	3.5025e-19	3.1315e-19
	MEAN	5.7765e-13	6.9243e-14	4.8238e-19	3.7296e-19	3.4849e-19
	STD	9.4536e-08	5.3360e-08	3.6210e-10	3.5949e-10	3.3510e-10
75	BEST	2.1971e-14	8.5037e-15	2.4712e-19	2.1517e-19	1.8296e-19
	MEAN	2.7859e-14	8.9453e-15	3.0923e-19	2.5441e-19	2.0259e-19
	STD	3.8077e-08	1.1950e-08	2.9628e-10	2.7108e-10	2.3355e-10
100	BEST	2.1969e-14	6.2853e-16	1.3896e-19	1.2292e-19	1.0773e-19
	MEAN	2.7857e-14	6.7945e-16	1.8726e-19	1.5567e-19	1.3181e-19
	STD	3.8075e-08	4.3518e-09	1.6758e-10	1.4226e-10	1.1758e-10
125	BEST	2.1966e-14	6.2850e-16	9.4996e-20	9.4996e-20	9.4994e-20
	MEAN	2.7854e-14	6.7941e-16	9.8050e-20	9.8050e-20	9.8048e-20
	STD	3.8073e-08	4.3515e-09	7.3795e-11	7.3794e-11	7.3793e-11
150	BEST	2.1963e-14	6.2847e-16	9.4995e-20	9.4995e-20	9.4993e-20
	MEAN	2.7851e-14	6.7939e-16	9.8049e-20	9.8048e-20	9.8046e-20
	STD	3.8072e-08	4.3513e-09	7.3793e-11	7.3792e-11	7.3791e-11
175	BEST	2.1961e-14	6.2843e-16	9.4994e-20	9.4994e-20	9.4991e-20
	MEAN	2.7849e-14	6.7936e-16	9.8047e-20	9.8046e-20	9.8044e-20
	STD	3.8070e-08	4.3511e-09	7.3792e-11	7.3791e-11	7.3789e-11
200	BEST	2.1960e-14	6.2842e-16	9.4992e-20	9.4992e-20	9.4989e-20
	MEAN	2.7848e-14	6.7934e-16	9.8045e-20	9.8044e-20	9.8041e-20
	STD	3.8067e-08	4.3509e-09	7.3791e-11	7.3790e-11	7.3787e-11

Table 5: Proposed method framework based assessment for solar irradiance forecasting

Proposed Strategy Associated Deep Neural Network Framework						
Amount of hidden neurons in each hidden layer		Evaluation Error Index (MSE)				
		1 Hidden layer	2 Hidden layers	3 Hidden layers	4 Hidden layers	5 Hidden layers
25	BEST	1.3817e-10	8.3329e-12	6.1778e-16	5.7043e-16	5.5391e-16
	MEAN	1.9765e-10	8.8697e-12	7.1217e-16	6.8408e-16	6.7055e-16
	STD	3.0253e-05	9.5365e-07	1.6657e-08	1.2863e-08	1.0124e-08
50	BEST	7.8323e-11	5.4472e-13	1.5071e-16	1.3392e-16	1.1289e-16
	MEAN	8.1119e-11	5.9677e-13	2.4955e-16	1.8235e-16	1.6409e-16
	STD	4.7436e-06	8.1119e-07	8.8476e-09	8.3987e-09	7.7091e-09
75	BEST	5.4630e-12	3.5414e-13	8.0134e-17	7.5709e-17	7.0529e-17
	MEAN	5.8436e-12	3.8327e-13	9.2974e-17	7.7845e-17	7.3656e-17
	STD	7.7115e-07	6.5318e-08	6.1778e-09	5.5170e-09	5.0207e-09
100	BEST	5.4625e-12	1.6196e-14	4.5258e-17	3.8112e-17	3.1220e-17
	MEAN	5.8431e-12	1.9760e-14	6.2275e-17	4.0959e-17	3.4734e-17
	STD	7.7112e-07	1.2292e-08	5.7720e-09	5.1030e-09	4.1121e-09
125	BEST	5.4618e-12	1.6189e-14	1.8526e-17	1.8526e-17	1.8523e-17
	MEAN	5.8426e-12	1.9752e-14	2.2941e-17	2.2940e-17	2.2938e-17
	STD	7.7109e-07	1.2287e-08	3.9419e-09	3.9418e-09	3.9416e-09
150	BEST	5.4617e-12	1.6186e-14	1.8524e-17	1.8524e-17	1.8522e-17
	MEAN	5.8424e-12	1.9750e-14	2.2939e-17	2.2938e-17	2.2937e-17
	STD	7.7105e-07	1.2284e-08	3.9415e-09	3.9414e-09	3.9412e-09
175	BEST	5.4615e-12	1.6183e-14	1.8523e-17	1.8523e-17	1.8521e-17
	MEAN	5.8423e-12	1.9747e-14	2.2938e-17	2.2936e-17	2.2935e-17
	STD	7.7103e-07	1.2281e-08	3.9413e-09	3.9412e-09	3.9410e-09
200	BEST	5.4615e-12	1.6182e-14	1.8522e-17	1.8522e-17	1.8520e-17
	MEAN	5.8422e-12	1.9746e-14	2.2936e-17	2.2935e-17	2.2932e-17
	STD	7.7101e-07	1.2279e-08	3.9411e-09	3.9410e-09	3.9408e-09

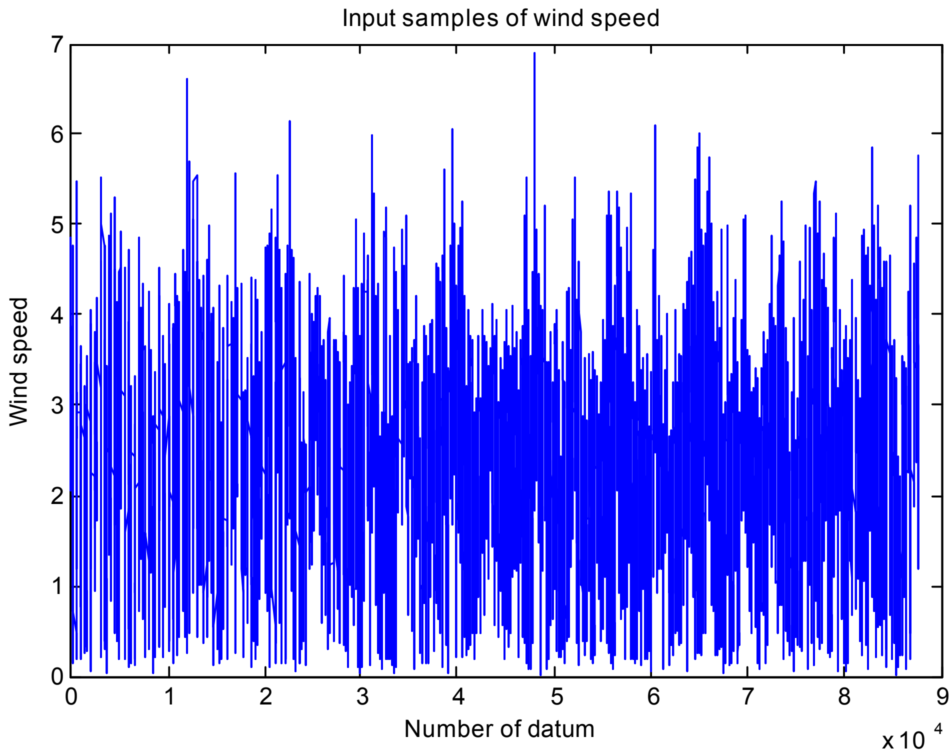

Fig. 4: Number of datum vs. Input samples of wind speed

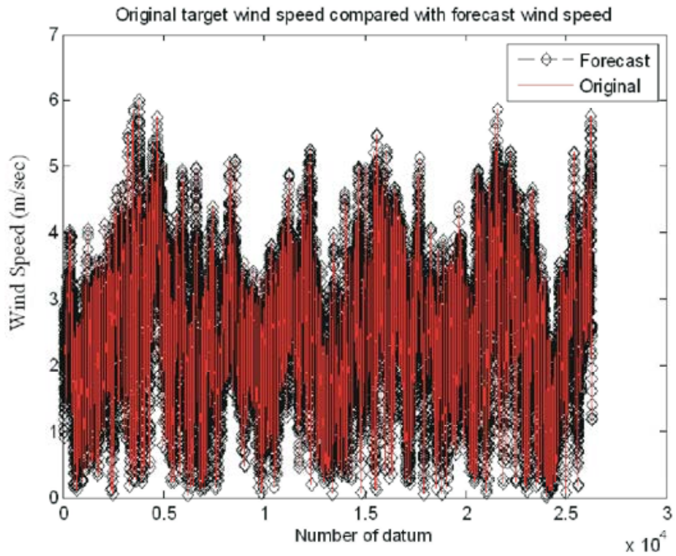

Fig. 5: Original target wind speed compared with forecast wind speed

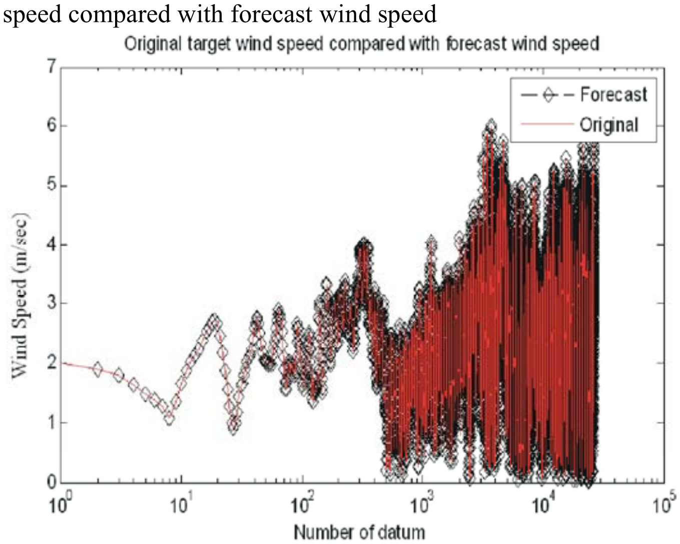

Fig. 6: Log plot of original target wind speed compared with forecast wind speed

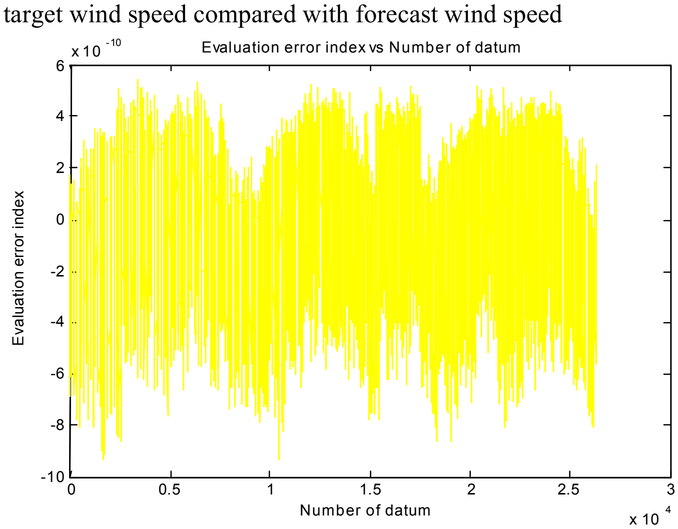

Fig. 7: Evaluation error index vs. Numbers of datum for wind speed forecasting

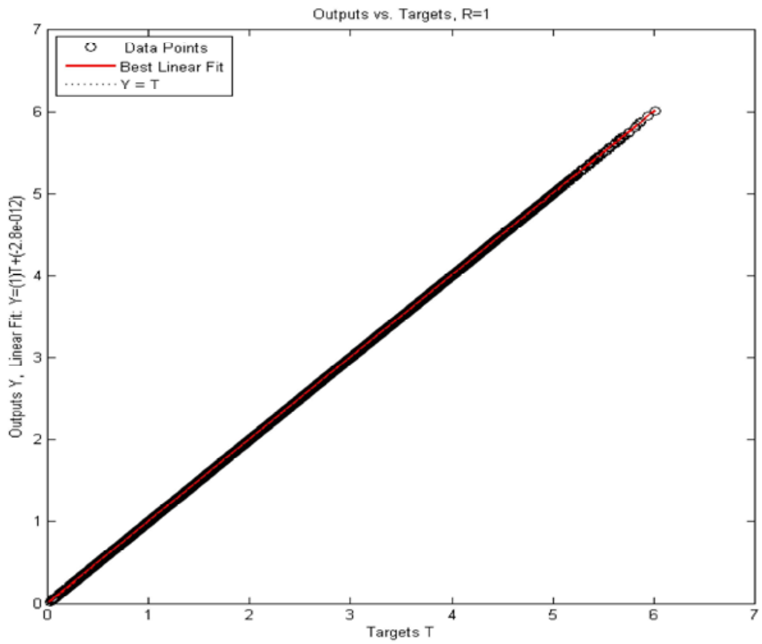

Fig. 8: Plot of outputs vs. targets for wind speed forecasting

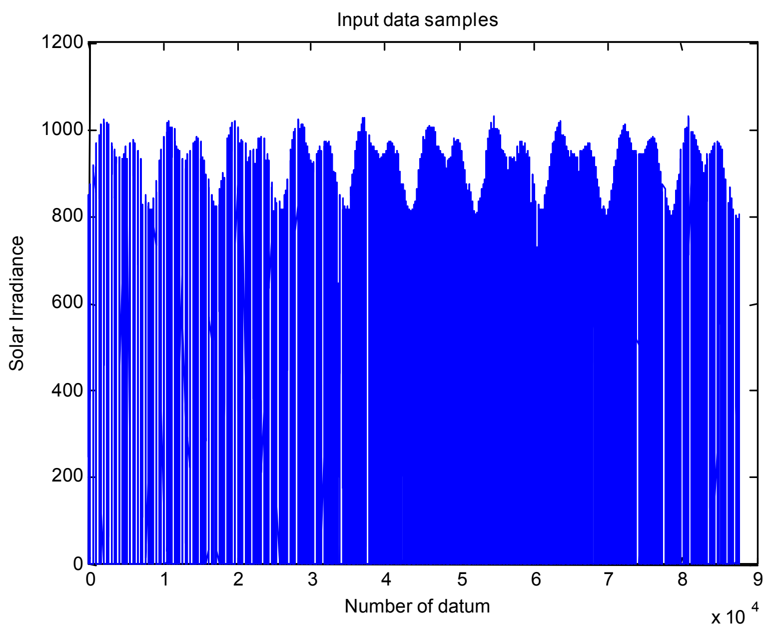

Fig. 9: Number of datum vs. Input samples of solar irradiance

Framework Based Assessment for Solar Irradiance Forecasting: Solar irradiance forecasting is carried out using the proposed method and performed analysis with respect to the framework.

Based on the results in Table 5 the best framework of the proposed method is determined as 3 hidden layers and 125 hidden neurons. The plots with respect to the best framework for solar irradiance forecasting are shown in Figures 9-13. Figure 9 represents the number of datum vs. input samples of solar irradiance. Forecast solar irradiance achieved by suggesting method compared with the original data respect to the number of data samples is represented in Figure 10, for better understanding log plot is also shown in Figure 11. Evaluation error index with respect to number of datum is depicted in Figure 12 and a plot of outputs vs. targets for solar irradiance forecasting is showcased in Figure 13. Proposed method makes effective forecasts of solar irradiance because of this

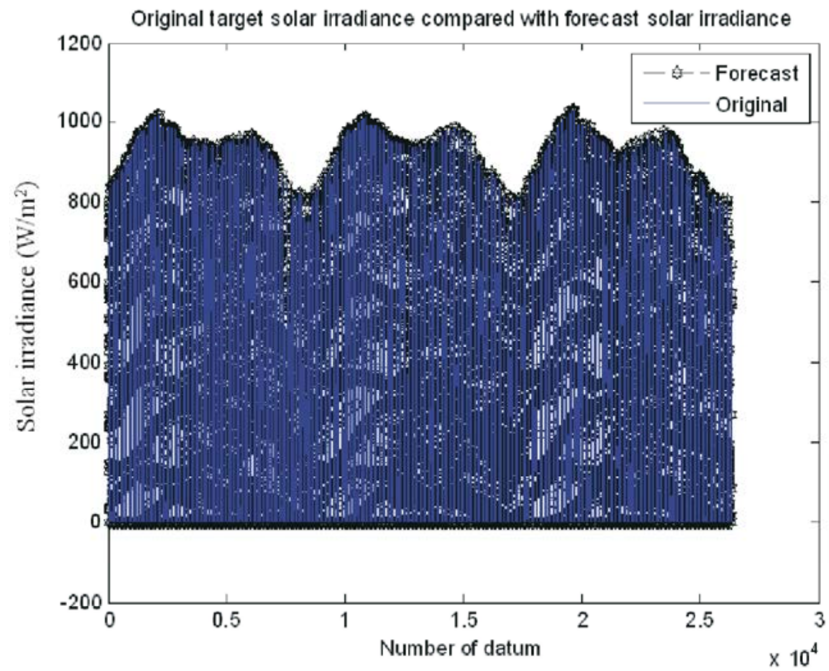

Fig. 10: Original target solar irradiance compared with forecast solar irradiance

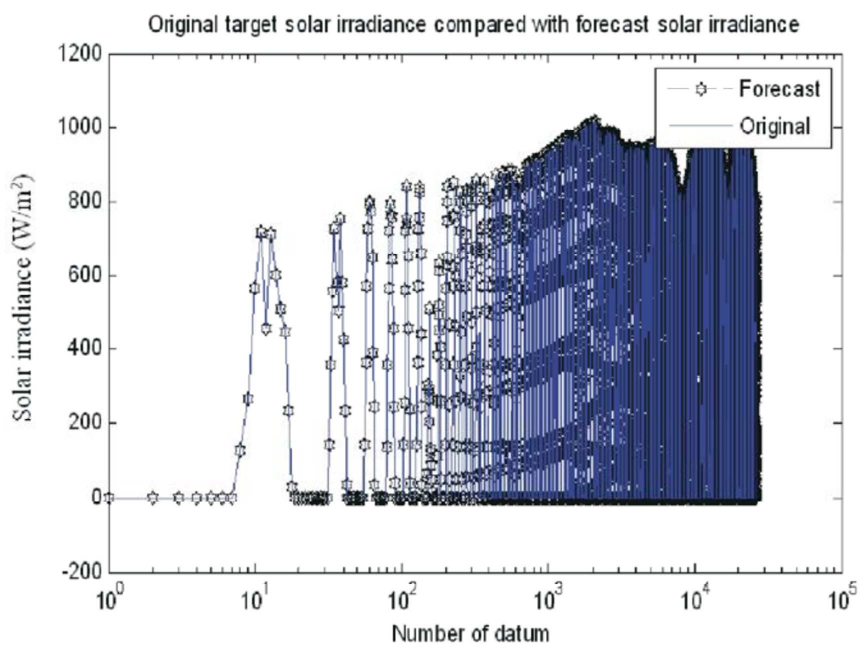

Fig. 11: Log plot of original target solar irradiance compared with forecast solar irradiance

precision the forecast solar irradiance akin to the original target which is inferred from Figure 10 & 11, thus the error index are very low and R (regression) =1 which is noticed from the Figures 12 &13 respectively.

The effective and optimal proposed strategy associated deep neural network framework is assessed by various hidden layers and hidden neuron numbers, in which the best framework is identified by means of the precision and evaluation error index. From the examination deep neural network contain 3 hidden layers with 125 hidden neurons in each hidden layer gives the best outcomes with respect to both wind speed and solar irradiance forecasting. The hidden layer is further increased to 4 and 5 but the performance was not further

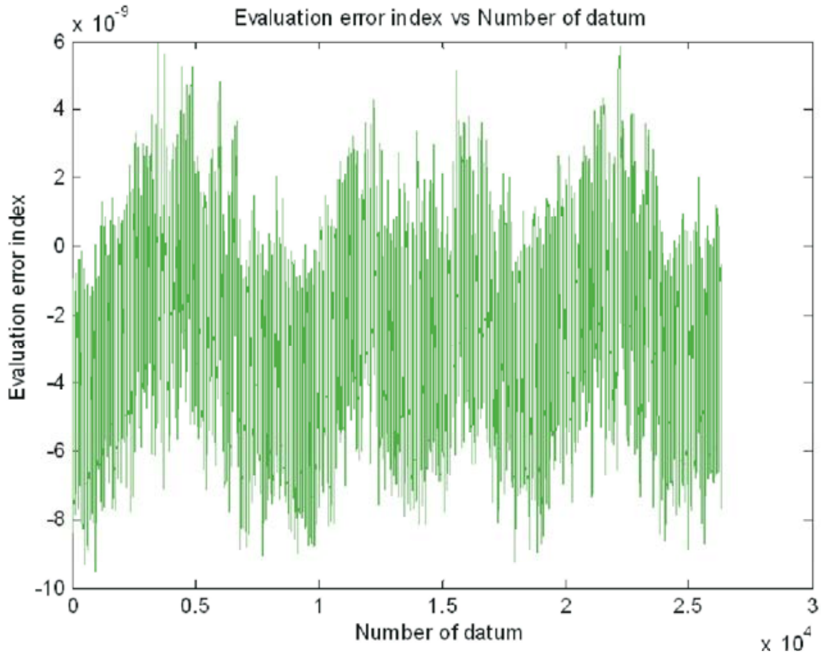

Fig. 12: Evaluation error index vs. Numbers of datum for solar irradiance forecasting

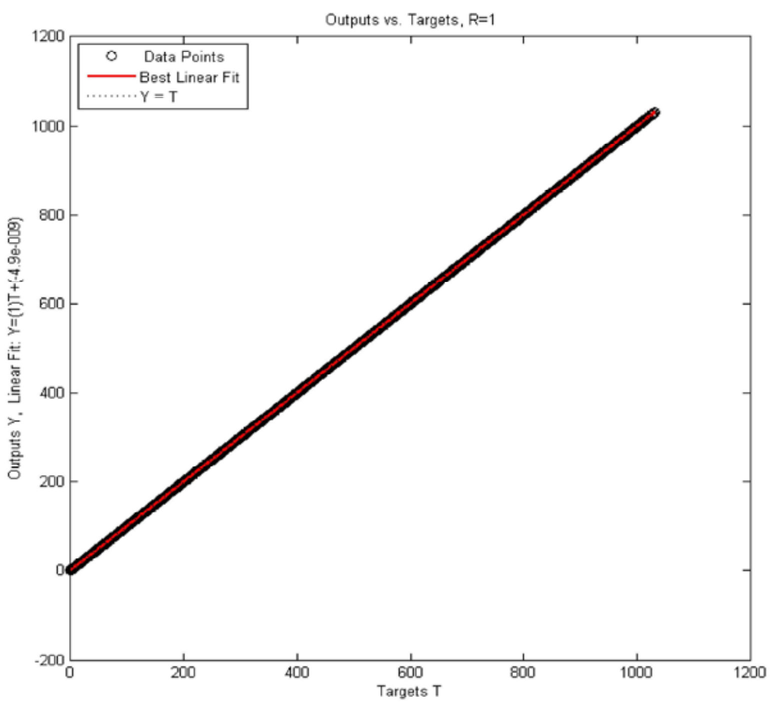

Fig. 13: Plot of outputs vs. targets for solar irradiance forecasting

improved, it also produces the error values similar near that of 3 hidden layers based proposed strategy associated deep neural network outcomes with much computational time. For this reason proposed strategy associated deep neural network with 3 hidden layers is a sensible one. This was believed with the help of Table 4 and 5. The SPSO based training of deep neural network was proposed after the SRBM based pre training, thus this method further enhances the forecasting accuracy with regards to very low evaluation error index.

Various Time Horizon Forecasting Discussion and Reckon Numerical Result: The proposed method forecasting performance, effectiveness is further investigated on various time horizons based forecasting. Category of forecasting concerns to various time horizons are categories as very short term forecasting, short term forecasting, medium term forecasting and long term forecasting. Forecasts of wind speed and solar irradiance is performed on this entire category and error is computed.

Comparison of a new training strategy based deep neural network performed with that of previous well known methods like multilayer perceptron (MLP), support vector machine (SVM), Extreme learning machine (ELM) and classical deep neural network following deep belief network topology (DNN) for wind speed and solar irradiance forecasting in order to prove the acute forecasting performance. The forecasting ability of the proposed and previously published methods gauged with respect to the least mean square error. The quantitative outcome of the proposed and aforementioned previous well known forecasting methods regards to various time horizons with seasonal based forecasting are reckoned and tabulated.

Execution Parameters: The execution design parameters for the proposed and considered previous methods are showcased in Table 6.

Table 6: Forecasting method experimentation designed values description.

Artificial Neural Network	Variables	Set Values
MLPN	Number of input neurons	12
	Number of hidden layer	1
	Number of hidden neurons	36
	Number of Output neurons	2
	Epochs	2000
	Threshold	1
	Learning Rate	0.01
SVM	Number of input neurons	12
	Number of Output neurons	2
	Epochs	1500
	Kernel function	RBF
	gamma	0
	C	1
	Learning rate	0.1
ELM	Number of input neurons	12
	Number of hidden layer	1
	Number of neurons	450
	Number of Output neurons	2
	Epochs	1500
	Learning rate	0.5
Classical Deep Neural Network	Number of input neurons	12
	Number of hidden layer	3
	Number of hidden neurons	125 (for each hidden layer)
	Number of Output neurons	2
	Epochs	50
	Threshold	1
	Learning rate	0.01
Proposed Deep Neural Network	Number of input neurons	12
	Number of hidden layer	3
	Number of hidden neurons	125(for each hidden layer)
	Number of Output neurons	2
	Epochs	50
	Threshold	1
	Learning rate	0.01
	Momentum Factor	0.9
	Number of Particle	60
	Number of Generation	100
	$c_{cb}^{'}$, $c_{cw}^{'}$ & $c_{s}^{'}$	2

Seasonal Based Forecasting: Effect of seasonal variations of wind speed and solar irradiance is also taken into account for the proposed method by validation of forecasting method for various seasons and various time horizons. Thus, various seasonal based forecasting with regards to various time horizons aid for better understanding about the future event. The gathered data samples are split based on the seasons, namely winter, spring, summer and autumn fall in order to overcome the seasonal effect on forecasting.

Various time horizon based reckon result regard to the application of wind speed forecasting:

Forecasting of wind speed is performed on various time horizons with dealing the seasonal variation using proposed method and previous methods. The Tables 7 to 10 are portrayed results related to very short term, short term, medium term and long term respectively with different seasons and average forecasting concern to the proposed and previous methods.

Table 7: Very short-term wind speed forecasting

		Evaluation Error index (MSE)				
Methods		Winter	Summer	Spring	Autumn Fall	Average
MLP		6.8790e-10	7.7478e-10	4.5715e-10	8.1769e-10	6.8438e-10
SVM		5.4149e-11	6.6277e-11	3.5624e-11	8.9017e-11	6.1267e-11
ELM	MEAN	1.4588e-12	2.5355e-12	3.6955e-12	1.8171e-12	2.3767e-12
	STD	8.7788e-06	8.8200e-06	7.1702e-06	9.1073e-06	8.4691e-06
Classical DNN	MEAN	3.1968e-15	3.4284e-15	2.7281e-15	4.7253e-15	3.5197e-15
	STD	2.0106e-09	2.6422e-09	1.8690e-09	3.0180e-09	2.3850e-09
Proposed DNN	MEAN	8.0392e-21	8.5176e-21	6.0189e-21	9.8069e-21	6.0957e-21
	STD	4.1028e-11	4.2969e-11	3.6211e-11	5.3024e-11	4.3308e-11

Table 8: Short-term wind speed forecasting

		Evaluation Error index (MSE)				
Methods		Winter	Summer	Spring	Autumn Fall	Average
MLP		5.7189e-10	9.2020e-10	7.5514e-10	9.7699e-10	8.0606e-10
SVM		7.6964e-11	1.4199e-10	9.8320e-11	2.2485e-10	1.3553e-10
ELM	MEAN	5.4837e-12	8.1369e-12	7.3274e-12	8.8200e-12	7.4420e-12
	STD	6.0732e-06	7.2551e-06	6.8410e-06	8.0080e-06	7.0443e-06
Classical DNN	MEAN	5.9235e-15	8.4643e-15	6.2114e-15	9.8694e-15	7.6172e-15
	STD	4.8570e-09	5.1029e-09	4.9255e-09	6.1308e-09	5.2541e-09
Proposed DNN	MEAN	9.4222e-21	1.6580e-20	1.1130e-20	2.0259e-20	1.4349e-20
	STD	5.0070e-11	6.5048e-11	6.3691e-11	7.1422e-11	6.2558e-11

Table 9: Medium-term wind speed forecasting

		Evaluation Error index (MSE)				
Methods		Winter	Summer	Spring	Autumn Fall	Average
MLP		2.3914e-09	1.7241e-09	1.1754e-09	3.2517e-09	2.1357e-09
SVM		2.6228e-10	2.0021e-10	1.0750e-10	3.1257e-10	2.2064e-10
ELM	MEAN	4.3317e-11	3.4064e-11	2.9161e-11	5.8071e-11	4.1153e-11
	STD	1.0125e-05	9.5810e-06	9.3858e-06	1.2660e-05	1.0438e-05
Classical DNN	MEAN	5.4001e-14	4.4894e-14	3.2883e-14	6.6846e-14	4.9656e-14
	STD	3.2955e-08	2.0410e-08	1.1880e-08	4.2237e-08	2.6871e-08
Proposed DNN	MEAN	7.9454e-20	6.5944e-20	5.3012e-20	8.3432e-20	7.0461e-20
	STD	8.0819e-11	7.1056e-11	6.0033e-11	8.9053e-11	7.5240e-11

Table 10: Long-term wind speed forecasting

		Evaluation Error index (MSE)				
Methods		Winter	Summer	Spring	Autumn Fall	Average
MLP		2.9706e-09	6.1588e-09	2.4000e-09	4.4248e-09	3.9886e-09
SVM		4.0012e-10	5.7464e-10	3.5424e-10	5.0148e-10	4.5762e-10
ELM	MEAN	7.7764e-11	8.8358e-11	7.3202e-11	8.0252e-11	7.9894e-11
	STD	2.8350e-05	4.0206e-05	2.1643e-05	3.7541e-05	3.1935e-05
Classical DNN	MEAN	8.2732e-14	9.1875e-14	7.2959e-14	8.6419e-14	8.3496e-14
	STD	6.0616e-08	7.4219e-08	5.6004e-08	7.0035e-08	6.5219e-08
Proposed DNN	MEAN	1.0079e-19	2.2223e-19	9.1222e-20	1.2330e-19	1.3439e-19
	STD	1.1606e-10	1.5810e-10	9.2581e-11	1.4051e-10	1.2681e-10

As a result, the proposed forecaster succeeds in wind speed forecasting concern to various time horizons in terms of very much reduced evaluation error index. According to the statistical qualitative evaluation study the proposed forecaster dominant other classical methods. The most notable accuracy improvement is achieved for the proposed method based forecasting which is inferred Tables 7-10. Forecasting outcomes are much closes to the original target values which are believed from the minimized evaluation error index.

Various Time Horizons Based Computed Result Concern to the Application of Solar Irradiance Forecasting: Proposed and considered previous methods are employed for solar irradiance forecasting on various time horizons with facing up the seasonal variation and the outcomes concern to very short term, short term, medium term and long term are tabulated in Table 11 to 14 respectively with different seasons and average forecasting respect to the proposed and previous methods. However, based on the various time horizons forecasting the proposed forecasting method results a competitive performance for forecasting of solar irradiance and yield reduced evaluation error index over the other considered previous methods.

Table 11: Very short-term solar irradiance forecasting

		Evaluation Error index (MSE)				
Methods		Winter	Summer	Spring	Autumn Fall	Average
MLP		2.2194e-08	1.4658e-08	1.7936e-08	2.0057e-08	1.8711e-08
SVM		4.8335e-09	3.7054e-09	4.0207e-09	4.5791e-09	4.2847e-09
ELM	MEAN	4.2388e-10	2.9343e-10	3.2074e-10	3.9048e-10	3.5713e-10
	STD	2.6031e-05	1.7130e-05	1.9707e-05	2.4993e-05	2.1965e-05
Classical DNN	MEAN	8.5558e-13	6.7735e-13	7.0286e-13	7.9980e-13	7.5889e-13
	STD	3.4736e-07	2.5793e-07	2.7562e-07	3.2645e-07	3.0184e-07
Proposed DNN	MEAN	5.4120e-18	4.2573e-18	4.6691e-18	5.0309e-18	4.8423e-18
	STD	7.6957e-10	6.4695e-10	6.7244e-10	6.9023e-10	6.9479e-10

Table 12: Short-term solar irradiance forecasting

		Evaluation Error index (MSE)				
Methods		Winter	Summer	Spring	Autumn Fall	Average
MLP		4.8327e-08	2.9455e-08	3.2390e-08	5.2627e-08	4.0699e-08
SVM		6.0042e-09	5.2410e-09	5.8346e-09	6.5218e-09	5.9004e-09
ELM	MEAN	5.4837e-10	4.7345e-10	4.9605e-10	5.9063e-10	5.2713e-10
	STD	4.1805e-05	3.0353e-05	3.4098e-05	4.8670e-05	3.8732e-05
Classical DNN	MEAN	9.6604e-13	8.4826e-13	8.9079e-13	9.9054e-13	9.2391e-13
	STD	4.1703e-07	3.3143e-07	3.8520e-07	4.4713e-07	3.9520e-07
Proposed DNN	MEAN	6.9830e-18	5.9686e-18	6.3367e-18	7.3183e-18	6.6517e-18
	STD	8.6004e-10	7.8057e-10	8.0012e-10	8.9518e-10	8.3398e-10

Table 13: Medium-term solar irradiance forecasting

		Evaluation Error index (MSE)				
Methods		Winter	Summer	Spring	Autumn Fall	Average
MLP		8.6905e-08	6.6034e-08	6.5339e-08	7.5737e-08	7.3504e-08
SVM		9.0013e-09	7.6504e-09	7.2411e-09	8.8560e-09	8.1872e-09
ELM	MEAN	8.7490e-10	6.1466e-10	5.8308e-10	7.6871e-10	7.1034e-10
	STD	6.2474e-05	5.0314e-05	4.8249e-05	5.9385e-05	5.5106e-05
Classical DNN	MEAN	2.1406e-12	9.9770e-13	9.8117e-13	1.5247e-12	1.4110e-12
	STD	5.9686e-07	4.5217e-07	4.3454e-07	5.0578e-07	4.9734e-07
Proposed DNN	MEAN	1.0922e-17	8.2198e-18	8.0963e-18	9.6023e-18	9.2101e-18
	STD	1.0005e-09	9.4039e-10	9.2082e-10	9.7655e-10	9.5957e-10

Table 14: Long-term solar irradiance forecasting

Methods		Evaluation Error index (MSE) Winter	Summer	Spring	Autumn Fall	Average
MLP		1.7971e-07	8.3585e-08	9.8305e-08	1.0166e-07	1.1582e-07
SVM		2.2826e-08	9.5506e-09	1.0837e-08	1.1716e-08	1.3732e-08
ELM	MEAN	3.0303e-09	8.9863e-10	9.6284e-10	2.0012e-09	1.7232e-09
	STD	2.6011e-04	6.6916e-05	7.5873e-05	1.8178e-04	1.4617e-04
Classical DNN	MEAN	4.2775e-12	2.6174e-12	3.0256e-12	3.5136e-12	3.3585e-12
	STD	7.0732e-07	4.8402e-07	5.6022e-07	6.4460e-07	5.9904e-07
Proposed DNN	MEAN	2.8466e-17	1.1750e-17	1.8821e-17	2.1987e-17	2.0256e-17
	STD	3.1026e-09	1.4644e-09	1.9781e-09	2.4231e-09	2.2421e-09

The pre training (SRBM) followed by the SPSO based training of deep neural network helped to achieve the best results for various time horizon forecasts of wind speed and solar irradiance.

Forecasting error based comparison with other methods such as MLP, SVM, ELM, classical DNN reveals the suggested method superiority concern to wind speed and solar irradiance forecasting, the proposed method makes more excellent forecasting accuracy with less evaluation error index and competitive outcomes are achieved in various time horizon forecasting. Thus, gain more eminent performance over the previous reported methods. The aforementioned conclusion reached basis on evidence of the Tables 7-14.

Research Contribution and Finding: Forecast of both wind speed and solar irradiance using deep neural network is not addressed by researchers. This motivates to propose the new training strategy associated deep neural network based forecasting of wind speed and solar irradiance is novel in the field of forecast. The established forecasting method makes an evaluation error index very close to zero for multi-time horizon forecasts. The knowledge of the forecasts wind speed and solar irradiance helps the renewable energy providers and power system operators to tackle the complexity related to uncertainty, manage the power system load and optimal way uninterrupted power supply to the consumer.

CONCLUSION

The forecasting of wind speed and solar irradiance overcome the dilemma related to power system working and management. Based on the forecast results usage of other resource can be incorporated to deliver the uninterrupted, high quality power supply with economic way. The much reduced forecasting error is benefiting regards to economics and technical aspects. This work proposes a new ways of training strategy (through the use of self regulated particle swarm optimization based training) for deep neural network, the best framework regard to hidden layer and hidden neurons is identified and realization of its ability in wind speed and solar irradiance forecasting is performed in this paper. Deficiency of the multi hidden layer associated neural network is made up by pre training followed SPSO based training. Compare to shallow neural network based forecasting methods; proposed method embodies a significant characteristic like fast learning, generalization and escape from local minima. Various seasonal effects involved in the forecasting of wind speed and solar irradiance are analyzed by seasonal based forecasting with various time horizons.

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