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A New Hybridized Optimization Algorithm to Optimize Echo State Network for Application in Solar Irradiance and Wind Speed Forecasting

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Abstract: The intermittent and volatility of solar energy and wind energy productions are caused because of the solar and wind resources (solar irradiance and wind speed) irregularity and haphazardness. The pressure regards with the planning and control of the solar farm, the wind farm and energy system are relieving based on the forecasts of spots on the solar irradiance and wind speed forecasting. This work handles the issues of the wind and solar energy integration to the electric grid by carrying out forecasting of wind speed and solar irradiance using echo state network (ESN) optimized based on the new hybridized optimization algorithm is termed as the gravitational search algorithm new particle swarm optimization (GSANPSO). This research works to demonstrate the ability of the proposed new hybridized (GSANPSO) optimization algorithm to perform the parameters and trainable weights optimization for ESN and viability of the hybrid approach is perceived with the help of solar irradiance and wind speed forecasting. The proposed forecasting approach betterment with respect to the existing approaches is visually realized based on the ROC (receiver operating characteristic). In the field of solar irradiance and wind speed forecasting, the proposed ESN–GSANPSO based hybrid forecasting approach is novel and procures excellent and unerring performance.

Key words: Echo State Network · Optimization · Hybrid Approach · Receiver Operating Characteristic · Wind Speed & Solar Irradiance Forecasting

INTRODUCTION

Now a day's growing electrical energy needs are fulfilled by means of the renewable energy such as the wind and solar energy because the wind and solar have salient features such as huge potential, availability and emission-free energy production. Energy system, wind farm and solar farm operators, investors and researchers are paid their focus towards wind speed and solar irradiance forecasting in order to improve the energy system integrity, efficiency, stability and reduce the economic burden. The enriched forecasts of solar irradiance and wind speed are required because the solar irradiance and wind speed plays a prime role in the solar energy and wind energy generation respectively. The uncertainty regards to wind energy and solar energy is occurring due to the changes in the wind speed and solar irradiance respectively. In order to ease the power system operation with the integration of solar energy and wind energy, perfect solar irradiance forecasting and wind speed forecasting is becoming inevitable. Thus, tremendous research performed on forecasting of solar irradiance and wind speed, some of the research works are reviewed and elucidated as follows:

Gordon Reikard [1] performed an investigation into solar radiation prediction with the help of hybrid, neural network, transfer function, unobserved component, ARIMA and regression in logs. S. Seme *et al*. [2] suggested error back propagation learning rule based three layered artificial neural networks to forecast daily distribute of solar irradiance. Soumya Ranjita Nayak *et al*. [3] performed solar insolation level forecasting by means

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of the artificial neural network and the PV system based power generation optimized by particle swarm optimization. Therefore, which is used to assist in the economic power dispatch. Demerit: Collected data is stored by manual process. Emad A. Ahmed., M. El-Nouby Adam [4] suggested back propagation training algorithm associated feed forward neural network to predict global solar radiation, the proposed model is evaluated in Qena. Lubna. B. Mohammed *et al*. [5] pointed out the hourly prediction model using neural network nonlinear autoregressive exogenous to forecast solar irradiances, Levenberg Marquardt learning is chosen as the best learning algorithm among seven different learning algorithms based on the maximum R and minimum RMSE. S.X. Chen *et al*. [6] developed fuzzy and neural network incorporated forecasting model to forecast solar radiation. The result reveals that compared to different methods such as statistical, fuzzy and neural network, the proposed method obtains 6.03- 9.65% of MAPE. Jianzhou Wang *et al*. [7] pointed out forecasting model employing optimally pruned extreme learning machine (OP-ELM) with a cuckoo search algorithm for the solar radiation forecasting, in which the proposed model weight coefficients are properly determined by the cuckoo search algorithm. Madhiarasan, M., Deepa, S. N. [8] suggested innovative neural network based solar irradiance estimation model for the betterment of generalization performance and the presented innovative neural network apt hidden neurons are identified with the help of novel deciding standard.

Kamal, L., Jafri, Y. Z. [9] pointed out wind speed prediction model with the help of ARIMA (autoregressive integrated moving average). Madhiarasan, M., Deepa, S. N. [10] implemented wind speed forecasting approach by means of improved back propagation network and the sufficient hidden neurons are selected based on a novel criterion. Madhiarasan, M., Deepa, S.N. [11] performed wind speed prediction based on an ensemble neural network with regards to various time horizons and accuracy is substantiated by K-Fold cross validation. Madhiarasan, M., Deepa, S. N. [12] carried out wind speed forecasting concern to various time scales with six artificial neural networks and the performances are analyzed with the help of computed errors. Madhiarasan, M., Deepa, S.N. [13] developed hybrid wind speed forecasting model based on modified grey wolf optimizer (MGWO) incorporated Elman neural network and the appropriate hidden neurons in the Elman neural network is determined by the new criterion. Madhiarasan, M., Deepa, S. N. [14] established wind speed forecasting model based on the multilayer perceptron network and the suitably hidden neurons is estimated by means of certain criteria. Madhiarasan, M., Deepa, S. N. [15] pointed out a novel wind speed forecasting model based on the recursive radial basis function network (RRBFN) and the RRBFN proper hidden neurons are evolved through the new criteria. Madhiarasan, M., Deepa, S. N. [16] suggested third generation neural network (Spiking neural network) based wind speed forecasting with respect to the long-term time scale, in which improved spike prop algorithm is adopted and the efficacy is further enriched by an improved modified grey wolf optimization algorithm for the purpose of parameter optimization. Vlastimir Nikolic´ *et al*. [17] presented wind speed prediction model by means of the extreme learning machine (ELM), which leads to speed up the learning process than that of the BP (back propagation) algorithm. Madhiarasan, M., Deepa, S. N. [18] developed new forecasting models to forecast wind speed and solar irradiance by dint of deep neural network association of new training strategy. Although the existing forecasting approaches perform well, shrewd forecasting is required.

The nonlinear systems are tackled efficiently by the artificial neural network, which is one of the salient features of artificial neural network (ANN) because of this salient feature ANN have been utilized for forecasting applications.

The problems associated with general recurrent or feedback neural networks are as follows:

- The network took much time to converge.
- Occurrence of local minima.
- Complexity related to learning which leads to high expensive.

The above-said problems are somehow overcome by Echo state network (ESN), Therefore, researchers tremendously herd ESN due to the key points such as a worthwhile learning approach, strengthen computational capabilities and so on. But concern to ESN, initialize the parameters and weights with optimal values are one of the toughest tasks. Hence, the best weights value and parameters with respect to ESN are explored by the new hybrid optimization algorithm is termed as GSANPSO. This work puts efforts to enhance the wind speed and solar irradiance forecasting accuracy based on a hybrid approach (ESN-GSANPSO).

Novelty of this Work: The need to promote efficient solar and wind energy corresponding power system working and management motivate perfect solar irradiance and wind speed forecasting. This research implements the

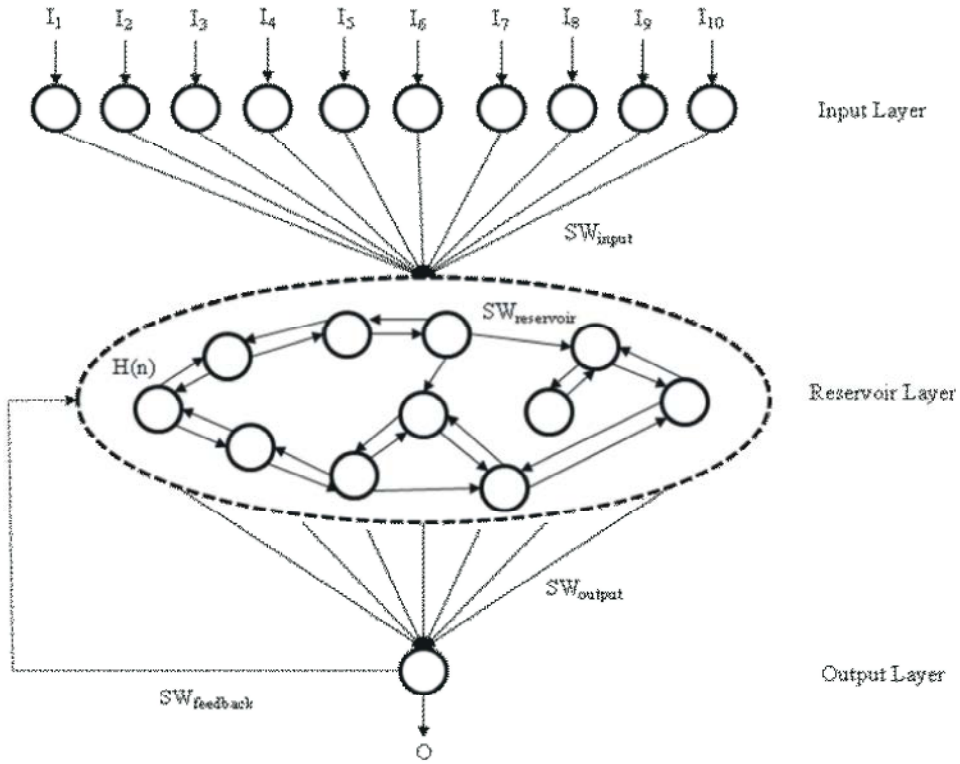

Fig. 1: Echo state network structural design

GSANPSO (gravitational search algorithm new particle swarm optimization) based echo state network for forecasting applications to provide both solar irradiance and wind speed forecasts. For the past year, none researchers performed the solar irradiance and wind speed forecasting by means of GSANPSO based optimized Echo state network. It proves the originality of this research.

Hybrid Forecasting Approach

Echo State Network (ESN): Jaeger, H 2001, 2003 [19, 20] developed the concept of echo state network. The Echo state network learning capability is improved by reservoir computing. Recurrent neural network with reservoir computing is known as echo state network. The Echo state network consists of an input layer, reservoir layer and the output layer, ESN structural design is represented in Figure 1.

In the case of echo state network, the input history has a profound influence on the recurrent nodes; the current state is getting impacted upon the most recent input. A large amount of hidden nodes associated reservoir layer are randomly initialized and huge amount interlinks exist in the reservoir layer which is sparse in nature. The input layer contained information is transformed into higher dimensional space by reservoir computing, the reservoir is a nonlinear layer in which hidden and recurrent nodes are randomly interlinked with the other by means of the randomly initialized weight matrix and the output layer is a linear layer. In this neural network, the activations are propagated with the help of processing elements and synaptic weight linkages.

The synaptic weight linkages between the inputs to the reservoir are randomly initialized. While the synaptic weight linkages between the reservoir layer are initialized based on the following conditions:

- Begin with weight matrix SW_{random} which is framed randomly.
- The ESP (echo state property) salient points are met by the equation:

$$SW = SW_{random} \gamma(SW_{desired}) \Big/ \gamma(SW_{random}) \quad (1)$$

Salient points regard to the echo state property (ESP) are as follows:

- Spectral radius $\gamma < 1$.
- Maximum singular value < 1.

ESP is assured with a contraction state transition function which is initialized by the reservoir. During the learning stages, the input and reservoir layer weight matrix

are not modified, the weight matrix related between the reservoir and output (SW_{output}) alone gets updated during the learning stage. This is the salient characteristic of echo state network.

The activation of hidden nodes in the reservoir layer is modified with the presented input as given below:

$$H(t) = f\left(SW_{input} \cdot [I(t),1] + SW_{reservoir} \cdot H(t-1) + SW_{feedback} \cdot O(t-1)\right) \quad (2)$$

The activation function of hidden nodes is represented as f, in which hyperbolic tangent sigmoid activation function is used. Weights matrix with respect to the input to hidden, hidden to hidden and output to hidden synaptic weight linkages are represented as SW_{input}, $Sw_{rservoir}$ and $SW_{feedback}$ respectively.

Echo state is a state created in a dynamic reservoir, which contains past input information. The reservoir states behavior such as stability and memory capacity are controlled by the spectral radius. The older input influence on the network state is much lesser compared to the recent input. Based on the past history the network state is framed as given below

$$H_{\text{int}}(t) = e_{\text{int}}\left(I(t), I(t-1), \ldots\right) \quad (3)$$

From the above equation, it can be observed that network state is a function of the input history.

Based on the spectral radius γ, the weight matrix with respect to the hidden link is rescaled, which is assured the favorable working of echo state network. The randomly produced weights matrix with respect to the hidden-hidden ($SW_{reservoir}$) each and every attribute is multiplied by $\gamma/\gamma_{\max}$, this process helps to obtain feasible echo state network. The original matrix spectral radius is represented as $\gamma_{\max}$. The presented input history, which influences the recurrent nodes is known as contractive dynamics. Network stability is guaranteed under the decay of network state gradually to zero by settings $\gamma < 1$.

The history of inputs is transformed in a nonlinear way for echo state network and the recurrent information is processed with dynamic memory feature. When the time passes $t \to \infty$, the previous state and history of inputs based influences on the forthcoming state $H(n + \text{t})$ fade gradually.

The output node activation is computed as follows:

$$O(t) = f(SW_{output} \,.\, [I(t), H(t), 1]) \quad (4)$$

Weight matrix with respect to the output is represented as SW_{output}. Only the synaptic weights with respect to the reservoir to output layer are modified, other weights are initialized randomly and kept as a fixed one or non-adjustable during the learning stage, which leads to ease of computation. Mean square error minimization is the main computation for learning of the Echo state network.

Hybrid Population-based Optimization Algorithm: Based on the concept of evolution process J. H. Holland [21] established GA (genetic algorithm). Based on the birds and fish social characteristic's inspiration Kennedy, J., Eberhert, R. [22] developed PSO (particle swarm optimization). PSO algorithm solution finding ability is further improved by NPSO (new particle swarm optimization) with the incorporation of the worst position pointed out by A. Immanuel Selvakumar, K. Thanushkodi [23]. Based on the physical Newton's theory inspiration E. Rashedi *et al*. [24] evolved gravitational search algorithm. The GSA and PSO merits are taken into account for the hybrid algorithm presented by Seyedali Mirjalili, Siti Zaiton Mohd Hashim [25]. In NPSO the best solution is searched by means of the particles revolving in the solution space. In solution space, many particles are revolving each one owns its best solution P_{best}, taken into account for the global best solution G_{best} and worst solution P_{worst}. By taking account for the worst position prompt to enhance the ability to find the best solution. Henceforth, this work makes an attempt to combine the GSA and NPSO.

GSANPSO (Gravitational Search Algorithm New Particle Swarm Optimization): From the various existing optimization algorithms, PSO and GSA are exhibiting better results from exploring the optimal solution to various types of issue related to the field of engineering, medical and so on. To enrich the searching capability this work endeavors hybrid optimization algorithm by combining the significant features of GSA and NPSO. Thus, the efficiency and effectiveness in terms of optimal solution finding capability are enhanced. The main idea underlying the GSANPSO is mixing the local best (GSA) and global best (PSO) finding ability. From the solution space finding the optimal solution is known as exploration meanwhile after finding the optimal solution begins to use that solution which leads to improving the convergence is known as exploitation. Hence, exploration and exploitation are the most significant properties for any

heuristic optimization techniques. The gravitational search algorithm possesses the much better exploration capability, while new particle swarm optimization algorithm possesses the much better exploitation capability in order to achieve the esteem exploration and exploitation this work developed a new mixed optimization algorithm by means of the GSA and NPSO. The proposed mixed optimization algorithm possesses both (GSA and NPSO) merits. Hence, it will lead to better optimal outcomes.

Mathematical Modeling of GSANPSO:

$$F_{ij}^{k}(n) = G(n) \cdot \frac{M_{pi}(n) \cdot M_{aj}(n)}{D_{ij}(n) + \varepsilon} \left(Y_j^k(n) - Y_i^k(n) \right) \tag{5}$$

$$G(n) = G_0 \cdot \exp\left(-\alpha n / N \right) \tag{6}$$

$$m_i(n) = \frac{fit_i(n) - worst(n)}{best(n) - worst(n)} \tag{7}$$

$$M_i(n) = \frac{m_i(n)}{\sum_{j=1}^{N} m_j(n)} \tag{8}$$

$$D_{ij}(n) = \left\| Y_i^k(n) - Y_j^k(n) \right\|_2 \tag{9}$$

$$F_i^k(n) = \sum_{j \in Kbest, j \neq i}^{N} r_j \cdot F_{ij}^k(n) \tag{10}$$

$$acc_i(n) = \frac{F_i^k(n)}{M_{ii}(n)} \tag{11}$$

The proposed GSANPSO algorithm velocity and position are modifying with the help of following formalism. Based on the velocity and position, the best global solution is obtained.

$$V_i^k(n+1) = w \cdot V_i^k(n) + c_{1g}^{'} \cdot r_1 \cdot acc_i^k(n) + c_{1b}^{'} \cdot r_2 \cdot \left(Y_i^k(n) - Pworst_i^k(n) \right) + c_2^{'} \cdot r_3 \cdot \left(Gbest_i^k(n) - Y_i^k(n) \right) \tag{12}$$

$$Y_i^k(n+1) = Y_i^k(n) + V_i^k(n+1) \tag{13}$$

where, ε- constant with small value, $D_{ij}(n)$- Euclidian distance between the candidates i and j, $M_{pi}(n)$- passive mass of candidate i, $M_{aj}(n)$- active mass of candidate j, $M_{ii}(n)$- inertia mass of the candidate i, $F_{ij}^k(n)$- force mass i by mass j, $F_i^k(n)$- force act on mass i in dimension k at iteration n, $best(n)$- minimum of fitness value, $worst$(n)- maximum of fitness value, $G(n)$- gravitational constant at n, G_0- initial value, r_j, r_1, r_2, r_3 - random variable whose value between range 0, 1, n- current iteration, N- Maximum number of iteration, α- constant specified by user, w-inertia weight, c'_{1g}, c'_{1b}- cognitive calculation acceleration factor, c_2'- social calculation acceleration factor, $Y_i^k(n)$ - current position of candidate i in dimension k at iteration n, $acc_i^k(n)$- acceleration of candidate i in dimension k at iteration n, $Pworst_i^k(n)$-worst position of candidate i in dimension k at iteration n, $Gbest_i^k(n)$- among the group of candidates the global best position, $V_i^k(n)$- velocity of candidate i in dimension k at iteration n.

Balancing of local search and global search is achieved by means of the c'_{1g}, c'_{1b} and c'_2 adjustment. The other candidates in the solution space are getting attracted by the candidate near to good solutions (fitness or objective). The use of global best is assisting in achieving faster convergence in the case of every candidate are near to a good solution.

Procedures incorporated into the proposed algorithm are described as follows:

1) Generate candidate solution and randomly initialize.
2) For all candidates (search agents) compute the objective function.
3) For each population modifies G, Global best and local worst.
4) For all candidates (search agents) compute mass, force and acceleration.
5) Do velocity and position updating.
6) Check for stopping criteria, if attaining record the best solution else goes for procedure 2 to 5.

This combination optimization algorithm results in the best searching ability for finding the optimal solution. With this motivation, the proposed new Avant-garde optimization algorithm is introduced to ESN in order to do the parameter optimization and trainable weights optimization. Searching the optimal value of the ESN parameters by means of GSANPSO reduces the computational resources, time and cost in spite of random experimentation.

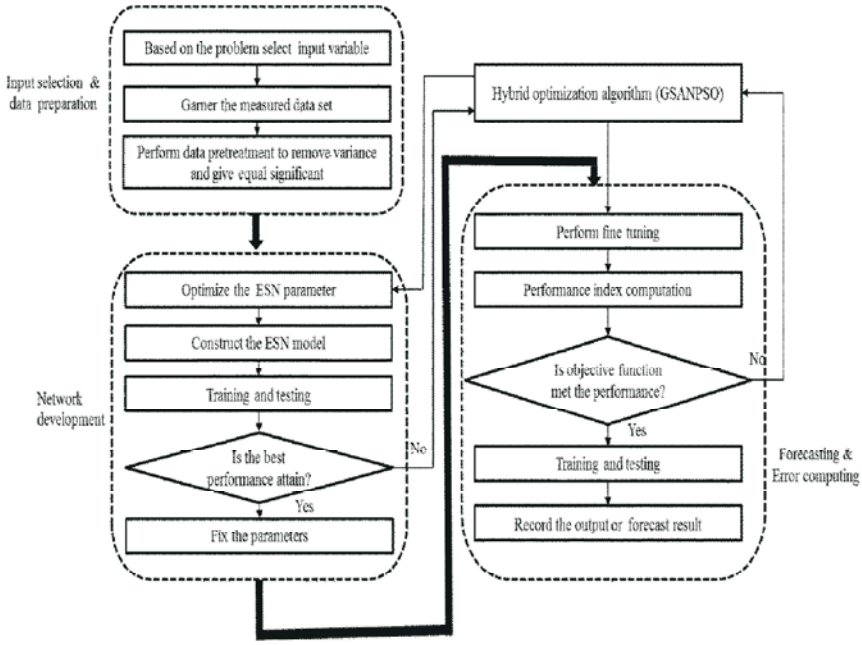

Fig. 2: Workflow of the proposed hybrid forecasting approach

Hybrid Forecasting Approach (ESN-GSANPSO): The workflow of the proposed hybrid forecasting approach (ESN-GSANPSO) is clearly depicted in Figure 2.

The input selection & data preparation, network development and forecasting & error computing are the main stages employed in the proposed hybrid approach workflow, which is described as follows:

Input Selection and Data Preparation: The solar irradiance and wind speed are highly affected by atmospheric phenomena. Thus, the proposed forecasting approach taken account of these atmospheric meteorological parameters such cloud cover, precipitation of water content, temperature, air pressure, wind speed, relative humidity, wind direction, dew point, solar irradiance, and sun shines hour as inputs variable. From National Oceanic and Atmospheric Administration, the United States measured real- time data's are garnered, garnered data set is totally consisting of 87600 data points of each input variable from January 2005 to December 2015 are used for this work.

Input variables,
I_1, I_2, I_3, I_4, I_5, I_6, I_7, I_8, I_9, I_{10}, = Cloud cover, Precipitation of water content, Temperature, Air pressure, Wind speed, Relative humidity, Wind direction, Dew point, Solar irradiance, Sun shines hour.

Output variables,
O_1, O_2 = Forecast solar irradiance, Forecast wind speed.

Measured all data points are realistic true values so, data pretreatment is essential to give equal significant by ranking the data points within the values of 0 to 1.

Normalized garnered data is obtained by means of the min-max method,

$$I'_{garner} = \left(\frac{I_{garner} - I_{garner\_\min}}{I_{garner\_\max} - I_{garner\_\min}} \right) \left(I'_{target\_\max} - I'_{target\_\min} \right) + I'_{target\_\min} \tag{14}$$

where, I_{gorner}- garnered input datum, $I_{garner\_\min}$- minimum of the garnered input datum, $I_{garner\_\max}$- maximum of the garnered input datum, $I'_{target\_\min}$- minimum of the measured target, $I'_{target\_\max}$ -maximum of the measured target.

Network Development: General echo state network meager in quality due to the non-optimal parameters thus leads to losing its generalization ability. Ishii *et al*. [26], Verstraeten *et al*. [27] pointed out ESN prime parameters. In this work Echo state network parameters, namely spectral radius, input scale, input shift, reservoir size, reservoir connectivity, output scale, output shift and weight matrix between the reservoir and output are optimized through GSANPSO. The optimization of Echo state network performed with the help of novel hybrid GSANPSO optimization algorithm. Specifications of the GSANPSO algorithm are described as a population: 60, max iteration: 300, w: gradually decay from 0.95 to 0.3, G_0: 1, α: 30, stopping criteria: max iteration. The effectiveness of the GSANPSO based Echo state network is investigated with the help of applications such as wind speed and solar irradiance forecasting. The best parameters of ESN are explored by means of a hybridized optimization algorithm (GSANPSO) thereafter the unmodified weights such as SW_{input}, $SW_{reservoir}$, $SW_{feedback}$ are generated and finally the trainable weights are obtained with the help GSANPSO.

Forecasting and Error Computing: Fitness function.

$$\text{MSE} = \frac{1}{T}\sum_{P=1}^{T}(O_P^{'} - O_P)^2 \tag{15}$$

$$\text{Fitness function} = \text{minimization of MSE} \tag{16}$$

where, T- Number of garnered data points, O'_P- Measured target, O_P- Forecast output, MSE- mean square error.

The best performance of ESN is achieved with the help of optimal parameters and optimal output weight matrix. For this reason, the optimal value of ESN significant parameters and trainable weight matrix (SW_{output}) are optimized based on the hybrid optimization algorithm (GSANPSO). The MSE (mean square error) is considered to be the fitness function of the proposed GSANPSO algorithm. GSANPSO algorithm is introduced into ESN for the purpose of finding the optimal parameters before training and explore optimal trainable weights during the training by taking the minimization of MSE as a fitness function. The ultimate idea to minimize MSE and improve the accuracy of the solar irradiance and wind speed forecasting using the hybrid approach (ESN-GSANPSO).

Interpretation on the Solar Irradiance and Wind Speed Forecasts: The changeability and volatile nature of the solar irradiance and wind speed have the tendency to worsen the power system stability, quality and economy when solar energy and wind energy are integrated with the power grid. Therefore, the possibility of the above-said problems is prevented by means of the forecasting of solar irradiance and wind speed, which give the future facts related to solar and wind energy it helps to attain an efficient, economic and effective solar farm, wind farm and power system operation and maintenance. The proposed hybrid forecasting approach is used to forecast the solar irradiance and wind speed. The gravitation search algorithm associated new particle swarm optimization is proposed to optimize the echo state network parameters and SW_{output}. The implementation of the proposed hybrid (ESN-GSANPSO) forecasting approach is performed with the help of MATLAB. In this work, the mean square error is chosen as a reasonable performance index to evaluate the performance of the proposed and existing approaches based results.

For ESN, reservoir designed for each parameter setting or combination thereafter the designed ESN is trained using a training dataset (70% of the garnering data's) and the testing data set (30% of the garnering data's) is used for evaluation. The optimal parameters are determined based on the minimal performance index (MSE). The optimal parameters with respect to ESN achieved through the incorporation of GSANPSO are described as reservoir size: 198, spectral radius: 0.96, input scale: 0.86, input shift: 0.73, output scale: 0.22 and output shift: 0.90. Meanwhile, the determined optimal parameters successfully fulfill the ESP (Echo state property). Finally, the network performance is further advanced by output weight matrix optimized with GSANPSO.

Forecasting Using ESN with GSANPSO Based Optimized Parameters: This work performs the monthly analysis of solar irradiance and wind speed in order to overcome the monthly variance because the solar irradiance and wind speed does not have a certain nature it possesses the nature of the irregular and changing characteristic over various months. The performances of various existing approaches, including proposed approach are discussed with the help of performance index (MSE).

Solar Irradiance Forecasting: GSANPSO based optimized parameters incorporated echo state network appropriateness is verified by the solar irradiance forecasting. Existing and proposed approaches based monthly solar irradiance forecast outcomes are tabulated in Table 1.

Table 1: Solar irradiance forecasting monthly analysis with proposed and existing approaches

	MSE						
Month	Persistent	ARIMA	BPN	ELMAN	ELM	General ESN	Optimized ESN
January	3.2799	0.0193	5.2741e-04	9.2788e-04	5.9072e-06	6.5009e-07	4.7732e-08
February	4.0489	0.0373	9.1392e-04	0.0036	1.2434e-05	3.7995e-06	9.2479e-08
March	2.7672	0.0135	1.9169e-04	6.0732e-04	3.5686e-06	3.4147e-07	1.7737e-08
April	2.9447	0.0167	3.2627e-04	7.9724e-04	4.4072e-06	4.1931e-07	2.4528e-08
May	2.4695	0.0109	9.4184e-05	4.5886e-04	8.7116e-06	1.5659e-07	2.1179e-09
June	3.5672	0.0245	7.0017e-04	0.0014	7.0370e-06	8.8278e-07	6.7339e-08
July	2.7706	0.0149	2.3384e-04	6.8056e-04	4.1134e-06	3.8682e-07	1.9429e-08
August	3.8483	0.0305	8.4961e-04	0.0029	9.4979e-06	1.1159e-06	8.4086e-08
September	2.5960	0.0128	1.5704e-04	5.8746e-04	2.8904e-06	2.1152e-07	1.0232e-08
October	3.0889	0.0174	4.6646e-04	8.6955e-04	5.0336e-06	5.4700e-07	3.8319e-08
November	3.4886	0.0213	6.1372e-04	9.9725e-04	6.2198e-06	7.3485e-07	5.6347e-08
December	3.7438	0.0260	7.8708e-04	0.0020	8.2162e-06	9.5666e-07	7.1930e-08
Average	3.2178	0.0204	4.8845e-04	1.3188e-03	6.5031e-06	8.5021e-07	4.4356e-08

Table 2: Wind speed forecasting monthly analysis with proposed and existing approaches

	MSE						
Month	Persistent	ARIMA	BPN	ELMAN	ELM	General ESN	Optimized ESN
January	2.1659	0.0064	6.8298e-05	9.4115e-04	5.6305e-08	8.9329e-09	5.9147e-11
February	2.3034	0.0076	7.3809e-05	0.0010	6.1408e-08	9.9154e-09	7.8095e-11
March	2.0066	0.0051	4.6148e-05	7.8946e-04	2.2609e-08	7.6248e-09	3.2383e-11
April	1.5726	0.0017	1.3979e-05	3.9017e-04	6.3035e-09	3.0965e-09	6.1616e-12
May	1.9800	0.0049	4.3471e-05	6.2647e-04	1.0372e-08	6.8992e-09	2.8309e-11
June	2.7066	0.0104	9.6824e-05	0.0037	1.1548e-07	2.8793e-08	9.4161e-11
July	1.4956	0.0013	9.2680e-06	3.4810e-04	5.4698e-09	2.1151e-09	1.7973e-12
August	1.8900	0.0035	3.4410e-05	5.7782e-04	9.1945e-09	6.0376e-09	2.3922e-11
September	2.4709	0.0087	8.9912e-05	0.0022	9.8417e-08	1.6728e-08	8.7138e-11
October	1.7814	0.0018	1.9156e-05	4.5394e-04	7.5904e-09	4.5304e-09	1.0487e-11
November	2.1377	0.0062	5.4629e-05	8.3511e-04	3.7654e-08	8.1473e-09	4.1854e-11
December	1.8375	0.0024	2.2205e-05	5.2407e-04	8.5773e-09	5.6384e-09	1.7690e-11
Average	2.0290	5.0000e-03	4.7675e-05	1.0322e-03	3.6615e-08	9.0382e-09	4.0095e-11

A part of solar irradiance data with respect to the number of data points are shown in Figure 3. The proposed forecasting approach based obtained solar irradiance forecasting outputs is exactly overlapped with the measured target values, which is evinced in Figure 4. Comparing measured target with forecast solar irradiance with respect to the number of data points is shown in Figure 4. Forecasts error with respect to the number of data points for the solar irradiance forecasting is indicated in Figure 5, which is depicted minimal performance index of the proposed approach. Figure 6 represents the regression plots with respect to solar irradiance forecasting, from this figure Regression coefficient (R) = 1 is inferred. The previous approach based forecasting inferior to that of the proposed forecasting approach. For each month based performance discuss proves that the proposed approach obtains the much smaller value of performance index than that of other existing approaches, which is perceived from Table 1.

Wind Speed Forecasting: The suitability of echo state network prime parameters is optimized through the GSANPSO algorithm is tested based on wind speed forecasting. Table 2 depicts the wind speed forecasting monthly analysis with proposed and existing approaches. Figure 7 represents a part of wind speed data with respect to the number of data points. Comparing measured target with a forecast wind speed with respect to the number of data points is shown in Figure 8, which infers that the wind speed forecasting results achieved based on the proposed hybrid approach are overlapped with measured target values exactly. Hence, obviously, the performance index is very minimal which is understood from Figure 9. Forecasts error with respect to the number of data points in wind speed forecasting is depicted in Figure 9. Regression plot with respect to wind speed forecasting is indicated in Figure 10. From the Figure 10, R= 1 is evincing clear.

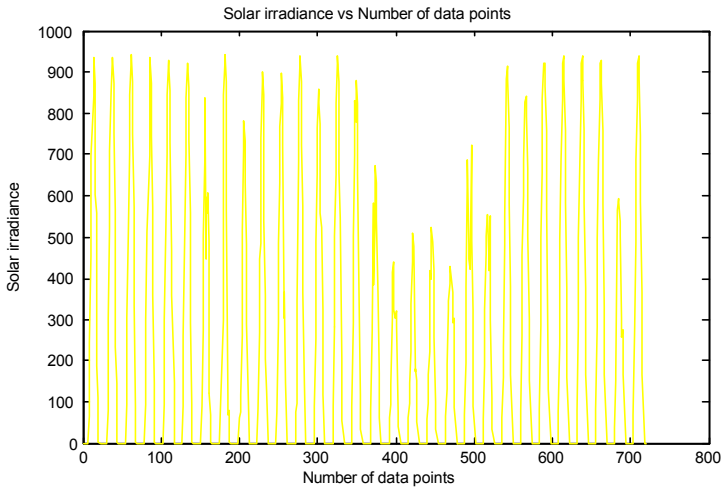

Fig. 3: Part of solar irradiance data with respect to number of data points

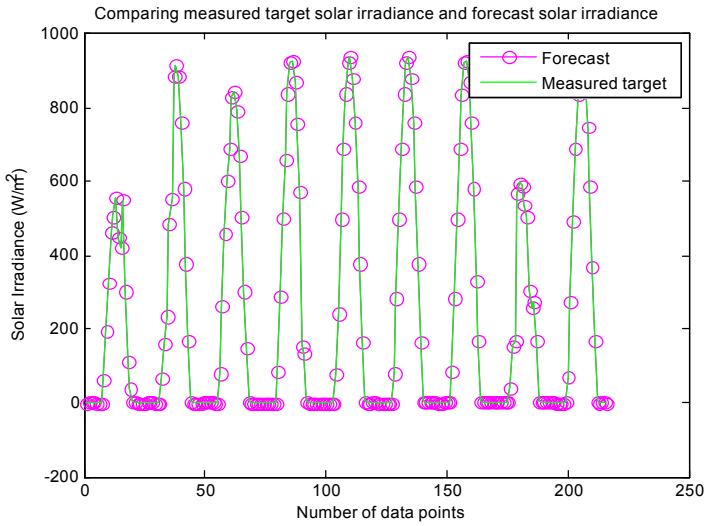

Fig. 4: Comparing measured target with forecast solar irradiance with respect to the number of data points

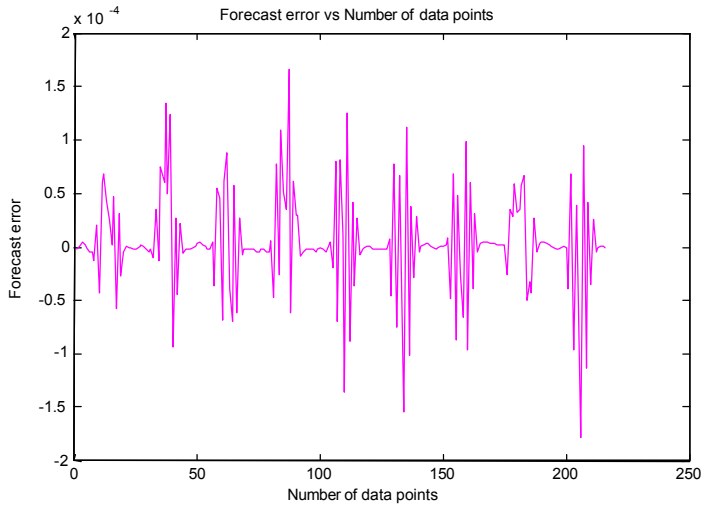

Fig. 5: Forecasts error with respect to number of data points for the solar irradiance forecasting

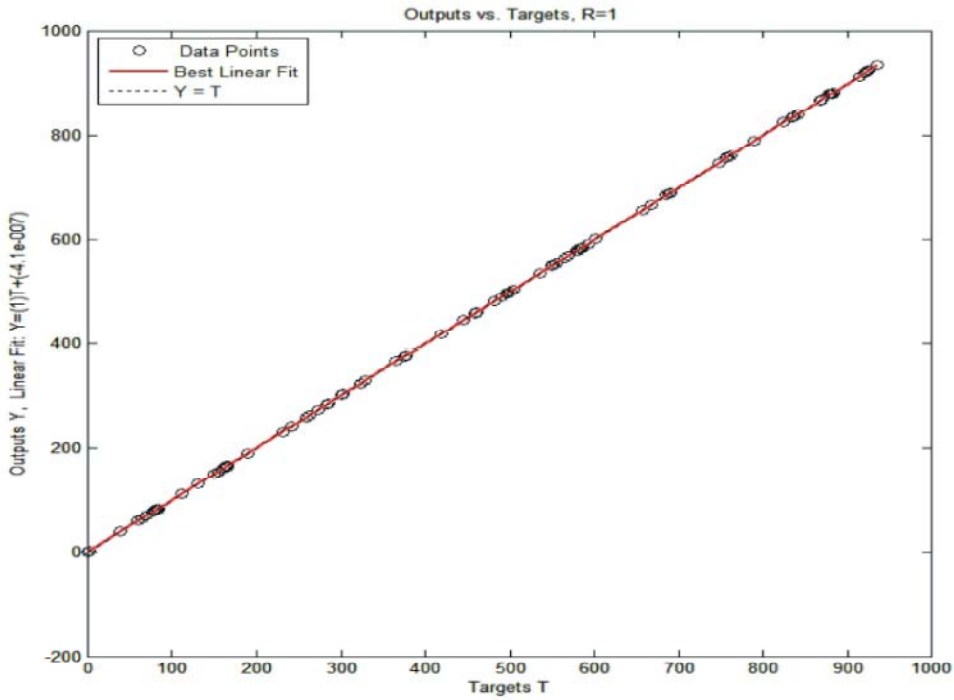

Fig. 6: Regression plot with respect to solar irradiance forecasting

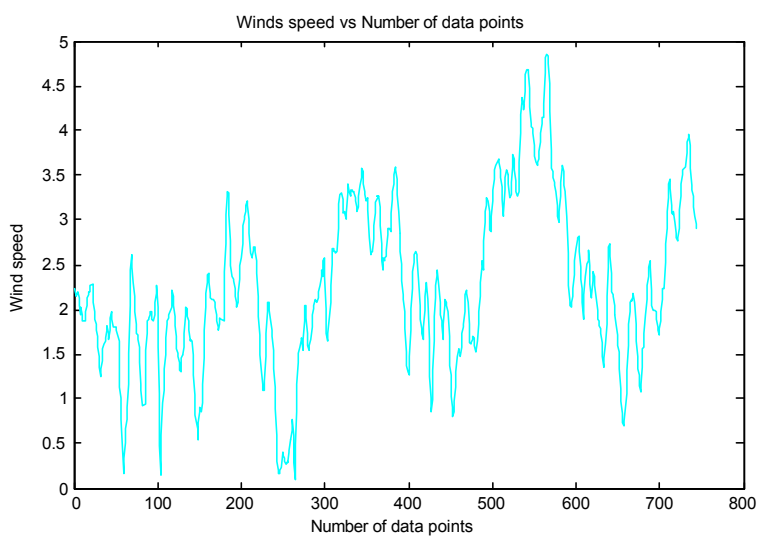

Fig. 7: Part of wind speed data with respect to number of data points

The solar irradiance and wind speed are varied over various months. Therefore, this work carried out forecasts of solar irradiance and wind speed for each month to evade the monthly variations. The experimental simulation manifests that the optimized ESN based forecasting approach proposed in this work enhances the forecasting performance regarding solar irradiance and wind speed forecasting in terms of the much smaller performance index. Compared to various months based forecasting, the May month forecasting for the solar irradiance and July month forecasting for the wind speed forecasting outperform than that of other months based forecasting. Thus, the output plots regard to this month were showcased in Figures 4-6 for the solar irradiance and Figures 8-10 for the wind speed forecasting. Due to the space limitation, only a part of the output is depicted in Figure 4-5 & 8-9. The average forecast outcome of solar irradiance and wind speed using optimized ESN by

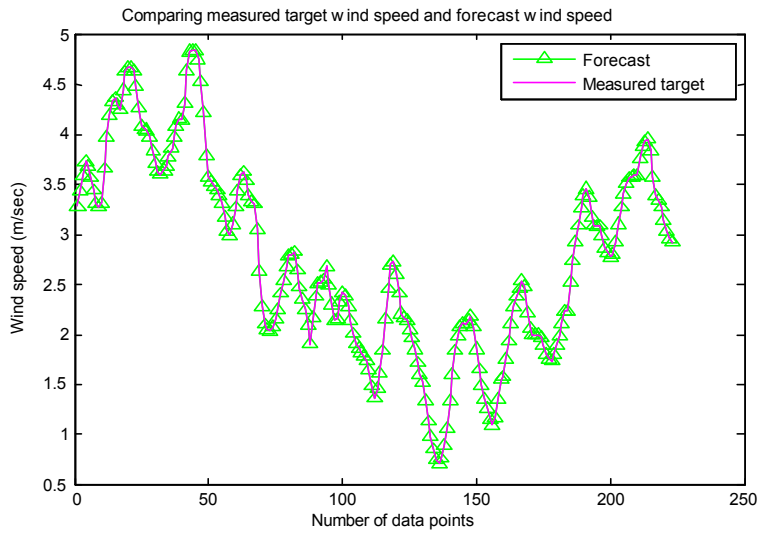

Fig. 8: Comparing measured target with forecast wind speed with respect to the number of data points

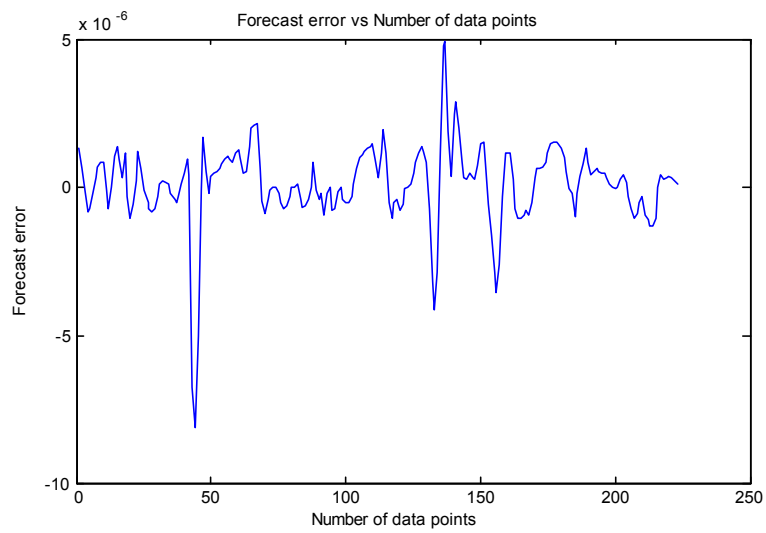

Fig. 9: Forecasts error with respect to number of data points for the wind speed forecasting

GSANPSO would procure performance index (MSE) of 4.4356e-08 and 4.0095e-11 respectively, which is very small one compared to the various existing approaches such as general ESN, ELM, BPN, Elman, ARIMA and persistence. The forecast values deviation from the real measured value is high for persistence, ARIMA, ELMAN, BPN, ELM, general ESN based forecasting while the forecast values deviation from the real measured value is very small for the proposed ESN with the parameters optimized by GSANPSO.

ROC: ROC (receiver operating characteristic) is a two-dimensional plot or graph in which the X-axis is represented by the false positive value; the Y-axis is represented by true positive value. For performance comparison and visual realization of the best forecaster, ROC based analysis receives the compelling irresistible important in confirming the performance of the forecaster. The ROC space is split by means of the diagonal line, the splitting of ROC space help to realize the effectiveness of the forecasting approach. If the points lie below the diagonal line (random) implies the worse performance ability, else the points lie above the diagonal line implies the best performance.

$$TPV = TP / (TP + FN) \tag{16}$$

$$FPV = FP / (FP + TN) \tag{17}$$

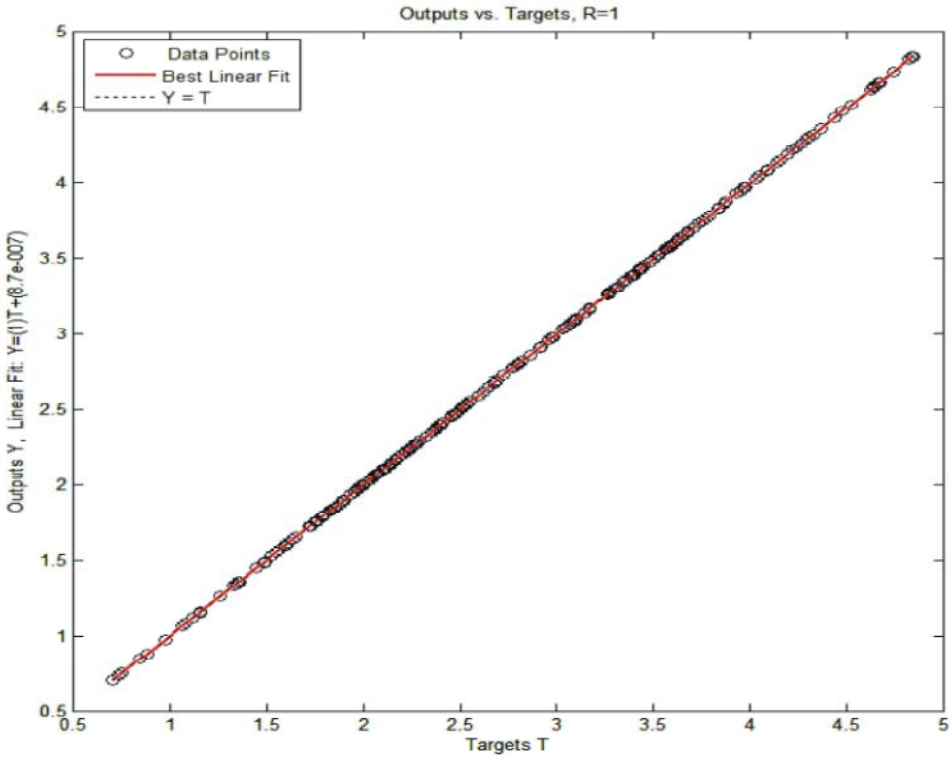

Fig. 10: Regression plot with respect to wind speed forecasting

where, *TPV*- True positive value, *FTP*- False positive value, *TP*- True positive (both forecast and original value are positive), *FP*- False positive (forecast positive and original negative), *FN*- False negative (forecast negative and original positive), *TN*- True negative (both forecast and original value are negative).

When there is null false positive value it has 100% specificity meanwhile, there is null false negative value it has 100% sensitivity. Practically getting 100% specificity and sensitivity are quite difficult and impossible, but the proposed approach endeavor near to 100%. The performance of various forecasters is quantified with the help of the ROC. The effectiveness of the proposed hybrid forecasting approach is perceived by the ROC with points are lies in the upper left corner. The ROC curves obtained from the proposed forecasting approach in which points are lies in the coordinate points of (0, 1) it means that the proposed hybrid forecasting approach perfect for forecasting applications like to forecast solar irradiances and wind speed.

The proposed novel hybrid approaches visualization of performance effectiveness (quality) and clarification of forecasting possibility are depicted in Figure 11 with the help of analysis based on the ROC (receiver operating characteristic). The ROC graph gives a clear picture about the capability of the proposed forecasting approach from the receiver operating characteristic space. The appropriate forecasting model is identified by means of the FP (smaller value) and TP (bigger value). Compared to the general ESN, ELM, BPN, Elman, ARIMA, persistence, the GSANPSO based identified parameters associated ESN obtain the best results with a minimal performance index.

Hybrid Approach (ESN-GSANPSO) Based Forecasting: The Echo state network performance is further enriched by output weight matrix optimized with GSANPSO and compared with the other existing algorithms. The behavior of wind speed and solar irradiance are varied in various months. Therefore, this work intensively forecasts the solar irradiance and wind speed for all months in order to overcome the monthly variation occurs in forecasting results.

The optimization based hybrid approach is not a deterministic approach, for this reason, an average of 30 trials is tabulated with standard deviation. Comparison between various optimization algorithms based ESN for the solar irradiance and wind speed forecasting is presented in Table 3 & 4 respectively. The comparative results of Table 3 & 4 proclaim the proposed hybrid

Table 3: Various optimization algorithms associated ESN based solar irradiance forecasting monthly analysis

		MSE					
Month		ESN-GA	ESN-PSO	ESN-NPSO	ESN-GSA	ESN-GSAPSO	ESN-GSANPSO
January	AVG	5.5587e-10	5.3239e-11	4.7027e-11	4.5031e-11	4.9783e-13	9.5757e-15
	STD	3.7092e-06	7.4915e-07	3.8950e-07	3.6542e-07	8.4429e-08	9.7856e-09
February	AVG	8.6667e-10	9.2740e-11	8.0062e-11	7.8793e-11	7.7740e-13	5.8552e-14
	STD	1.0815e-05	1.1045e-06	5.2055e-07	5.5027e-07	4.5642e-07	7.6519e-09
March	AVG	2.2440e-10	3.2154e-11	2.6375e-11	2.3748e-11	1.8577e-13	2.0064e-15
	STD	4.3669e-06	2.5807e-07	2.1148e-07	2.0118e-07	9.6252e-08	3.1723e-09
April	AVG	3.9674e-10	4.1923e-11	2.9907e-11	2.9073e-11	3.2415e-13	3.9159e-15
	STD	4.1982e-06	3.8263e-07	3.0219e-07	2.3716e-07	4.2099e-08	1.9789e-09
May	AVG	9.5308e-11	2.3318e-11	1.3737e-11	1.2576e-11	1.0929e-13	1.6023e-15
	STD	1.5740e-06	1.9818e-07	1.0352e-07	1.0080e-07	1.1684e-08	1.2658e-09
June	AVG	6.3793e-10	7.2573e-11	6.1637e-11	5.8919e-11	6.4951e-13	2.4898e-14
	STD	4.0815e-06	5.1577e-07	4.3901e-07	9.7048e-07	3.5521e-08	4.9898e-09
July	AVG	2.7584e-10	3.4240e-11	2.8438e-11	2.7111e-11	2.2872e-13	2.7222e-15
	STD	3.0040e-06	3.1519e-07	2.5660e-07	2.1892e-07	1.2852e-08	1.6499e-09
August	AVG	7.3887e-10	8.2004e-11	7.2809e-11	6.9907e-11	7.1889e-13	4.9783e-14
	STD	9.0476e-06	7.8448e-07	5.1733e-07	4.6977e-07	4.0732e-07	7.0557e-08
September	AVG	1.8406e-10	2.5215e-11	1.5414e-11	1.3659e-11	1.2676e-13	1.9308e-15
	STD	2.6979e-06	2.2990e-07	2.1086e-07	1.9749e-07	3.7079e-08	1.3895e-09
October	AVG	4.7043e-10	4.5862e-11	3.0477e-11	3.0400e-11	4.4710e-13	6.7291e-15
	STD	5.0257e-06	3.3927e-07	2.7717e-07	2.5293e-07	1.9765e-08	2.5941e-09
November	AVG	6.0652e-10	6.8321e-11	5.7309e-11	5.2669e-11	5.3805e-13	9.7426e-15
	STD	4.0705e-06	4.7453e-07	4.1574e-07	4.0473e-07	3.1105e-08	9.8704e-09
December	AVG	6.8110e-10	7.5703e-11	6.4748e-11	6.0535e-11	6.9485e-13	3.2828e-14
	STD	8.9946e-06	5.7645e-07	4.7718e-07	3.9413e-07	2.5128e-08	1.8118e-09
Average	AVG	4.7781e-10	5.3941e-11	4.3995e-11	4.1868e-11	4.4153e-13	1.7024e-14
	STD	5.1321e-06	4.9401e-07	3.4342e-07	3.6361e-07	1.0497e-07	9.7264e-09

Table 4: Various optimization algorithms associated ESN based wind speed forecasting monthly analysis

		MSE					
Month		ESN-GA	ESN-PSO	ESN-NPSO	ESN-GSA	ESN-GSAPSO	ESN-GSANPSO
January	AVG	7.9305e-14	9.9243e-15	2.0174e-15	8.0161e-16	9.1497e-17	7.5181e-19
	STD	5.6684e-07	8.2584e-08	1.6499e-08	6.9425e-09	7.3107e-10	5.1144e-12
February	AVG	9.0844e-14	1.0497e-14	3.9928e-15	9.5199e-16	9.5348e-17	8.6738e-19
	STD	8.4392e-07	1.1636e-07	2.6508e-08	8.9139e-09	8.2111e-10	6.4483e-12
March	AVG	6.5106e-14	8.4191e-15	1.1761e-15	6.7643e-16	7.2726e-17	5.7961e-19
	STD	4.7334e-07	7.5836e-08	1.4549e-08	5.5153e-09	6.7007e-10	2.7750e-12
April	AVG	1.9818e-14	4.0862e-15	5.3642e-16	2.4696e-16	2.6131e-17	2.2923e-19
	STD	2.0668e-07	5.8174e-08	4.2645e-09	2.6572e-09	2.3570e-10	1.3733e-12
May	AVG	6.2686e-14	7.8448e-15	9.4183e-16	6.0989e-16	6.4483e-17	5.1143e-19
	STD	4.2059e-07	6.9939e-08	7.3342e-09	5.1548e-09	5.2546e-10	2.6134e-12
June	AVG	1.0353e-13	2.0161e-14	8.2705e-15	3.0368e-15	2.1921e-16	1.1475e-18
	STD	9.6281e-07	1.4736e-07	7.0511e-08	2.5153e-08	2.7099e-09	1.6275e-11
July	AVG	1.7647e-14	3.3437e-15	4.7798e-16	2.0213e-16	1.7617e-17	1.8979e-19
	STD	1.8105e-07	4.3524e-08	3.6722e-09	1.3610e-09	1.6195e-10	1.2701e-12
August	AVG	5.3206e-14	7.3164e-15	8.3323e-16	5.9034e-16	5.4637e-17	4.9443e-19
	STD	4.4976e-07	6.3633e-08	6.5038e-09	5.1162e-09	4.5593e-10	2.4662e-12
September	AVG	9.8931e-14	1.3485e-14	4.5289e-15	1.9492e-15	1.0362e-16	9.6906e-19
	STD	8.6545e-07	1.9503e-07	3.8143e-08	9.0041e-09	1.0959e-10	1.2118e-11
October	AVG	2.3347e-14	5.5158e-15	6.8201e-16	3.6065e-16	3.4812e-17	3.0106e-19
	STD	2.2896e-07	4.7625e-08	4.7092e-09	3.4141e-09	2.4521e-10	2.2236e-12
November	AVG	7.0651e-14	9.2845e-15	1.3892e-15	7.7138e-16	8.5654e-17	6.1541e-19
	STD	5.0046e-07	7.9066e-08	1.8632e-08	6.4258e-09	8.2705e-10	3.9480e-12
December	AVG	3.5459e-14	6.3940e-15	7.6411e-16	4.2842e-16	4.6535e-17	3.5638e-19
	STD	2.8389e-07	5.7007e-08	5.9142e-09	3.6892e-09	3.7351e-10	2.5172e-12
Average	AVG	6.0044e-14	8.8560e-15	2.1342e-15	8.8548e-16	7.6023e-17	5.8442e-19
	STD	4.9865e-07	8.6345e-08	1.8103e-08	6.9456e-09	6.5554e-10	4.9285e-12

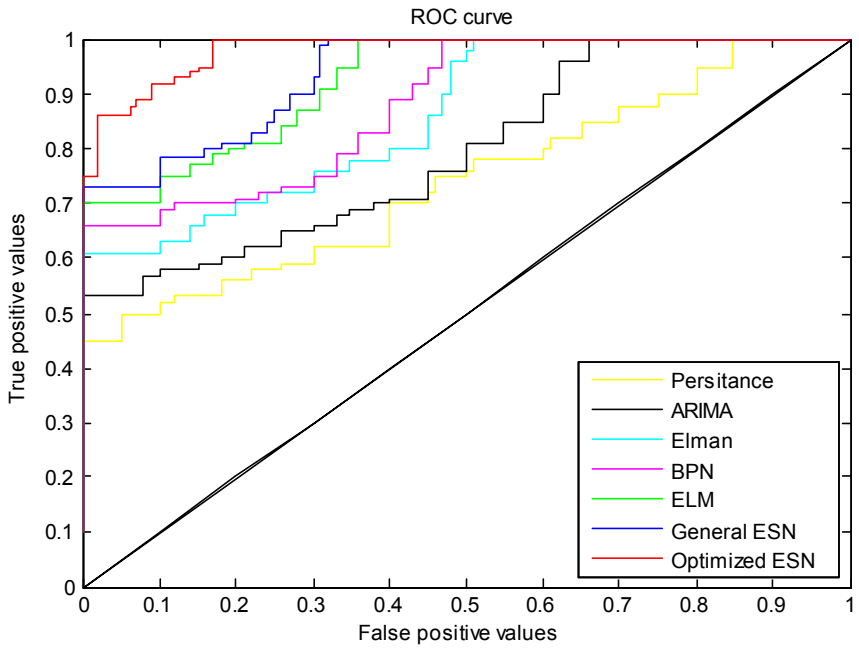

Fig. 11: Forecaster analysis using ROC

approach (ESN-GSANPSO) precocious performance for the applications of solar irradiance and wind speed forecasts. Even though each month based solar irradiance forecasting produce better results, among other months the best solar irradiance forecasting with reduced performance index is achieved in May month, which is understood from Table 3.

Although wind speed forecasting with respect to each month performing better with minimum performance index, the July month based wind speed forecasting possesses outperforming results among other months, which is perceived from Table 4. Compared to the existing and general ESN based approach, the ESN weight matrix linkages between the reservoir and output are optimized by GSANPSO which reduces the mean square error instead of multilayer regression based weight optimization. Analysis of solar irradiance and wind speed forecasting based on the performance index is shown in Figure 12 & 13 respectively. This research work introduces a new hybrid forecasting approach for the solar irradiance and wind speed forecasting, which enhance the performance of forecasting than that of other approaches, namely ESN-GA, ESN-PSO, ESN-NPSO, ESN-GSA and ESN-GSAPSO, which is clearly realized from Figure 12 & 13. The simulation outputs showcased that the proposed hybrid approach based solar irradiance and wind speed forecasting enrich the performances in terms of the much smaller performance index (MSE). The proposed hybrid optimization algorithm based ESN furtherance the solar irradiance and wind speeds forecasting results of each month and overall monthly average than that of GA, PSO, NPSO, GSA and GSAPSO based ESN which is perceived from Table 3 & 4.

Parameters and weights optimization are a generic issue in echo state network modeling; this paper is endeavoring to resolve the issue by dint of the new hybridized optimization algorithm. However the proposed GSANPSO (new hybridized optimization algorithm) gleans rigorous performances on the comparative analysis (Table 3 and Table 4) with well familiar algorithms such as GA, PSO, NPSO, GSA and GSAPSO in order to justify the novelty of the proposed approach further comprehensive comparison result analysis with the recent algorithms like EA/G (evolutionary algorithm with guided mutation) [28], MBAT (Modified Bat) [29], GAACO (Genetic algorithm and ant colony optimization) [30], ICOA (Improved cuckoo optimization algorithm) [31], MFA (Modified firefly algorithm) [32], HGICA (hybrid genetic-imperialist competitive algorithm) [33], IMA (Improved memetic algorithm) [34], MBFO (modified bacterial foraging optimization) [35], PSOGA (Particle swarm optimization genetic algorithm) [36], BMO (Bird mating optimizer) [37], IKH (improved krill herd algorithm) [38], GWO (Grey wolf optimizer) [39], hGAGSA (hybrid genetic algorithm gravitational search algorithm) [40], MPSOGA (Modified particle swarm optimization genetic algorithm) [41] and

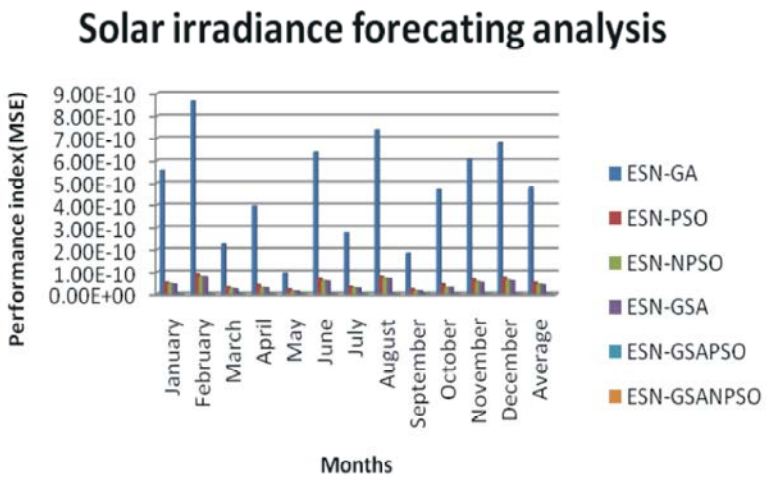

Fig. 12: Performance index based analysis for the solar irradiance forecasting

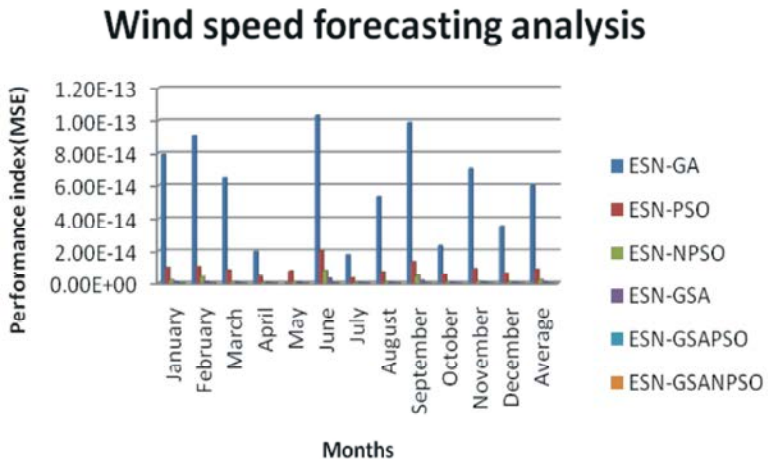

Fig. 13: Performance index based analysis for the wind speed forecasting

MEPSOTVAC (modified evolutionary particle swarm optimisation-time varying acceleration coefficient) [42] is performed and the monthly average MSE (mean square error) AVG (average) and STD (standard deviation) are tabulated in Table 5. The concern to recent optimization algorithms and previous existing optimization algorithm pros and cons are inevitable. For the considered applications (solar irradiance and wind speed forecasting) the proposed hybridized optimization (GSANPSO) algorithm based optimized echo state network result in a promising, reliable and the rigorous forecasting of solar irradiance and wind speed, which is justified by dint of achieved results of Table 5.

Significant Contribution: Even though good forecasters have been suggested by many researchers in wind speed and solar irradiance forecasting still lacks in aspects like faster convergence, generality and stability. They are failing to meet the ease of computation, generality, quick convergence, consistency and stability. To resolve the above-said problems this research endeavors a new hybrid approach based shrewd forecasting models for the purpose to forecasts solar irradiance and wind speed. The generalization ability and error minimization of ESN achieved with the help of a GSANPSO based optimization algorithm are superior to the recent and existing optimization algorithms. This paper focused significant original contribution to model the new hybridized optimization algorithm (GSANPSO) for the purpose of echo state network parameters and weights optimization, which is very simple in nature, but possess effective capability of exploration and exploitation, it can be observed in forecasting applications as is seen in the outputs of the solar irradiance and wind speed obtained.

Table 5: Echo state network optimized through new hybrid optimization algorithm and recent algorithms for the solar irradiance and wind speed monthly average forecasting

ESN with Optimization Algorithms		Monthly Average MSE	
		Solar Irradiance Forecasting	Wind Speed Forecasting
ESN-EA/G	AVG	2.3856e-10	2.1046e-14
	STD	4.7175e-06	3.4882e-07
ESN-MBAT	AVG	5.1268e-11	8.2791e-15
	STD	4.6251e-07	7.9521e-08
ESN-GAACO	AVG	4.1415e-11	2.0389e-15
	STD	3.4829e-07	1.5546e-08
ESN-ICOA	AVG	3.5997e-11	1.1855e-15
	STD	3.3183e-07	1.0765e-08
ESN-MFA	AVG	1.2908e-11	7.9552e-16
	STD	3.2114e-07	5.4365e-09
ESN-HGICA	AVG	9.9584e-12	6.6025e-16
	STD	3.0185e-07	4.6464e-09
ESN-IMA	AVG	7.0051e-12	5.8639e-16
	STD	2.9918e-07	4.1304e-09
ESN-MBFO	AVG	5.6432e-12	5.2193e-16
	STD	2.9402e-07	3.8591e-09
ESN-PSOGA	AVG	4.4751e-12	4.9601e-16
	STD	2.8649e-07	3.2153e-09
ESN-BMO	AVG	3.7736e-12	4.0113e-16
	STD	2.8075e-07	2.8466e-09
ESN-IKH	AVG	3.3198e-12	3.4785e-16
	STD	2.7153e-07	1.7813e-09
ESN-GWO	AVG	1.5329e-12	2.9022e-16
	STD	2.4372e-07	1.0408e-09
ESN-hGAGSA	AVG	9.9613e-13	1.4405e-16
	STD	2.0024e-07	9.3526e-10
ESN-MPSOGA	AVG	8.9110e-13	9.3830e-17
	STD	1.7013e-07	7.1590e-10
ESN-MEPSOTVAC	AVG	6.7653e-13	7.7313e-17
	STD	1.4317e-07	6.6091e-10
ESN-GSANPSO	AVG	1.7024e-14	5.8442e-19
	STD	9.7264e-09	4.9285e-12

CONCLUSION

The energy productions from the solar energy and wind energy are directly impacted by the solar irradiance and wind speed respectively. If solar irradiance and wind speed decay, the power generations are also dropping. Energy generations from the solar energy and wind energy are not continuous energy production resources, which are mutable in nature. This makes conundrum for integration, maintenance, economic planning, scheduling and dispatching, which is the most prominent issues with respect to the solar energy and wind energy, for well-organized integration of renewable energy resources, namely solar energy and wind energy to the electric grid incite enrich solar irradiance and wind speed forecasting. To mitigate the above-said plight, this work proposes a shrewd hybrid forecasting approach based on ESN-GSANPSO. This work first implements the monthly solar irradiance and wind speed forecasting by means of the proposed GSANPSO based optimized parameters incorporated ESN and existing approaches such as persistence, ARIMA, BPN, Elman, ELM and general ESN, then compared the obtained results and comparative analysis is performed with the help of performance index. Next forecaster performance ability, usefulness is analyzed and realized with the help of the ROC. Finally, the GSANPSO based optimized parameters associated ESN trainable synaptic weight linkages are

optimized with the help of various previously existing optimization algorithms namely GA, PSO, NPSO, GSA, GSAPSO, recent algorithms and proposed GSANPSO. The applicability is verified by the solar irradiance and wind speed forecasting. It is found that GSANPSO based optimized parameters and synaptic weight linkages incorporated Echo state network (ESN) accomplish the betterment results for the solar irradiance and wind speed forecasting with better accuracy and very smallest performance index. Hence, make the successful advancement of power system operation and management.

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