Design and Simulation of Hybrid Renewable Energy system design by Artificial Neural Network approach

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Abstract-Nowadays, most of the research is being done on renewable based energy sources. Renewable energy is created from the processes which are natural and frequently replaced. There are different forms of Renewable Energy Sources (RES) such as Photo-Voltaic (PV), Wind, Hydro-electric power and Biomass. Research proves that the cost of this electrical energy remains constant over the year. Because of that, most of the countries uses RES as the main source of major energy producer. And it can regulate both the active power and reactive power injected into the grid autonomously using only marginally appraised power converters. Reactive power has an intense result on the safety of the systems for the reason that it disturbs voltage all over the system. In order to control the reactive power to make the system as healthy one. Micro-Grid (MG) have many benefits for both utility grids and consumers such as higher power quality. For that, in this paper, Hybrid Renewable Energy Sources (HRES) are used with Artificial Neural Network (ANN) to improve the variation of active/reactive power flows based on consumer necessities and mitigate the Total Harmonic Distortion (THD). The performance measurement of the HRES with ANN is validated in MATLAB/Simulink, which showed the value of Total Harmonic Distortion (THD) is 0.9103%.

Keywords—Artificial Neural Network (ANN), Hybrid Renewable Energy Sources (HRES), Photo-Voltaic (PV), Total Harmonic Distortion (THD).

I. INTRODUCTION

Fossil fuel stays the main sources in the worldwide energy fusion and are related with the increase of carbon dioxide (CO2) radiations. The deployment of Renewable Energy Sources (RES) can plays a significant role to minimize both CO2 radiations and fossil fuel dependence [1]. Fossil-fuel powered distillation methods absorb extensive amounts of energy and has extremely damaging influence on the atmosphere [2]. Consistency and price are the two important inter-linked concepts considered by system operators in many power systems [3]. By integrating RES into a single hybrid energy network connected through informatics bonds would allow to overcome the drawbacks present in the above concepts Stand-alone Hybrid RES have the potential to [4]. produce continuous power related to the utility grid. Although, the energy provided by RES such as solar and wind, is irregular due to the uncertain and varying natures of these energy resources [5]. The potential impacts of inconsistency and interruption in renewable based sources on the design of standalone RES systems integrating storages are explained at the design stage. Hybrid power system strategy comprising numerous structure of RES choose the optimal arrangement of parameters with different optimization techniques [6, 7]. Optimization includes one or more objectives such as minimize energy costs, size and balance the uncertainty of energy, minimization of greenhouse gas emissions [8].

Hybrid Energy Storage System (HESS) is described by a valuable combination of two or more energy storage machineries with auxiliary operating features. In order to consider system design specifications, it presents along with a standard method for the power flow decomposition based on double low-pass filtering and peak shaving. Result shows that a system outline with the similar level of reliability as in the deterministic situation denotes the cost is very high [9, 10]. By using thermo-economic model in TRNSYS environment, allows to determine the best system configuration and increase the economic profitability of the system [11]. HRES has been demonstrated continuously effective in making use of renewable energies [12]. Conversely, the capital cost of these sources is typically high; therefore, minimizing the cost with an improved installation is one of the imperious prospects of nowadays research [13]. Most of the researches focused on only sizing of the grid-independent HRES using numerous optimization techniques. Some of these studies used the iterative optimization procedure which is frequently inefficient and may not attain precise Another difficulty with the control outcomes [14]. strategies is that energy systems and external environment in which they operate - cannot be designed accurately, may change in random manner and may be subject to substantial disturbances [15]. Among the RES, PV panel

and wind turbine are most favourable renewable based power generation tools. The development of solar and wind energy generation systems has surpassed the most enthusiastic assessments. Although, environmental and regular weather conditions disturb the PV-wind energy output. Hence, a backup network is desirable to enhance the reliability of energy supply. Thus, the energy systems are additionally added which ideally satisfies the essential for any start up power. To conquer the above mentioned problems, Hybrid Renewable energy sources (PV, Wind, Hydro-electric and Biomass) is designed with Artificial Neural Network (ANN) to compensate the variation active and reactive power flows based on consumer and mitigate the harmonic disturbances. Once the complexity of a system is enlarged other methods are not used for modelling, because it takes more processing time to attain the results. But in that condition, ANN modelling can produce good results with less processing time. ANN is non-parametric and nonlinear design that is easy to handle and recognize when compared to other statistical approaches. Even though most of the statistical procedures are parametric model that requires higher background of measurements. So, in this research, a feed-forward back propagation type of ANN architecture is developed for the control of hybrid power system. Hidden layers are employed in the ANN training process. The profitable tool of MATLAB for the ANN method is exploited for the declared training action. Probable predicted values of the ANN inputs and outputs are given as the initial training data. ANN delivers a regression for the input and the values that have not been primarily clear using the given training data-set. The trained ANN employed in the system provides the maintenance process with the power share of hybrid system components during the supply of load. Results shows the effective performance of ANN when compared with other traditional approach approaches.

The paper is organized as follows. Section II provides a brief description of the related works. Section III focus on ANN methodology. In section IV, comparative study of the results and discussion for proposed system and existing system is presented. Section V gives a summary of this paper.

II. LITERATURE REVIEW

Several researchers recommended many techniques in the field of HRES. In this scenario, a brief evaluation of some important contributions to the existing literatures are represented below.

J.B. Fulzele, and M.B. Daigavane [16] has proposed the design and optimization of hybrid renewable energy sources (Solar, Wind and Battery energy sources). The design considerations were developed with the help of Improved Hybrid Optimization Genetic Algorithm. By using this technique to access the consequence of insecurity or variation in the variable and discover the most appropriate resolution for the hybrid system. Selection of suitable sizing and control strategy improve the efficiency of the system. But the accurate design of such system is the challenging task as the coordination between the different energy sources; energy storage and loads are very difficult. A. Thornton, S.J. Kim, and S. Kara [17] has developed hybrid renewable energy system to reduce the cost at various levels of robustness for an industrial site. This system is designed by using Mixed Integer Linear Programming framework to improve the potential cost savings and provide efficient energy supply. But the industries have been slow down to adopt non-dispatch able renewable sources partly because of the integral inconsistency.

N.H. Saad, A.A. El-Sattar, and A. El-Aziz M. Mansour [18] has proposed a novel control strategy for grid connected hybrid renewable energy sources. The control technique used in this system is Improved Particle Swarm Optimization (IPSO) algorithm which acts as a main controller to control the power of the sources. And it is succeeded to manage the energy between micro grids under different scenarios. The control method using IPSO approach enhances the dynamics of the hybrid system connected to the grid. But the main issues with microgrids is the management control between the dissimilar distributed generations and the utility service.

F. Shahnazian, J. Adabi, E. Pouresmaeil, and J.P.S. Catalão [19] has developed a modular multilevel converter (MMC) for grid integration of renewable energy sources. In order to attain a steady operation for the interfaced MMC for the period of connection of renewable based energy sources into the power grid. The developed method is able to alleviate the converter circulating current by injecting a second harmonic allusion in the modulation procedure of the MMC. The range of voltage and power in switching devices are limited because of semiconductor technology in case of high power applications.

J. Jung, and M. Villaran [20] has proposed an optimal planning and design of hybrid renewable based energy sources for micro grid. The type and size of distributed energy sources are determined by customer adoption model. It proves the proficiency of optimization analyses, in order to maximize the efficiency of renewable sources integration and to help implement net-zero buildings, campuses and communities. However, addressing the improved application-specific value delivered by this technique still remains a challenging one that must be established by future trainings.

To overcome the above mentioned problems in the previous works, an effective methodology is proposed which is named as Artificial Neural Network (ANN) which is described briefly in the below section.

III. ARTIFICIAL NEURAL NETWORK (ANN) WITH HYBRID RENEWABLE ENERGY SOURCES

ANN designs seems like to be more suitable to enhance the proficiency of RES. ANN have various usage areas in simulation, modelling and control of RES. ANNs are very simple to use and to develop RES designs. So, in this paper, ANN applications of HRES which comprises of PV, Wind, Hydro and Biomass are presented.

A. Hybrid Renewable Energy Sources

In this research work, a hybrid renewable energy network which comprises Solar (PV) power, Wind

Turbine (WT), Hydro-electric power and Biomass energy sources. Figure 1 shows the architecture of Hybrid Renewable Energy source. The hybrid power system is coupled to AC network with the help of power electronic components. The advanced control procedures for each subsystem (solar, wind, hydro-electric and biomass) is applied to meet the load requirements. These subsystem control requires also the development of a supervisor. This supervisor based on artificial neural network (ANN). It is very robust method for many disturbed models and it can be well selected for all RES of production which are very inconsistent in very short time. ANN model decides the energy transfer type of all the sources (transfer energy / no transfer energy) and take decision like ON/OFF status. These two parameters are selected respectively to determine the control mode of the hybrid system. The supervisor inputs are the reference power of hybrid power system (power demanded by the grid), the power generated by solar power, wind generator, hydro-electric and biomass. The main purpose of the control and supervision of hybrid networks are to fulfill the reference power of hybrid power system, to regulate the energy transfer between hybrid system and the grid. And to optimize the use of solar, wind energy, and to reduce the use of remaining other two resources. A data base is established and it contains all inputs and outputs which will be trained and tested by ANN model; this base values treats all probable cases of the system. The ANN is accomplished using Matlab software by "nftool" function, and after that various tests are determined to find the final parameters and its architecture.

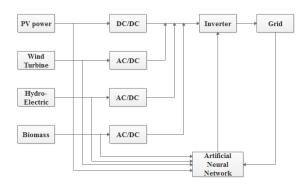


Fig. 1 Architecture of HRES

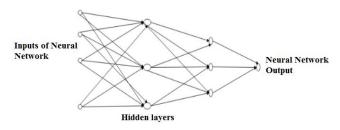


Fig. 2 Architecture of ANN

B. Architecture and Operation of ANN

Artificial neural networks (ANN) are extensively recognized as a knowledge offering marginal way to attack difficult and ill-defined issues. It can learn from examples, fault tolerant in the sense that can able to handle noisy and imperfect data, able to deal with nonlinear issues, once trained, can perform forecast and simplification at high speed. It is extensively used in diverse applications such as forecasting, control, medicine, robotics, pattern recognition, power systems, optimization, signal processing, manufacturing, and social/psychological sciences. Specifically, it is very useful in system modelling such as employing complex mappings and scheme identification.

A Neural Fitting (nftool)	
Neural Fitting (nftool) Welcome to the Neural Network Fitting app. Solve an input-output fitting problem with a two-layer feed-forward Infting problems, you want a neural network to map between a data set of numeric inputs and a set of numeric targets. Examples of this type of problem include estimating engine emission levels based on measurements of fuel consumption and speed (engine_dataset) or predicting a patient's bodyfat level based on body measurements (bodyfat_dataset).	
The Neural Fitting app will help you select data, create and train a network, and evaluate its performance using mean square error and regression analysis.	A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons (fitnet), can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. The network will be trained with Levenberg-Marquardt backpropagation algorithm (trainlm), unless there is not enough memory, in which case scaled conjugate gradient backpropagation (trainscg) will be used.
To continue, click [Next].	
Reural Network Start Welcome	Back Sext Cance

Fig. 3 I/O layer of ANN

📣 Neural Fitting (nftool)	
Select Data What inputs and targets define your fitting problem?	
Get Data from Workspace	Summary
Input data to present to the network. Input data to present to the network. simplefitInputs	Inputs 'simplefitInputs' is a 1x94 matrix, representing static data: 94 samples of 1 element.
Target data defining desired network output. Image: Comparison of the structure	Targets 'simplefitTargets' is a 1:94 matrix, representing static data: 94 samples of 1 element.
Samples are: (I) Matrix columns (I) (I) Matrix rows	
Want to try out this tool with an example data set?	
Load Example Data Set	
To continue, click [Next].	
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Fig. 4 Data sets of ANN

The architecture of ANN is shown in figure 2. It consists of three principal layers of neuron: First the input layer then the hidden layer and output layer. ANN model can be established in different structures. Generally, ANN provides implementation of various paradigms, presents the comparative analyses and applications. Of these models, the more used is the back propagation paradigm. Each layer (i) is composed of neurons (Ni), which take

their inputs on Ni-1 neurons in the preceding layer. Each pattern is connected with a synaptic weight, so that Ni-1 is multiplied by this weight and then aggregated by the neuron level (i), which is corresponding to multiply the input vector by a transformation matrix. Placed one after the other layers of a neural network would cascading numerous transformation matrix and could be minimized to a single matrix. The other products, if there were placed at each layer, output function presents a nonlinearity at each step. Above mentioned feature shows the significance of the choice of decent output function: a neural network whose outputs are linear has no attentiveness.

The I/O layer of ANN is shown in figure 3. This diagram shows the general layer for ANN model. It gives the common introduction about networks and it shows types of architecture that used inside the ANN. In ANN, the back propagation architecture each neuron receives inputs from the real-word environment. Feed-forward ANN (FANN) doesn't have any closed paths and the output nodes are linked with the input nodes without any feedback paths. The global minimum is reached by using the Levenberg-Marquardt (LM) algorithm in Back Propagation Algorithm (BPA) and this LM algorithm is used for training the FANN. The back propagation algorithm uses the supervised training technique. An estimated suitable rule is exploited in a back propagation algorithm. The approximate form of the performance index is V and it is written as follows Eq. (1).

$$\hat{V} = \frac{1}{2} e_r^U e_r \tag{1}$$

Where, r is the error of the r input and is indicated as $e_r = u_r - b_r^N$ and the squared errors for a single input/output pair is substituting the total amount of errors. The approximate steepest (gradient) algorithm is specified as Eq. (2) and (3),

$$\Delta w^{l}(j,k) = -\beta \frac{\partial \tilde{v}}{\partial w^{l}(j,k)}$$
⁽²⁾

$$\Delta c^{l}(j) = -\beta \frac{\partial \bar{v}}{\partial c^{l}(j)} \tag{3}$$

Where the learning rate is denoted as β .

The performance index sensitivity alter the input 1 at the layer of l and it is written as follows Eq. (4).

$$\gamma^{l}(j) = \frac{\partial \tilde{v}}{\partial m^{l}(j)} \tag{4}$$

The back propagation is a steepest algorithm is executed and the LM algorithm is used to estimate the newton's method. The function V(y) is reduced with respect to the parameter y. The Newton's method is expressed as Eq. (5).

$$\Delta y = [\nabla^2 V(y)]^{-1} \nabla V(y) \tag{5}$$

Where the HM is denoted as $\nabla^2 V(y)$, the gradient is represented as $\nabla V(y)$, y is expressed as Eq. (6).

$$y = [w^{1}(1,1)w^{1}(1,2) \dots w^{1}(S1,Q)c^{1}(1) \dots^{T} c^{1}(S1)w^{2}(1,1) \dots c^{N}(S,N)]$$
(6)

If the V(y) is the sum of squares function, then it can be expressed as Eq. 7.

$$V(y) = \sum_{j=1}^{M} e_j^2(y)$$
(7)

Where M is expressed as following Eq. (8),

$$M = R \times SN \tag{8}$$

The HM and gradient is expressed as following Eq. (9) and (10).

$$\Delta V(y) = J^{T}(y)e(y) \tag{9}$$

$$\nabla^2 V(\mathbf{y}) = J^T(\mathbf{y})J(\mathbf{y}) + S(\mathbf{y}) \tag{10}$$

Where I(y) is defined as the Jacobian matrix. The Jacobian matrix is computed by the simple modification in the back propagation algorithm as well as it is used for avoiding the mapping problem in y of Eq. (10) in the neural network. The I(y) expressed in the form matrix as given below Eq. (11) and (12).

$$j(y) = \begin{bmatrix} \frac{\partial \varepsilon_1(y)}{\partial y_1} & \frac{\partial \varepsilon_1(y)}{\partial y_2} & \dots & \frac{\partial \varepsilon_1(y)}{\partial y_m} \\ \frac{\partial \varepsilon_2(y)}{\partial y_1} & \frac{\partial \varepsilon_2(y)}{\partial y_2} & \dots & \frac{\partial \varepsilon_2(y)}{\partial y_m} \\ \vdots \\ \frac{\partial \varepsilon_m(y)}{\partial y_1} & \frac{\partial \varepsilon_m(y)}{\partial y_2} & \frac{\partial \varepsilon_m(y)}{\partial y_m} \end{bmatrix}$$
(11)

And

$$S(y) = \sum_{j=1}^{M} e_j(y) \nabla^2 e_j(y)$$
⁽¹²⁾

These equations are leads to the Levenberg-Marquardt method expressed as Eq. (13).

$$\Delta y = [J^{T}(y)J(y) + \varphi I]^{-1} J^{T}(y)e(y)$$
(13)

If the $V(\mathcal{Y})$ is increased, the parameter φ is multiplied some factor that is α . While the parameter φ is small, the procedure becomes the LM algorithm.

The terms are designed by the standard propagation is expressed in Eq. (14).

$$\frac{\partial \hat{V}}{\partial w^l(j,k)} = \frac{\partial \sum_{n=1}^{SN} er^2}{\partial w^l(j,k)}$$
(14)

The standard propagation algorithm with one modification at the final layer is expressed in Eq. (15).

$$\Delta^N = -F^N(m^N) \tag{15}$$

In Eq. (15), the back propagation is completed at each column of the matrix that is sensitivity vector to provide one row of the Jacobian.

The figure 4 shows the data sets of ANN. In this portion, fix the data for input and target. Both the input and target should have same set of matrix. Then to select the way of matrix order either it is column wise or row wise. And then click next. This neural network has one or more amount of hidden layers of sigmoid neurons followed by an output layer of linear neurons as well as it is used as a general function approximation. The hidden layer has adequate amount of neurons for approximate any function with a finite amount of discontinuities. In backpropagation networks, the number of hidden neurons determines how well a problem can be learned. If too many are used, the network will tend to try to memorize the problem, and thus not generalize well later. If too few are used, the network will generalize well but may not

have enough "power" to learn the patterns well. Getting the right number of hidden neurons is a matter of trial and error, since there is no science to it. Three types of data files are required; a training data file, a test data file and a validation data file.

C. ANN Training

The ANN training section is the most stimulating phase. The major stage for this training is the establishment of data base for preferred input and output. ANN is trained to recognize the connection between the input and output data. In this system, the interlayer connection weights and the processing features thresholds are mainly initialized to create small random values. Before creating the network, to develop a data base which gives all potential scenarios which can be accessible for the hybrid system. ANN model comprises of four nodes of input and only one node of output. A set of coordinated input and output patterns used for training the system, typically by appropriate alteration of the synaptic weights.

Figure 5 shows the training set of ANN. After given the input and target data sets, to choose the training algorithm, depends upon that training process occurs. Inside the training process, different types of results with different scenarios generated and then it moves onto testing portion. The output of the networks are the dependent variables that network produces the values for the corresponding input data's. It is very important that all the statistics from the network needs to be learned, that is supplied to the system as a data set. When each configuration is read, the system uses the input data to produce an output, which is then compared with the training configuration, i.e. the accurate or preferred output. If there is any variance, the connection weights are modified in such a direction that the error is minimized. After the system has run through all the input data sets, if the inaccuracy is still superior to the maximum preferred tolerance, ANN runs once again through all the input data repeatedly until all the inaccuracies are within the requisite tolerance. When the training reaches an acceptable level, the system holds the constant weights and uses the trained network to make choices, identify the patterns or define associations in new input data sets not used to train it. And figure 6 shows the results of training section.

A Neural Fitting (nftool)		
Train Network Train the network to fit the inputs and targets.		
Train Network Choose a training algorithm: Levenberg-Marquardt train algorithm typica automatically stops Scaled Conjugate Gradient an increase in the me Scaled Conjugate Gradient amples. Train using Levenberg-Marquardt. (trainim) Retrain Notes Training multiple times will generate different results due to different initial conditions and sampling.	Mesults Samples MS Training: 66 1.22270e Validation: 14 8.83831e Testing: 14 3.18124e Plot Fit Plot Error Histo Plot Fit Plot Error Histo Plot Regression Plot Regression Mean Squared Error is the average squared differ between outputs and targets. Lower values are b means no error. Regression R Values measure the correlation betwoer outputs and targets. An R value of 1 means a clo relationship. 0 a random relationship.	4 9.99993-1 5 9.99995-1 4 9.99979e-1 gram
 Open a plot, retrain, or click [Next] to continue. Weural Network Start Welcome 	🗇 Back 🗬	Next 🙆 Cancel

Fig. 5 Training set of ANN

Neural Network									
		Inp 1		lden	Output W + b	Outp	ut		
lgorithms									
Data Division: Random Fraining: Levenbe Performance: Mean Sq Calculations: MEX	rg-Marquardt								
rogress									
poch: Time:	0	19 iterations 0:00:01	1000						
erformance:	324	9.25e-05	0.00						
	414	0.000292	1.00e-						
Лu: 0.00		1.00e-05	1.00e+	10					
/alidation Checks:	0	6	6						
lots									
Performance	(plotperform)								
Training State	(plottrainstate)								
	(ploterrhist)								
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	(plotfit)	,							
гя	(piotrit)								
		F	lot Interval: 🛛		1	epochs			
Validation stop.									
								Stop Training	Cance

Fig. 6 Results of Training model

D. ANN Testing

At first, ANN model is tested after its convergence to desired outputs values, simulate the system with Matlab-Simulink software. In this research work, power from the solar, wind, hydro-electric and biomass used as a profile which is applied as a reference power for hybrid renewable energy system. If the load demand is high, feedback from the load and reference power from the hybrid networks are calculated in the ANN to produce an efficient output which completely satisfies the load requirement. For example, it shows the ON/OFF status of solar power, the power from the PV panel is always OFF and its generated power is null, which means the reference power of hybrid renewable energy system is satisfied by the other renewable sources (i.e.), without the intervention of solar panel.

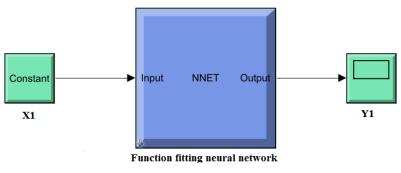


Fig. 7 Results of Testing

Figure 7 shows the results of testing process. The input for the neural network is given from the hybrid renewable energy sources and the output values are displayed depends upon the load conditions. Inside the neural network, already data sets are created with different scenarios. Regarding load conditions, reference values are checked with the load requirements. After that, the output generated by the ANN satisfies the load demands, which are clearly mentioned in the below section.

IV. RESULT AND DISCUSSION

In the recent years, the ANN models are largely used in the renewable based energy conversion system such as in Solar (PV panel), Wind Turbine model and in hybrid power system. In order to determine the efficiency of the proposed proposed algorithm, the methodology performance was compared with existing methodologies: DSTATCOM [21] and ANFIS [22]. In [21], a high speed and cost efficient D-STATCOM device was suggested for minimizing the harmonic problem and preserve voltages at both side in distribution network. From the simulation results, it exposed that the recommended network is more compressive than the other traditional controller. By using D-STATCOM in distribution network, THD are decreased up to 5.73%. In [22], Power quality problems existing in incorporation of PV structure with grid, among those problems THD are major issue for current injection into the grid. To reduce the above mentioned issue, control with ANFIS and fuzzy and are analysed. In this two control systems, ANFIS provide better performance in harmonic decrease of injected current. The THD content in grid connected PV system with ANFIS controller (1.87 %) is very less when compared to FLC control (2.41 %). In this research work, an ANN supervisor model for HRES control is developed. A supervisor model based on artificial neural network is established then to determine the reference values of each RES. The supervisor's inputs are variation between the reference power of renewable energy system and produced load power; this power is not characterized by a value, it is symbolized by the parameter which designates its boundaries, and that can be 0 or 1.A concept of hybrid power system behavior with its accessibility under different scenarios at different configurations of the consumer can be accomplished. The Simulink model is mainly designed for the analysis of HRES usage for their energy controlling in the design phase and for the study of issues that may happen due to the assumed resolution. The adopted resolution concerns the management explanations that can be accepted, but also the control, monitoring, command of RES and consumer's demand also be analyzed. In addition, after running the Simulink model, power flow graphs among hybrid system based on renewable based energy resources, public/local power system and instantaneous voltages/currents graphs can be obtained. In the simulation process, behaviour of proposed system is tested. The solar radiation, biomass power, hydro power, wind speed and load profiles are all used to check the performance of ANN based hybrid system model. This model was considered at different formations and situations of hybrid renewable energy sources availability and different types of consumers. In this model, the availability of renewable energy resource was taken the input source of 100KW as maximum power from each RES, depends on weather and its fuel usage its gets varied, which is shown in below figures 8, 9, 10 & 11 respectively. The dynamic relations among the renewable energy sources and the load requirements can lead to dangerous complications in steadiness and power quality features that are not very common in traditional power systems. As a result, handling the energy flow throughout the entire hybrid system is necessary to maximize the operating life of the network and to make sure the continuous power flows also. For that reason, an optimized energy management based control technique has been implemented for hybrid power systems. The statistical analysis of the results indicates that the ANN-based model developed in this work can predict the Maximum power from the network with high accuracy. The proposed method introduced the controller between four energy sources comprises PV array, Wind source, Hydro power and Biomass energy. The overall aim is to optimize the active and reactive power flow between system power sources. Additionally, results of the proposed method shows better performance compared to the existing results.

Figure 12 shows the active power variation in the local power network by the HRES. It can be noted that if the load requirements are very low, at that time specific sources of parameters by the hybrid renewable energy is operated, the system provides about two fourth of the electricity produced in the public network. When the load requirements are high, it can be noted that, by the time all the resources from the renewable energy runs to compensate the load demands, if it is fully balanced, energy is absorbed from the public network. The figure 13 shows the variation of reactive power in the local power system by the HRES. It can be perceived that the hybrid renewable energy based system can be used to provide reactive power. The most positive condition is the convenience of all renewable energy sources (solar, wind, hydro-electric and biomass).

It is noticed that the power produced from the hybrid renewable based energy sources is used for balancing the load demands for industries, at the consumers or to protect the losses and surplus amount of power is injected into the public network. If the insulated power evolution of consumer is stabilized resulting an equivalent constant level according to power and its losses. When the consumer power is protected, the existence of reactive power is affected by nonlinear components used in the Simulink model: like power transformers and power converters based electronic switching elements.

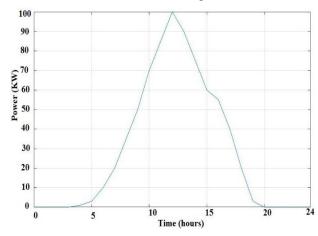


Fig. 8 Maximum input power of Solar

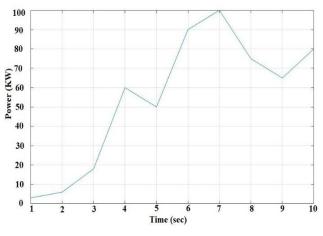


Fig. 9 Maximum input power of Wind

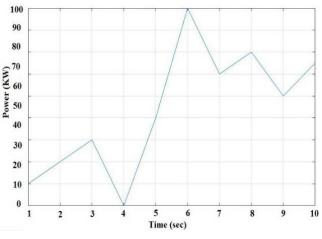


Fig. 10 Maximum input values of Hydro

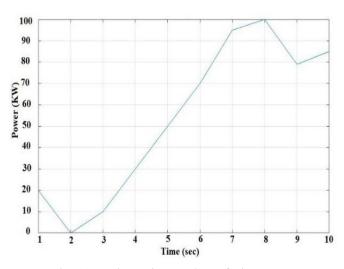


Fig. 11 Maximum input values of Biomass

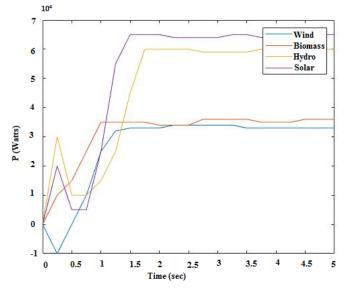
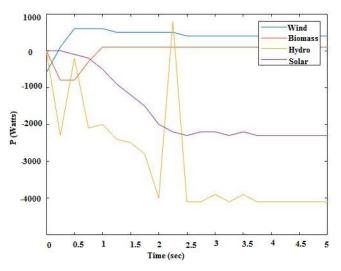
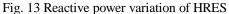


Fig. 12 Active power variation of HRES





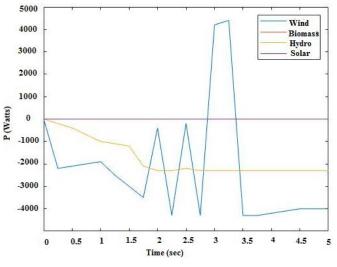


Fig. 15 Consumer Reactive power variation

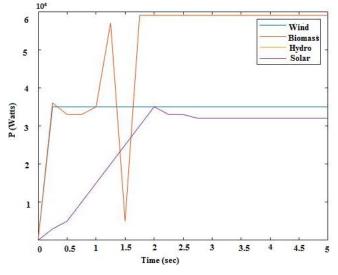
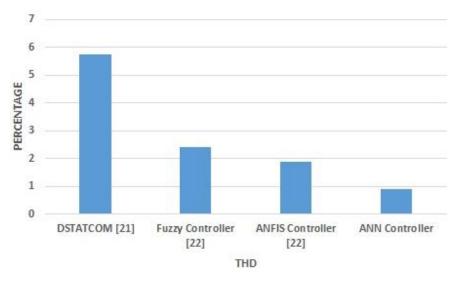


Fig.	14	Consumer	active	power	variation	





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 TABLE I.
 COMPARISON TABLE

Parameter	Facts Device [21]	Fuzzy & ANFIS controller [22]	ANN controller
THD	DSTATCOM = 5.73	Fuzzy = 2.41 % ANFIS = 1.87 %	0.9103 %

The performance measurement of THD comparison with ANN is mentioned in the below table 1. The figure 16 shows the comparison graph for proposed system with existing approaches.

A. Consumer based HRES

In general, consumers are geographically insulated and use in their actions by variable speed drives based applications (i.e.: fans, mills, circular saws and conveyors). To examine such a case, a consumer which has a network based on variable drives that use well-organized rectifiers (for example, a fan whose speed varies when temperature changes) has been modeled. Figure 14 and 15 shows the active power and reactive power variation at consumer level in the local network.

V. CONCLUSION

Generally, several number of local control methods are developed for the energy production subsystems which organize the hybrid renewable based energy system (Solar power, Wind Turbine, Hydro-electric power and Biomass) proposed and modelled. In this research work, a supervisory control based on Artificial Neural Network (ANN) model is developed for system control. By using ANN to fulfill the power demanded by the grid, to regulate the power transfer between the hybrid system and the grid, to optimize the use of RES and to balance the power flow of the system. Afterwards the control parameters are validated with MATLAB/Simulink software. It is observed that the load voltage THD is reduced to the level of 0.9103%. The THD and the amount of unbalance in load voltage are decreased with the application of ANN. The simulation results show that the benefits of hybrid renewable energy network and its control as solution for the compensation of active/reactive power and THD. This solution enhances the power quality features and maximizes the penetration of power generation in the electrical supply systems without causing any danger to interrupt their steadiness. This work can be extended for different types of RES combination with storage devices and THD can be decreased. Recent optimization techniques may be used to find out an optimal result, and also their performances can be compared. The manufacturing price of renewable energy requires a substantial reduction because the high capital cost leads to an increased payback time.

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