Electrical Power and Energy Systems 113 (2019) 792–806

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Optimum control strategies for short term load forecasting in smart grids

Mansoor Ali, Muhammad Adnan, Muhammad Tariq*

National University of Computer and Emerging Sciences, Pakistan

ARTICLE INFO

Keywords:
Short term load forecasting
Power flow control
Overloading
Fuzzy control

ABSTRACT

Nonlinearity in load profile and variations in demand due to error margin in short term load forecasting cause power network overloading. The state of a power system is more severe when a fault occurs in the power system network that leads to overloading. Analyzing the effect due to these disturbances on power system network is an important feature of this work. This paper proposes a control algorithm that focuses on sophisticated fuzzy logic approach. Advanced fuzzy control takes overloading and variation in demand profile as input, which mitigate these disturbances by incorporating optimal power dispatch of renewable energy resources (RERs). To show the effectiveness and validity of the proposed model and fuzzy control design, 9 Bus test system of the transmission network is adopted. Not only normal mode but fault and overloading modes are used to verify the proposed approach. Competitiveness of the proposed control design in terms of reliability and optimal utilization of RERs are verified through simulation results.

1. Introduction

Electric power infrastructure is the backbone for every country and is an important factor that directly affects the economic policy of a country. The traditional conventional electric power grid is not advancing in terms of control and reliability. The era is now moving toward the smart grid that incorporates advanced sensing, communication, security, and control technologies, which make a grid more reliable and efficient [1]. One of the most important features of the smart grid is that it gets power from different type of Distributed Generation (DGs) sources in order to meet the power demand at a cheaper cost. Besides providing cheaper power, there are some drawbacks associated with DGs and an important one is reliability [2]. If a power grid is totally supported by renewable energy resources (RERs), it leads to serious overloading failure because of limited load handling capability of RERs.

In order to meet demand profile and low power losses in the power system, electrical load forecasting is a very important factor for utilities and power system operators. Many operating decisions such as economic dispatch of the power plant, designing of the power network and security network depend upon load forecasting. Electrical load forecasting mainly consists of four types: very short term, short term, medium term, and long term. The short term load forecasting (STLF) is mostly done for duration varies from hours to weeks. New advanced technologies are introduced for monitoring of demand response profile and integration of generation sources in smart grids. These technologies use intelligent and adaptive elements that require more advanced techniques to perform accurate generation and demand forecasting in order to work optimally. The authors in [3] briefly defined various types of load forecasting, which can be efficiently utilized in a power system network. Similar to very short term load forecasting (VSTLF), which is used for power flow control, STLF is used for the adjustment of the generation and demand, where as medium term load forecasting (MTLF) and long term load forecasting (LTLF) are used to plan assets' utilities. Load forecasting is further classified into two groups in [3] first group is used to forecast single value while second group is used to forecast multiple variables. Authors in [3] also mentioned different forecasting techniques their respective accuracy and in which scenario they will be more useful. Authors in [4] forecasted aggregated load using artificial neural network (ANN) while taking in account different variables that affects the forecasted aggregated load. Among different variables that are analyzed the most important one is the climate. Different testing model are suggested in [4] and some of the model include climate as input variable in order to show how forecasted aggregated load is affected by climate variable. STLF is an important factor used in determining of power plants' work plan and choosing of best production group. Energy companies face many economic and technical problems such as operation, planning, and control of power system network. Decisions about energy production, infrastructure development, and load switching are made easier for utility companies through STLF. Therefore, forecasting a load correctly is an important factor in the competitive market for utility companies [5,6]. The electrical utilities must manage the supply from generation sources in order to meet the demand of its consumers. It is therefore very important for the utilities for having advance knowledge of their related consumers

* Corresponding author.
E-mail address: tariq.khan@nu.edu.pk (M. Tariq).

https://doi.org/10.1016/j.ijepes.2019.06.010
Received 22 December 2018; Received in revised form 30 May 2019; Accepted 6 June 2019
Available online 17 June 2019

demand. Load forecasting is an important factor especially for interconnected utilities where they share their respected loads in peak hours hence reduces the burden on individual utility. Load forecasting helps the utilities to understand the behavior of consumer demand in advance and enables the company to make economically viable decision in regard to future generation and transmission investment. Through understanding the future demand trend of the consumers, forecasting enables the utility to schedule the maintenance of power network with minimum impact on consumers and with less revenue losses.

Day ahead planning and scheduling of RERs balance the electrical loads based on forecasted demand that is implemented by providing security, integrity, power quality, and reliability constraints of power system network. Balancing of a power network is done in advance mostly a day ahead on forecasted values given by the demand side. The behavior of a power system is highly nonlinear and quite different because of the nature of various types of loads. Because of that nonlinearity in power system, there will be an error associated with forecast due to which an imbalance will occur in the system causing the cost to increase [7]. Forecasting for the electrical loads on power system can be performed by using different techniques [5]. Different methods used by various groups are based on regression analysis [8], time series analysis [9,10], artificial neural networks (ANN) [11–13], similar day approach [14], support vector machine [15], fuzzy logic [16–18], adaptive neuro-fuzzy inference system (ANFIS) [19], genetic algorithms [20,21] and some other hybrid techniques [22,23]. STLF using ANN was also presented in [24]. Back propagation algorithm was adopted for the training of neural network (NN). The model presented was tested under different cases like taking load inertia, load at particular hours and correlation in selected pattern. The NN was trained under these circumstances. Authors in [25] performed STLF using ANN and wavelet transform (WT). Different forecasting techniques like auto regression moving average (ARMA) are used for linear model. For non linear model ANN is preferred but it treats high and low frequency components in the same manner. Hence to improve forecasting ability, WT is used with ANN. STLF while using weather parameters through bat algorithm based back propagation is presented in [26].Two important parameters, such as temperature and humidity were considered. It was noted that back propagation does not ensure getting global optimum solution in training time. To overcome this drawback, a new approach to STLF using radial basis function neural network (RBFNN) was presented in [27].

STLF is applied in power sector especially in Energy Management System (EMS) and load balancing. The most important problem about STLF, which needs to be addressed is to develop new approaches to make a sophisticated prediction with fewer error margins. In order to tackle this problem, techniques like Evolutionary Algorithms (EA) [28–30] and hybrid methods [31–33] are already applied by researchers. Based on the available data in literature it is clearly demonstrated that techniques to solve complex and nonlinear systems give us good approximation [34,35]. Harmony search (HS) is one of the EA algorithms, which received more attention due to its less complexity in terms of calculation and application [36–40]. The authors in [41] used different hybrid methods for STLF and shows that combining neural network model with offline and online learning gives good approximation. The predicted average errors are 1.72%, 1.75% and 2.06% for different weekdays. The authors in [42] performed hourly load forecast using ANN for different regions in Turkey and found mean absolute percentage error (MAPE) to be 2.90 and 5.47 for these regions respectively. The authors in [43] performed STLF by combining ANN with mathematical model. The Absolute Percentage Error (APE) for these models are found to be 5.38 and 8.80, respectively. STLF using fuzzy logic and ANFIS was already implemented in [44,45]. In these model, a load is forecasted by comparing different parameters like temperature, seasonal and historical load. At last MAPE and absolute percentage error (APE) are compared for both methods to show their effectiveness in [44,45]. However, load forecasting was performed on historical statistical data without considering unexpected disturbances. Main issue will be if forecasting varies a bit and forecasted load at time exceed than expected. There is no uncertainty and unexpected event involve in doing forecasting in [44,45]. Due to that unwanted variation in demand profile the system may collapse. In this paper, the authors perform STLF by using fuzzy logic. The authors also propose a methodology to design a controller to avoid that unseen event, hence increases the reliability of the system.

STLF using ANN, ANN with wavelet transform, bat algorithm based back propagation and radial basis function neural network (RBFNN) was presented in [24–27]. Similarly, STLF using fuzzy logic and ANFIS was implemented in [44,45]. A common drawback of the above research works is that whatever method is used for STLF there are some forecasting errors associated with them. If appropriate actions in order to mitigate these errors in terms of dispatching power reserves are not taken then the whole electric power network can collapse and some serious overloading scenario may arise. As a result excess reserve power of utilities will be of no use if it cannot be utilized in state of emergency situation. In addition to that, if a power system network crashes it will cause loss of power and ultimately increase the maintenance cost. The best way to avoid overloading in an electric power system is to use optimal and economic time ahead scheduling and dispatching of RERs like a wind turbine, solar etc. The forecasting methods do not include the counter measure for unexpected disturbances like overloading and faults as in [44,45] and also in [60,61]. The main objective of this work is to counter these deficiencies in STLF which are due to forecasting errors and also due to unexpected disturbances. These errors are due to statistical historical data used for forecasting in forecasting method which is why actual demand deviates more from forecasted demand. There are different ways to tackle this problem. One is the use of different optimal control algorithms incorporating advanced mathematical, traditional and hybrid methods. Due to the nonlinearity of the power system, many optimization techniques have been developed to solve this problem. Methods like dynamic programming [46], stochastic dynamic programming [47] and mixed integer programming [48] are already employed to solve optimal scheduling problems. But these methods are highly complex and not suitable for real time scheduling of renewable reserves. Hence, new intelligent algorithms were introduced to solve this optimization problem. Algorithms like genetic algorithms [49–53], particle swarm optimization [54–56] and harmony search algorithms [57,58] are used for optimal dispatching of renewable sources. The authors in [49,50] used chaotic quantum genetic algorithm which borrows the quantum computing concept. Quantum bits are used to encode the chromosomes. In order to improve effectively the global search ability to get global optimal solution rather than local optimal solution this algorithm used the quantum probability vector encoding mechanism. The main objective function which are need to optimize are generation cost values and green house emission cost. The authors in [51] uses genetic algorithm (GA) with optimal power flow (OPF) to minimize the active power losses. Optimal location and size of wind turbines are determined through GA while OPF, nested in GA is used to find optimal number of wind turbines. The objective function that is minimized through GA is the annual active power loss. The authors in [52] used GA for data optimization and then this optimized data is used for the training of the neural network. Two parameters temperature and irradiance are input data to GA and optimal voltages are obtained. These optimized parameters are then used to train neural network. However, these algorithms have some shortcomings. For example lots of sensitive parameters are required and complex calculation is needed. In these algorithms many iterations are performed to achieve optimal solution which are not time efficient.

Different control algorithms have already been employed for optimal day ahead load scheduling. Hybrid techniques incorporating hybrid harmony search algorithm with differential evolution (HSDE) was implemented in [58] for microgrid day ahead load scheduling. The algorithm takes into account different constraints like state of charge of battery, thermal capability of generator, voltage limits and power line

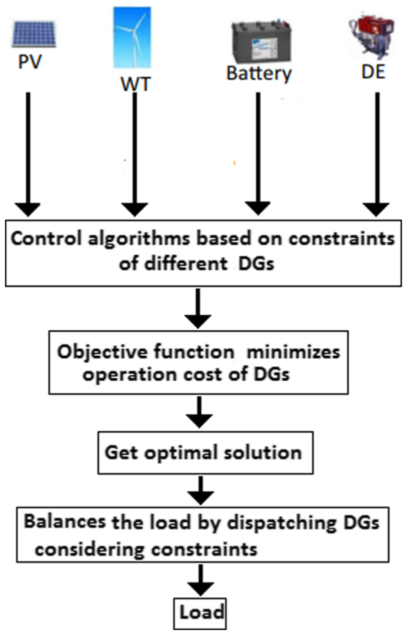

Fig. 1. Control algorithm.

capacity. Considering these constraints, the algorithm compiles and gets an optimal solution through minimizing overall operation cost and balances the demand profile. The algorithm does not consider any unexpected disturbances especially overloading state of power system as depicted in Fig. 1. Furthermore if more constraints are presented then algorithm gets more complex and number of iterations and time to get optimal solution are increased. In case of severe overloading state in power system the control algorithm in [58] takes more time to achieve an optimal solution, which leads to the power system instability. In order to tackle these deficiencies in [58] the proposed methodology includes designing of fuzzy controller that stabilizes the power system network even in case of power system network overloading. The response time of the controller for unexpected disturbances is faster then that of control algorithm in [58] hence reduces the chances of power system instability. The controller also provide a real time energy management through monitoring of real time demand profile and forecasted value by incorporating RERs in the power network as shown in Fig. 2.

Now, the second way is the integration of the controller directly to the electric power network as shown in Fig. 2. The controller will take action based on the errors arise due to forecasting method and variation in demand profile, hence reduce the uncertainty of whether to dispatch the reserve power into the network or not to avoid overloading cases. This will increase the reliability and efficiency of the whole electric power network. In this paper we use the second approach. Instability of the power system and PQ disturbances are critical issues, which may occur due to overloading and faults that can cause a significant effect on the power system. Due to these disturbances, power system restoring capability becomes weak, which makes it more vulnerable and sensitive to any other variation in demand and supply profile. This paper aims to identify the causes of occurrence of such disturbances, its effect on the power system and how to compensate these disturbances through the proposed methodology.

Load forecasting specially STLF and economical use of RERs are ongoing challenges in the smart grid. STLF is performed using modern forecasting techniques and load flow is controlled through the data received from these techniques. To the best of authors, knowledge, this is the first work that incorporates modern forecasting techniques and controller to maintain load flow balance between demand and supply based on forecasted errors data received due to these techniques. The controller is implemented on the source side, which continuously track

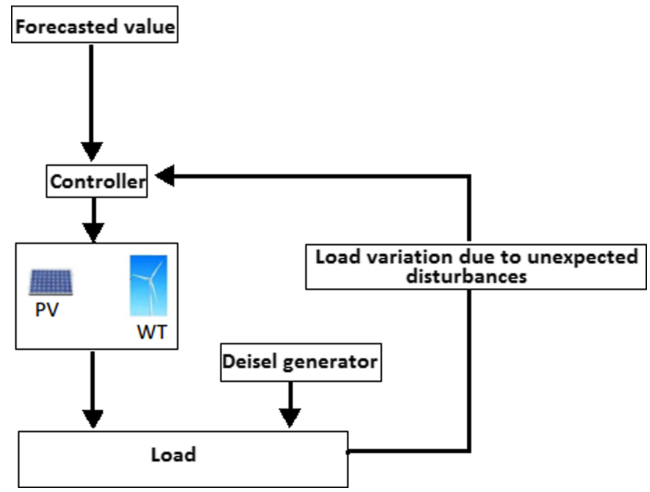

Fig. 2. Controller in power network.

the load with the passage of time to keep a balance between demand and supply. This improves the reliability and efficiency of the whole electric power network. In this paper, the behavior of the overloading affects on normal transmission line and generation sources are investigated.

The key contributions of this paper are as follows.

1. STLF is performed using fuzzy logic in order to maintain balance between supply and demand but excluding unexpected disturbances like faults and overloading in power system network.
2. In case of these disturbances fuzzy controller is implemented in closed loop to balance the actual and forecasted load profile.
3. Probabilistic model including variation and controller is developed for STLF and is tested under fault and overloading modes.

The remainder of this paper is organized as follows. Section 2 includes the mathematical model of proposed algorithms in detail. Section 3 includes result, discussion, and testing of the controller in different conditions. Section 4 concludes the paper.

2. Methodology

Reliability of a power grid is affected by many parameters and load forecasting is one of them. Especially, due to integration of RERs which are not that much reliable and more use of them can make the system more vulnerable to the overloading. The proposed methodology comprises of two parts. Part first includes STLF using fuzzy logic approach because it gives realization to real world incidents compared to the complex mathematical algorithms. STLF using fuzzy logic involves less calculation and easy comprehending. In addition to less complexity and computation cost, it gives a nearly good approximation to actual values hence, less MAPE and APE, respectively. Part second includes designing of the controller by using the fuzzy logic. The controller is implemented to continuously observe the state of the system, in other words, it regularly monitors the load side real power with respect to time. Due to any change in load, the control signal will be given to RERs to incorporate it in power networks. This will help the system to avoid power system network overloading. Overloading effects on the power system network will be more if the duration is longer. Due to excessive overloading sometimes even if extra load is disconnected from the system to maintain balance between demand and supply, power network still becomes highly unstable. A power system network as a whole becomes less reliable if overloading is not taken care off at the acquired time. The power system is potentially vulnerable to any kind of unseen disturbances. Similarly, a design algorithm will also be used for power system stability due to overloading and faults using probabilistic modeling. That is, in case of disturbances, a decision in term of switching of RERs on the source side will be performed.

Algorithm 1. Generation of control pulses under overloading

Input 1: A set of normal operating states of power system $(no_1, no_2, \ldots\ldots\ldots, no_n)$

Input 2: A set of overloaded states of power system $(Os_1, Os_2, \ldots\ldots\ldots, Os_n)$

$//Os_1$ corresponds to overloaded state while $Os_2 \rightarrow Os_n$ corresponds to n overloaded state

Input 3: A set of fault and overloaded states of power system $(FOs_1, FOs_2, \ldots\ldots\ldots, FOs_n)$

$//FOs_1$ corresponds to fault plus overloaded state while $FOs_2 \rightarrow FOs_n$ corresponds to n fault plus overloaded state

Input 4: A set of error or variation states due to STLF of power system $(E_1, E_2, \ldots\ldots\ldots, E_n)$

$//E_1$ corresponds to error or variation state

Output : A sets of control pulses due to overloading or fault plus overloading state $(c_1, c_2, \ldots\ldots\ldots, c_n)$

```
while (Os1||FOs1||E1) do
    If any of the power system line is disturbed then;
    if (E1) then
        Control pulse c1 → windtubine;
    else
        if (Os1) then
            Control pulse c1 → wind turbine/mitigate the disturbances;
        else
            if (FOs1) then
                Control pulse c1 → wind turbine/mitigate the
                 disturbances;
            else
                The next transition, no1 → non(noaction);
                //The power system is operating under normal state.
            end
        end
    end                                   11
    Send the variation as input to Algorithm 1 to further evaluate the
     state;
end
```

Algorithm 1 is used to facilitate stability analysis and power outage in power system network in case of overloading and fault in overloading state. A decision is taken by giving control pulse to wind turbine. Fuzzy controller is operated in closed loop that links load with supply. Any randomness in demand is detected by controller and RERs will be operated to mitigate the variations. If ($Os_1 \rightarrow Os_n$) or if ($FOs_1 \rightarrow FOs_n$) in both these scenarios a wind turbine operates, hence optimal utilization of RERs. Also transients arise due to fault and overloading in power system network. If proper remedial action is not taken then these disturbances will damage power components as noted in [2]. To show the effectiveness of the algorithm these cases also verified through simulation results in Section 3.

The time complexity for the algorithm *ifelse* is of the order of one $O(1)$ means constant time complexity. However, as condition statement for *whileloop* executed continuously up to n times then overall time complexity of the Algorithm 1 is of order of $nO(n)$, which mean linear time complexity. Here n does not mean that time complexity increase as number of conditions increases but it means that state of the system is continuously observed with respect to time. The algorithm in [58] is the order of $n^2O(n^2)$, which means quadratic time complexity. This clearly shows that proposed methodology is better than algorithm in [58] in terms of time complexity.

2.1. Mathematical model for STLF using fuzzy sets

There are various technical issues associated with RERs. Electric power output from RERs mostly depends on certain conditions. In case of wind power it has the advantage of no pollution and low generation cost, the quality of the wind power is adversely affected by randomness, fluctuation and intermittent nature of the wind speed. In addition, these RERs are more vulnerable and sensitive to power quality (PQ) disturbances especially when overloading of power system network occurs. Because they cannot provide all of the power and must be used occasionally. The authors in [45] performed load forecasting using fuzzy logic and the authors in [44] used STLF using fuzzy logic and ANFIS based on different parameters. Detailed mathematical model for STLF is explained in this section. Fuzzy logic gives realization to real values by assigning membership function to each input and output. Membership functions have different ranges but all of them have the same degree varies between 0 and 1. Closer the membership degree value to 1, more the element belongs to the respective set and vice versa. Two known parameter temperature (T) and humidity (F) are used for forecasting the load (L). Temperature has two while humidity and load have three membership functions each having different ranges. These three parameters can be represented in the fuzzy set for the operation because operations on sets are easy to compute. Generalized mathematical model for forecasting is as follows.

$$T = (x_1, \mu_A(x_1)), (x_2, \mu_B(x_2)). \tag{1}$$

For humidity, the fuzzy set equation becomes,

$$H = (x_1, \mu_A(x_1)), (x_2, \mu_B(x_2)), (x_3, \mu_C(x_3)). \tag{2}$$

Similarly, for forecasted load the fuzzy sets equation becomes,

$$L = (x_1, \mu_A(x_1)), (x_2, \mu_B(x_2)), (x_3, \mu_C(x_3)). \tag{3}$$

where x is the member elements of H, T, L having different range. The $\mu(x)$ shows the membership function in fuzzy sets H, T, L. In case of N number of membership function, (1), (2) and (3) become:

$$T = (x_1, \mu_A(x_1)), (x_2, \mu_B(x_2)), \ldots,(x_n, \mu_n(x_n)), \tag{4}$$

$$H = (x_1, \mu_A(x_1)), (x_2, \mu_B(x_2)), (x_3, \mu_C(x_3)), \ldots,(x_n, \mu_n(x_n)), \tag{5}$$

$$L = (x_1, \mu_A(x_1)), (x_2, \mu_B(x_2)), (x_3, \mu_C(x_3)), \ldots,(x_n, \mu_n(x_n)). \tag{6}$$

For both input and a single output, triangular membership functions are used. The generalized form for triangular membership function is,

$$\mu_A = \left\{ \begin{matrix} 0 & x \leqslant a \\ \frac{x-a}{m-a} & a < x \leqslant m \\ \frac{b-x}{b-m} & m < x < b \\ 0 & x \geqslant b \end{matrix} \right\}. \tag{7}$$

where a, b and m are the lower limit, upper limit and mid value, respectively. These limits will be different for each membership function. The limits for the membership functions should be within the range of the parameter used. Let's take a simple rule and show how fuzzy set operation will be performed in that case.

If H is low1 and T is low2 then L is low3. Where H, T and L are the three parameters and $low1$, $low2$ and $low3$ are the membership functions. Let's suppose μ_{low1}, μ_{low2} and μ_{low3} are the membership functions then the fuzzy set operation will be,

$$(\mu_{low1} \cap \mu_{low2})(x) = \min[\mu_{low1}(x), \mu_{low2}(x)]. \tag{8}$$

It means the fuzzy set operation for the AND operator. For the operation of the OR operator (8) becomes,

$$(\mu_{low1} \cup \mu_{low2})(x) = \max[\mu_{low1}(x), \mu_{low2}(x)]. \tag{9}$$

Which is for the fuzzification and antecedent part of the rule. For defuzzification, we use the centroid method to get crisp output and also easy to understand with less complexity. The crisp output is represented as,

$$F(\mu_A) = \frac{\sum_{i=1}^{R} \int x\mu_A(x)dx}{\sum_{i=1}^{R} \int \mu_A(x)dx}, \tag{10}$$

where R is the number of rules classify in the rule base. Variable x shows the member element of the membership function $\mu_A(x)$, where the rule will be triggered and integral shows the area under the membership function that is triggered. Eq. (10) is for continuous values. In case of discrete state, (10) becomes,

$$Z = \frac{\sum_{i=1}^{n} \mu_A(x_i)\, x_i}{\sum_{i=1}^{n} \mu_A(x_i)}. \tag{11}$$

Different rules will be triggered depending upon the temperature and humidity. These rules are the combination of the AND and OR operators and on that basis, different mathematical steps will be followed. End results will be forecast load as crisp values. As mentioned earlier forecasting always contains some error and there must be some countermeasure to solve this problem. Error in forecasting can be calculated as MAPE and APE. Combine these two terms can be represented as E for error.

$$APE = \left[\frac{actual(i) - forecast(i)}{actual}\right] 100\%. \tag{12}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{actual(i) - forecast(i)}{actual(i)}\right] 100\%. \tag{13}$$

Fig. 3 shows demand response schematic as feedback control loop system for controller modeling in case of disturbances. The controller operates as closed loop system to continuously monitor power system and able to take proper remedial action to maintain a balance between demand and supply pattern. Provide a mechanism for optimal power dispatchability in case of unseen disturbances. Terms regarding detail in Fig. 3 are discussed in the next section.

2.2. Controller probabilistic modeling for overloading

Unseen incident and unexpected change in load variation make the system unreliable and more vulnerable to overloading and faults. In addition, this will cause serious damage to the whole power system network. Therefore, the utility must take extra care for the unseen incident and there must be some alternate way to solve the problems. A closed loop control model for the power grid is formed with penetration

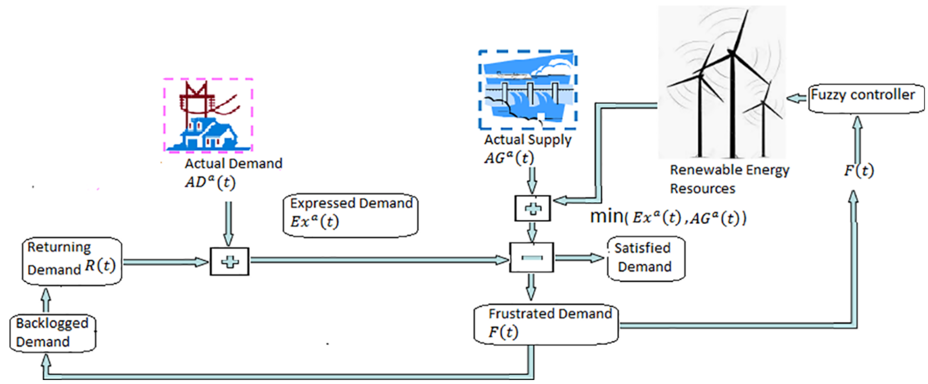

Fig. 3. Demand response closed loop system.

of fuzzy controller, overloading and faults. Overloading scenarios arise due to penetration of the abrupt load on the power network. Generation source does not have enough power to support such load due to which a system might collapse. As a result, power transients may also occur. This mostly happens when a utility designs a system without taking into account the unexpected events and future load demand. In order to analyze the future behavior of the power network due to overloading, we consider the scenario of forecasted demand $FD^f(t)$, forecasted generation $FG^f(t)$, error in forecasting $E(t)$ and applying controller. Relation between demand and generation is,

$$FG^f(t) = FD^f(t) + n_r + E(t). \tag{14}$$

where n_r is the nominal reserve and $E(t)$ is the error in the forecast. Nominal reserve is supply from RERs through the controller to minimize the effect of error and provide a balance between demand and supply. Our main aim is the utilization of RERs in the efficient and economic way. As control loop run continuously the parameter changes in each interval, so (14) becomes,

$$FG_i^f(t) = FD_i^f(t) + n_r + E_i(t). \tag{15}$$

Similarly, in real time scenarios, we want actual demand $AD^a(t)$ to be synchronized with forecasted demand with some variation $R_v(t)$,

$$AD^a(t) = FD^f(t) + R_v(t). \tag{16}$$

By incorporating the error term due to STLF, (16) becomes,

$$AD^a(t) = FD^f(t) + R_v(t) + E(t). \tag{17}$$

To continuously observe the power system, the control loop is implemented as

$$AD^a(t) = \sum_{i=1}^{n} (FD_i^f(t) + R_{Vi}(t) + E_i(t)). \tag{18}$$

where $R_{Vi}(t)$ is the randomness or deviation in the forecasted and actual demand. We want balance between actual and forecasted demand and that is possible only if $R_{Vi}(t)$ is reduced to zero. If $E_i(t)$ is kept to minimum, then $R_{Vi}(t)$ will automatically be reduced. In that case,

$$FG^f(t) = FD^f(t). \tag{19}$$

Similarly, to address the actual generation real power generation is equal to forecasted generation, a control parameter, randomness and error term,

$$AG^a(t) = G(t-1) + R_G(t) + E_i(t) + FG^F(t). \tag{20}$$

where $G(t-1)$ is control parameter used to control the loop in order to meet demand and response. $R_G(t)$ is the deviation factor and it is due to some unwanted incident due to which $E_i(t)$ increases. As the system work in closed loop (20) becomes,

$$AG^a(t) = \sum_{i=1}^{n} (G_i(t-1) + R_{Gi}(t) + E_i(t) + FG_i^f(t)). \tag{21}$$

The control parameter is of very significance. It must be very carefully adjusted so that random parameter and error term are reduced. If in case, randomness is reduced to zero then forecasted generation and demand will be equal.

Moreover, shortage due to overloading can be expressed as frustrated demand $F(t)$, which is,

$$F(t) = Ex^a(t) - AG^a(t). \tag{22}$$

$Ex^a(t)$ is the expressed demand and it is equal to:

$$Ex^a(t) = R(t) + AD^a(t). \tag{23}$$

where $R(t)$ is the returning demand. Returning demand occurs when generation is not much and some of the load demand accumulates on power system. $Ex^a(t)$ will be equal to $AD^a(t)$ if $R(t)$ approaches to zero and is only possible if control parameters are accurately adjusted.

$F(t)$ occurs when,

$$Ex^a(t) > AG^a(t). \tag{24}$$

$F(t)$, will be more serious when uncertainty or error factor is included. By combining error closed loop (20) becomes,

$$F(t) = \sum_{i=1}^{n} (Ex_i^a(t) - AG_i^a(t) + E_i(t)). \tag{25}$$

$F(t)$ will be fed back into power network but with some delay α. Combine both delay and $F(t)$ it will become backlogged demand $R(t)$. As network operates in closed loop, the error approximation $R(t)$ will be,

$$R(t) = \alpha * \sum_{i=1}^{n} (Ex_i^a(t) - AG_i^a(t) + E_i(t)). \tag{26}$$

Similarly, the reserve can be expressed as,

$$r(t) = AG^a(t) - Ex^a(t). \tag{27}$$

Excess power will be stored for worst scenarios and will be in reserve state if,

$$AG^a(t) > Ex^a(t). \tag{28}$$

Considering the error factor and closed loop constraint (27) becomes,

$$r(t) = \sum_{i=1}^{n} (-Ex_i^a(t) + AG_i^a(t) + E_i(t)). \tag{29}$$

The boundary condition for $r(t)$ should be:

$$r(t) < n_r(t). \tag{30}$$

Then increase supply through controller based on an error in forecasting to make $r(t)$ closer to $n_r(t)$ otherwise,

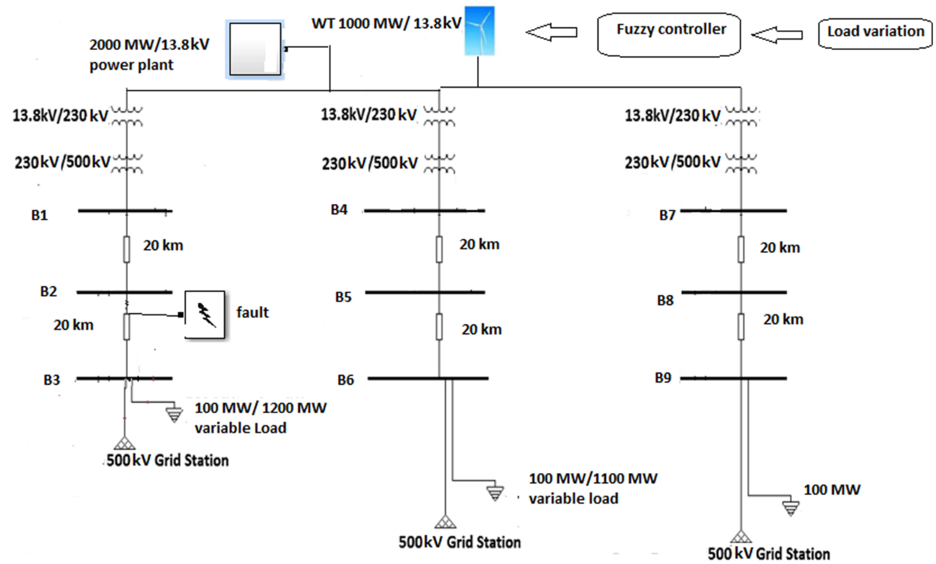

Fig. 4. 9 Bus test system.

$$r(t) > n_r(t). \tag{31}$$

Then decrease the supply to make $r(t)$ closer to $n_r(t)$. The ramping constraints will be,

$$n_r(t) \leqslant AG^a(t) - G(t-1) \leqslant r(t). \tag{32}$$

From (20), $AG^a(t) - G(t-1)$ will be,

$$n_r(t) \leqslant R_G(t) + E_i(t) + FG^F(t) \leqslant r(t). \tag{33}$$

The problem is to avoid overloading and it can be achieved by minimizing backlogged demand. This can be achieved by using a controller that will reduce $E_i(t)$ so ultimately $R_G(t)$ will also be reduced, then (33) becomes,

$$n_r(t) \leqslant FG^F(t) \leqslant r(t). \tag{34}$$

From (14), $FG^F(t)$ can be synchronized with $FD^F(t)$, so (34) can be written as,

$$n_r(t) \leqslant FD^F(t) \leqslant r(t). \tag{35}$$

By using a controller at an appropriate time, while countering the effect of randomness in the load and error in forecasting, supply and demand can be balanced.

3. Simulation results

In order to verify and evaluate the analysis, a series of simulations were performed. The simulations were performed in MATLAB as a simulation tool. This study proposes STLF for power system network using fuzzy logic and design of fuzzy control for optimal utilization of RERs. The main aim of this study is to provide a balance between demand and supply profile during any disturbances. Here in this section, 9 Bus test system as shown in Fig. 4 is considered to check the effect and validation of the proposed algorithm and deficiencies in STLF. Then to verify the robustness of the proposed algorithm, 9 Bus test system will be operated under different modes, in normal and in any disturbance modes. Test system includes power plant of 2000 MW that provides major power. Wind turbine of 1000 MW is used as a reserve source that gets signal from the controller which contains variable load and transmission network of 20 km each as depicted in Fig. 4.

The proposed study is based on a more general case in which an impact on the power system is more than just normal fault. The problem under study is new from previous ones. As a result, proposed algorithm is indirectly compared with STLF in [44,45] by including variations in demand profile. As discussed in Section 1, the authors in [45] performed STLF but excluding the uncertainties and operated on constant data. As for the fuzzy control, direct implementation in power network is new, however there are numerous amount of literature about optimal control algorithm for RERs. Similarly, hybrid techniques for the optimal day ahead scheduling of RERs were proposed in [58] but the algorithm used was complex and involved larger number of iterations to get an optimal solution for minimizing overall operational cost of RERs.

In order to address the problem to improvise the deficiencies in STLF of power network through fuzzy control, two types of case studies are presented in this paper. To prove the robustness and reliability of proposed algorithm, firstly STLF of power network by taking statistical data from [44,45] is performed and deficiency to tackle unseen disturbances have been visualized. Instability in real power pattern on different buses due to variation in demand is demonstrated. The need of controller to tackle overloading and fault scenarios can be clearly observed. Secondly, the controller is designed and tested during disturbances to further show the effectiveness of the proposed algorithm. Initially, the balance between demand and supply is maintained through the continuous spinning reserve. When overloading scenario arise the controller will detect these variations and will mitigate them by incorporating RERs in a power network.

3.1. Case 1: STLF using fuzzy logic and effects of overloading

Fuzzy logic has the advantage over the conventional method due to robustness and ease in implementation because of the rule base. Fuzzy logic is an effective tool to overcome power system problems such as load forecasting, system planning, system control and power system stability. Load forecasting involves many uncertainties, such as variation in temperature, humidity, seasonal variation, rainfall and weekdays with corresponding loads. The fuzzy logic approach will be more suitable in these scenarios than numerical methods to determine values.

The fuzzy logic approach is more suitable to map the non-linear relationship (using membership functions) between various weather parameter and their consequences on corresponding demand pattern. Two parameters of temperature and humidity [44,45] are used as an input to fuzzy logic while forecasted load as an output in this study. Between these two parameters temperature is the most important meteorological variable that brings major changes in the load curve. Effect on the load is not uniform due to temperature variation. Increase or decrease in temperature causes the use of air conditioner and heaters, respectively [44,45]. Heat accumulates in the atmosphere because of

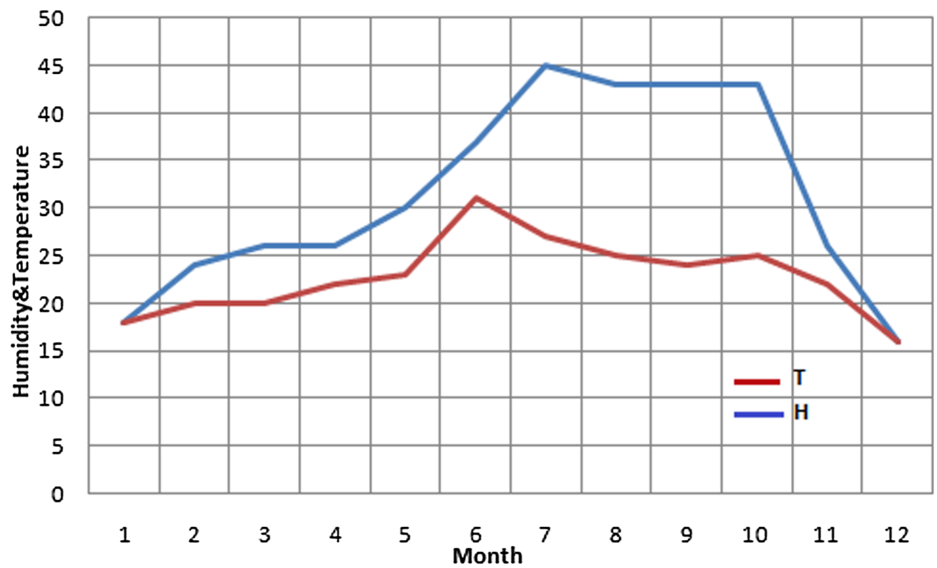

Fig. 5. Historical data of 2014.

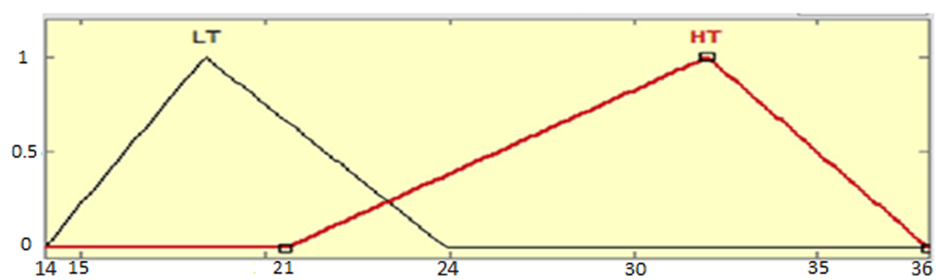

Fig. 6. Membership function of temperature.

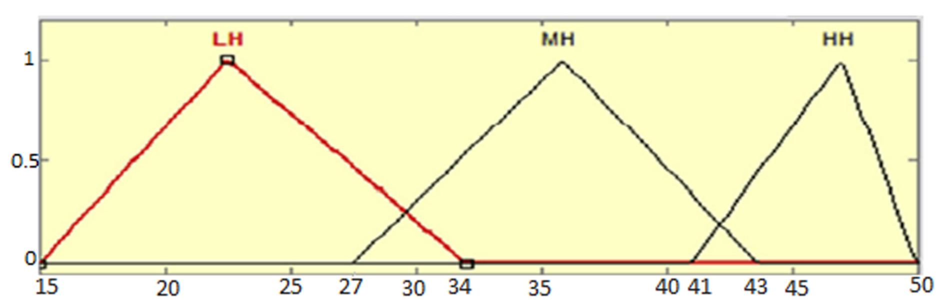

Fig. 7. Membership function of humidity.

high temperature days consecutively and causes variation in peak demand pattern. Fig. 5 shows temperature and humidity data for the year 2014.

STLF is performed using fuzzy logic base on historical data of temperature and humidity. Variation in forecasted load that is output of the system is observed based on the temperature and humidity fluctuations. The membership functions for the corresponding input/output are represented in figures given below. The two membership functions for the temperature is shown in Fig.6 in which *LT* shows low temperature and *HT* shows high temperature. Humidity has three memberships functions shown in Fig. 7. These are *LH* for low humidity, *MH* for medium humidity and *HH* for high humidity. The forecasted load has also three memberships functions shown in Fig. 8, which are *LL* for low load, *ML* for medium load and *HL* for high load. Among other membership functions triangular membership function is chosen arbitrary for this study as is used in [44,45]. Various subsets of the fuzzy sets have different ranges. Humidity can be best classified in (15–34), (27–43), and (41–50) as *LH*, *MH* and *HH*, respectively. Temperature is classified in (14–24), (21–36) as *LT* and *HT*, forecasted load is classified as (0.5–1.5), (1–2) and (1.7–2.5) as *LL*, *ML* and *HL*.

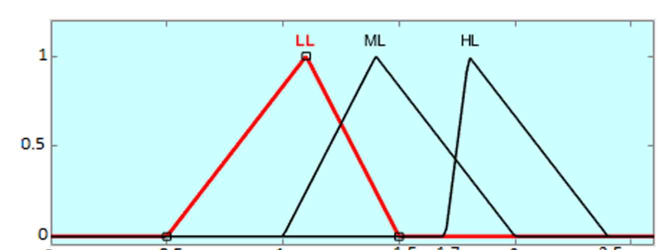

Fig. 8. Membership function of forecasted load.

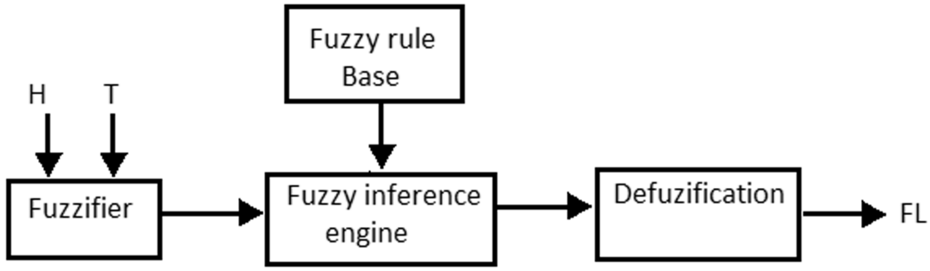

Fig. 9. Flow chart for STLF.

Table 1
Actual and load forecasting for the year 2014.

H	T	Actual load (MW)	Forecasted load (MW)	APE%
18	18	1.05	1.25	19
24	20	1.15	1.25	8
26	20	1.15	1.25	8
26	22	1.4	1.25	10
30	23	1.45	1.53	5
37	31	2.1	2.25	7
45	27	2	1.7	15
43	25	1.9	1.7	11
43	24	1.6	1.7	6
43	25	1.7	1.7	0
26	22	1.4	1.25	10
16	16	1.1	1.25	14

Fig. 9 shows a flowchart for STLF in which H and T are inputs to the system. Output of the fuzzifier and fuzzy rule base enters into fuzzy inference system where these rules are computed by using (11) and gives out forecasted load. Table 1 shows the relation between forecasted and actual demand pattern corresponding to the change in T and H for the year 2014. APE by using (12) is also calculated. Fig. 10 shows the graphical representation of the tabulated data. As can be visualized from the figure, actual load curve and the forecasted load curve have almost a similar trend.

Load forecasting using reliable techniques are essential for STLF. In this study STLF of power network using fuzzy logic is demonstrated that produces appropriate results. However, forecasting is evaluated using historical and statistical data without considering any disturbances more specifically overloading and faults. To validate the efficiency of the STLF, 9 bus test power system is operated under different scenarios. The 9 bus test system includes one CSR with $AG^a(t)$ of 2000 MW and combine load of 300 MW, 100 MW on individual line. Fig. 11 shows operation of the system under normal conditions. Respective real power at Bus (B3), that is load side bus and at Bus (B1), that is source side bus are shown.

$AD^a(t)$ may be more or less than $AD^f(t)$ and that deviation is due to APE. If $AG^a(t)$ is more then it can produce balance between both the $AD^a(t)$ and $AD^f(t)$, which is possible in above scenario. Because the network provide more power than needed. The behavior of the power network in case of fault occurrence and its effect on B1 and B3 can be visualized in Fig. 12. Fault effect at bus B7 and B9 which are source and load buses of non faulty lines respectively, can be observed from Fig. 13.

Symmetrical fault line to line (L-L-L) occurs for one second from 10s to 11s. Due to which real power reduces to zero at B1, however at B3 negative power flows and corresponding line overloaded. Once fault occured, system restoring capability is not that much weak which is why system is capable to restore itself to original state with some transients as depicted in Fig. 12. It is because of $AG^a(t)$, which is more than $AD^a(t)$ and help to reduce the $R_v(t)$ and $E(t)$ ultimately equalizing $FD^f(t)$ and $AD^a(T)$ from (17) even though a fault occurs in the power system network. The effect is more severe at B7 and B9 at which transients are present within fault duration as shown in Fig. 13. As the faulty line tripped during fault time there is an unbalance in power distribution and load sharing on non faulty lines due to which peaks in power at B7 and B9 is observed during the fault time. Variation in current and voltage profiles can be observed in [59] during fault

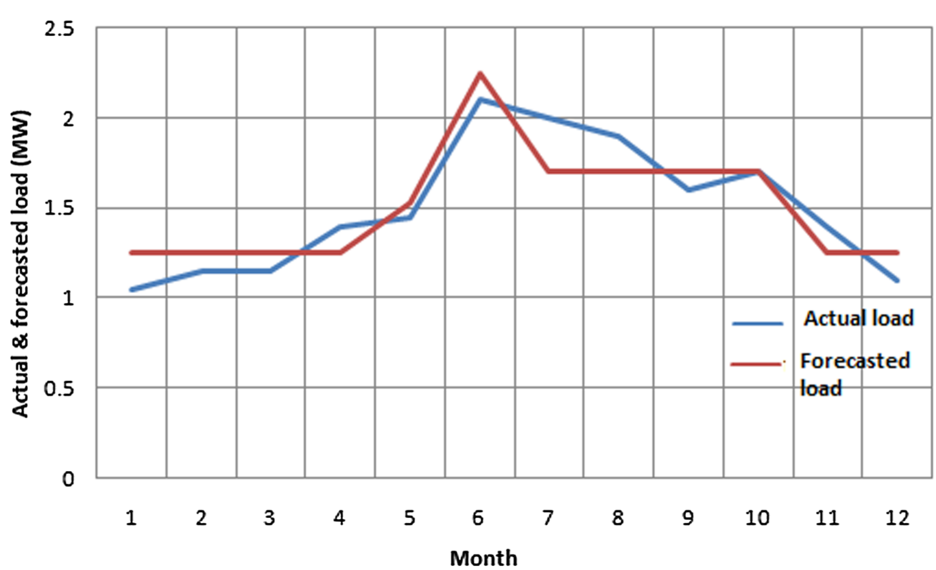

Fig. 10. Graphical results for 2014.

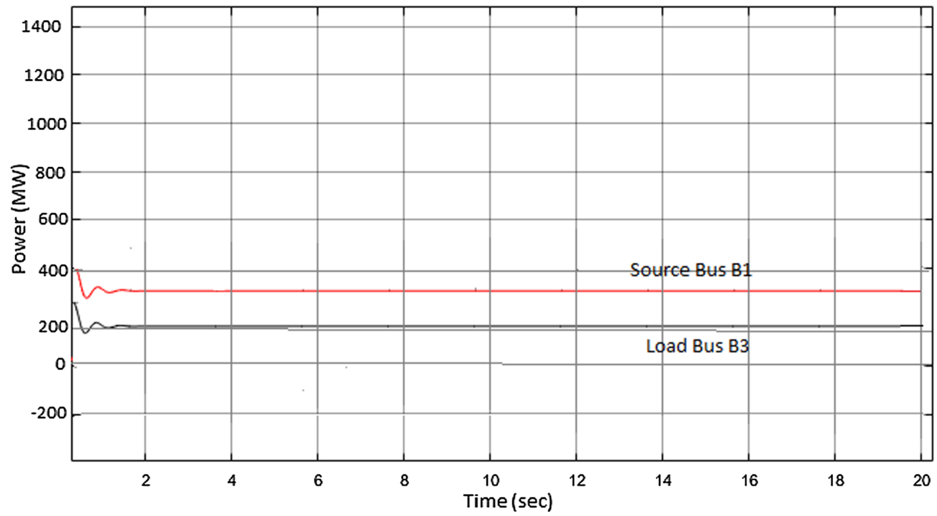

Fig. 11. Normal operation of the system.

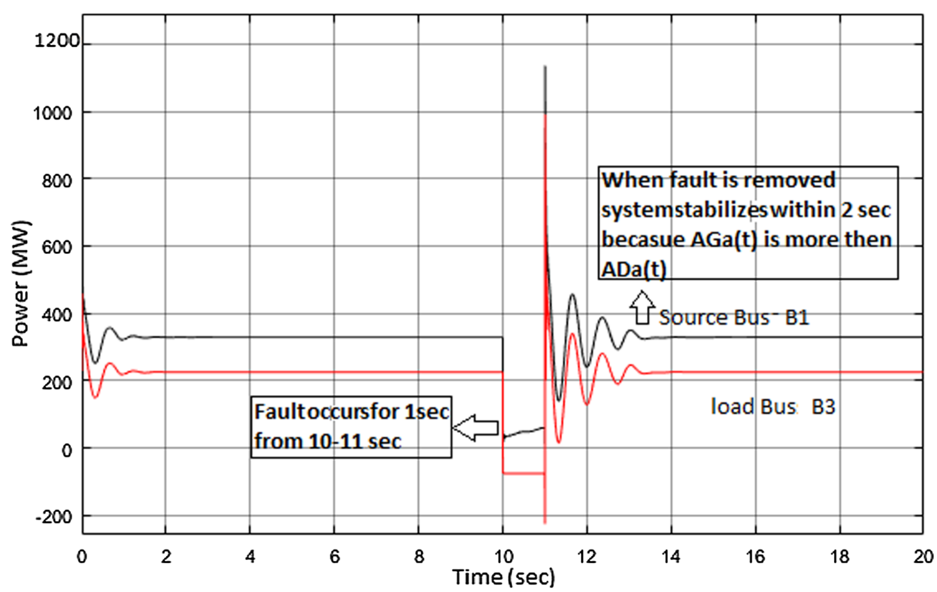

Fig. 12. System operations under fault.

situation. However, system gets stable within 2 s after clearing the fault. It means that restoring capability of a power network is at an optimum condition.

Power system operation under full load can be visualized in Fig. 14. From 0 s to 5 s system is operated under normal state with $AD^a(t)$ of 300 MW while $AG^a(t)$ is of 2000 MW. From 5 s to 11 s additional demand of 1700 MW falls on the network. Now total $AD^a(T)$ is of 2000 MW and $AG^a(T)$ is of 2000 MW, so $AD^a(t)$ is equal to $AG^a(t)$ and system is operated under full load as depicted from Fig. 14. Initially there is some negative power flow in the network because of sudden extra demand of 1700 MW but the system restores itself to this fluctuation because demand and supply are equal. When full load operation is clear at 11 s system stabilize itself within 4s with little bit of transients which shows that system is still operating in optimal way.

3.2. Overloading and fault scenarios

The operation of the power network under fault state will cause serious consequences to the power system components. Recovery measure to compensate for the loss in case of fault scenarios is also an important research issue. Making a reliable algorithm in advance for fault modes will greatly reduce losses in the power system network in state of any disturbances.

The situation will be more severe if overloading occurs in the power system network, only if one of the generation sources, trips or some heavy industries switch into the power network. To mitigate any kind of disturbances, protective system must operate at the right time. However, if circuit breaker operates at multiple time slot in overloading state, transients generate, which will ultimately lead to the fault mode. Instability issues arise due to these disturbances in power network hence reduces restoring capability of the network. Deficiencies in STLF using fuzzy logic in [44,45] is that, the authors did not consider these disturbances due to which real demand pattern differed than forecasted demand pattern. Effects of these disturbances and error margin on STLF can be clearly demonstrated from Table 2 that contains the same parameter as Table 1 but with variable term $V(T)$. Those variations can be easily observed in Fig. 15.

In case when one of the feeders trips or a fault occurs on one of the

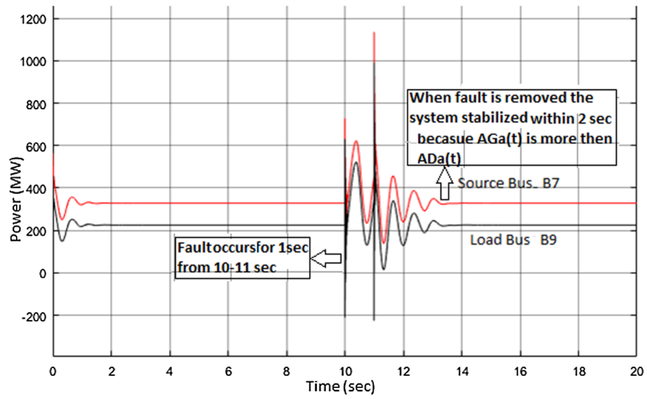

Fig. 13. Effect of fault on normal line load.

Table 2
STLF with variable term $V(T)$.

H	T	Actual load (MW)	Forecasted load (MW)	APE%	Variation in load $V(T)$ (MW)
18	18	1.05	1.25	19	1.05
24	20	1.15	1.25	8	1.15
26	20	1.15	1.25	8	1.15
26	22	1.4	1.25	10	1.4
30	23	1.45	1.53	5	6
37	31	2.1	2.25	7	5
45	27	2	1.7	15	6
43	25	1.9	1.7	11	7
43	24	1.6	1.7	6	3.5
43	25	1.7	1.7	0	1.6
26	22	1.4	1.25	10	1.7
16	16	1.1	1.25	14	1.7

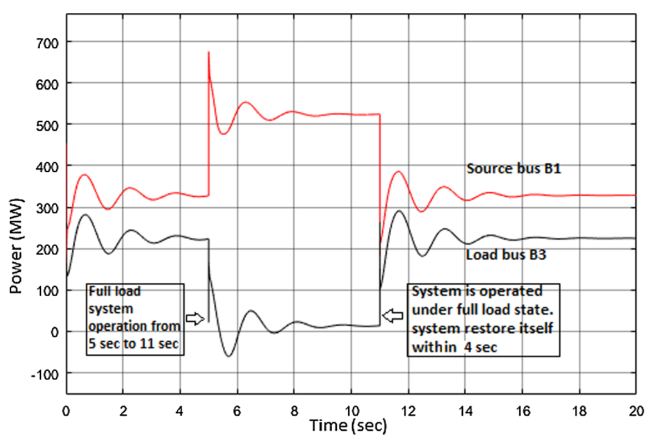

Fig. 14. System operation under full load.

lines then corresponding feeders and line will be overloaded and an unbalance in power distribution will occur. Due to unexpected disturbance, the current demand on power system network deviates more than forecasted and actual demand as shown in Fig. 15. The proposed control algorithm will detect these changes to incorporate RERs that provide extra power needed by the network. This will make the current demand profile to match with forecasted and actual demand hence reducing APE and providing real time power management of a power system network. In order to validate the above statement and to visualize the deficiencies in STLF of power network, 9 bus test system is operated under different scenarios. Operation of the power system network under overloaded state is depicted in Figs. 16, 17. B1 and B2 are in the overload condition as illustrated in Fig. 16, while its effect on normal B7 and B9 is shown in Fig. 17. $AG^a(t)$ is the same as in the normal operation of 2000 MW and combine load of 300 MW and 100 MW on individual line which is $AD^a(T)$. However additional variable load $R_v(t)$ of 2000 MW falls on the network from 5 s to 11 s due to $E_i(t)$. $E_i(t)$ causes $AD^a(T)$ deviate more than $FD^f(T)$. Now the total demand is 2300 MW including $AD^a(t)$ which is 300 MW and $R_v(t)$ which is 2000 MW on power system network while $AG^a(t)$ is of 2000 MW. $R_v(t)$ and $E_i(t)$ make $FD^f(t)$ deviate more than $AD^a(t)$ from (17). Power system network can support little bit of the transients, however extra demand of 300 MW is too much for the network to handle, which is why overloading scenario arises.

As mentioned overloading of power system network occurs on single line containing B1 and B3 while other lines operate under normal circumstances. In normal situation the network operates in optimum state through equal sharing of the power as load on individual lines are same hence balanced system. But as $R_v(t)$ of 2000 MW falls on B3 due to $E_i(t)$ the power distribution gets disturbed and the relationship between $AG^a(t)$ and $FG^f(t)$ are also disturbed as shown in (21). As noted B7 needs a little power to support its load of 100 MW so the excess power will be drawn by B1 to support the $R_v(t)$ at B3. Which is why increase of supply profile at B1 is observed as shown in Fig. 16. Even though B1 draws power from the network it is still unable to mitigate the overloading and to handle the extra demand because $AG^a(t)$ is still the same 2000 MW. As a result, power at B7 reduces, hence unable to support its own load of 100 MW. Therefore overloading occurs at B7 and B9 also, which is shown in Fig. 17. As variable load is removed at 11s, there are transients present in the network and power network takes time to stabilize.

The scenario will be more severe if fault arises in overloading condition. System operation under these disturbance are shown in Fig. 18. Overloading occurs from 5s-11s and fault for the duration of 1s from 7 s to 8 s. Electric power network response at B1 and B3 are observed.

It can be clearly visualized from Fig. 18 that how dangerous overloading plus fault in power network is. $FD^f(t)$ deviates more than expected forecasted value due to $E_i(t)$. Even though variable load is removed at 11s and system wants to stabilize itself for few seconds onward but unable to do so. It is mostly due to faults in power network that make the system more vulnerable and less reliable. Thus it causes instability and system restorability issues. Due to $R_v(t)$ and $E_i(t)$, the $AG^a(t)$ does not meet the $AD^a(t)$ and also due to $E_i(t)$, the $FG^f(t)$ cannot be easily determined. $FG^f(t)$ depends upon $FD^f(t)$ and $E_i(t)$ as in (15). Due to unexpected disturbance, transients are observed on both buses B1 and B3 which will make serious damage to power system equipments. The authors in [44,45] performed STLF excluding unexpected disturbances and countermeasure to such cases if these scenarios arise.

3.3. Case 2: Control design to avoid overloading

An optimum way of performing STLF in power system network was proposed in [44,45]. The only drawback is that authors did not include variation in load profile due to which deviation occurred between generation and demand response pattern. These limitations are clearly visualized in Case 1. Previously several algorithms were already implemented to tackle this problem. Authors in [58] minimize the objective function to provide an optimal power dispatch in a microgrid. However, to mitigate uncertain load variations due to unexpected disturbances in power system, there is still certain deficiencies present in the literature. In order to address these deficiencies, the proposed model in Case 2 utilizes fuzzy controller to continuously monitor the real power at load buses. This fuzzy controller senses any unexpected variations in load and gives feedback control signal to RERs. This will optimize the power system network in terms of compensation of

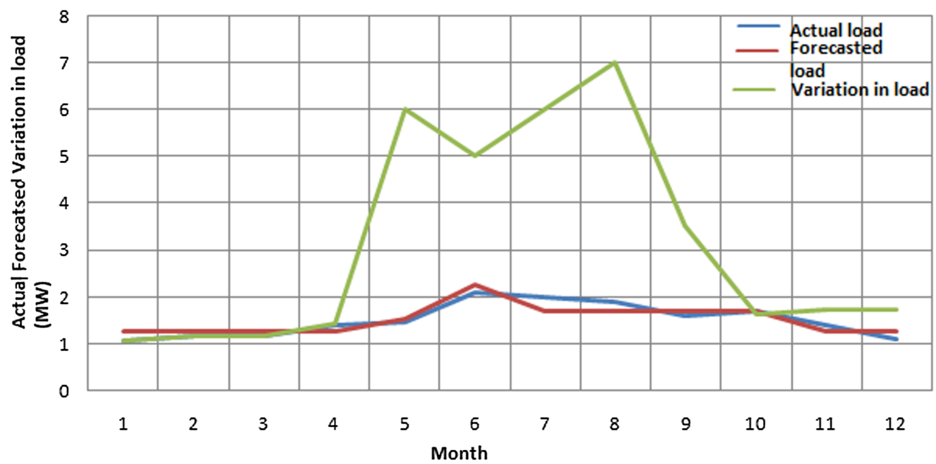

Fig. 15. Actual and forecasted load with variation in load.

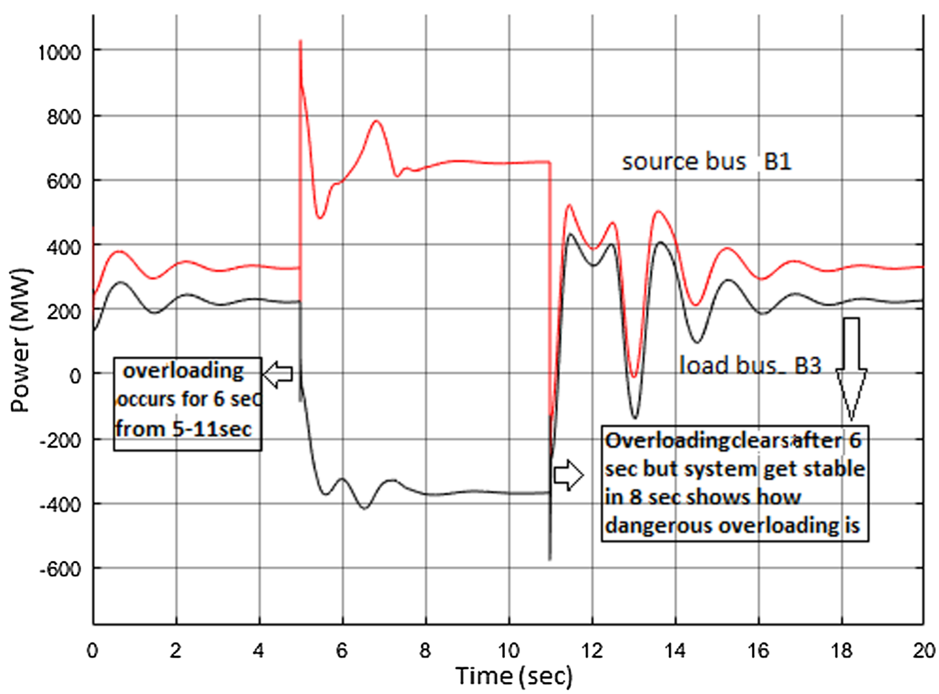

Fig. 16. System operation under overload condition.

uncertain loads. All three input have same membership function while individual input has two membership functions with norm stand for normal and flt stand for overloading case as shown in Fig. 19. Whereas output has two membership functions with on and off states for disturbance and normal condition, respectively as presented in Fig. 20.

In real power system, in order to make the system to work in stable and optimum way, operator in power center needs to take urgent decisions to take emergency corrective measures in case of any disturbances. Different control algorithms are implemented in [58] for optimal day ahead scheduling of RERs and are tested under disturbances to validate the algorithms. However, existing algorithms for eliminating fault involves, highly complex, highly specific and time consuming mathematical operation and also overloading of the power system network is not considered in control algorithms. Also, the control algorithm in [58] which uses HSDE exclude the real time management and optimization of the power system network. The case where actual demand exceeds more than the $AG^{a}(t)$ or the case where $AD^{a}(t)$ is less than scheduled generation is not considered. The microgrid will utilize all scheduled RERs even though $AD^{a}(t)$ is not that much hence not optimal utilization of the RERs. The proposed control algorithm in this paper will provide real time energy management through optimal utilization of RERs through fuzzy control approach. In this study, controller base on fuzzy logic approach is proposed that takes decision in least expected time. In doing so, emphasis is given to power flow control and optimal dispatched of RERs in order to prevent overloading failure. To show the effectiveness and superiority of the proposed control algorithm the proposed model is tested when fault and overloading occur simultaneously in power system and result are being compared with another competitive algorithm proposed in [58] as visualized from Fig. 22. Moreover our control algorithm also counters the deficiencies in STLF which were not mentioned in [58]. The proposed model under overloading scenario is depicted in Fig. 21.

Overloading occurs from 13 s to 19 s for total of 6s. Control pulse is generated at exact same time on which overloading occurs. However, to

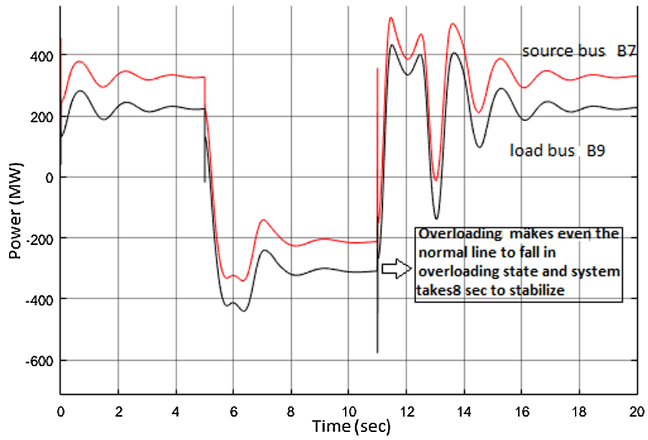

Fig. 17. Overloading effect on normal line loads.

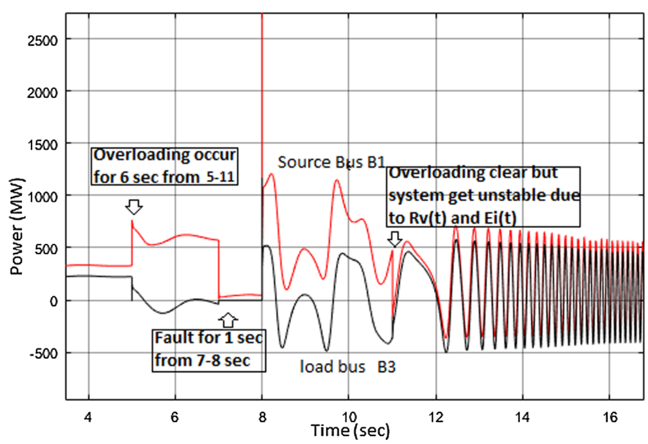

Fig. 18. System operation under fault and overload.

show the effectiveness of the controller in mitigating the disturbance for the stability of the electric power network, time constraint is added that gives a control pulse to wind turbine in 1s delay time as shown in Fig. 21. $AG^{a}(t)$ is of 2000 MW while $AD^{a}(t)$ is 2300 MW due to that 300 MW, extra demand occurs. To achieve balance between demand and supply pattern, generated control pulse will be fed to wind turbine of 1000 MW, which gives the excess supply to network at emergency state in this case, which is 300 MW of extra power needed by power system network. Through optimum utilization of RERs, stability is achieved within 2 s approximately. Due to fast response time of fuzzy control the system get out from overloading state within 1.5 s with negligible transients. As overloading is clear at 19s the controller automatically disconnect the RERs from the network to reserve the excess power for future use. The proposed control algorithm operates under closed loop to continuously observe any state of abnormalities in power system to increase the reliability of the power system network.

For further evaluation of proposed algorithm, power system network is operated under fault plus overloading condition. The proposed model is compared with another algorithm in [58] as shown in Fig. 22. Due to transients, a fault state arises and is from 13.2 s to 13.8 s and an overloading state is also present from 13 s to 22 s. Fault state clears at 13.8 s but overloading condition is still present in network. Controller will sense these disturbances and incorporate RERs to clear overloading state soon after fault is removed. As visualized from Fig. 22, there are some transients present due to the fault but system stabilizes within 2.5 s. Increase in power at the source bus clearly shows that RERs are incorporated to the network. The overloading is cleared at 22 s and RERs will be automatically disconnected by controller to ensure optimal

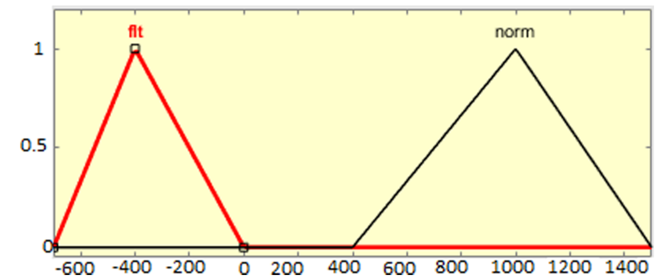

Fig. 19. Membership function for inputs.

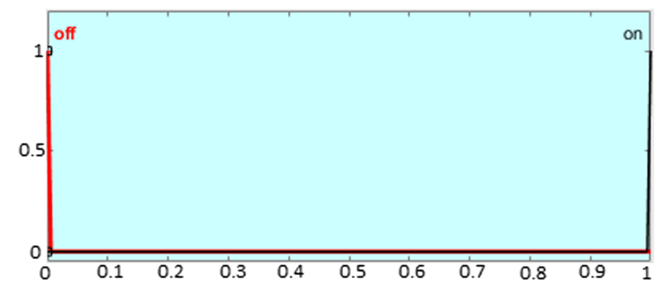

Fig. 20. Membership function for output.

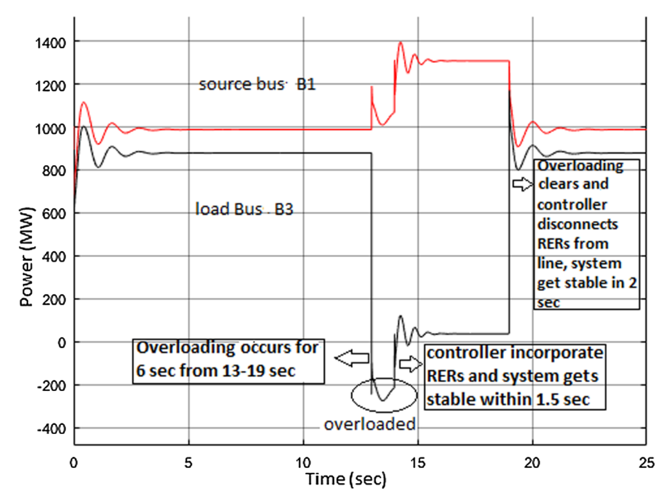

Fig. 21. System operation under proposed algorithm in overload condition.

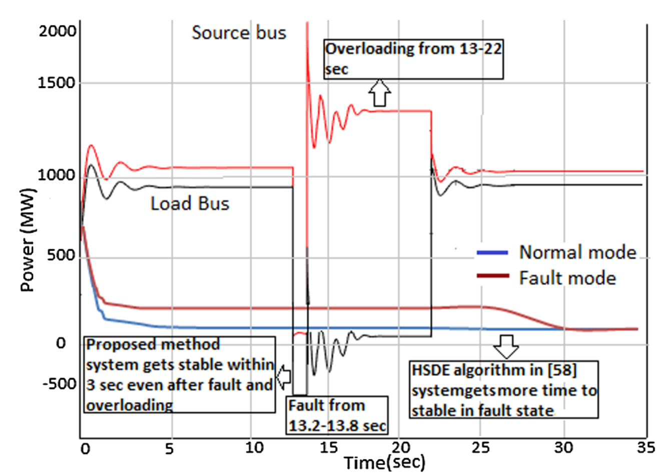

Fig. 22. Proposed method under fault and overloading with existing algorithms.

utilization of RERs and system will come to its normal state within 3 s, hence no surplus power from RERs, which results in optimum utilization of RERs. While the algorithm proposed in [58] stabilizes the system faster in normal mode but in case of disturbances like fault it will take more time to find optimal solution and to stabilize the system. The more the system will take time to stabilize the more it will harm the power system network. Power system network is operated under different states as depicted in Figs. 21 and 22, which clearly shows the effectiveness of proposed algorithm in mitigating deficiencies in STLF and control algorithm in [44,45,58].

4. Conclusion

The objective of this research work is to show that a fuzzy logic based controller is highly suitable in mitigating disturbances due to variation in STLF. The problem is formulated to optimize RERs' usage to increase reliability of the power system network. An effective fuzzy control approach is adopted to detect any randomness in the power system due to the occurrence of overloading and faults. This modeling technique provides balance between demand and supply pattern in an efficient way. The effectiveness and validity of the proposed controller are tested through a 9 Bus system. The optimal result are compared when electric power system that are operated without considering variation in demand profile and with other proposed algorithms. Results show that proposed algorithm is reliable under normal as well as disturbances modes. From the results it is concluded that due to the fast response time of the controller towards unexpected disturbances, the system gets stable in less time as compared to the other algorithms. This research work can be further extended to the cascaded overloading failure and energy management system of the smart grid in case of these disturbances and STLF using extreme machine learning under unexpected disturbances.

References

[1] Tariq M, Poor HV. Electricity theft detection and localization in grid-tied microgrids. IEEE Trans Smart Grid 2018;9(3):1920–9. https://doi.org/10.1109/TSG.2016.2602660.

[2] Adnan M, Tariq M, Zhou Z, Poor HV. Load flow balancing and transient stability analysis in renewable integrated power grids. Int J Electr Power Energy Syst 2019;104:744–71. https://doi.org/10.1016/j.ijepes.2018.06.037. URL http://www.sciencedirect.com/science/article/pii/S0142061518307555.

[3] Hernandez L, Baladron C, Aguiar JM, Carro B, Sanchez-Esguevillas AJ, Lloret J, Massana J. A survey on electric power demand forecasting: future trends in smart grids, microgrids and smart buildings. IEEE Commun Surv Tutor 2014;16(3):1460–95. https://doi.org/10.1109/SURV.2014.032014.00094.

[4] Hernández L, Baladrón C, Aguiar J, Calavia L, Carro B, Sánchez-Esguevillas A, García P, Lloret J. Experimental analysis of the input variables' relevance to forecast next day's aggregated electric demand using neural networks. Energies 2013;6(6):2927–48.

[5] Chaturvedi D, Sinha A, Malik O. Short term load forecast using fuzzy logic and wavelet transform integrated generalized neural network. Int J Electr Power Energy Syst 2015;67:230–7. https://doi.org/10.1016/j.ijepes.2014.11.027. URL http://www.sciencedirect.com/science/article/pii/S0142061514007091.

[6] Fan S, Hyndman RJ. Short-term load forecasting based on a semi-parametric additive model. IEEE Trans Power Syst 2012;27(1):134–41. https://doi.org/10.1109/TPWRS.2011.2162082.

[7] A.C. TOKER, O. KORKMAZ, Türkye kisa sürel elektrk talebnn saatlk olarak tahmn edlmes.

[8] Yildiz B, Bilbao JI, Sproul AB. A review and analysis of regression and machine learning models on commercial building electricity load forecasting. Renew Sustain Energy Rev 2017;73:1104–22.

[9] Clements AE, Hurn A, Li Z. Forecasting day-ahead electricity load using a multiple equation time series approach. Eur J Oper Res 2016;251(2):522–30.

[10] Cancelo JR, Espasa A, Grafe R. Forecasting the electricity load from one day to one week ahead for the spanish system operator. Int J Forecast 2008;24(4):588–602. https://doi.org/10.1016/j.ijforecast.2008.07.005. energy Forecasting. URL http://www.sciencedirect.com/science/article/pii/S016920700800071X.

[11] Khwaja A, Naeem M, Anpalagan A, Venetsanopoulos A, Venkatesh B. Improved short-term load forecasting using bagged neural networks. Electr Power Syst Res 2015;125:109–15. https://doi.org/10.1016/j.epsr.2015.03.027. URL http://www.sciencedirect.com/science/article/pii/S0378779615000942.

[12] Wang L, Zeng Y, Chen T. Back propagation neural network with adaptive differential evolution algorithm for time series forecasting. Expert Syst Appl 2015;42(2):855–63.

[13] Çunkaş M, Altun AA. Long term electricity demand forecasting in turkey using artificial neural networks. Energy Sources B: Econ Plan Pol 2010;5(3):279–89. https://doi.org/10.1080/15567240802533542.

[14] Selakov A, Cvijetinović D, Milović L, Mellon S, Bekut D. Hybrid PSO–SVM method for short-term load forecasting during periods with significant temperature variations in city of Burbank. Appl Soft Comput 2014;16:80–8. https://doi.org/10.1016/j.asoc.2013.12.001. URL http://www.sciencedirect.com/science/article/pii/S1568494613004183.

[15] Sousa JC, Jorge HM, Neves LP. Short-term load forecasting based on support vector regression and load profiling. Int J Energy Res 2014;38(3):350–62.

[16] Mamlook R, Badran O, Abdulhadi E. A fuzzy inference model for short-term load forecasting. Energy Policy 2009;37(4):1239–48. https://doi.org/10.1016/j.enpol.2008.10.051. URL http://www.sciencedirect.com/science/article/pii/S0301421508006563.

[17] Lee W-J, Hong J. A hybrid dynamic and fuzzy time series model for mid-term power load forecasting. Int J Electr Pow Energy Syst 2015;64:1057–62.

[18] Aggarwal S, Kumar M, Saini L, Kumar A, et al. Short-term load forecasting in deregulated electricity markets using fuzzy approach. J Eng Technol 2011;1(1):24.

[19] Ying L-C, Pan M-C. Using adaptive network based fuzzy inference system to forecast regional electricity loads. Energy Convers Manage 2008;49(2):205–11. https://doi.org/10.1016/j.enconman.2007.06.015. URL http://www.sciencedirect.com/science/article/pii/S019689040700177X.

[20] Kebriaei H, Araabi BN, Rahimi-Kian A. Short-term load forecasting with a new nonsymmetric penalty function. IEEE Trans Power Syst 2011;26(4):1817–25. https://doi.org/10.1109/TPWRS.2011.2142330.

[21] Çunkaş M, Taşkiran U. Turkey's electricity consumption forecasting using genetic programming. Energy Sour B: Econ Plan Pol 2011;6(4):406–16.

[22] Çevikş HH, Harmanci H, Çunkaç M. Forecasting hourly electricity demand using a hybrid method. International Conference on Consumer Electronics and Devices (ICCED) 2017;2017:8–12. https://doi.org/10.1109/ICCED.2017.8019981.

[23] Abdoos A, Hemmati M, Abdoos AA. Short term load forecasting using a hybrid intelligent method. Knowl.-Based Syst. 2015;76:139–47. https://doi.org/10.1016/j.knosys.2014.12.008. URL http://www.sciencedirect.com/science/article/pii/S0950705114004468.

[24] Reddy SS, Momoh JA. Short term electrical load forecasting using back propagation neural networks. North American Power Symposium (NAPS), 2014, IEEE 2014:1–6.

[25] Reddy SS, Jung C-M. Short-term load forecasting using artificial neural networks and wavelet transform. Int J Appl Eng Res 2016;11(19):9831–6.

[26] Reddy SS. Bat algorithm-based back propagation approach for short-term load forecasting considering weather factors. Electr Eng 2017:1–7.

[27] Salkuti SR. Short-term electrical load forecasting using radial basis function neural networks considering weather factors. Electr Eng 2018:1–11.

[28] Wang B, Ling Tai N, qing Zhai H, Ye J, dong Zhu J, bo Qi L. A new ARMAX model based on evolutionary algorithm and particle swarm optimization for short-term load forecasting. Electr Pow Syst Res 2008;78(10):1679–85. https://doi.org/10.1016/j.epsr.2008.02.009. URL http://www.sciencedirect.com/science/article/pii/S0378779608000709.

[29] Zhaoyu P, Shengzhu L, Hong Z, Nan Z. The application of the PSO based bp network in short-term load forecasting. Phys Procedia 2012;24:626–32.

[30] Hong W-C. Application of chaotic ant swarm optimization in electric load forecasting. Energy Policy 2010;38(10):5830–9. https://doi.org/10.1016/j.enpol.2010.05.033. the socio-economic transition towards a hydrogen economy - findings from European research, with regular papers. URL http://www.sciencedirect.com/science/article/pii/S0301421510004040.

[31] Nie H, Liu G, Liu X, Wang Y. Hybrid of ARIMA and SVMs for short-term load forecasting. Energy Procedia 2012;16:1455–60. https://doi.org/10.1016/j.egypro.2012.01.229. 2012 International Conference on Future Energy, Environment, and Materials. URL http://www.sciencedirect.com/science/article/pii/S1876610212002391.

[32] Yadav V, Srinivasan D. A SOM-based hybrid linear-neural model for short-term load forecasting. Neurocomputing 2011;74(17):2874–85. https://doi.org/10.1016/j.neucom.2011.03.039. URL http://www.sciencedirect.com/science/article/pii/S0925231211002852.

[33] Hooshmand R-A, Amooshahi H, Parastegari M. A hybrid intelligent algorithm based short-term load forecasting approach. Int J Electr Power Energy Syst 2013;45(1):313–24. https://doi.org/10.1016/j.ijepes.2012.09.002. URL http://www.sciencedirect.com/science/article/pii/S0142061512005327.

[34] Lee W-J, Hong J. A hybrid dynamic and fuzzy time series model for mid-term power load forecasting. Int J Electr Pow Energy Syst 2015;64:1057–62. https://doi.org/10.1016/j.ijepes.2014.08.006. URL http://www.sciencedirect.com/science/article/pii/S0142061514005328.

[35] Chaturvedi D, Sinha A, Malik O. Short term load forecast using fuzzy logic and wavelet transform integrated generalized neural network. Int J Electr Pow Energy Syst 2015;67:230–7.

[36] Zou D, Gao L, Li S, Wu J, Wang X. A novel global harmony search algorithm for task assignment problem. J Syst Softw 2010;83(10):1678–88. https://doi.org/10.1016/j.jss.2010.04.070. URL http://www.sciencedirect.com/science/article/pii/S0164121210001470.

[37] Yousefi M, Enayatifar R, Darus AN, Abdullah AH. Optimization of plate-fin heat exchangers by an improved harmony search algorithm. Appl Therm Eng 2013;50(1):877–85. https://doi.org/10.1016/j.applthermaleng.2012.05.038. URL http://www.sciencedirect.com/science/article/pii/S1359431112004164.

[38] Yadav P, Kumar R, Panda S, Chang C. An intelligent tuned harmony search algorithm for optimisation. Inf Sci 2012;196:47–72. https://doi.org/10.1016/j.ins.2011.12.035. URL http://www.sciencedirect.com/science/article/pii/S002002551200014X.

[39] Wang L, Yang R, Xu Y, Niu Q, Pardalos PM, Fei M. An improved adaptive binary harmony search algorithm. Inf Sci 2013;232:58–87. https://doi.org/10.1016/j.ins.2012.12.043. URL http://www.sciencedirect.com/science/article/pii/S0020025513000352.
[40] Miguel LFF, Miguel LFF, Kaminski J, Riera JD. Damage detection under ambient vibration by harmony search algorithm. Expert Syst Appl 2012;39(10):9704–14. https://doi.org/10.1016/j.eswa.2012.02.147. URL http://www.sciencedirect.com/science/article/pii/S0957417412004101.
[41] Mohammed J, Bahadoorsingh S, Ramsamooj N, Sharma C. Performance of exponential smoothing, a neural network and a hybrid algorithm to the short term load forecasting of batch and continuous loads. PowerTech 2017 IEEE Manchester, IEEE 2017:1–6.
[42] Bilgic M, Girep C, Aslanoglu S, Aydinalp-Koksal M. Forecasting turkey's short term hourly load with artificial neural networks, 2010.
[43] Filik UB, Gerek ON, Kurban M. Hourly forecasting of long term electric energy demand using a novel modeling approach. 2009 Fourth International Conference on Innovative Computing, Information and Control (ICICIC) 2009. p. 115–8. https://doi.org/10.1109/ICICIC.2009.231.
[44] Çevik HH, Çunkaş M. Short-term load forecasting using fuzzy logic and ANFIS. Neural Comput Appl 2015;26(6):1355–67. https://doi.org/10.1007/s00521-014-1809-4.
[45] Ali D, Yohanna M, Puwu M, Garkida B. Long-term load forecast modelling using a fuzzy logic approach. Pacific Sci Rev A: Nat Sci Eng 2016;18(2):123–7. https://doi.org/10.1016/j.psra.2016.09.011. URL http://www.sciencedirect.com/science/article/pii/S2405882316300217.
[46] An LN, Quoc-Tuan T. Optimal energy management for grid connected microgrid by using dynamic programming method. IEEE Power Energy Soc General Meet 2015;2015:1–5. https://doi.org/10.1109/PESGM.2015.7286094.
[47] Livengood D, Larson R. The energy box: locally automated optimal control of residential electricity usage. Serv Sci 2009;1(1):1–16.
[48] Hong M, Yu X, Yu N, Loparo KA. An energy scheduling algorithm supporting power quality management in commercial building microgrids. IEEE Trans Smart Grid 2016;7(2):1044–56. https://doi.org/10.1109/TSG.2014.2379582.
[49] Liao G-C. Solve environmental economic dispatch of smart microgrid containing distributed generation system – using chaotic quantum genetic algorithm. Int J Electr Power Energy Syst 2012;43(1):779–87. https://doi.org/10.1016/j.ijepes.2012.06.040. URL http://www.sciencedirect.com/science/article/pii/S014206151200302X.
[50] Hong Y, Hsiao M, Chang Y, Lee Y, Huang H. Multiscenario underfrequency load shedding in a microgrid consisting of intermittent renewables. IEEE Trans Power Del 2013;28(3):1610–7. https://doi.org/10.1109/TPWRD.2013.2254502.
[51] Mokryani G, Siano P, Piccolo A. Optimal allocation of wind turbines in microgrids by using genetic algorithm. J Amb Intell Humanized Comput 2013;4(6):613–9. https://doi.org/10.1007/s12652-012-0163-6.
[52] Rezvani A, Izadbakhsh M, Gandomkar M. Microgrid dynamic responses enhancement using artificial neural network-genetic algorithm for photovoltaic system and fuzzy controller for high wind speeds. Int J Numer Model Electron Networks Devices Fields 2016;29(2):309–32.
[53] Zhao B, Zhang X, Li P, Wang K, Xue M, Wang C. Optimal sizing, operating strategy and operational experience of a stand-alone microgrid on Dongfushan island. Appl. Energy 2014;113:1656–66. https://doi.org/10.1016/j.apenergy.2013.09.015. URL http://www.sciencedirect.com/science/article/pii/S0306261913007629.
[54] Kerdphol T, Fuji K, Mitani Y, Watanabe M, Qudaih Y. Optimization of a battery energy storage system using particle swarm optimization for stand-alone microgrids. Int J Electr Pow Energy Syst 2016;81:32–9. https://doi.org/10.1016/j.ijepes.2016.02.006. URL http://www.sciencedirect.com/science/article/pii/S0142061516000806.
[55] Li P, Xu D, Zhou Z, Lee W, Zhao B. Stochastic optimal operation of microgrid based on chaotic binary particle swarm optimization. IEEE Trans Smart Grid 2016;7(1):66–73. https://doi.org/10.1109/TSG.2015.2431072.
[56] Wang S, Fan X, Han L, Ge L. Improved interval optimization method based on differential evolution for microgrid economic dispatch. Electric Power Componen Syst 2015;43(16):1882–90. https://doi.org/10.1080/15325008.2015.1057783.
[57] Rhee S-B, Kim K-H, Kim C-H. An application of harmony search algorithm for operational cost minimization of microgrid system. Trans Kor Inst Electr Eng 2009;58(7):1287–93.
[58] Zhang J, Wu Y, Guo Y, Wang B, Wang H, Liu H. A hybrid harmony search algorithm with differential evolution for day-ahead scheduling problem of a microgrid with consideration of power flow constraints. Appl Energy 2016;183:791–804. https://doi.org/10.1016/j.apenergy.2016.09.035. URL http://www.sciencedirect.com/science/article/pii/S030626191631337X.
[59] Davoudi M, Sadeh J, Kamyab E. Parameter-free fault location for transmission lines based on optimisation. IET Gener Transmiss Distribut 2015;9(11):1061–8.
[60] Tariq M, Adnan M. Stabilizing super smart grids using V2G: A probabilistic analysis. In: Proceeding of 89th IEEE VTC. KL Malaysia; 2019.
[61] Tariq M, Zhou Z, Jun W, Macuha M, Sato T. Smart home and building automation standards. In: Proceeding of 12th IEEE POWERCONN. Auckland, New Zealand; 2012. p. 1–6.