Analysis of DFIG-STATCOM P2P control action using simulated annealing techniques

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ABSTRACT

This paper discusses the performance of Double Fed Induction Generator (DFIG) and static synchronous compensator (STATCOM) in a transmission system using simulated annealing techniques. The rotor speed of DFIG is always changing with respect to wind speed in a nonlinear manner, which makes the system to be more unstable. Under such a condition the performance of the system is disturbed. To improve voltage stability throughout the line, an integration of STATCOM is essential at proper location of the transmission system. The STATCOM integrated DFIG system can enhance the system voltage profile and flexible flow of power in a transmission system. In case of a large disturbance or during the shunt fault condition, the performance study is very important which can be assessed using simulated annealing techniques. The proposed model present in this research work is a multi-objective optimization problem. The parameters for the objective function were identified as voltage at the point of common coupling of wind turbine and low frequency oscillation present in the post restored active power. Therefore a stochastic algorithm based on normalized simulated annealing has been applied where the performance of the system can be tested. Coordinated reactive power control combining with DFIG and STATCOM has been analysed together during various shunt fault condition. To achieve better performance of the system Low voltage rides through the capability of the wind farm and FRT (Fault Ride Through) have been tested under the presence of STATCOM including mutual coordinated control action.

1. Introduction

Renewable energy is becoming more flexible and wide spread attention to fulfill the load demand both in standalone and grid connected mode. The conventional sources of power generations are limited and would be depleted in the years to come. Many challenges are associated with DFIG system while connected to grid. From these challenges, the variation of the generated power due to the environmental changes (wind speed and frequency control), non-linear power generation characteristics, power quality issues due to power electronics components (converters and inverters), stability and reliability of the system [1, 2]. However, recent observations indicate that renewable energy is arguably the fastest growing energy source in the world [3, 4]. Wind energy is a common renewable energy that can generate electricity without emissions and will never be exhausted [5].

However, from an economic and ecological point of view, the location of wind farms has many advantages, but the expansion of wind farms will also disturb the stability and performance of the power grid [6, 7]. Sudden changes in wind speed can cause grid outages. Therefore an intermittent wind speed (5-15 rpm) has been maintained and beyond this range difficulty may arise to manage properly. This makes it very difficult to adjust energy supply according to demand [8, 9, 10, 11]. The grid code requires voltage control from the wind turbine, just like a traditional power plant, for reactive power control [12]. In order to maintain reactive power control and voltage regulation properly wind farms are connected to the grid [13, 14]. Wind farms must exchange reactive power with the grid (inj ect or draw the reactive power to the grid or from the grid depends on power generation and load demand of the grid). The quantity and exchange rate are determined by TSO [16, 17, 18, 19, 20, 21, 22, 23]. Active power regulation emphasizes that the deviation between active power and actual output power must be maintained in compliance with the voltage or frequency diagram specified according to the grid code [20, 21]. Many supervision
methods have been addressed in the grid code related to power and frequency attributes. The control is adjusted according to the requirements of TSO [22].

In long transmission lines, successful reactive power absorption compensation can improve steady-state stability, improve the natural characteristics of transmission lines, which can provide more active power to the load, and sufficient control over the timing of the voltage curve. Reactive power compensation equipment such as static reactive power compensator, bypass capacitor and STATCOM can provide excellent compensation & enhances the system stability. The operation system is more complex when DFIG-STATCOM connected to the grid. The active power and reactive power of the system changes frequently due to the nonlinear variation of wind speed. Therefore a FACTS device preferably STATCOM is used here with DFIG to sort out the problem. STATCOM has some applications in power flow control related to reactive power [23]. It reduces the symmetrical share of electricity and suppresses the electricity fluctuations of integrated renewable energy.

In this case, we studied a wind farm with dual dynamic induction generators (DFIG) in order to use STATCOM to improve transient stability [24]. STATCOM is a parallel compensation device that can generate and absorb sufficient reactive power from grid during power flow problems. The STATCOM output can be changed to control certain performance measure in the power system. Shaigan M. et al., it is described that the static voltage stability has been improved using STATCOM and it has been analyzed for the stability improvement in active and reactive power losses. They clearly pointed out that power electronic compensator (FACTS) equipment can increase the static stability and can be implemented in basic systems and load systems. The stability of the voltage is less affected by the dynamics of the system. Therefore, the static method can be used to study the possibility of reaching a balance point limited by the specific boundary of the system [25].

The installation cost of FACT equipment is very high; therefore, it is not economically feasible to run it on all buses, so the power system needs an optimal STATCOM location [26, 27]. As mentioned in the paragraph, the performance of the system is less dependent on the dynamic performance of the system, so that a static robust analysis under the steady state condition of network can result into a good solution [28]. The most important challenge involved in choosing a best location for STATCOM is solving the energy flow equation, which is often nonlinear and complex [29, 30]. The literature describes various optimization methods to solve this problem, such as continuous power flow, optimal power flow (OPF) along with effective cost analysis, loss prediction sensitivity analysis, heuristic optimization methods, and stochastic algorithms. This may be further categorise into genetic algorithms (GA), particle swarm optimization (PSO), evolutionary search and harmony search algorithms [32], [33].

W. Qian et al. suggested the STATCOM connection including DFIG, in which it establishes the coordination among wind power plant and STATCOM [34]. In another article, the author described heuristic dynamic programming to establish a bi directional relationship among wind power plant and STATCOM based on the voltage drop at its connection [35].

Talebi et al. [15] used GA-based optimization methods to provide SVC to balance the load in a discrete time range. In the distribution feeder, the unbalanced load usually has two functions. The speed of the unbalanced load varies with time and distributed between the feeders. The imbalance between actual feeder samples checked using pre-developed software was processed within 7 days, and the proposed algorithm was tested on the 27 bus test system. Karami et al. [17] have demonstrated the total active power compensation. The result shows that the algorithm optimizes the location, size and configuration of FACTS equipment more effectively in an accurate manner. Preethi et al. [18] have proposed to use various FACTS devices to improve line voltage stability. In this paper, the traditional Newton-Raphson method is used to obtain load flow analysis considering different types of load conditions. Deependra et al. [19] presented an AI-GA-based congestion management method that uses FACTS equipment to be incorporated into the deregulated power system. There are two ways to reduce congestion. Because of the high cost of FACTS equipment, a truly better location is needed. The objective function is considered to be non-linear, so GA technology is needed to find the best solution.

The main reason for using the PSO method is to implement a computer model that simulates the social behaviour of a flock of birds and a flock of fish through some modifications. The modality of such social behaviour is also very effective to optimize the system. This phenomenon is used to obtain ideal solutions to a variety of mathematical optimization problems. PSO is also applicable to various real-world optimization problems. PSO is a simple and reliable method. PSO is also very useful in various fields of energy systems. Ravi et al. [31] have proposed an improved PSO method to implement a FACTS device to reduce losses in the power system and to improve voltage distribution in an advanced particle swarm optimization algorithm. In this algorithm, SVC and STATCOM are selected for the best position and size in the power system. Advanced PSO technology provides the best settings and ideal location size and control settings for today’s infrastructure STATCOM block. An IEEE 30 bus test system has been considered as an example to illustrate this method. The calculation results show that the reliability of the power grid and the efficiency of this modern technology have been improved. Palaniraj et al. [54] have proposed the PSO program for optimizing SVC positioning and resizing to improve the voltage stability during the failure of the most critical line in the power system. This modern method of measuring the severity of line faults, consider the improved reactive power generation. Majundar et al. [36] proposed PSO technique for optimal location and sizing of SVC with the objective of transmission loss including cost function. In this process, SVC was selected as the compensation devices. Placement of SVC was suggested empirically as the pilot study [35, 37]. Effectiveness of this process was checked on IEEE 26-bus test system. Another method based on PSO is proposed to minimize the transmission loss while considering the voltage distribution and cost function. SVC was selected as the compensation driver. It is designed as a source of computer iterations compiled on the system bus. Saravanan et al. [38] proposed a PSO technique to obtain the ideal location of FACTS devices with lower cost of installation of fact devices and to enhance system load ability. Here thermal limit of bus were considered as constraints, while obtaining ideal location of fact. In this process SVC, TCSC and UPFC were used [39].

Gitzadeh et al. [26] proposed a modified simulated algorithm to optimise the congestion problem appearing in the transmission line. The proposed method has been analysed in terms of placing the facts devices at specified bus and also evaluating the size of facts devices. In this approach both static variable compensator and thyristor controlled series capacitor where employed to reduce the congestion in power system. The proposed method has the ability to consider the economic limitation of the power system by incorporating the size of the system and the amount of reactive power to be concerned.

Unlike, single-objective optimization, multi-objective optimization problems can be modelled as a priority-based decisions, allowing users to make any decisions based on economic feasibility [52, 53]. In addition to random convergence, normalized simulated annealing can provide better results because it cannot capture local minima [40, 41].

The strong motivation of considering shunt compensator, STATCOM used in this paper is to improve the voltage profile and flexible power transfer capability. It not only enhances the transient and dynamic stability also voltage regulation of the system. The main purpose of this research is to develop a multi-objective optimization problem, namely the main function of reactive power between wind farm and STATCOM [42]. The low-voltage operating capability determines the converter’s ability to handle voltage fluctuations. The capacity utilization can be improved by reducing voltage fluctuations [43, 44]. Hence, the change in voltage deviation can be treated as a multi objective function. The second prime objective of the presented research work is the transient
severity index, it measures the parameters of network under post fault condition. This vertical function changes with the initial state variable, i.e. reactive power. Important decision makers use adaptive neuro-fuzzy inference systems to coordinate reactive power management among wind power plants and STATCOM [45, 46].

Through the external controller interface based on output voltage and reactive power, the coordinated control between the wind farm and STATCOM can be realized. Multi-criteria optimization problems are formulated together with stochastic algorithms, and then an adaptive neuro-fuzzy inference system. In this simulation, doubly-fed induction generators and STATCOM are taken into account because most wind farms are equipped with doubly-fed motors [47]. It is worth mentioning here that the proposed control strategy is applicable to all types of wind turbines, not only DFIG. However, the station can be replaced by a static compensator VAR.

2. Problem identification and modelling of DFIG-statcom

Induction generator operating under normal steady-state conditions, the slip and speed changes are small. When the slip is closer, the reactive power absorbed by the machine is the least significant, but increasing the load and power will also increase the slip and reactive power consumption of the motor. Therefore, stator voltage and Flux

\[
\begin{align*}
V_r &= R_i I_x + \frac{\partial \phi_i}{\partial t} + \frac{d\phi_i}{dt} \\
\phi_i &= L_i I_x + L_m I_y 
\end{align*}
\]

(1)

Similarly, the rotor side voltage and flux becomes

\[
\begin{align*}
V_r &= R_i I_x + \frac{\partial \phi_i}{\partial t} - j\omega_m \phi_i \\
\phi_i &= L_i I_x + L_m I_y 
\end{align*}
\]

(2)

By using (1) and (2) the rotor and stator voltage equation becomes

\[
\begin{align*}
V_r &= R_i I_x + j\omega_m L_m I_y + j\omega_o L_m (I_x + I_y) \\
V_s &= R_i I_x + j\omega_o L_m I_y + j\omega_o L_m (I_x + I_y) 
\end{align*}
\]

(3)

where “s” represents the slip of the system. Again by using (3) the stator active power and rotor active power becomes

\[
\begin{align*}
P_s &= \frac{3}{2} \text{Re}(V_r I_x) = \frac{3}{2} R_i I_x^2 + \frac{3}{2} j\omega_m L_m R_i (I_x I_y) \\
Q_s &= \frac{3}{2} \text{Re}(V_r I_y) = \frac{3}{2} R_i I_y^2 + \frac{3}{2} j\omega_o L_m R_i (I_x I_y) 
\end{align*}
\]

(4)

Again the three phase line voltage is given by

\[
\begin{align*}
V_{ab} &= I_a R_a + L \frac{dI_a}{dt} + V_{fa} \\
V_{bc} &= I_b R_b + L \frac{dI_b}{dt} + V_{fb} \\
V_{ca} &= I_c R_c + L \frac{dI_c}{dt} + V_{fc} 
\end{align*}
\]

(5)

Deriving the d-q component from (5) it becomes

\[
\begin{align*}
V_d &= I_d R_d + L \frac{dI_d}{dt} - L a I_y + V_{fd} \\
V_q &= I_q R_q + L \frac{dI_q}{dt} - L a I_d + V_{fq} 
\end{align*}
\]

(6)

Now, eq. (6) results in three different contradicting features. Like voltage compensation, decoupling item and correction factor. In this research work the voltage correction factor has been used in the form of a STATCOM.

Now, the reference current control loop equation becomes

\[
\begin{align*}
I_{d}^* &= \frac{V_{d}^* + K_p V_{d}}{V_{d}^* + K_p V_{d}} \\
I_{q}^* &= \frac{V_{q}^* + K_p V_{q}}{V_{q}^* + K_p V_{q}} 
\end{align*}
\]

(7)

In order to achieve Unity power factor, \(I_{q}^* = 0\) and therefore

\[
\theta = \tanh \frac{V_{q}}{V_{d}} 
\]

(8)

The magnitude of power converter i.e. STATCOM Voltage can be proportional to DC Voltage and hence

\[
\begin{align*}
V_d &= m V_{dc} \cos(\theta) \\
V_q &= m V_{dc} \sin(\theta) 
\end{align*}
\]

(9)

and therefore by utilising eq. (6), (8) and (9) the power balance equation becomes

\[
\begin{align*}
\frac{P}{3} &= \frac{3}{2} (V_d I_d + V_q I_q) \\
\frac{Q}{3} &= \frac{3}{2} (m j \cos(\theta) - \delta q \sin(\theta)) 
\end{align*}
\]

(10)

3. Simulated annealing optimization & problem formulation

SA algorithm is one of the most optimal heuristic methods for solving optimization problems. The annealing process determines the optimal arrangement of the metal particle molecules, in which the mass potential is the smallest, and describes the gradual cooling of the metal after being exposed to high temperatures. The SA algorithm uses iterative motion based on the variable temperature parameters of the simulated annealing metal operation.

The basic process to achieve this analogy with the annealing process is to generate random points near the optimal flow point and evaluate the problem function there. Then accept the point and update the optimal value of the function. If the value of the function is greater than the currently known best value, the point will sometimes be accepted and sometimes rejected. The point acceptance is based on the value of the probability density function of the Boltzmann-Gibbs distribution [49, 55, 56].

If the value of this probability density function is greater than the random number, then the control point is used as the best solution, even if its value is greater than the best known value. When calculating the probability density function, a parameter called temperature is the same. For optimization problems, the temperature can be used as the target of the optimal value of the cost function [60].

Here the function as derived from section 2 consists of

\[
f(i_x, i_y, v_{dc}) = m_1 x + m_2 y 
\]

(11)

where \(m_1\) and \(m_2\) represent the states of the controlled variables. The state variable represents the circuit parameter in terms of \(R, L\) and \(C\). The followings steps are used to solve the above optimization problem using Simulated Annealing tool.

- Set the initial temperature \(T_0\) by assuming the test temperature as global minimum cost function and a feasible trial point \(x^{(0)}\).
- Compute the \(f(x^{(k)})\) by limiting the number of trials before reaching the minimum values. Initialize the iteration to zero.
- Set the new point to \(x^{(k)}\) and evaluate the cost function. If the cost function is greater than zero then the new set point becomes the first point and choose the next neighbour in the space. In each iteration compute

\[
\delta f(x^{(k)}) = f(x^{(k)}) - f(x^{(0)}) 
\]

and the probability distribution function becomes

\[
P(\delta f) = \exp \left( \frac{\delta f}{T_k} \right) 
\]

(13)

Fig. 1 shows the process flowchart of simulated annealing STATCOM algorithm. The algorithm starts with data collection followed by equation formation using curve fittings. Based on the constraints of the problem a random variable has been selected. The function has been evaluated at the selected random variable, in order to check the stuck of optimization solutions in the local minima. Ziegler–Nichols method (Z-N Method) has been used to evaluate the \(K_p, K_i,\) and \(K_d\) which is again used as proportional, integral and derivative in PID controller tuning.
parameter in the Inner current control loop. In another parallel algorithm the quadrature component for grid side converter (GSC) has been evaluated with the help of rotor side converter (RSC). Frequency domain analysis has been carried out for evaluating the convergence point. In this method adaptive cooling trend has been adopted, which again shows 20% more efficient than fixed cooling trends [51].

4. Benchmarking models

The proposed algorithm for coordinated control of DFIG-STATCOM has been tested for both inside and outside fault zone. Fig. 2 shows the DFIG-STATCOM coordinate control using ANFIS Controller. Two types of converter such as Rotor side converter (RSC) and Grid side converter (GSC) are connected back to back to achieve independent control action on rotor side as well as grid side. However, in the present model an ANFIS based PI controller has been installed, where Vdc is taken as reference quantity and that of Vr and Vgc are supplied as controlled voltage reference quantity to RSC and GSC, thereby making both the converter to work in a coordinate manner indirectly. The reference quantity such as voltage and frequency are supplied from Grid Side Converter using PLL and that of the DC reference quantities are supplied from the Wind turbine side. Again the STATCOM is powered by DC source and controlled by the voltage and current reference quantities received from GSR. In order to prove the robustness of the controller the model has been compared with two different techniques as follows,

- Case-1: ANFIS tuned PI controller for achieving coordinated control of DFIG-STATCOM.
- Case-2: FPA tuned Gaussian PI Controller.

4.1. Case-1

In order to design an ANFIS controller, the input parameters must be configured to vary linearly according to the process requirements. First, select two inputs for the controller, which represent the output state (provided by the output of the object). The output of PI controller
is used as the target of the production process, and is also used in the final step to train the neural network and copy the model. Triangular membership functions are used as parameters. The five membership functions of NL, NS, ZE, PS and PL are used as language variables to construct the input and output variables of the controller. These control parameters are trained during training at 10 epoch intervals. Fig. 3 shows the basic ANFIS based PI controller for the proposed system. Here the Id and Iq parameters were processed using the conventional PI controller. The output of the controller is given to layer-1, where it will be converted into crisp variable. In the present model, 5 Membership Function (MF’s) are used. Two different types of weight (w1 and w2) were evaluated using the back propagation algorithm by taking reference from MF. Normalization property has been used to convert the same into 2nd level of crisp variable and finally converted back into the original physical variable after layer-5 using summing operation.

The curve fitting application shows that, all the program agents use linear dependence rule among each other. As this can be established by rules of ANFIS based Takagi–Sugeno fuzzy inference system, hence in this paper it has been adopted for establishing the rules. Output of ANFIS usually uses a linear combination of input variables with some constant variables. These linear combined variables are generally treated as weight function. The final output of ANFIS controlled structure is usually a flat weighted sum average of input transformed into output. In fuzzification process sometimes the number of rules increases with the increase in number of input and membership function making the system more complex and burden to handle the variables in the system inside the boundary. A Sugeno-type method (or Takagi-Sugeno) has fuzzy inputs and a crisp output. The method is very much efficient to work for adaptive optimization which makes it more suitable for solving control problems. Basic ANFIS structure consisting two input such as x and y and one output z can be coded as follows:

Rule table for Takagi–Sugeno fuzzy system is a If & Then rules.
Rule–1= If x is X1 and y is Y1 then function (f1)=A1x+b1x+r1
Rule–2= If x is X2 and y is Y2 then f2=A2x+b2x+r2
Layer-1:-

In the present layer for each and every nodal point i, the square node point functional parameter becomes

\[ O_{i,i} = \mu_{R,i}(x) \quad \text{where } i=1, 2 \]
\[ O_{i,i} = \mu_{R,i}(y) \quad \text{where } i=1, 2 \]

Here x stands for input to the node 1 or here referred as layer-1 and “X” & “Y” show linguistic informational weighted variables present at that node. Two types of linguistic variables may be implemented over here like triangular or Gaussian membership values. Variables assigned to the layer-1 are named as premise parameters.

Layer-2:-

The Node value for set layer-2 is \( \pi \). Similarly, Output of layer-2 is the product of all incommers.

\[ O_{i,i} = \mu_{R,i}(x) \times \mu_{R,i}(x) \quad \text{where } i=1, 2 \]

The Output of fixed layer-2, shows the strength of fuzzy logic rules.

Layer-3:-

The Node level for layer-3 is N. It is the ratio of strength of fuzzy rules to the sum of strength of fuzzy rule tables.

\[ O_{i,i} = w_i w_i / \sum_{i=1}^{N} w_i w_i \quad \text{for } i=1, 2 \]

The Output of layer-3 shows the normalised solution of fuzzy rules.

Layer-4:-

This layer is referred as adaptive fuzzy node. The Nodal function for layer-4 can be shown as

\[ O_{i,i} = w_i f_i + w_i (p_i x + q_i y + r_i) \]

Layer-5:-

Output of layer-5, shows the sum average of linearly time dependent input variable. The crisp output equation to this layer can be

\[ O_{i,i} = \sum w_i f_i \]

Again, from the above discussion it is confirmed that adaptive neural fuzzy inference system (ANFIS) is same in all conditions to that of Takagi–Sugeno type fuzzy system.

The efficiency of the ANFIS controller can be evaluated by calculating the error between predicted output and actual output. Here in this paper sparse categorical cross entropy type of loss function has been used. Accordingly the layer output in terms of its probability distribution can be written as

\[ h(p) = -\log P_i (\sum \omega_i f_i) \]  \hspace{1cm} (14)

The entropy for h(P) as shown in eq. (14) can be written as

\[ H(p) = - \sum \omega_i \log P_i (\sum \omega_i f_i) \]  \hspace{1cm} (15)

In eq. (14) the negative sign represents that the result is always positive or zero. The output of eq. (14) is zero, if the probability distribution of output layer is 1. Similarly from eq. (15), it is understood that H(P) will be minimum if there is only one output.

ANFIS requires accurate data to create a well-trained FIS file that is optimized for the fuzzy logic controller implemented in ANFIS. Therefore, it is necessary to obtain the data with the largest possible error. Data verification is required before processing FIS files. It is used to check the data received from the PI controller. The parameters \( I_p \) and \( I_q \) are extracted from the input and output of the PI controller to achieve the best results. Fig. 3 shows the inputs and outputs of the PI controller, which are fed to the data inspector to find errors. The error between the input, output and output of the neural network is shown in Fig. 3, under error analysis. After about 30 seconds, the error showed transient behaviour due to load changes. In addition, it also shows that the common error range is 0.012 to 0.012, except transition state i, within 30 seconds. The Levenberg-Marquardt algorithm used here has a total throughput of 3.92e06 and a slope of 1.04e05.

Fig. 4 shows data training involving neural network structure. It shows that the training is successful under the training conditions, and the minimum error is 0.01. Fig. 5 shows that in epoch 7 of the training set ID 1, the gradient remains 0.00048193. The regression analysis shown in Fig. 5 was performed for \( R = 0.99977 \) and \( R = 0.99874 \), respectively.

Similar to Id, Iq is simulated, and sample 2 is taken from data collected using PI controllers. Fig. 6 shows the PI controller inputs and outputs entered into the data validation field to find errors. The error at
the output and an error at the output of the neural network are shown in Fig. 6. Due to changes in load and wind speed, the error shows two transients approximately 4.85 seconds and 30 seconds later. In addition, it also shows that the typical error range is 0.01-0.015, and there is no transition state by 4.85 seconds and 30 seconds.

Fig. 7 shows training involving neural network structure. Here you can see that the minimum error of training under training conditions is equal to 0.01. The training state of the neural network expressed in the form of gradient and mu is shown in Fig. 8. As shown in the Fig. 8, the training error sample 2 supports the gradient 1.2044e05 of epoch 200. Regression analysis was performed on R = 0.99983 and R = 0.99972 respectively.

In order to further reduce the error, the gradient descent procedure is applied to the collected samples through the input and output of the controller. The test here is regarded as a test on samples 3 and 4. Fig. 9 and Fig. 12 show the input and output of the PI controller for Iq, which are sent to the data validator to find errors. The output and output of the neural network are shown in Fig. 10 and Fig. 13, respectively. Due to load changes, the error shows transient behaviour after about 30 seconds, and it also shows that the error range is usually 0.001 and 0.001, except for transient i. up to 30 seconds (Fig. 15).

Again, the time series regression for Id and Iq (sample 3 and 4) are presented in Fig. 11 and 14. Like sample-2, here also the best 4 samples
Fig. 12. NN regression analysis for sample-3, (a) training of ref. and actual with R = 0.99977, (b) validation of ref. and actual with R = 0.99874.

Fig. 13. Training of data using Neural Network for sample-4, (a) plant input \((I_{plant})\), (b) reference plant output \((I_{actual})\), (c) controller from actual output to ref. output, (d) ANFIS plant output \((I_{dist,act})\).

Fig. 14. Validation of data using Neural Network for sample-4, (a) actual plant input \((I_{plant})\), (b) actual plant output \((I_{actual})\), (c) controller from actual output to ref. output, (d) ANFIS plant ref. output \((I_{dist,act})\).

Fig. 15. NN regression analysis for sample-4, (a) training of ref. and actual with R = 0.99645, (b) validation of ref. and actual with R = 0.99771.

Table 1. Analysis of different Gaussian models with GBW = 0.95.

| Sigma | Type of Gaussian surface | RMSE  | Response time | RF   |
|-------|--------------------------|-------|---------------|------|
| 0.8   | Squared Exponential      | 1.6723| 3.87          | 9.3  |
|       | Matern 5/2 GPR           | 1.8179| 3.82          | 17.8 |
|       | Exponential GPR          | 1.3233| 3.67          | 6.33 |
| 0.9   | Squared Exponential      | 1.481 | 3.18          | 9.4  |
|       | Matern 5/2 GPR           | 1.547 | 3.07          | 11.28|
|       | Exponential GPR          | 1.192 | 2.98          | 4.87 |
| 0.94  | Squared Exponential      | 1.682 | 3.89          | 9.35 |
|       | Matern 5/2 GPR           | 1.7798| 3.1           | 9.18 |
|       | Exponential GPR          | 1.4653| 3.09          | 7.03 |

Table 2. Analysis of different Gaussian models with GBW = 0.96.

| Sigma | Type of Gaussian surface | RMSE  | Response time | RF   |
|-------|--------------------------|-------|---------------|------|
| 0.8   | Squared Exponential      | 1.6723| 3.87          | 9.3  |
|       | Matern 5/2 GPR           | 1.8179| 3.82          | 17.8 |
|       | Exponential GPR          | 1.3233| 3.67          | 6.33 |
| 0.9   | Squared Exponential      | 1.617 | 3.224         | 9.167|
|       | Matern 5/2 GPR           | 1.029 | 3.113         | 11.17|
|       | Exponential GPR          | 1.228 | 2.86          | 4.902|
| 0.94  | Squared Exponential      | 1.682 | 3.89          | 9.35 |
|       | Matern 5/2 GPR           | 1.9208| 3.105         | 9.192|
|       | Exponential GPR          | 1.3865| 3.124         | 7.148|

have been analysed which will be made use under section 5 for SA-PI controller [47, 48].

4.2. Case-2

The process begins with two step solutions like two parallel form Flower Pollination Algorithm (FPA) will be fitted back to main algorithm to decide the 5-fold cross validation and higher parameter estimation. Some of the important steps involved in the process are as follows:

- Step-1: Call and execute the parallel algorithm with regression analysis and Flower Pollination Algorithm, set the time to \( t = 0 \).
- Step-2: Calculate the similarity and pollen distance between two pairs of data.
- Step-3: Calculate the flatness in FPA from 0.3 to 0.99 in pollen space.
- Step-4: Check for global and local optimization with reference to decision variables.
- Step-5: Once \( G_{best} \) reached, set the outcome to stopping criteria.
- Step-6: Create two databases of training set and testing set.
- Step-7: Change the Gaussian surface if Best solution not achieved.

Table 1 & Table 2 show the Analysis of different Gaussian models of flower pollination algorithm to optimize the controller parameter. Stratified analysis has been carried out for the FPA optimization, however
the best result has been presented over here for a band width (GBW) of 0.95. Three different types of Gaussian surface have been analyzed.

Again from Table 2, it can be found that for sigma 0.8 the three Gaussian surface exhibit similar properties with that of the GBW = 0.95 in terms of RMSE, Response time and RF.

5. Result analysis

In the previous section, we defined mathematical models such as the objective function and secondary conditions of the rotor-side controller and the line-side controller. The SA-PI controller was used for decision-making. A MATLAB Simulink model was developed for the algorithm, which can test the stability of the controller under various error schemes. For the sake of safety and feasibility, three types of faults: single line to ground fault, two-line to ground fault and three-phase to ground fault are analyzed.

Before starting the analysis with different types of fault, determining the annealing schedule is the most important task in SA. In classical approach all the SA parameters such as $P_i$, $\alpha$ and $\beta_n$ were evaluated through extensive experimental investigation and as a result the best optimised solution may not be evaluated all the times. A large no. of developments in the process of optimal scheduling has been proposed by many researchers such as simplex method (Non-linear Programming), graphical partitioning problem, permutation flow-shop scheduling problem, short term production scheduling problem. All these above stated methods require an initial assumption of temperature to start the iteration. Therefore the application of these classical methods requires experience and expertise to select the initial temperature and step size. Again all these methods lack segregation capacity or create confusion about selecting the initial parameters when the test point lies on the boundary edge [57]. In this research work as all the test points exist at edge, therefore, hyper tuning simulation using SVM has been applied to increase the flexibility in choosing the initial state. The following procedure has been adopted in tuning the parameters:

- Model performance has been evaluated by choosing the random variable for all present hyper plane in a system.
- Update the performance of neighbourhood state by altering the current state of data.
- Evaluate the model for all combination of hyper plane present in the neighbourhood state.

In the present research work in addition to the above procedure, the tuning of SA parameter has been carried out with the following steps [58] [59] [61].

- Time series analysis has been applied to forecast the normalizing constant ($\beta$), which depends upon the performance of expected variation.
- The initial temperature has been evaluated through cost function analysis. As per the theory of SVM cost function analysis acceptance rate should be taken 98% and above for best result. However, with the present research work an acceptance rate of 93.33% has been taken as derived from the probability function.
- Search space has been restricted to smaller value of $\alpha$, this is only to limit the search operation and for fast convergence of the optimization.

5.1. Case-1: single line to ground fault

The simulation model is used to analyze a single line to ground fault and calculate the fault performance for a fault location at 3.2 km away from the wind turbine installation site. The purpose here is to examine the behaviour of the ground fault in mutual coordination control actions among STATCOM and DFIG wind park and how they jointly manage the required performance in the event of a failure. The downtime of simulation tool is 0.02 sec. The interference only lasts for 1 cycle. Fig. 16 shows the Simulated Annealing optimization search of agents under SLG Fault, here referred as temperature under the single line to ground fault condition. The central contour represents the optimised area for finding the best solution using simulated annealing techniques and which is found to be here as 0.07883.

Fig. 17 shows the Objective singular function and Optimization under SA during SLG Fault. The lower Fig. under Fig. 22 represents the behaviour of x and y under the boundary condition and that of the fitness result is shown in Fig. 22. The iteration convergence at about 50 iterations. Fig. 18 shows the per unit (p.u.) voltage at the point of common coupling (pcc) of STATCOM and GSC under single line to ground (SLG) fault condition. As the fault occurs at the initial point of operation of simulation therefore a voltage dip has been noticed here for a time period from 0 to 0.2 sec. Similarly during the operation of STATCOM from 1 to 1.5 sec the voltage has been increased by 30%. Fig. 19 shows the real and reactive power exchanged at pcc of STATCOM and GSC under SLG. Here it can be noticed that the real power exchange occurs three times in the present simulation and that of the reactive power has been changed by 4 times [49], this is because of the increase in LVRT.

![Fig. 16. (a) Squared exponential Non-linear regression with $\sigma = 0.9$, (b) matern 5/2 GPR Non-linear regression with $\sigma = 0.9$, (c) exponential Non-linear regression GPR $\sigma = 0.9$.](image-url)
Fig. 17. Simulated annealing for SLG Fault.

Fig. 18. Objective function and optimization using SA for SLG Fault.

Fig. 19. P.u. voltage at the pcc of STATCOM and GSC under SLG.

Table 3. Comparison of performance parameter under SLG.

| Parameter | ANFIS-PI | GA-PI | SA-PI | SA+ANFIS-PI |
|-----------|----------|-------|-------|-------------|
| Kp        | 0.32     | 0.29  | 0.304 | 0.289       |
| Ki        | 0.57     | 0.57  | 0.57  | 0.538       |
| Tr        | 0.88     | 0.83  | 0.833 | 0.78        |
| Tp        | 0.97     | 0.99  | 0.914 | 0.883       |
| Ts        | 1.2      | 1.4   | 1.21  | 1.18        |
| Mp        | 11.24    | 11.007| 11.11 | 11.03       |

Fig. 20 shows the coupling dc voltage between the RSC and GSC. Due to single line to fault this dc voltage also under gone certain transient from 0 to 1 sec and again at 1.5 sec before settling down to a steady state.

Table 3 shows the comparison of performance parameter under SLG. Here it can be found that SA + ANFIS-PI provides better optimal result as compared to GA and ANFIS in-terms of Tr and Mp. The Mp as shown in the table is 11.03%.

5.2. Case-2: line-line to ground fault

Compared with single ground faults, double ground faults are rare, and their probability is about 66% of single ground faults. The stability of the controller to various errors such as small errors and large errors. Fig. 21 and Fig. 22 represent the Simulated Annealing optimization using SA under LLG fault condition respectively. Fig. 23 represents the p.u. voltage at the pcc of STATCOM and GSC under LLG. Here it can be found that the voltage waveform under goes 5 fold changes before settling to 1 p.u. Fig. 24 shows the real and reactive power exchanged with the grid at the pcc of STATCOM and GSC under LLG. Here it can be found that the system is highly non-linear and hence shows a power spike at 0.44 sec with 2 oscillations and 17 sub transient oscillations.

Similarly the reactive power exchanged as shown in Fig. 24 shows an increase in reactive power in between 0.5 to 1 sec and again at 1.5 sec. Fig. 25 shows the DC reference voltage of STATCOM under LLG. Here it can be found that the reference voltage is increased by 22% under fault condition before settling at 33 kV under post fault condition. Table 4 shows the comparative analysis of performance parameters under LLG-fault. Here it can be found that the rise time remains constant for GA-PI,
SA-PI and SA + ANFIS-PI. Similarly the settling time also varies very less as compared to other techniques. The peak over shoot has been reduced by 4.77% against ANFIS-PI and less than 2% for GA-PI based control action.

5.3. Case-3: line-line-line to ground fault

Compared with LLG, LLLG fault is rare, and the probability of LLG fault is about 20%. In this research paper, all types of fault analysis are performed to determine the robustness of the controller under various fault conditions.

Fig. 26: As compared to SLG and LLG the line-line-line-ground involves high non-linearity and therefore the system becomes convex before optimizing itself. Here optimization suffers from a number of local minima and therefore chances are there that it sticks in some local minima. Therefore, here step size has been increased as compared to other fault analysis. Fig. 27 shows the Objective function and Optimization using SA for LLLG Fault. Here it can be found that, due to higher non-linearity the agents move randomly and cannot settle down and leading to permanent disconnection of DFIG from the grid after LVRT period which can be depicted in the Fig. 28.

In Fig. 28 it can be visualized that, between 0.2 to 0.5 sec the fault has been applied for 10 cycles. The controller tries to maintain the terminal voltage after first drop at 0.22 sec but due to the unavailability of reactive power, 2nd time it also fails to maintain the voltage. Therefore, it takes the DFIG into a floating state by supplying the reactive power to the pcc and there by maintaining a voltage of 0.9 p.u. This is only to withstand the LVRT capability of the wind turbine. At about 1 sec the STATCOM injects a reactive power almost 30% extra to that of the 0.9 p.u. i.e. after the clearance of the fault and finally the voltage settles down at 1 p.u. at about 1.5 sec. Fig. 29 shows the Real and Reactive Power at the PCC of STATCOM and GSC under LLLG. As already discussed fault occurs at 0.2 sec therefore, it can be seen from the Fig. 29 that real power oscillates at 0.2 sec and again at the same time reactive power was also inserted into the grid by GSC molded by STATCOM so as to maintain the voltage profile flat PCC.

Fig. 21. DC reference voltage of STATCOM.

6. Conclusion

In this research work, the performance of Double Fed Induction Generator (DFIG) in coordination with STATCOM using simulated annealing techniques has been discussed. In order to improve the performance of the system, the different grid disturbances such as LG, LLG, and LLLG have been investigated with STATCOM. Low voltage rides through the capability of the wind farm and FRT (Fault Ride Through) have been tested under the presence of STATCOM including mutual coordinated control action [50, 51]. Different power quality issues such as reactive power demand and voltage level at PCC have also been discussed in this work. From power system analysis it is found that based on the internal relationship among the real and reactive power and their association with the rotor angle and speed leads to voltage disturbance after and sometimes after the disturbance has been cleared or during the fault condition. All these issues have been thoroughly identified by using a STATCOM near the Wind Farm. It is found that the STATCOM would able to support the voltage at the PCC during the fault condition and thereby increasing the fault ride-through capability of the DFIG.

A Simulink model was developed for DFIG and STATCOM. After that different types of shunt fault (L-G, LL-G, L-L-G) were created. Using the machine learning techniques, fault applied has been classified, type of fault detection & severity of the fault has also been addressed. Based on the gain factor, PI controller will give a proper signal for its operation. The present system can supply reactive power compensation for 25 to 30% dip in the voltage level. However, it does not guarantee the full protection of the system to which it is connected. The reliability and quality of the scheme have to be considered while comparing the system with the traditional wind farm grid-connected system. Furthermore, compensation against reactive power balance, dynamic voltage restorer can also be implemented. The following suggestion can be implemented in the future research work which can further improve the system performance.

- Experimental validation in terms of hardware needs to be implemented for further verification and robustness checking of the proposed controller.
- The impact of coordinated control action on different relays and their protection features.
- Research work on the plug and play-based STATCOM based system.

Table 5. Comparison of performance parameter under LLLG.

| Parameter | ANFIS-PI | GA-PI | SA-PI | SA + ANFIS-PI |
|-----------|----------|-------|-------|---------------|
| Kp        | 0.27     | 0.22  | 0.21  | 0.22          |
| Ki        | 0.33     | 0.33  | 0.28  | 0.30          |
| Tr        | 0.92     | 0.88  | 0.88  | 0.88          |
| Tp        | 0.99     | 0.992 | 0.891 | 0.83          |
| Ts        | 2.83     | 3.41  | 3.34  | 3.31          |
| Mp        | 23.81    | 22.07 | 22.03 | 21.73         |

Declarations

Author contribution statement

R.R. Hete: Conceived and designed the experiments.
Fig. 22. Simulated annealing optimization for LLG Fault.

Fig. 23. Objective function and optimization using SA for LLG Fault.

Fig. 24. P.u. voltage at the pcc of STATCOM and GSC under LLG.

Fig. 25. (a) Real power at the pcc of STATCOM and GSC under LLG; (b) Reactive power at the pcc of STATCOM and GSC under LLG.

Fig. 26. DC reference voltage of STATCOM under LLG.

Ritesh Dash: Performed the experiments; Wrote the paper.
Sanjoy Kumar Mishra: Analyzed and interpreted the data.
Adithya Ballaji, Vivekananda Subburaj, Kalvakurthi Jyotheeswara Reddy: Contributed reagents, materials, analysis tools or data.

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Fig. 27. Simulated annealing optimization for LLLG Fault.

Fig. 28. Objective function and optimization using SA for LLLG Fault.

Fig. 29. Objective function and optimization using SA for LLLG Fault.

Fig. 30. (a) Real power at the pcc of STATCOM and GSC under LLLG; (b) Reactive power at the pcc of STATCOM and GSC under LLLG.

Additional information

No additional information is available for this paper.

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References

[1] X. Chen, W. Wu, N. Gao, H.S.-H. Chung, M. Liserre, F. Blaabjerg, Finite control set model predictive control for LCL-filtered grid-tied inverter with minimum sensors, IEEE Trans. Ind. Electron. 67 (Dec 2020) 9980–9990.

[2] N.G. Hingorani, High power electronics and flexible AC transmission system, IEEE Power Eng. Rev. 7 (1988) 3–4.
Fig. 31. DC reference voltage of STATCOM under LLLG.

[3] A. Parizad, M. Kalantar, A. Khazali, Application of HSA and GA in optimal placement of FACTS devices considering voltage stability and losses, in: International Conference on Electric Power and Energy Conversion Systems, 2009, pp. 1–7.

[4] V.P. Rajderkar, V.K. Chandrarakar, Comparison of series FACTS devices via optimal location in a power system for congestion management, in: 2009 Asia-Pacific Power and Energy Engineering Conference, March 2009, pp. 1–5.

[5] Iraj Kheirizad, Amir Mohammadi, Mohammad Hadi Varahram, A novel algorithm for optimal location of FACTS devices in power system planning, J. Electr. Eng. Technol. 3 (2009) 177–183.

[6] W. Zhang, F. Li, M.L. Tolbert, Optimal Allocation of Shunt Dynamic Var Source SVC and STATCOM: A Survey, Department of Electrical and Computer Engineering, the University of Tennessee, Knoxville, 2006, pp. 1–6.

[7] K. Saranjeet, Evolutionary Algorithm Assisted Optimal Placement of FACTS Controllers in Power System, Master Thesis, Thapar University, 2009, pp. 16–18.

[8] Y.L. Tan, Analysis of line compensation by shunt-connected FACTS controllers: a comparison between SVC and STATCOM, IEEE Power Eng. Rev. 17 (August 1999) 57–58.

[9] A. Sode-Yome, N. Mithulananthan, Kwang Y. Lee, A comprehensive comparison of FACTS devices for enhancing static voltage stability, in: 2007 IEEE Power Engineering Society General Meeting, June 2007, pp. 1–8.

[10] M. Khajehzadeh, M.F. Taba, A. El-Shafie, M. Eslami, A survey on meta-heuristic global optimization algorithms, Res. J. Appl. Sci. Eng. Technol. (2011) 569–578.

[11] M.R. Al Rashidi, M.E. El-Hawy, Applications of computational intelligence techniques for solving the revived optimal power flow problem, Electr. Power Syst. Res. 79 (2009) 694–702.

[12] A. Rezaee-Jordhei, M. Joorabian, Optimal placement of multi-type FACTS devices in power systems using evolution strategies, in: The 5th International Power Engineering and Optimization Conference, June 2011, pp. 352–357.

[13] J.C. Mendes, O.K. Sauvedra, J.O. Pessanha, Power system restoration with priority loads using an evolutionary strategy, in: 34th North American Power Symposium, Arizona, 2002, pp. 254–260.

[14] M. Santiago, R. Maldonado, Optimal placement of FACTS controllers in power systems via evolutionary strategies, in: IEEE International Conference on Transmission and Distribution Evolutionary Computation, 2006, pp. 1–6.

[15] M.A. Talebi, A. Kazemi, A. Gholami, M. Rajabi, Optimal placement of static VAR compensator in distribution feeder for load balancing by genetic algorithm, in: 18th International Conference on Electricity Distribution, Tehran, 2005, pp. 1–6.

[16] I. Piscia, C. Balac, L. Toma, M. Eremia, Optimal SVC placement in electric power systems using a genetic algorithms based method, in: Power Tech Conference, June 2009, pp. 1–6.

[17] M. Karami, N. Marvin, M.Z.A. Abkadir, Determining optimal location of Static Var Compensator by means of genetic algorithm, in: International Conference on Electri
cal Control and Computer Engineering Pahang, Malaysia, June 2011, pp. 172–177.

[18] V.A. Preethi, S. Muradilaharan, S. Rajasekar, Application of genetic algorithm to power system voltage stability enhancement using facts devices, in: International Conference on Recent Advancements in Electrical, Electronics and Control Engi
eering, 2011, pp. 333–338.

[19] Deependra Singh, K.S. Verma, GA-based congestion management in deregulated power system using FACTS devices, in: 2011 International Conference & Utility Exhibition on Power and Energy Systems: Issues and Prospects for Asia (ICUEC), September 2011, pp. 1–6.

[20] J.S. Huang, Michael Negnevitsky, A messy genetic algorithm based optimization scheme for SVC placement of power systems under critical operation contingence,
[44] M. Molinas, J.A. Suá, T. Undeland, Low voltage ride through of wind farms with
cage generators: STATCOM versus SVC, IEEE Trans. Power Electron. 23 (3) (2008)
1104–1117.
[45] P. Shamoolizadeh, O.P. Malik, An adaptive power system stabilizer using online trained
neural networks, IEEE Trans. Energy Convers. 12 (4) (1997) 382–387.
[46] Arup Das, Subhojit Dawn, Sadhan Gope, A review on optimal placement of FACTS
devices, Int. J. Comput. Intell. IoT 2 (3) (2019).
[47] S.K. Mishra, L.N. Tripathy, A novel relaying approach for performance enhancement
in a STATCOM integrated wind-fed transmission line using single-terminal measure-
ment, Iran. J. Sci. Technol. Trans. Electr. Eng. 44 (2020) 897–910.
[48] K. Karthikeyan, P.K. Dhal, Investigation of optimal location and tuning of STATCOM
by genetic algorithm based transient stability improvement, J. Electr. Syst. 14 (2)
(2018) 103–117.
[49] Ritesh Dash, Dillip Ku Dash, G.C. Biswal, Classification of crop based on macronutri-
ents and weather data using machine learning techniques, Results Eng. (ISSN 2590-
1230) 9 (2021) 100203.
[50] Saket Saurabh, Md Irfan Ahmed, Optimal placement of STATCOM for improving
voltage stability using GA, Int. J. Sci. Technol. 2 (6) (August 2014) 1349–1353.
[51] Q. Wang, T. Wang, J.H. Zhao, H. Zhen, Online adjustment control of fuzzy PI pa-
rameters for platform stability loop, Navig. Control 17 (4) (2018) 41–45.
[52] G.F. Leng, S.W. Fang, R. Wang, Z.D. Bi, X.L. Lian, Development and practice of
online setting software for relay protection setting, Huge Data Electr. 21 (5) (2018)
78–81.
[53] Y.D. Guan, L. Xu, Z.W. Li, S.T. Zhu, K. Tan, Relay protection online distribution man-
gagement system and its security protection, Electr. Meas. Instrum. 55 (23) (2018)
7–14.
[54] X.L. Wang, M.M. Fu, Calculation method of short-circuit current in coal mine high-
voltage power grid based on parallel computing, Softw. Guide 17 (6) (2018) 35–38.
[55] H.H. Cao, Y.M. Zhang, W. Niu, Simulated annealing algorithm for solving overlay
grid topology problem, Comput. Eng. Appl. 43 (36) (2007) 68–70.
[56] P. Palaniraj, G. Sakthivel, Hybrid motion estimation algorithm based on PSO
with dynamic threshold on static block detection, Proc. Comput. Sci. 132 (2018)
1487–1496.
[57] Moon-Won Park, Yeong-Dae Kim, A systematic procedure for setting parameters in
simulated annealing algorithms, Comput. Oper. Res. (ISSN 0305-0548) 25 (3)
(1998) 207–217.
[58] Simulated annealing: an efficient hyper parameter tuning algorithm, https://arxiv.
org/pdf/1906.01504.pdf.
[59] Z. Fayyaz, N. Mohammadian, F. Salimi, A. Fatima, M.R.R. Tobar, M.R. Avanaki, Sim-
ulated annealing optimization in wavefront shaping controlled transmission, Appl.
Opt. 57 (21) (2018) 6233–6242.
[60] M.R. Nasir-Avanaki, S. Hojjatoleslami, H. Paun, S. Tuohy, A. Meadway, G. Dobre,
A. Podoleanu, Optical coherence tomography system optimization using simulated
annealing algorithm, in: Proceedings of Mathematical Methods and Applied Com-
puting, vol. 669, 2009.
[61] M.C. Das, R. Dash, S.C. Swain, V. Subbaraj, Performance enhancement of PI-
controller using SVM for DFIG-grid interconnected system, in: 2021 2nd Interna-
tional Conference for Emerging Technology (INCET), 2021, pp. 1–6.