Dynamic Self Adjusting FACTS-Switched Filter Compensation Schemes for Wind-Smart Grid Interface Systems

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Abstract- This paper validates a number of Flexible AC transmission system (FACTS) filter compensator devices on voltage stabilization and reactive power compensation in a distribution network with embedded wind energy conversion system (WECS). The FACTS filter compensator schemes provide Better voltage stabilization, improved power quality, Interface security, efficient utilization, minimum harmonics levels and energy loss minimization of electricity networks with reactive power and FACTS control, while satisfying the network operating voltage. A novel optimal modified PID controller based on Asymmetrical Switched Pulse Width Modulation (ASPWM) for a set of FACTS devices has been developed for enhancing the dynamic performance of a power system with wind power generation in a wide range of transient conditions including wind gusts. The low cost FACTS filter compensator devices are tested for standalone system (No AC Grid interface) and for AC-Grid interface. The paper presents the application of Multi Objective Particle Swarm Optimization (MOPSO) and Multi Objective Genetic Algorithm (MOGA) techniques in online optimal modified PID controller gain adjusting that dynamically minimize the global dynamic error.

Keywords- Switched Filter Compensator (SFC), Genetic Algorithm GA, Particle Swarm Optimization PSO, and Wind Energy Conversion System (WECS).

1. Introduction

The growing demand for renewable and green energy (Wind, Solar, PV, Wave, Tidal, Fuel Cell, Biogas, Hybrid ...) is motivated by economic viability and environmental concerns. The increasing reliance on fossil fuels with the accelerating rate of resource depletion is causing a strategic shift to energy conservation, clean fuel replacement and energy displacement of all or part of conventional sources to green and renewable energy sources [1-3]. By 2020, it is expected that the wind power generation will supply around 12% of the total world electricity new demands [4-5]. However, integration of such wind resources into the power system grids has caused new and persisted challenges to security, control, reliability, power quality and stability of modern electric power systems. The more critical aspect is the voltage stability and power quality of the power network [6-7]. Connecting a wind turbine with an induction generator directly to the transmission network without proper compensation and control can be troublesome. Dynamic control of the wind system that generates power from a stochastically varying prime mover input such as the wind presents control and stabilization challenges. The wind speed varies from time to time due to gusts and is further disturbed by the effect of supporting tower shadow [8-9].

The paper has a focus on wind power efficient utilization that meets performance and economic requirements for successful integration of large wind generation units into the power grid. A new stabilization control strategy which uses novel FACTS filter compensator devices is presented to dynamically ensure voltage regulation and energy utilization. SFC FACTS devices can provide fast active and reactive power compensations and voltage support as well as efficient utilization. The FACTS based dynamic switched power filter compensator is expected to provide:

- Power factor improvement (at the generator and load sides)

- Reduction in transient over voltage during short circuit as well as safe neutral by eliminating hot grounds
- Improved damping of transient conditions
- Efficient wind energy Utilization

Time-domain simulations using MATLAB/SIMULINK under various disturbance conditions including wind gusts and three-phase fault at the generator terminal, illustrate the effectiveness and robustness of the optimized MOGA/MOPSO. The new MOGA/MOPSO proposed controller offers significant improvement in terms of damping of power system oscillations in comparison with the conventional controller previously designed using fixed gains.

MOGA/MOPSO search and gain optimization techniques are used to adjust the control gains and settings to minimize each controller total absolute error. This control scheme is extremely effective in ensuring voltage stabilization and enhancing power/energy utilization under severe load and wind prime mover/wind velocity excursion. The proposed switched dynamic power filter compensator with the self regulating dynamic error driven controller is an attractive and viable solution for dynamic voltage stabilization, power factor correction, power quality enhancement , efficient-utilization, and loss reduction for distribution and utilization electric grid feeders.

2. Sample Study Wind-Facts Scheme

The simulation of FACTS is essential in order to provide insight on the interaction of FACTS, wind energy conversion system and the grid prior to any application of such systems. Figure 1 shows a typical wind FACTS arrangement. A squirrel-cage induction generator is connected to a rotor, a gear box, and a capacitor bank as illustrated in fig. 2. Four switched smart filter compensated FACTS devices are utilized as shown in fig. 2. All filters objectives can be either: (a) harmonic reduction and power quality enhancement; or (b) electric power/energy savings and (c) dynamic reactive compensation for the wind system. Figure 3 shows the proposed tri-loop dynamic tracking controller to provide Better voltage stabilization, improved power quality, Interface security, efficient utilization, minimum harmonics levels and energy loss minimization of electricity networks.

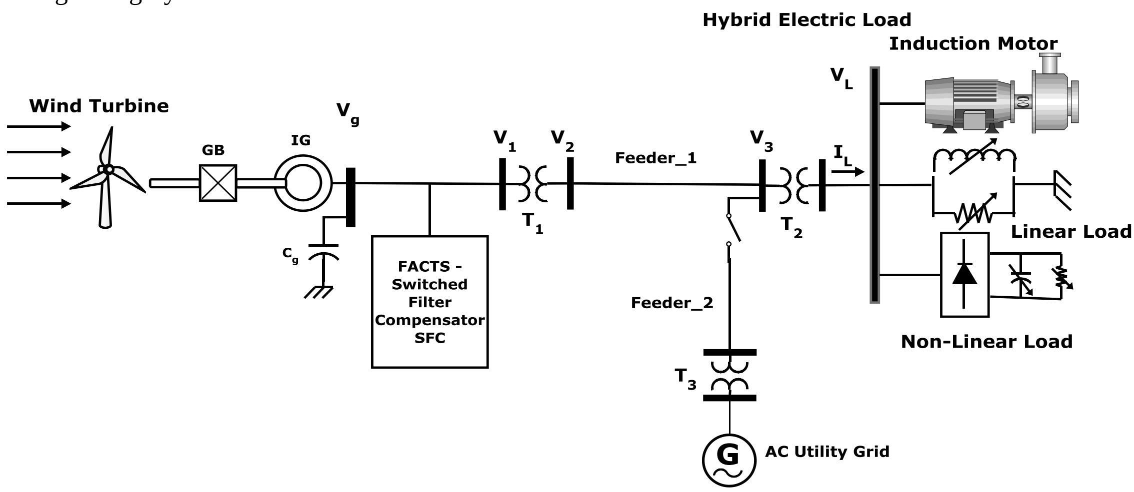

Fig. 1. The proposed (Wind-FACTS) energy utilization system

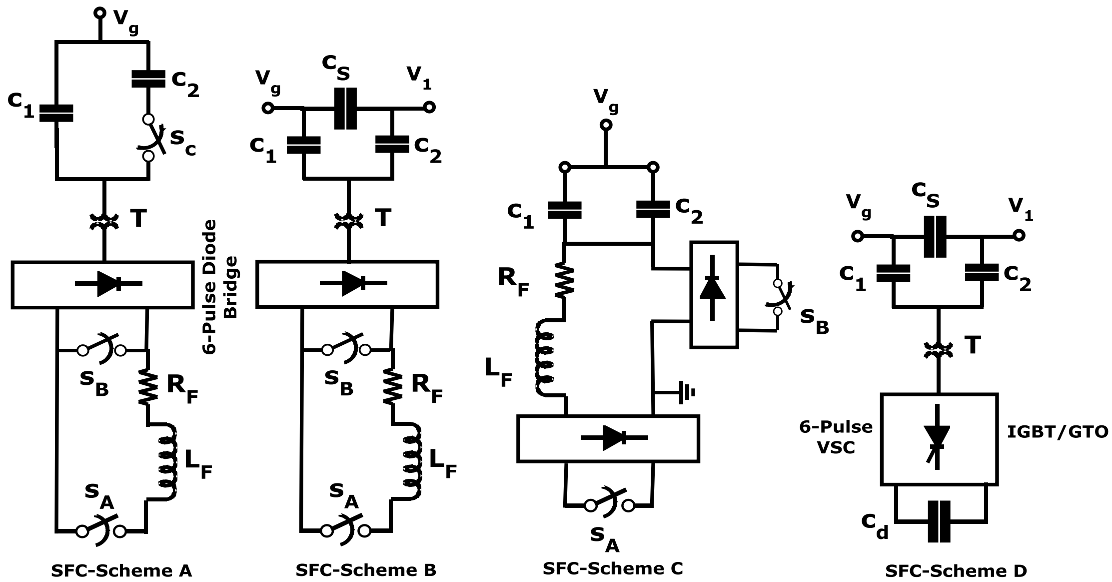

Fig. 2. Proposed family of Switched filter compensators

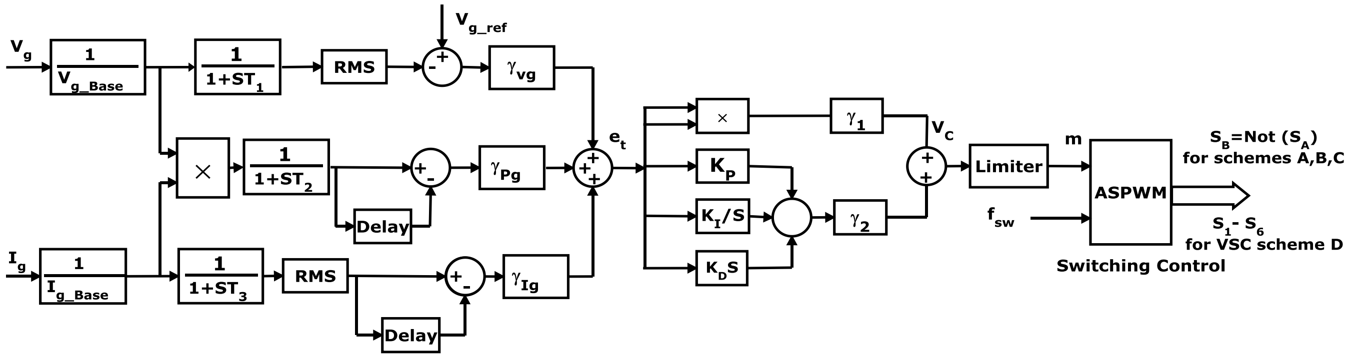

Fig. 3. The block diagram of the Tri-loop error driven self regulating dynamic modified weighted PID controller for the (Wind-FACTS) energy utilization system

The novel PSO and GA self tuned multi regulators and coordinated controller are used. The global error is the summation of the three loop individual errors including voltage stability, current limiting and synthesize dynamic power loops. The multi loop dynamic control scheme is used to reduce a global error based on a tri-loop dynamic error summation signal in addition to other supplementary motor current limiting and dynamic power loops are used as auxiliary loops to generate a dynamic global total error signal that consists of not only the main loop speed error but also the current ripple, over current limit and dynamic over load power conditions.

To compare the global performances of all controllers, the NMSE deviations between output plant variables and desired values (in this paper the generated voltage Vg is the output variable and Vg-ref is the desired generated voltage), and NMSEVg is defined as:

$$NMSE_{Vg} = \frac{\sum \left(V_g - V_{g-ref}\right)^2}{\sum \left(V_{g-ref}\right)^2} \quad (1)$$

A number of conflicting objective functions are selected to optimize using the MOGA/MOPSO algorithms. These functions are defined by the following:

J1 = Minimize the Total Harmonic Distortion of the Load current (THD_i) (2)

J2 = Minimize the Total Harmonic Distortion of the Load Voltage (THD_v) (3)

J3 = Maximize the electric energy efficiency (4)

J4 = Maximize the Power factor (5)

J5 = Minimize the NMSEVg of the generated voltage (6)

Fundamentally, the conventional PID controller comprises three basic control actions. They are simple to implement and they provide good performance. The tuning process of the gains of PID controllers can be complex because is iterative: first, it is necessary to tune the "Proportional" mode, then the "Integral", and then add the "Derivative" mode to stabilize the overshoot, then add more "Proportional", and so on. The proposed modified weighted PID controller has the following form in the time domain:

$$u(t) = \gamma_1 \left[K_P e(t) + K_I \int e(t)dt + K_D \frac{de(t)}{dt} \right] + \gamma_2 [e(t)]^2 \quad (7)$$

Where e(t) is the selected system error, u(t) the control variable, K_P the proportional gain, K_I the integral gain, and K_D is the derivative gain. Each coefficient of the PID controller adds some special characteristics to the output response of the system. Because of this, choosing the right parameters becomes a crucial decision for putting into practice this controller. The PSO and GA optimization and parameters searching algorithms shown in the following sections are implemented for tuning the gains K_P, K_I, K_D, γ_1 and γ_2 to minimize the selected objective functions (J_1 - J_5).

3. Multi-Objective Optimization

The general MO problem requiring the optimization of N objectives may be formulated as follows [10-12]:

Minimize

$$\vec{y} = \vec{F}(\vec{x}) = \left[\vec{f}_1(\vec{x}), \vec{f}_2(\vec{x}), \vec{f}_3(\vec{x}), ..., \vec{f}_N(\vec{x})\right]^T \quad (8)$$

$$\textit{subject to } g_j(\vec{x}) \le 0 \qquad j = 1,2,\ldots,M \quad (9)$$

Where: $\vec{x} = \left[\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_P\right]^T \in \Omega$ (10)

$\vec{y}$ is the objective vector, the $\vec{g}_i(\vec{x})$ represents the constraints and $\vec{x}$ is a P-dimensional vector representing the decision variables within a parameter space Ω. The space spanned by the objective vectors is called the objective space. The subspace of the objective vectors satisfying the constraints is called the feasible space. A decision vector $\vec{x}_1 \in \Omega$ is said to dominate the decision vector $\vec{x}_2 \in \Omega$ (denoted by $\vec{x}_1 \prec \vec{x}_2$), if the decision vector $\vec{x}_1$ is not worse than $\vec{x}_2$ in all objectives and strictly better than $\vec{x}_2$ in at least one objective. A decision vector $\vec{x}_1 \in \Omega$ is called Pareto-optimal, if there does not exist another $\vec{x}_2 \in \Omega$ that dominates it. An objective vector is called Pareto-optimal, if the corresponding decision vector is Pareto-optimal.

3.1. Multi-Objective Genetic Algorithm

Genetic algorithm is an optimization method inspired by Darwin's reproduction and survival of the fittest individual [13]. This algorithm looks for the fittest individual from a set of candidate solutions called population. The population is exposed to crossover, mutation and selection operators to find the fittest individual. The fitness function assesses the quality of each individual in evaluation process. The selection operator ensures the fittest individuals for the next generation. The crossover and mutation operators are used for variety of populations. The NSGA is a multi-objective genetic algorithm that was developed by Deb, et. al. [14]. The basic idea behind NSGA is the ranking process executed before the selection operation, as shown in fig. 4. This process identifies non dominated solutions in the population, at each generation, to form non dominated fronts [15], after this, the selection, crossover, and mutation usual operators are performed. In the ranking procedure, the non dominated individuals in the current population are first identified. Then, these individuals are assumed to constitute the first non dominated front with a large dummy fitness value [15].

Chromosome Representation

The search and gain optimization techniques are used to adjust the control gains and settings to ensure voltage stabilization and enhancing power/energy utilization under severe load and wind prime mover/wind velocity excursion. It is important to select appropriate optimal variables for optimization process and WECS optimal performance. We select ten variables for genetic algorithm optimization, which correlate closely with the fundamental WECS operation. Five variables define the gains of the proposed modified weighted PID controller (KP, KI, KD, g1, g2). Other five variables define the selected objective functions (J1, J2, J3, J4, J5). The first work to operate the genetic algorithm for WECS optimization problem is to choose the appropriate chromosome representation, which represents the potential solution to control strategy. Chromosome representation describes each individual of the population in genetic algorithm. Based on the selected objective functions and optimization variables, we define the chromosome with the following genes shown in fig. 5. According to the multi-objective genetic algorithm, the computational procedure to optimize the specific cycles is listed as follows:

a) Initialization. Set the initial values of six parameters for genetic algorithm, including

1) The maximal number of generations,

2) The population size,

3) The generation number,

4) The crossover probability,

5) The mutation probability,

6) The constraint parameters,

b) Evaluation of fitness function. Compute the fitness value for each chromosome in each generation. After validating by the constraints, record and modify the "best" chromosome to the next generation, update the archive vector of Pareto optimal solutions.

c) Reproduction. Compute the reproduction probability and the cumulative probability. Generate a random number r in [0, 1] according to uniform distribution. Operating the reproduction process will produce a new generation

d) Crossover. For each selected pair, apply a crossover operation to generate two new strings. Generate a random number in [0, 1] according to uniform distribution in turn. Set up a parent chromosome population. Select two chromosomes in the parent chromosome population and a breakpoint for each chromosome in random. Crossover the two chromosomes, save the new chromosome and delete the parents from the population. Operate the crossover process until all of parent chromosomes are computed with crossover.

e) Mutation. Mutation increases the diversity of the population by introducing random variation to the population.

f) Finish Condition. If the present generation number equals to the maximal number of generations, optimization processes of genetic algorithm finish and the optimal operation parameters come into being.

3.2. Multi-Objective Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary computation optimization technique (a search method based on a natural system) developed by Kennedy and Eberhart [16]-[19]. The system initially has a population of random selective solutions. Each potential solution is called a particle. Each particle is given a random velocity and is flown through the problem space. The particles have memory and each particle keeps track of its previous best position (called the Pid) and its corresponding fitness. There exist a number of Pid for the respective particles in the swarm and the particle with greatest fitness is called the global best (Pgd) of the swarm. The basic concept of the PSO technique lies in accelerating each particle towards its Pid and Pgd locations, with a random weighted acceleration at each time step. In MOPSO [15-17], a set of particles are initialized in the decision space at random. For each particle i, a position xi in the decision space and a velocity vi are assigned. The particles change their positions and move towards the so far best-found solutions. The non-dominated solutions from the last generations are kept in the archive. The archive is an external population, in which the so far found non-dominated solutions are kept. Moving towards the optima is done in the calculations of the velocities as follows:

$$\begin{aligned} \mathrm{V_{id}} &= \omega \times V_{id} + C_1 \times rand_1 \times \left(P_{pd} - X_{id}\right) \\ &\quad + C_2 \times rand_2 \times \left(P_{rd} - X_{id}\right) \end{aligned} \tag{11}$$

$$X_{id} = X_{id} + V_{id} \tag{12}$$

Each particle has to change its position $X_{i,d}$ towards the position of the two guides $P_{r,d}$, $P_{p,d}$ which must be selected from the updated set of non-dominated solutions stored in the archive. The particles change their positions during generations until a termination criterion is met. Figure 6 shows the flow chart of the Multi-Objective Particle Swarm Optimization MOPSO.

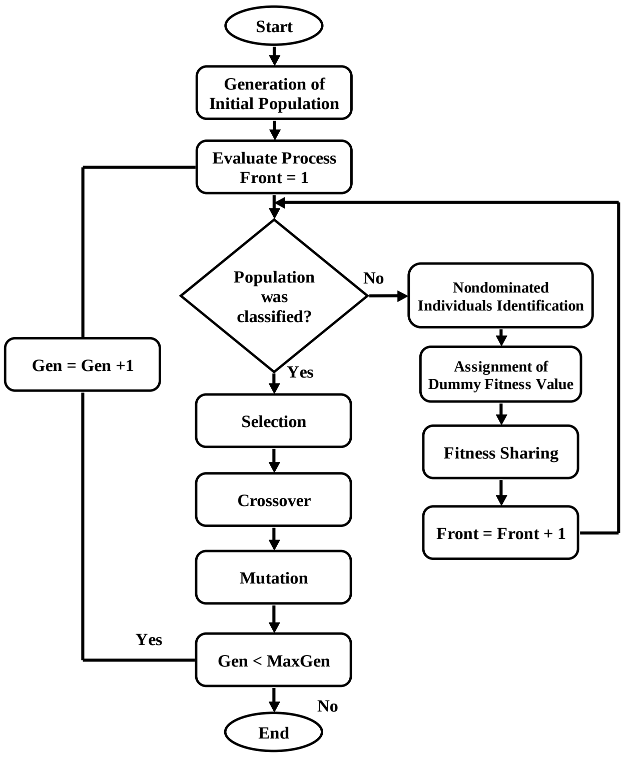

Fig. 4. Flow chart of GA search and optimization algorithm.

K_P	K_I	K_D	γ_1	γ_2	J_1	J_2	J_3	J_4	J_5

Fig. 5. The chromosome coding scheme

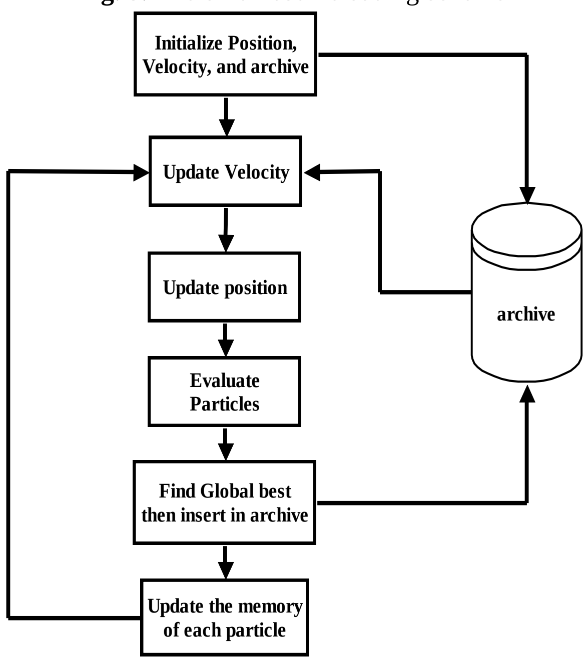

Fig. 6. Flow chart of the MOPSO search and optimization algorithm

4. Digital Simulation Results

The proposed FACTS devices performance is compared for two cases; with fixed and self tuned type controllers using either GA or PSO. Matlab-Simulink Software was used to design, test, and validate the effectiveness of the FACTS devices to minimize network losses while satisfying the grid code connection requirement for reactive power control. The control system comprises a dynamic multi loop error driven regulator is coordinated to minimize the selected objective functions. SOO obtains a single global or near optimal solution based on a single weighted objective function. The weighted single objective function combines several objective functions using specified or selected weighting factors as follows:

$$\text{minimize}(J_W) = \alpha_1 J_1 + \alpha_2 J_2 + \alpha_3 \left(\frac{1}{J_3}\right) + \alpha_4 \left(\frac{1}{J_4}\right) + \alpha_5 J_5 \tag{13}$$

Where α1 = 0.20, α2 = 0.20, α3 = 0.20, α4 = 0.20, α5 = 0.20 are selected weighting factors. J1, J2, J3, J4, J5 are the selected objective functions. On the other hand, the MO finds the set of acceptable (trade-off) optimal solutions. This set of accepted solutions is called Pareto front. These acceptable trade-off multi level solutions give more ability to the user to make an informed decision by seeing a wide range of near optimal selected solutions. In order to test the performance of the system for variable speed wind energy generation, a variable speed wind profile has been applied to the wind turbine emulator. Tables I-V show the response of the proposed SFC schemes for wind energy conversion system under the constant gains, the SOGA based tuned gains, the SOPSO based tuned gains, the MOGA based tuned gains, and the MOPSO based tuned gains, modified weighted PID controller, respectively. Comparing the system dynamic response results of the two study cases, with GA and PSO tuning algorithms and traditional controller with constant controller gains results, it is quite apparent that the GA and PSO tuning algorithms highly improved the system dynamic performance from a general power quality point of view. The GA and PSO tuning algorithms had a great impact on system efficiency which is improved by 9.4 % in comparison with that under the constant gains controller. The system power factor increment is 7.34 %. THD of the load bus voltage improvement of 10.23% is obtained. In addition the improvement of THD of the load bus current is 12.45%.

Table 1. System efficiency comparison

	SFC- A	SFC- B	SFC- C	SFC- D
Constant Parameters modified weighted PID Controller	0.7138	0.7119	0.7071	0.7075
GA Based Tuned modified weighted PID Controller	0.7528	0.7624	0.7650	0.7695
PSO Based Tuned modified weighted PID Controller	0.7688	0.7645	0.7640	0.7696
MOGA Based Tuned modified weighted PID Controller	0.7705	0.7786	0.7698	0.7782
MOPSO Based Tuned modified weighted PID Controller	0.7893	0.7759	0.7725	0.7736

Table 2. Motor power factor comparison

	SFC- A	SFC- B	SFC- C	SFC- D
Constant Parameters modified weighted PID Controller	0.9527	0.9586	0.9495	0.9408
GA Based Tuned modified weighted PID Controller	0.9851	0.9897	0.9907	0.9925
PSO Based Tuned modified weighted PID Controller	0.9968	0.9973	0.9936	0.9985
MOGA Based Tuned modified weighted PID Controller	0.99928	0.99915	0.99913	0.99921
MOPSO Based Tuned modified weighted PID Controller	0.99961	0.99959	0.99956	0.99985

Table 3 . THD (%) of load bus voltage comparison

	SFC- A	SFC- B	SFC- C	SFC- D
Constant Parameters modified weighted PID Controller	11.5106	12.2887	12.2937	12.1365
GA Based Tuned modified weighted PID Controller	6.6067	6.4695	7.8817	7.9032
PSO Based Tuned modified weighted PID Controller	6.2070	5.0333	6.4420	6.8687
MOGA Based Tuned modified weighted PID Controller	5.4006	5.3419	5.7991	5.3733
MOPSO Based Tuned modified weighted PID Controller	4.9432	4.9775	5.3453	4.4367

Table 4. THD (%) of load bus current comparison

	SFC- A	SFC- B	SFC- C	SFC- D
Constant Parameters modified weighted PID Controller	14.2155	14.8896	14.5258	14.7357
GA Based Tuned modified weighted PID Controller	8.6831	8.0631	8.6379	8.3932
PSO Based Tuned modified weighted PID Controller	7.1544	7.0382	7.4777	8.7958
MOGA Based Tuned modified weighted PID Controller	6.0328	6.3971	7.6420	6.8992
MOPSO Based Tuned modified weighted PID Controller	5.7254	5.4951	5.3099	6.2791

Table 5. The Normalized Mean Square Error (NMSE) of the generated voltage comparison

	SFC- A	SFC- B	SFC- C	SFC- D
Constant Parameters modified weighted PID Controller	0.078	0.073	0.088	0.095
GA Based Tuned modified weighted PID Controller	0.0099	0.0088	0.0082	0.0090
PSO Based Tuned modified weighted PID Controller	0.0072	0.0070	0.0078	0.0070
MOGA Based Tuned modified weighted PID Controller	0.0055	0.0052	0.0052	0.0055
MOPSO Based Tuned modified weighted PID Controller	0.0026	0.0021	0.0029	0.0027

5. Experimental Implementation

In order to verify the effectiveness of the proposed FACTS schemes and the validity of the system dynamic performance based on GA/PSO, experiments are carried out on FACTS scheme (A) shown in fig. 4. The parameters of the selected controller have been experimentally adjusted according to the GA/PSO search procedure. The setup includes a tri-loop error driven controller with an optimal efficiency search voltage controller based on GA/PSO search algorithms. The wind speed model provides a variable wind speed to the turbine model. The turbine output is fed to the induction generator model. The generator outputs are connected to the load bus through a transmission line model and the grid model. The propped FACTS-based devices are applied in order to flatten voltage profile, preserve stability, correct power factor, and decrease power and energy losses by minimizing reactive power flow in the network. Within a scope of voltage control and reactive power compensation problem, power conditions are analyzed as a part of the whole problem related to technical aspects of grid integration of the WECS. The wind turbine simulator is designed to have the characteristics equivalent to a wind turbine system. A DC machine fed by a 3-phase thyristor controlled bridge rectifier with a separately excited field winding fed by a 1-phase controlled rectifier is used to drive the induction generator shaft. Real wind data of turbine torque and speed were used as reference values to control the DC motor. The proposed wind emulator scheme uses a control system (fig. 7), where the input variables are the wind speed, the shaft speed and torque of the motor. Motor torque can be measured, but in most cases it is estimated from the motor current. These input variables are introduced into the host PC computer that has recorded the turbine curves and whose output is the torque reference of the DC motor. The wind turbine system model is either based on an equation or a look up table. A complete discussion of the emulation technique is found in [20]. The reference voltage was set to maintain the wind voltage at l PU. Before the MOPSO Based Tuned modified weighted PID Controller was applied (fig. 8), the load voltage was 6 % below the nominal voltage, and varied about 6% between the extremes of 0.945 and 1.06. After the MOPSO Based Tuned modified weighted PID Controller was applied (fig. 9), the bus voltage magnitude at the point of the WECS connection to the network is kept at a constant value and the overall variation in the voltage was about 0.2%. The SFC reactive power flow control enforces minimum reactive power exchange with the network. It makes an advantage not only in keeping power factor at unity (figures 10-11), but in decreased power loss on the WECS radial distribution feeder as well. The energy loss results are presented in Table VI. From Table VI, it can be seen that with the coordinated optimal control of SFC, power losses can be reduced significantly by over 9% with respect to that of base case without optimal control. A FFT analysis for the load bus current using Constant Parameters modified weighted PID Controller was performed (fig.12), which indicated a considerable 11th and 13th wind farm current harmonic. The total harmonic distortion was 16%. Finally, a FFT analysis for the load bus current using MOPSO Based

Tuned modified weighted PID Controller was performed (fig.13). The total harmonic distortion was 4.67 %.

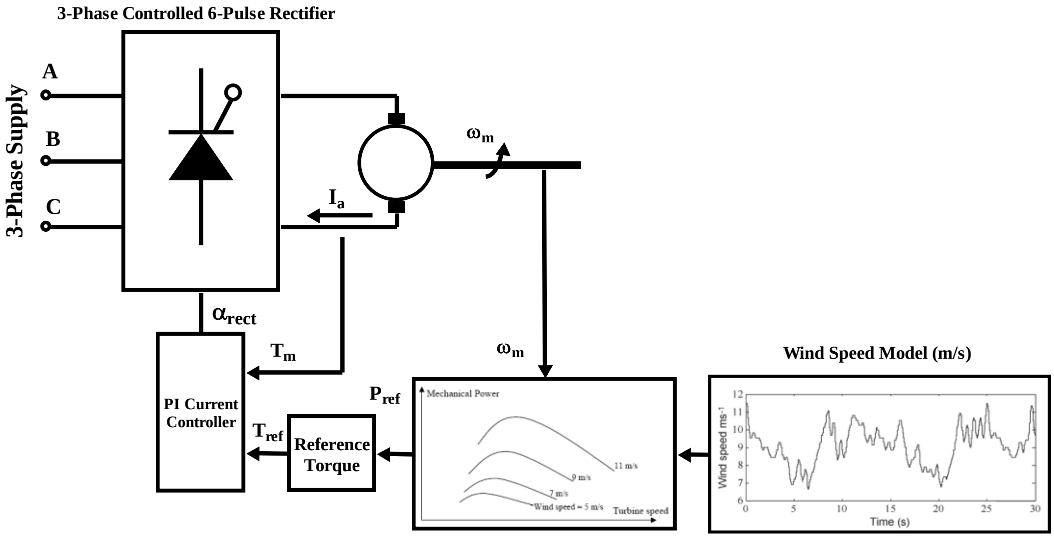

Fig.7. Wind turbine simulator using DC motor drive

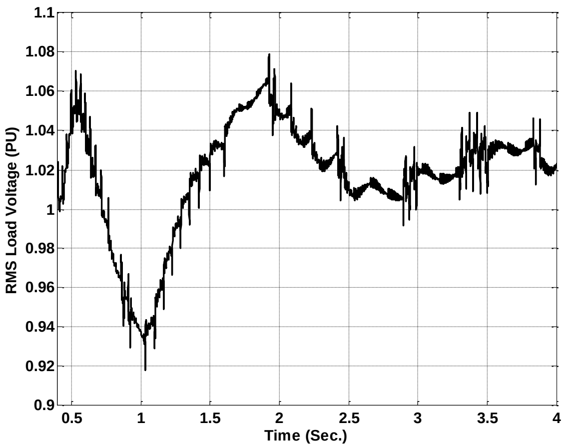

Fig. 8. RMS Load Voltage using Constant Parameters modified weighted PID Controller (experimental)

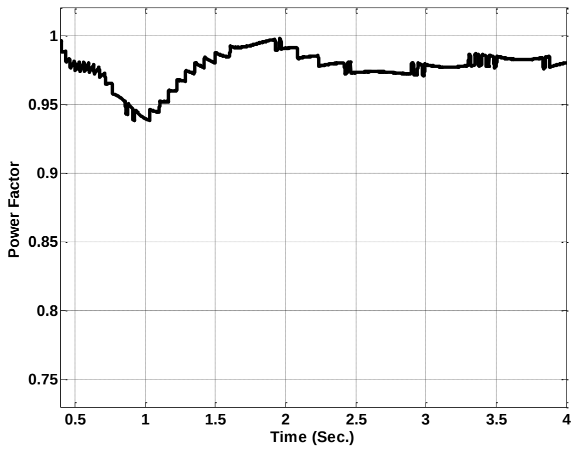

Fig. 10. Power factor using Constant Parameters modified weighted PID Controller (experimental)

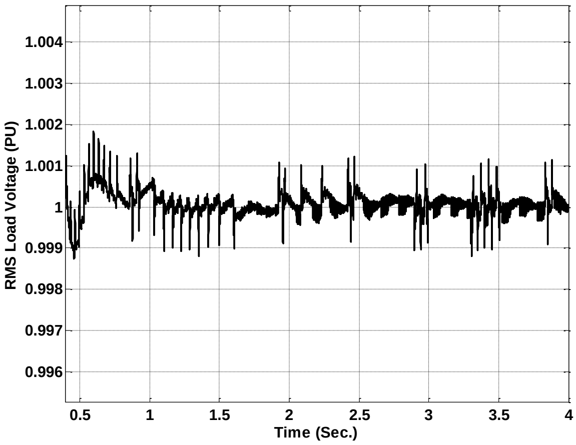

Fig. 9. RMS Load Voltage using MOPSO Based Tuned modified weighted PID Controller (experimental)

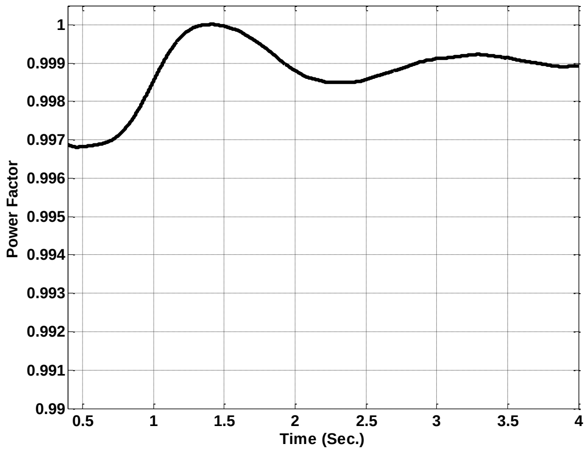

Fig. 11. Power factor using MOPSO Based Tuned modified weighted PID Controller (experimental)

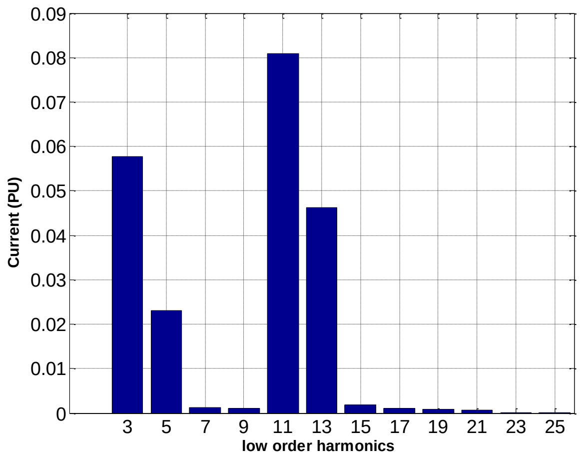

Fig. 12. Load Current using Constant Parameters modified weighted PID Controller (experimental)

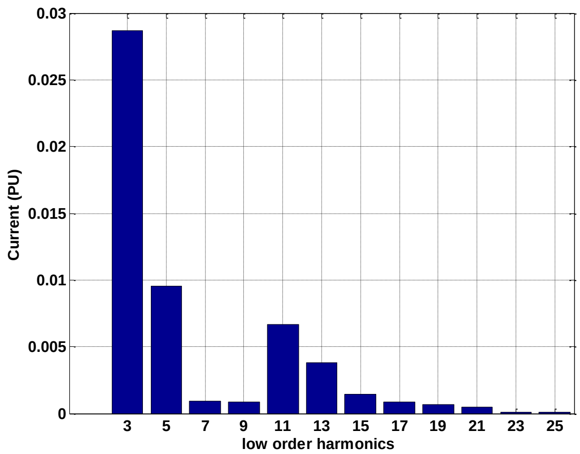

Fig. 13. Load Current using MOPSO Based Tuned modified weighted PID Controller (experimental)

Table 5. Energy loss results (PU) of the proposed SFC Schemes (experimental)

	SFC-Scheme A	SFC-Scheme B	SFC-Scheme C	SFC-Scheme D
Constant Parameters modified weighted PID Controller	0.2839	0.2814	0.2971	0.2996
GA Based Tuned modified weighted PID Controller	0.2398	0.2454	0.2571	0.2449
PSO Based Tuned modified weighted PID Controller	0.2371	0.2379	0.2485	0.2415
MOGA Based Tuned modified weighted PID Controller	0.2227	0.2299	0.2395	0.2256
MOPSO Based Tuned modified weighted PID Controller	0.2120	0.2100	0.2269	0.2256

6. Conclusion

The paper validated the concept of a number of FACTS switched filter compensator devices to enhance the dynamic and transient performance of power systems with distributed wind generation using self-excited induction generators. MOGA/MOPSO search and optimization techniques have been successfully utilized to stabilize the voltage, minimize the electricity transmission network losses, eliminate transient overload and enhance energy utilization while satisfying the grid code connection requirement. MOGA/MOPSO has been tested in distribution networks and it has been proved its ability to reach the global optimal control gain selections. Digital simulation results show that the FACTS switched filter compensator devices provide an effective dynamic voltage stabilization control enhance the capability of the wind farm to ride through the grid disturbances, reduce dynamic voltage and current transients and ensure efficient wind energy utilization under varying wind conditions, load changes and faults.

7. Appendix

Wind Turbine Model: The mechanical power in the wind depends on a few factors and is given by:

$$P_w = \frac{1}{2}\rho A V_W^3$$

where ρ is the air density (1.225 kg/m3 at 15o C and 1 atm.), A is cross-sectional area of the blades and V_w is the wind speed. Betz's Law states that only a fraction of this power can be captured by the wind turbine. This fraction of the power in the wind that can be captured by the wind turbine is called the Power Coefficient (C_p) and is defined as:

$$C_P = \frac{P_{shaft}}{P_{wind}}$$

The maximum theoretical C_p value is 0.593 or 59.3%

The power in the shaft can be represented by the torque generated in the shaft depending on the shaft speed:

$$T_{shaft} = \frac{P_{shaft}}{\omega_{shaft}}$$

Wind Turbine Induction Generator: 3.6 MVA, 0.85 PF, 11 KVL-L, Nm = 1800 rpm.

Self excited capacitor (at common generation bus) Cself = 400 mF.

Transformer T1: 11/25 KV, 5 MVA

Transformer T2: 25/4.16 KV, 5 MVA

Transformer T3: 25/230 KV, 5 MVA

Utility AC Grid: 230 KV, Short circuit level = 60 GVA, R = 0.0654 W, X = 0.854 W

Feeder : 10 Km, 25 KV, Rf = 0.4 W/Km, Xf = 0.35 W/Km.

SFC-Scheme A: C1 = 75 μF, C2 = 75 μF, Rf = 0.35 W, Lf = 6 mH.

SFC-Scheme B: Cs =145 μF, C1 = 115 μF, C2 = 115 μF, Rf = 0.35 W, Lf = 6 mH.

SFC-Scheme C: C1 = 100 μF, C2 = 100 μF, Rf = 0.25 W, Lf = 5 mH.

SFC-Scheme D: Cs =80 μF, C1 = 45 μF, C2 = 45 μF, Cd = 175 μF

Nomenclature

WECS	Wind Energy Conversion System
SEIG	Self-Excited Induction Generator
FACTS	Flexible AC Transmission Systems
SFC	Switched Filter Compensator
SOO	Single-Objective Optimization
MOO	Multi-Objective Optimization
PSO	Particle Swarm Optimization
MOPSO	Multi-Objective Particle Swarm Optimization
GA	Genetic Algorithm
NSGA	Non-Dominated Sorting Genetic Algorithm
MOGA	Multi-Objective Genetic Algorithm
ASPWM	Asymmetrical Switched Pulse Width Modulation
V_{id}	The velocity of the i_th particle with d dimensions,
X_{id}	The position of the i_th particle with d dimensions,
$rand_1$, $rand_2$	Two uniform random functions on the range [0.1]
ω	The inertia weight which is chosen beforehand
C_1	The cognitive learning rate
C_2	The social learning rate
P_{id}	The location along dimension d at which the particle previously had the best fitness measure
P_{gd}	The current location along dimension d of the neighborhood particle with the best fitness
$P_{r,d}$, $P_{p,d}$	randomly chosen from a single global Pareto archive
α_1, α_2, α_3, α_4, α_5,	Selected weighting factor for the proposed single objective function
$NMSE\_{Vg}$	The Normalised Mean Square Error deviations between the generated voltage and the desired value of the genertaed voltage
THD	The total harmonic distortion

References

[1] Beekmann, A.; Marques, J.; Quitmann, E.; Wachtel, S.; "Wind energy converters with FACTS Capabilities for optimized integration of wind power into transmission and distribution systems" Integration of Wide-Scale Renewable Resources Into the Power Delivery System, 2009 CIGRE/IEEE PES Joint Symposium , Page(s): 1-7

[2] Adamczyk, A.; Teodorescu, R.; Mukerjee, R.N.; Rodriguez, P.; "Overview of FACTS devices for wind power plants directly connected to the transmission network" Industrial Electronics (ISIE), 2010 IEEE International Symposium on , Page(s): 3742 - 3748

[3] Shakib, A.D.; Spahic, E.; Balzer, G.; "Optimal location of series FACTS devices to control line overloads in power systems with high wind feeding" PowerTech, 2009 IEEE Bucharest , Page(s): 1 - 7

[4] Varma, R.K.; Auddy, S.; Semsedini, Y.; "Mitigation of Subsynchronous Resonance in a Series-Compensated Wind Farm Using FACTS Controllers" Power Delivery, IEEE Transactions on Volume: 23 , Issue: 3 , Publication Year: 2008 , Page(s): 1645 - 1654

[5] Zhang, X.P.; "Energy loss minimization of electricity networks with large wind generation using FACTS" Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE , Page(s): 1 - 5

[6] Grunbaum, R.; "FACTS for grid integration of wind power" Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES , Page(s): 1 - 8

[7] Bian, Xiaoyan; Tse, C. T.; Chung, C. Y.; Wang, K. W.; "Dynamic modeling of large scale power system with FACTS and DFIG type wind turbine" Power Electronics for Distributed Generation Systems (PEDG), 2010 2nd IEEE International Symposium on Page(s): 753 - 758

[8] Nguyen, T. T.; Kandlawala, M. F.; "An optimal fuzzy-logic controller of a FACTS device for damping oscillations in power system with wind generation"Advances in Power System Control, Operation and Management (APSCOM 2009), 8th International Conference on , Page(s): 1 - 6

[9] Luna, A.; Rocabert, J.; Vazquez, G.; Rodriguez, P.; Teodorescu, R.; Corcoles, F.; "Grid synchronization for advanced power processing and FACTS in wind power systems" Industrial Electronics (ISIE), 2010 IEEE International Symposium on , Page(s): 2915 – 2920

[10] Ngatchou, P.; Zarei, A.; El-Sharkawi, A.; (2005) "Pareto Multi Objective Optimization" Intelligent Systems Application to Power Systems, 2005. Proceedings of the 13th International Conference on 6-10 Nov. 2005 Page(s):84 – 91

[11] Berizzi, A., M. Innorta, and P. Marannino. (2001) "Multiobjective optimization techniques applied to modern power systems". In 2001 IEEE Power Engineering Society Winter Meeting, Jan 28-Feb 1 2001.

[12] C. A. Coello Coello and M. S. Lechuga. (2003) "MOPSO: A proposal for multiple objective particle swarm optimization". In IEEE Proceedings World Congress on Computational Intelligence, pages 1051–1056, 2003.

[13] L. Davis, "Handbooks of genetic algorithm", New York: Van Nostrand, Reinhold, 1991

[14] K. Deb, A. Paratap, S. Agarwal, and T. Meyarivan, "A Fast and Elitist Multi-objective Genetic Algorithm: NSGA-II," IEEE Trans. Evolutionary Computation, no. 2, pp. 182-197, 2002.

[15] N. Srinivas and K. Deb, "Multiobjective optimization using nondominated sorting in genetic algorithms," Tech. Rep., Dept. Mechanical Engineering, Kanput, India, 1993.

[16] J. Kennedy and R. Eberhart, "Particle swarm optimization" Proceedings, IEEE International Conf. on Neural Networks, Vol. 4, pp.1942–1948, 1995

[17] Y. Shi and R. Eberhart, "Empirical study of particle swarm optimization" Proceedings of the 1999 Congress on Evolutionary Computation, Vol. 3, 1999.

[18] R. Eberhart and Y Shi, (2001) "Particle swarm optimization: developments, applications and resources" Proceedings of the 2001 Congress on Evolutionary Computation, Vol. 1, pp. 81 - 86, 2001.

[19] Y. Shi and R. Eberhart, (1998) "Parameter Selection in Particle Swarm Optimization" Proc. Seventh Annual Conf. on Evolutionary Programming, pp. 591-601, 1998.

[20] R. Cárdenas, R. Peña, M. Perez, J. Clare, G. Asher, and P.Wheeler, "Control of a switched reluctance generator for variable-speed wind energy applications," *IEEE Trans. Energy Convers.*, vol. 20, no. 4, pp. 781–791, Dec. 2005