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A Coordinated FACTS-Based (Wind-FC-Diesel-Battery) Hybrid Renewable Energy Scheme for Island/Village Electricity

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Abstract: *The paper presents a hybrid (Wind–Diesel-Fuel Cell-Battery) renewable energy scheme for island/village electricity utilisation. The proposed hybrid renewable energy scheme with Flexible AC Transmission System (FACTS) stabilisation devices ensures efficient energy utilisation and robusts low impact interface of hybrid wind, diesel and the fuel cell. The stand-by diesel generator set is mainly used to balance the steady state load demand according to dynamic power changes to minimise the diesel fuel consumption. The stochastic nature of the wind energy system requires new FACTS stabilisation devices to maximise the wind energy utilisation. The paper also presents a application of soft computing self regulating Multi Objective Genetic Algorithm (MOGA) and Particle Swarm Optimisation (MOPSO) techniques to dynamically select optimal control gains for the 6-pulse rectifier interface converter, additional FACTS Dynamic Filter/Capacitor Compensation (DFC) on the AC side and Green Power Filter Compensator (GPFC) on the DC side schemes using dynamic self regulating objective functions based on minimal error tracking. A tri-loop error driven dynamic time-de-scaled controller is used to adjust the switching PWM sequence of the DFC on the AC side filter compensator and the GPFC for stabilisation and energy efficiency. Power factor correction and power quality are improved under different excursions and operating conditions, including load changes disturbances, faults and FC/wind velocity excursions. The multi-objective search and optimisation technique are used to find the optimal dynamic control gain settings that minimise the selective number of objective functions based on control system absolute errors.*

Keywords: *Diesel-Hybrid, Fuel Cell, Backup Battery, Flexible AC Transmission System (FACTS), Multi-Objective Particle Swarm Optimisation (MOPSO), Multi-Objective Genetic Algorithm (MOGA)*

1. Introduction

The continuous and pressing need to utilise renewable energy and green energy sources (such as wind, solar, wave, tidal, fuel cell, biogas, small hydro, and geothermal) is motivated by both economic viability and environmental concerns. The continued reliance on depleting fossil fuels sources with increasing rate of green house gases and hydrocarbon emissions is causing a strategic and basic shift to energy conservation, clean fuel replacement and renewable energy utilisation of wind and photovoltaic as environmentally safe and economically viable alternatives (Billinton and Gao, 2008, Hu et al., 2008). Photovoltaic and wind generation schemes are leading viable choices for large-scale and small-scale micro-grid electrical energy generation (Strachan and Jovcic, 2008).

This paper presents a standalone hybrid renewable energy utilisation that uses a combination of wind turbine, fuel cell and a diesel generator with a DC battery backup in a typical standalone scheme capacity usually ranging in small and midscale sizes from 15 KW to 1500 KW (Hilloowala and Sharaf, 1994, 1996). Typical use and applications include electricity supply to remote (isolated Islands/villages, heating, water pumping, ventilation and air conditioning systems.

For this standalone wind energy scheme, the induction generator terminal voltage and frequency are totally dependent on the rotor speed, shunt capacitance size and the electrical load equivalent impedance, which are subject to both wind gusting and dynamic electric load excursion/changing conditions (Lang et al., 2008). Such low-cost green energy scheme is usually used for combined passive/motorised loads such as water pumps/ventilation and air circulation/air conditioning loads, which are generally insensitive to small frequency variations (Singh et al., 2007). The serious voltage instability and possible loss of excitation problem is usually a byproduct of load excursions/changes and wind velocity gusting conditions (Pan et al., 2008).

The diesel driven synchronous generator provided a smooth AC output, whereas the output power of the wind turbine generation depended on the wind velocity. The fuel cell was added to help stabilise power flow. The voltage stabilisation and regulation is dependent upon self-excitation and loading condition of the induction generator and the capacitors available in the power grid (Muljadi et al., 2004). The need for voltage and reactive power requires the use of dynamic modulated reactive compensation systems (Sugiarto and Tan, 2007; Munteanu et al., 2008). This can be achieved by using the DC and AC side dynamic filter capacitor compensation schemes of Flexible AC Transmission System (FACTS) and switched using a flexible dynamic multi-loop error self-adjusting controller to ensure AC and DC side voltage stability for the hybrid renewable energy using wind turbine, fuel cell (FC), diesel generator and battery backup.

Depending on wind velocity and rate of change in kinetic energy, fluctuations in the Induction Generator output voltage and frequency can cause severe generator voltage instability and loss of excitation and shutdowns. Severe power quality issues, such as voltage waveform RMS-value distortions and variations can reduce energy utilisation (Pan et al., 2008). Excessive inrush reactive currents can also increase distribution feeder active and reactive losses reduce system power factor and cause large variations in bus voltages.

The paper presents two FACTS devices and Multi-Regulation control strategies for harmonic mitigation using modulated power filter to improve power factor, energy utilisation and power quality of the hybrid AC-DC renewable energy scheme. The AC and DC side FACTS-based power filter and switched capacitor compensation devices are dynamically adjusted and controlled using Multi-Objective Particle Swarm Optimisation (MOPSO) and Multi-Objective Genetic Algorithm (MOGA) techniques. The degree of reactive power compensation is controlled by the duty ratio of the PWM switching.

The FACTS AC and DC dynamic power filter compensators are expected to provide (Sharaf et al., 2007):

- Improved power factor (at the generator and load buses);
- Limited dynamic and transient over voltages and current inrush conditions;
- Enhanced damping of transient conditions; and
- Efficient energy utilisation

Several AI-related/soft computing techniques (such as Genetic Algorithms (GA)) can be used to solve this optimisation problem. GA is an iterative search algorithm based on natural selection and genetic mechanism. However, GA is very fussy; it contains selection, copy, crossover and mutation scenarios and so on. Furthermore, the process of coding and decoding not only impacts precision, but also increases the complexity of the genetic algorithm. Particle swarm optimisation (PSO) is an emerging intelligence which was flexible optimisation algorithm proposed in 1995 (Sharaf et al., 2007).

There are many common characteristics between PSO and GA. First, they are flexible optimisation technologies. Second, they all have strong universal property independent of any gradient information. However, PSO is much simpler than GA, and its operation is more convenient, without selection, copy, and crossover. Switched/Modulated power filters are mainly used to provide measured filtering in addition to avoiding tuning problems associated with the use of passive power filters. The modulated power filter and compensators are controlled by the on-off timing sequence of switching pulses that are generated by the error driven dynamic controller.

The AC and DC FACTS devices and the associated multi-regulator Controllers is an effective low-cost energy utilisation and power quality enhancement tool for reducing dynamic voltage and current transients and load excursions. In this paper, the effectiveness and validation of the proposed FACTS stabilisation schemes for both power quality improvement and power factor correction is fully validated with PSO/GA online dynamic gain scheduling using MATLAB/Simulink software environment of the unified wind energy conversion scheme utilising an induction generator.

2. Single Objective Optimisation (SOO) Using GA and PSO

Genetic algorithm is a random search and optimisation method inspired by Darwin's reproduction and survival of the fittest individual (Davis, 1991). 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 steps of genetic algorithm are described below:

1) **[Start]** Generate random population of *n* chromosomes (suitable solutions for the problem).
2) **[Fitness]** Evaluate the fitness *f(x)* of each chromosome *x* in the population.
3) **[New population]** Create a new population by repeating following steps until the new population is complete.
    a) **[Selection]** Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected).
    b) **[Crossover]** With a crossover probability cross over the parents to form a new

offspring (children). If no crossover was performed, offspring is an exact copy of parents.

c) **[Mutation]** With a mutation probability mutate new offspring at each locus (position in chromosome).
d) **[Accepting]** Place new offspring in a new population.

4) **[Replace]** Use new generated population for a further run of algorithm.
5) **[Test]** If the end condition is satisfied, **stop**, and return the best solution in current population
6) **[Loop]** Go to step **2.**

Particle Swarm Optimisation (PSO) is an evolutionary computation optimisation technique (a search method based on a natural system) developed by Kennedy and Eberhart (Shi and Eberhart, 1998, 1999; Eberhart and Shi, 2001). 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 P_{best}) and its corresponding fitness. There exist a number of P_{best} for the respective particles in the swarm and the particle with greatest fitness is called the global best (G_{best}) of the swarm. The basic concept of the PSO technique lies in accelerating each particle towards its P_{best} and G_{best} locations, with a random weighted acceleration at each time step.

The main steps in the particle swarm optimisation algorithm and selection process are described as follows:

1) Initialise a population of particles with random positions and velocities in d dimensions of the problem space and fly them.
2) Evaluate the fitness of each particle in the swarm.
3) For every iteration, compare each particle's fitness with its previous best fitness (P_{best}) obtained. If the current value is better than P_{best}, then set P_{best} equal to the current value and the P_{best} location equal to the current location in the dimensional space.
4) Compare P_{best} of particles with each other and update the swarm global best location with the greatest fitness (G_{best}).
5) Change the velocity and position of the particle according to Equations 1 and 2, respectively.

$$V_{id} = \omega \times V_{id} + C_1 \times rand_1 \times (P_{id} - X_{id}) + C_2 \times rand_2 \times (P_{gd} - X_{id}) \quad \text{...... Eq.1}$$

$$X_{id} = X_{id} + V_{id} \quad \text{...... Eq.2}$$

Where: V_{id} and X_{id} represent the velocity and position of the i_th particle with d dimensions, respectively. $rand_1$ and $rand_2$ are two uniform random functions, and ω is the inertia weight, which is chosen beforehand.

6) Repeat steps 2 to 5 until convergence is reached based on some desired single or multiple criteria.

The PSO optimisation random search utilised the dynamic total error minimisation algorithm that has many key parameters and these are described as follows: ω is called the inertia weight that controls the exploration and exploitation of the search space because it dynamically adjusts velocity. The use of GA and PSO in search and optimisation requires the specifications of a number of objective functions based on control errors to be dynamically minimised using random direct search PSO/GA algorithm.

3. Multi-Objective Optimisation MOO

The following definitions are used in the proposed Multi-Objective Optimisation (MOO) search algorithm (Ngatchou et al., 2005; Berizzi et al., 2001; Coello and Lechuga, 2003):

Def. 1 The general MO problem requiring the optimisation of N objectives may be formulated as follows:

Minimise

$$\vec{y} = \vec{F}(\vec{x}) = \left[\vec{f}_1(\vec{x}), \vec{f}_2(\vec{x}), \vec{f}_3(\vec{x}), ..., \vec{f}_N(\vec{x})\right]^T \quad \text{...... Eq.3}$$

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

$$\text{Where: } \vec{x}^* = \left[\vec{x}_1^*, \vec{x}_2^*, \dots, \vec{x}_P^*\right]^T \in \Omega \quad \text{...... Eq.4}$$

$\vec{y}$ 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.

Def. 2 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.

Def. 3 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.

Def. 4 The non-dominated set of the entire feasible search space Ω is the Pareto-optimal set. The Pareto-optimal set in the objective space is called Pareto-optimal front.

3.1 Multi-Objective Genetic Algorithm MOGA

The Non-Dominated Sorting Genetic Algorithm (NSGA) is a multi-objective genetic algorithm that was developed by (Deb et al., 2002). This algorithm has been chosen over a conventional genetic algorithm for three principal reasons: (a) no need to specify a sharing parameter, (b) a strong tendency to find a diverse set of solutions along the Pareto optimal front, and (c) the ability to specify multiple objectives without the need to combine them using a weighted sum. The basic idea behind NSGA is the ranking process executed before the selection operation, as shown in Figure 1. This process identifies non-dominated solutions in the population, at each generation, to form non-dominated fronts, after this, the selection, crossover, and mutation usual operators are performed.

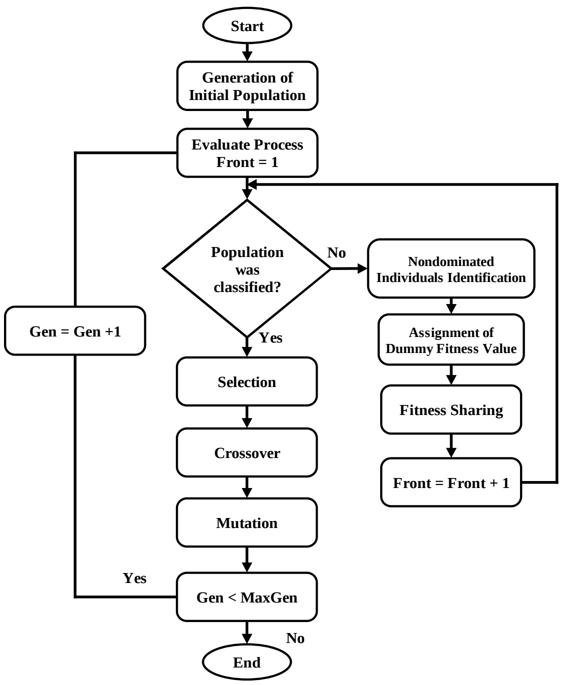

Figure 1. Flow chart of GA search and optimisation algorithm

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 (Srinivas and Deb, 1993). The same fitness value is assigned to all of them. In order to maintain diversity in the population, a sharing method is then applied. Afterwards, the individuals of the first front are ignored temporarily and the rest of population is processed in the same way to identify individuals for the second non-dominated front. A dummy fitness value that is kept smaller than the minimum shared dummy fitness of the previous front is assigned to all individuals belonging to the new front. This process continues until the whole population is classified into non-dominated fronts. Since the non-dominated fronts are defined, the population is then reproduced according to the dummy fitness values.

3.2 Multi-Objective Particle Swarm Optimisation MOPSO

In MOPSO, a set of particles is initialised in the decision space at random (Ngatchou et al. 2005; Berizzi et al., 2001; Coello and Lechuga, 2003). For each particle i, a position x_i in the decision space and a velocity v_i 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:

$$\mathrm{V_{id}} = \omega \times V_{id} + C_1 \times rand_1 \times (P_{pd} - X_{id}) + C_2 \times rand_2 \times (P_{rd} - X_{id}) \quad \text{…… Eq.5}$$

Where $P_{r,d}$, $P_{p,d}$ are randomly chosen from a single global Pareto archive, ω is the inertia factor influencing the local and global abilities of the algorithm, $V_{i,d}$ is the velocity of the particle i in the d_th dimension, c_1 and c_2 are weights affecting the cognitive and social factors, respectively. r_1 and r_2 are two uniform random functions in the range [0, 1]. According to Equation 5, each particle has to change its position $\mathbf{X_{i,d}}$ towards the position of the two guides $\mathbf{P_{r,d}}$, $\mathbf{P_{p,d}}$ 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. Finding a relatively large set of Pareto-optimal trade-off solutions is possible by running the MOPSO for many generations. Figure 2 shows the Algorithm-Flow Chart of the Multi-Objective Particle Swarm Optimisation MOPSO.

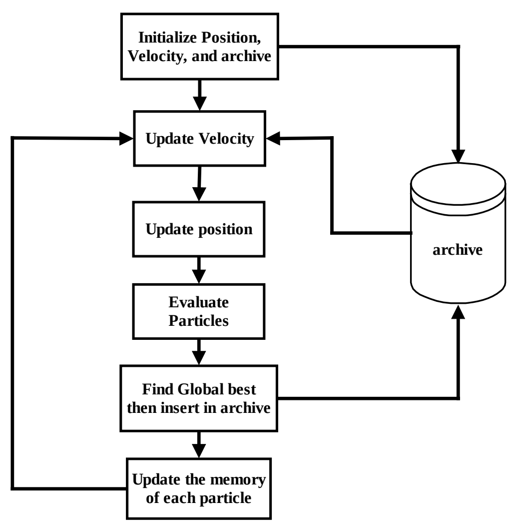

Figure 2. Flow chart of the MOPSO optimisation search algorithm

4. Sample Study System Description

A hybrid renewable green energy Conversion Scheme is validated using two FACTS devices with soft dynamic regulating control strategies under a set of imposed excursions of load variations, and prime mover excursions. The standalone hybrid scheme is connected to the load bus over a radial transmission line. The hybrid renewable energy comprises the following main components, as shown in Figure 3.

- Wind turbine,
- Gear box,
- Synchronous Generator driven by the Diesel Engine
- Fuel Cell,
- Battery Backup System,
- Induction generator driven by the wind turbine,
- Stabilisation interface scheme and stabilisation controller, and
- The hybrid electric load.

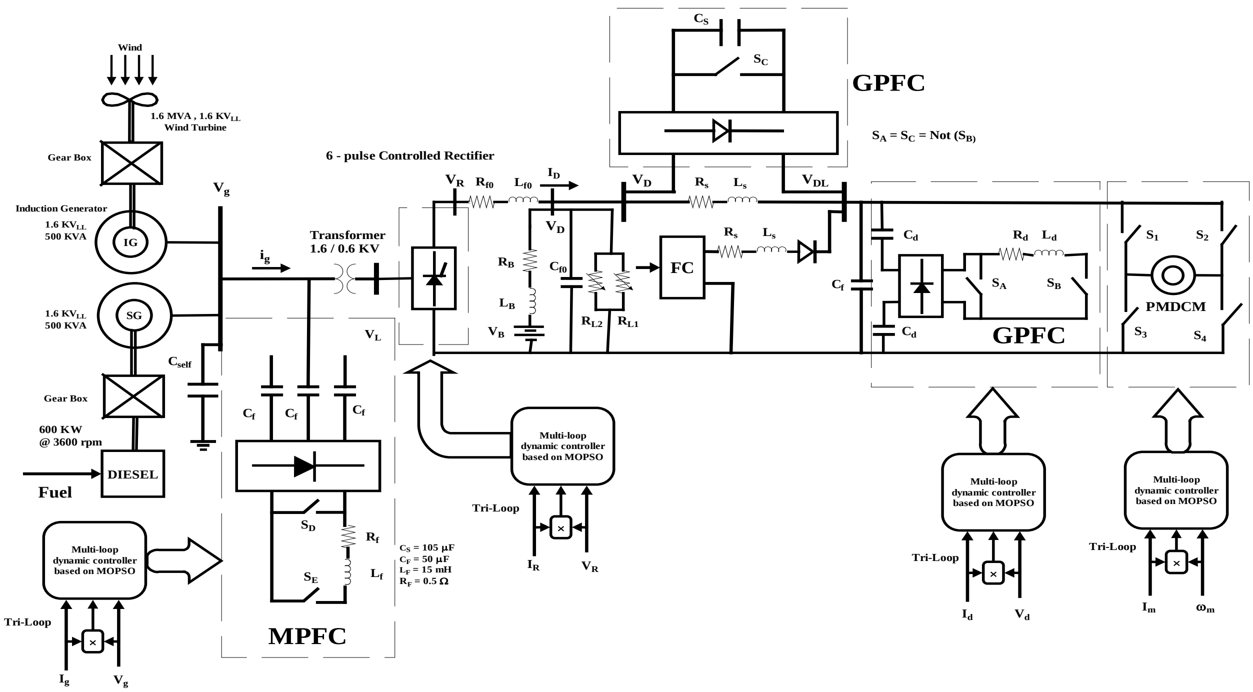

Figure 3. Sample three-phase Study AC system with the AC Dynamic Filter Compensator (DFC) and DC-side Green plug filter compensator

The hybrid renewable energy scheme was subjected to severe combined sequence of load switching/load variation/load excursion and wind speed variation, diesel and fuel cell source conditions.

The hybrid AC-DC (Wind-FC-Diesel-Battery) scheme is combined with four regulators controllers. The multi-regulator error-driven, self-regulating multi-loop controller is utilised with MOGA and MOPSO search algorithms. Each regulator has multi-loop error driven time decoupled, descaled configuration, AC side filter compensator, 6-pulse controlled rectifier, DC side GPFC and large DC-PM motor drive. The FACTS AC side dynamic modulated filter and compensator scheme can also be an attractive solution for energy conservation and loss reduction in distribution and utilisation radial circuits, feeding a nonlinear type load.

Figures 4-7 depict the dynamic self-regulating PID controller and self-tuned variable structure sliding mode dynamic controller for adjusting the switching duty-cycle-ratio based on MOPSO search and optimisation technique. The effective reactance of the combined hybrid fixed capacitors and the modulated tuned arm filter depends on the duty cycle and the frequency of the SPWM output which in turn is a function of the self tuned variable structure sliding mode controller output. The output of the SPWM generator is a train of pulses with variable duty cycles and constant frequency. The degree of filtering and compensation is dependent on the duty cycle of the generated pulses. This would in turn vary the effective reactance of the hybrid power filter.

The tri-loop error-driven dynamic controller is a time de-scaled structure and used to control GPFC, MPFC, and PMDC motor. The global error is the summation of the three loop individual errors including voltage stability, current limiting and synthesize dynamic power loops. The (per-unit) three dimensional-error vector (e_{vg} ,e_{Ig}, e_{pg}) of the FACTS modulated MPFC AC filter scheme is governed by the following equations:

$$e_{vg}(k) = V_g(k)\left(\frac{1}{1+ST_g}\right)\left(\frac{1}{1+SD}\right) - V_g(k)\left(\frac{1}{1+ST_g}\right)$$

…… *Eq.6*

$$e_{Ig}(k) = I_g(k)\left(\frac{1}{1+ST_g}\right)\left(\frac{1}{1+SD}\right) - I_g(k)\left(\frac{1}{1+ST_g}\right)$$

…… *Eq.7*

$$e_{Pg}(k) = I_g(k)\times V_g(k)\left(\frac{1}{1+ST_g}\right)\left(\frac{1}{1+SD}\right) - I_g(k)\times V_g(k)\left(\frac{1}{1+ST_g}\right)$$

…… *Eq.8*

The total or global error $e_{tg}(k)$ for the MPFC AC side scheme at a time instant:

$$e_{tg}(k) = \gamma_{vg} e_{vg}(k) + \gamma_{ig} e_{ig}(k) + \gamma_{pg} e_{pg}(k)$$

……*Eq.9*

In the same manner, The (per-unit) three dimensional-error vector (e_{vd} ,e_{Id}, e_{pd}) of the GPFC scheme is governed by the following equations:

$$e_{vd}(k) = V_d(k)\left(\frac{1}{1+ST_d}\right)\left(\frac{1}{1+SD}\right) - V_d(k)\left(\frac{1}{1+ST_d}\right)$$

……*Eq.10*

$$e_{Id}(k) = I_d(k)\left(\frac{1}{1+ST_d}\right)\left(\frac{1}{1+SD}\right) - I_d(k)\left(\frac{1}{1+ST_d}\right)$$

……*Eq.11*

$$e_{Pd}(k) = I_d(k)\times V_d(k)\left(\frac{1}{1+ST_d}\right)\left(\frac{1}{1+SD}\right) - I_d(k)\times V_d(k)\left(\frac{1}{1+ST_d}\right)$$

……*Eq.12*

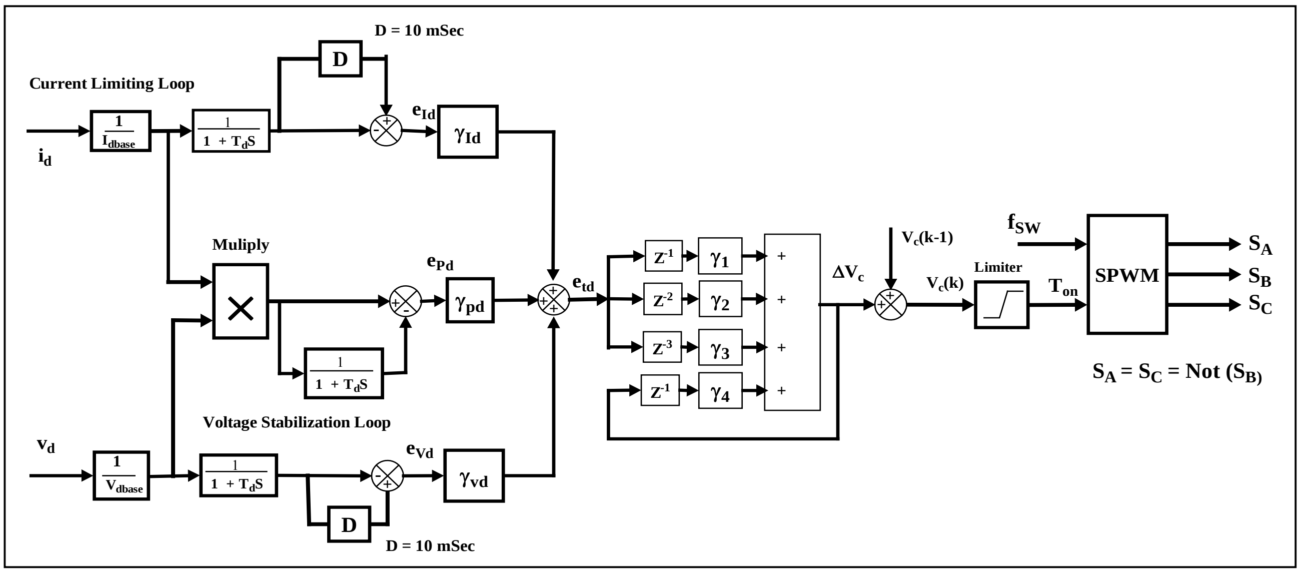

Figure 4. Dynamic tri-loop error-driven Self-Tuned Multi-Loop Recurrent/recursive incremental Controller for the DC side series-parallel GPFC compensation scheme

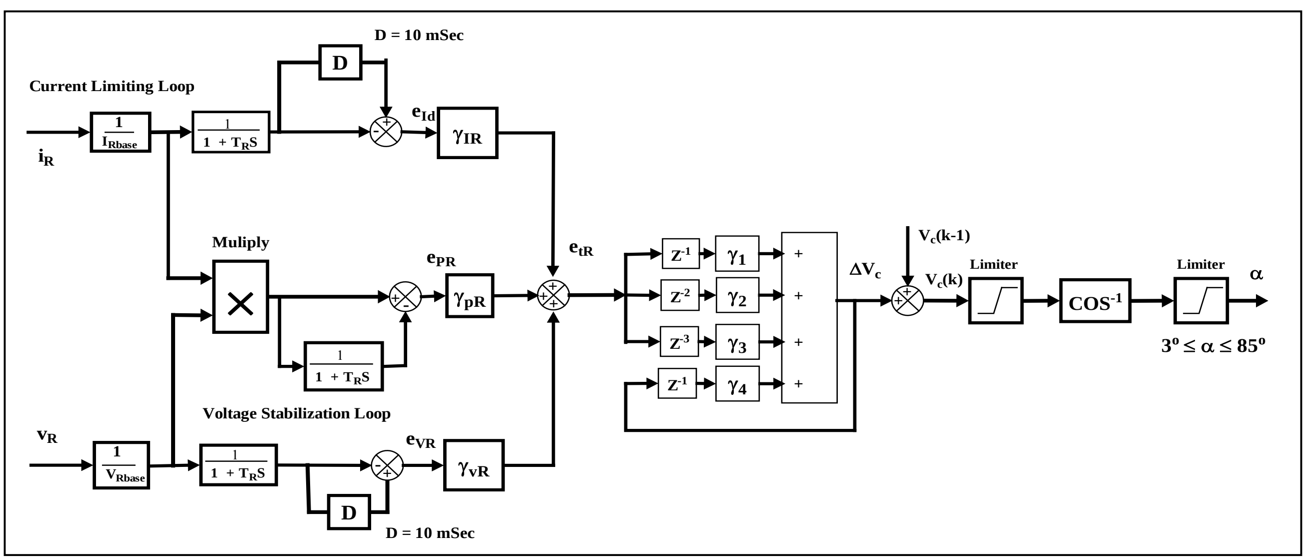

Figure 5. Dynamic tri-loop error-driven Self-Tuned Multi-Loop Recurrent/recursive incremental Controller for the AC side converter-α control scheme

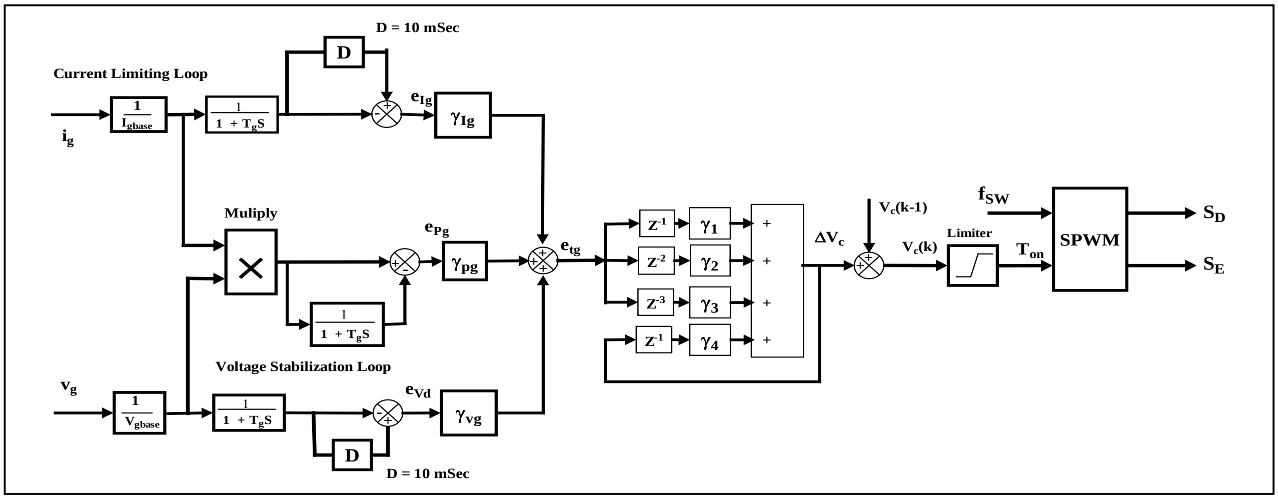

Figure 6. Dynamic tri-loop error-driven Self-Tuned Multi-Loop Recurrent/recursive incremental Controller the AC side MPFC filter compensation scheme

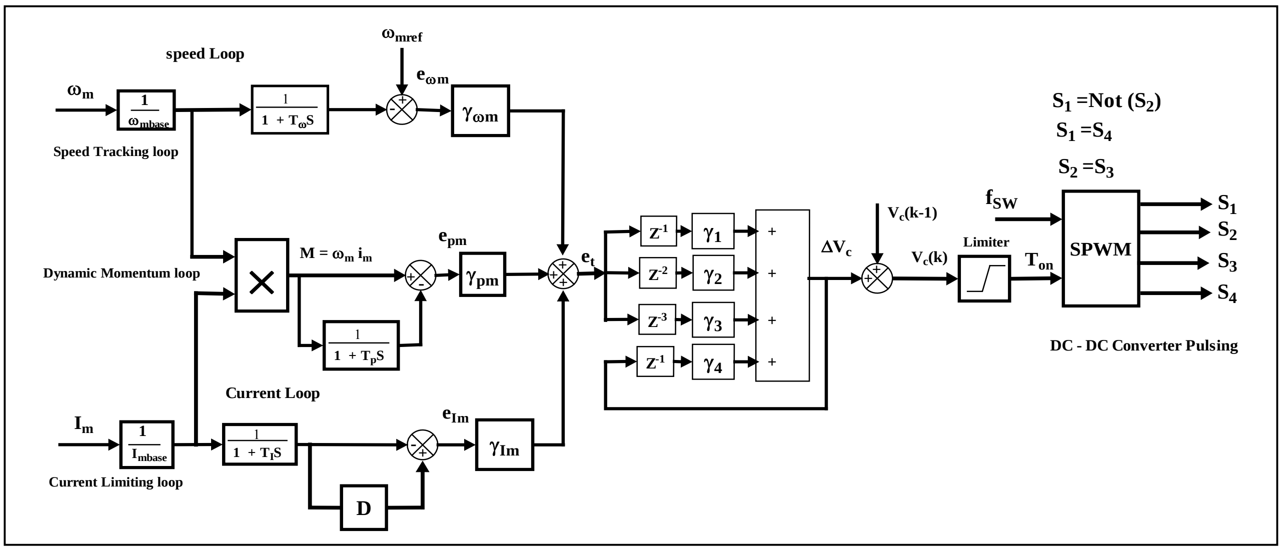

Figure 7. Dynamic tri-loop error-driven Self-Tuned Multi-Loop Recurrent/recursive incremental Controller for speed regulation of PMDC motor drive

The total or global error e_{tg} (k) for the DC side green plug filter compensator GPFC scheme at a time instant:

$$e_{td}(k) = \gamma_{vd} e_{vd}(k) + \gamma_{id} e_{id}(k) + \gamma_{pd} e_{pd}(k) \quad \text{……Eq.13}$$

In addition, the (per-unit) three dimensional-error vector (e_{vR}, e_{IR}, e_{pR}) of the three phase controlled rectifier scheme is governed by the following equations:

$$e_{vR}(k) = V_R(k)\left(\frac{1}{1+ST_R}\right)\left(\frac{1}{1+SD}\right) - V_R(k)\left(\frac{1}{1+ST_R}\right) \quad \text{……Eq.14}$$

$$e_{IR}(k) = I_R(k)\left(\frac{1}{1+ST_R}\right)\left(\frac{1}{1+SD}\right) - I_R(k)\left(\frac{1}{1+ST_R}\right) \quad \text{……Eq.15}$$

$$e_{PR}(k) = I_R(k)\times V_R(k)\left(\frac{1}{1+ST_R}\right)\left(\frac{1}{1+SD}\right) - I_R(k)\times V_R(k)\left(\frac{1}{1+ST_R}\right) \quad \text{……Eq.16}$$

The total or global error e_{tg} (k) for the three phase controlled converter rectifier scheme at a time instant:

$$e_{tR}(k) = \gamma_{vR} e_{vR}(k) + \gamma_{iR} e_{iR}(k) + \gamma_{pR} e_{pR}(k) \quad \text{……Eq.17}$$

Finally, the (per-unit) three dimensional-error vector ($e_{\omega m}$,e_{Im}, e_{pm}) of the PMDC motor scheme is governed by the following equations:

$$e_{\omega m}(k) = \omega_m(k)\left(\frac{1}{1+ST_m}\right)\left(\frac{1}{1+SD}\right) - \omega_m(k)\left(\frac{1}{1+ST_m}\right) \quad \text{……Eq.18}$$

$$e_{Im}(k) = I_m(k)\left(\frac{1}{1+ST_m}\right)\left(\frac{1}{1+SD}\right) - I_m(k)\left(\frac{1}{1+ST_m}\right) \quad \text{……Eq.19}$$

$$e_{Pm}(k) = I_m(k)\times \omega_m(k)\left(\frac{1}{1+ST_m}\right)\left(\frac{1}{1+SD}\right) - I_m(k)\times \omega_m(k)\left(\frac{1}{1+ST_m}\right) \quad \text{……Eq.20}$$

The total or global error e_{tg} (k) for the MPFC scheme at a time instant:

$$e_{tm}(k) = \gamma_{\omega m} e_{\omega m}(k) + \gamma_{im} e_{im}(k) + \gamma_{pm} e_{pm}(k) \quad \text{……Eq.21}$$

The change in the control voltage ΔV_c of the Multi-Loop Incremental Controller is defined as:

$$\Delta V_c(k) = \gamma_1 e(k-1) + \gamma_2 e(k-2) + \gamma_3 e(k-3) + \gamma_4 e(k-4) + \gamma_5 \Delta V_c \quad \text{……Eq.22}$$

$$V_c(k) = \Delta V_c(k) + V_c(k-1) \quad \text{……Eq.23}$$

In this strategy, the PSO and GA searching algorithms are implemented for tuning the recurrent weighting gains (γ_1, γ_2, γ_3, γ_4) minimise the selected objective functions ($J_1 - J_5$).

A set of conflicting objective functions is selected for GA/PSO search and optimisation. These objective functions are defined by the following:

$$J_1 = Minimize \quad \{|e_{td}|, |e_{tg}|, |e_{tR}|, |e_{tm}|\} \quad \text{……Eq.24}$$

$$J_2 = Steady\ State\ Error = |e_\omega(k)| = |\omega_{ref}(k) - \omega_m(k)| \quad \text{……Eq.25}$$

$$J_3 = Settling\ Time \quad \text{……Eq.26}$$

$$J_4 = Maximum\ Over\ Shoot \quad \text{……Eq.27}$$

$$J_5 = Rise\ Time \quad \text{……Eq.28}$$

5. Digital Simulation Results

The hybrid Multi-source AC-DC operation of a wind turbine, the diesel generator set, and the fuel cell with a back-up battery is compared for the two cases, with fixed and self-tuned type controller based on MOGA and MOPSO. MATLAB-Simulink software was used to design, test, and validate the effectiveness of the two FACTS devices and the associated dynamic SPWM controllers.

The test results are presented for MPFC on the test system using MOGA and MOPSO algorithms. The unified system performance is compared for two cases, with fixed and self-tuned type controllers using either GA or PSO. The second case is to compare the performance with Artificial Neural Network (ANN) controller and Fuzzy Logic Controller (FLC) with the self-tuned type controllers. Self-tuned multi-stage incremental recurrent/recursive controller has been applied to the speed tracking control of the PMDCM for performance comparison.

There are three different speed references. In the first speed track, the speed increases linearly and reaches the 1 PU at the end of the first five seconds, and then the reference speed remains speed constant during five seconds. At tenth second, the reference speed decreases with same slope as at the first five seconds. After fifteen second, the motor changes the direction and motor increases its speed through the reverse direction. At twentieth second, the reference speed reaches the -1 PU and remains constant speed at the end of twenty-fifth second and then the reference speed decreases and becomes zero at thirtieth second. The second reference speed waveform is sinusoidal and its magnitude is 1 PU and the period is 12 seconds. The third reference track is constant speed reference starting with an exponential track.

In all references, the system responses have been observed. MATLAB-Simulink Software was used to design, test, and validate the proposed renewable generation system with the FACTS devices. The digital dynamic simulation model allows for low cost assessment and prototyping, system parameters selection and optimisation of control settings. The use of PSO-search algorithm is used in online gain adjusting to minimise controller absolute value of total error. This is required before full-scale prototyping which is both expensive and time consuming.

The effectiveness of dynamic simulators brings on detailed sub-models selections and tested sub-models MATLAB library of power system components already tested and validated. The common DC bus voltage reference is set at 1 PU. Digital simulations are obtained with sampling interval Ts = 20µs. Dynamic responses obtained with GA are compared with ones resulting from the PSO for the proposed Self-tuned multi-stage incremental recurrent/recursive controller. The dynamic simulation conditions are identical for all tuned controllers. To compare the global performances of all controllers, the Normalised Mean Square Error (NMSE) deviations between output plant variables and desired values, and are defined as:

$$NMSE_{V_{DC-bus}} = \frac{\sum (V_{DC-bus} - V_{DC-bus-ref})^2}{\sum (V_{DC-bus-ref})^2} \quad \text{……Eq.29}$$

$$NMSE_{\omega_m} = \frac{\sum (\omega_m - \omega_{m-ref})^2}{\sum (\omega_{m-ref})^2} \quad \text{……Eq.30}$$

The digital simulation results validated the effectiveness of both GA and PSO based tuned controllers in providing effective speed tracking for three test speed reference trajectories with minimal steady-state errors. Transients are also damped with minimal overshoot, settling time, and fall time. The GA and PSO based self-tuned controllers are more effective and dynamically advantageous in comparison with the ANN controller, the FLC and fixed type controllers. The self-regulation is based on minimal value of absolute total or global error of each regulator.

The control system comprises the three dynamic multi-loop regulators is inherently using weight assignment and time-scale decoupling coordinated to minimise the selected objective functions. SOO obtains a single global or near optimal solution based on a single weighted objective function. The use of a weighted single objective function combines several conflicting objective functions requires assigned and selected weighting factors as follows:

$$J_{weighted} = \alpha_1 J_1 + \alpha_2 J_2 + \alpha_3 J_3 + \alpha_4 J_4 + \alpha_5 J_5 \quad \text{……Eq.31}$$

Where α_1 = 0.20, α_2 = 0.20, α_3 = 0.20, α_4 = 0.20, α_5 = 0.20 are selected assigned equal weighting factors. J_1, J_2, J_3, J_4 and J_5 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.

Table 1 shows the proposed system behavior comparison using the traditional controllers; constant gains Multi-Loop Recurrent Controller, ANN controller and FLC controller under normal conditions for the three selected reference tracks. For comparison, Table 2 shows the proposed system behavior comparison using the GA- and PSO-based self-tuned multi-loop recurrent controller under normal conditions for the three selected reference tracks. These results show the effectiveness of MOPSO and MOGA search and optimised control gains in tracking the PMDC motor three reference speed trajectories.

Comparing the unified AC-DC system dynamic response results for the two study cases, using GA and PSO search and gain tuning algorithms and traditional controllers with constant gains controller, ANN and FLC incremental controllers, it is quite apparent that the GA and PSO tuning algorithms highly improved the PMDC system dynamic performance from a general power quality point of view.

Table 1. Comparison of PMDC motor response using the fixed gains and soft regulating dynamic controllers

	Self Tuned Multi-Loop Recurrent Controller			ANN Controller			FLC		
	First Speed Reference	Second Speed Reference	Third Speed Reference	First Speed Reference	Second Speed Reference	Third Speed Reference	First Speed Reference	Second Speed Reference	Third Speed Reference
System Efficiency	0.81490	0.82633	0.81224	0.84428	0.85079	0.84814	0.86241	0.85618	0.86143
AC Bus Power Factor	0.94643	0.93974	0.93207	0.96360	0.94491	0.95402	0.95440	0.94889	0.95071
RMS of Motor current (PU)	0.84425	0.85439	0.86054	0.74595	0.74650	0.74432	0.76028	0.74571	0.76157
THD_DC_Bus_Voltage (%) ×100	0.25375	0.26323	0.24542	0.14390	0.15091	0.15160	0.15136	0.15177	0.15084
THD_DC_Current (%) ×100	0.26204	0.25703	0.26319	0.14632	0.15869	0.15078	0.15247	0.14369	0.15476
THD_ AC Bus _Voltage (%) ×100	0.25074	0.25962	0.25968	0.15097	0.14822	0.15012	0.16332	0.15301	0.15066
THD_ AC Bus _Current (%) ×100	0.25903	0.25085	0.26189	0.14675	0.15066	0.16226	0.15378	0.14479	0.15841
DC Voltage Over/Under Shoot (PU) $\times 10^{-1}$	0.4298	0.5562	0.6309	0.5127	0.5833	0.15734	0.16355	0.14718	0.15541
DC Current– Over/Under Shoot (PU) $\times 10^{-1}$	0.6298	0.4838	0.5375	0.5632	0.5135	0.5316	0.5873	0.4555	0.4379
AC Voltage Over/Under Shoot (PU) $\times 10^{-1}$	0.5071	0.5752	0.6264	0.5297	0.4561	0.5310	0.6285	0.5065	0.4982
AC Current– Over/Under Shoot (PU) $\times 10^{-1}$	0.5920	0.4916	0.4664	0.5747	0.4845	0.5255	0.6070	0.6150	0.5766
Motor Speed Over/Under Shoot (PU) $\times 10^{-1}$	0.5884	0.6346	0.5137	0.4565	0.5819	0.6188	0.4649	0.4379	0.5300
NMSE_$V_{DC\text{-}Bus} \times 10^{-1}$	0.4486	0.5661	0.6299	0.5255	0.5422	0.4428	0.5331	0.5170	0.4905
NMSE_$\omega_m \times 10^{-1}$	0.4900	0.5880	0.4492	0.4450	0.5811	0.5903	0.5678	0.6000	0.5078
Motor Speed Steady State Error $\times 10^{-1}$	0.4935	0.5071	0.5781	0.4644	0.6007	0.5273	0.5813	0.6389	0.5054
Control System Total Error $\times 10^{-1}$	0.5832	0.5660	0.5727	0.4304	0.5670	0.6284	0.5583	0.5942	0.4295
Motor Speed Rise Time	0.5971	0.5644	0.4665	0.5406	0.4750	0.5445	0.4411	0.5529	0.5167
Motor Speed Settling Time	0.4682	0.4423	0.4446	0.4943	0.6282	0.6359	0.5460	0.6376	0.5749

Table 2. Comparison of PMDC motor response using soft regulating gains adjusting GA- and PSO-based self-tuned multi-loop recurrent/recursive incremental dynamic controller

	SOGA			MOGA			SOPSO			MOPSO		
	First Speed Reference	**Second Speed Reference**	**Third Speed Reference**	**First Speed Reference**	**Second Speed Reference**	**Third Speed Reference**	**First Speed Reference**	**Second Speed Reference**	**Third Speed Reference**	**First Speed Reference**	**Second Speed Reference**	**Third Speed Reference**
System Efficiency	0.9095	0.9176	0.9070	0.92314	0.93170	0.92898	0.91252	0.91327	0.91023	0.93227	0.92588	0.92961
AC Bus Power Factor	0.96235	0.9847	0.9660	0.9845	0.9964	0.9925	0.9854	0.9875	0.9810	0.9933	0.9905	0.9909
RMS of Motor current (PU)	0.7158	0.7176	0.7178	0.6856	0.6863	0.6708	0.71320	0.7065	0.70228	0.6556	0.6672	0.6572
THD_DC_Bus_Voltage (%) ×10	0.6075	0.6397	0.5716	0.5708	0.4058	0.4329	0.5727	0.5089	0.5045	0.4350	0.4786	0.4194
THD_DC_Current (%) ×10	0.7931	0.6689	0.6697	0.6729	0.5927	0.6432	0.6607	0.6762	0.7087	0.4104	0.5091	0.4542
THD_ AC Bus _Voltage (%) ×10	0.6337	0.6188	0.6023	0.5650	0.5016	0.5682	0.6010	0.5900	0.6009	0.4416	0.5824	0.4941
THD_ AC Bus _Current (%) ×10	0.7059	0.6488	0.6070	0.5772	0.5442	0.6228	0.5755	0.6600	0.5967	0.5309	0.4392	0.4147
DC Voltage Over/Under Shoot (PU) $\times 10^{-2}$	0.1653	0.3357	0.1861	0.1821	0.3138	0.2845	0.1576	0.1313	0.3176	0.1709	0.1919	0.2685
DC Current – Over/Under Shoot (PU) $\times 10^{-2}$	0.1889	0.2279	0.1425	0.3375	0.2519	0.2182	0.2377	0.1993	0.2202	0.1765	0.2513	0.2894
AC Bus Voltage Over/Under Shoot (PU) $\times 10^{-2}$	0.2407	0.2641	0.1730	0.2090	0.2942	0.2726	0.2262	0.2487	0.2965	0.1413	0.2561	0.1394
AC Bus Current – Over/Under Shoot (PU) $\times 10^{-2}$	0.2165	0.1932	0.3135	0.1320	0.2910	0.3338	0.3379	0.2954	0.2214	0.2340	0.1740	0.2647
Motor Speed Over/Under Shoot (PU) $\times 10^{-2}$	0.1964	0.3316	0.2823	0.2158	0.2861	0.1854	0.2217	0.3259	0.2731	0.1737	0.3060	0.2616
NMSE_$V_{DC\text{-}Bus}$ $\times 10^{-2}$	0.1571	0.1725	0.2570	0.2618	0.2070	0.2503	0.2241	0.1381	0.1345	0.1948	0.1315	0.2099
NMSE_ω_m $\times 10^{-2}$	0.2731	0.1484	0.1363	0.2581	0.2573	0.1321	0.1323	0.1689	0.2528	0.1410	0.2064	0.2622
Motor Speed Steady State Error $\times 10^{-2}$	0.2804	0.2751	0.1466	0.2248	0.2221	0.2034	0.1612	0.2715	0.2765	0.2824	0.2298	0.2460
Control System Total Error $\times 10^{-2}$	0.1544	0.2240	0.2800	0.3174	0.1865	0.1826	0.3116	0.1779	0.2988	0.3207	0.1778	0.1793
Motor Speed Rise Time	0.1393	0.1454	0.2641	0.1691	0.3070	0.1655	0.1649	0.3388	0.2217	0.2006	0.1952	0.2059
Motor Speed Settling Time	0.2119	0.2537	0.1541	0.1369	0.2257	0.3125	0.3261	0.1847	0.1627	0.3131	0.1790	0.2652

6. Conclusions

The paper presents a hybrid AC-DC renewable (Wind–Diesel-FC-Battery) energy scheme with two dynamic FACTS-based devices and a coordinated multi regulator dynamic controller. The unified scheme with multi-regulation dynamic gain scheduling controllers is validated for efficient energy utilisation and stabilised operation. The MOGA and MOPSO techniques are used to adjust all four regulator-control gains online to minimise a set of specified objective functions.

The multi-regulator multi-loop error-driven time de-scaled and decoupled control scheme and the two FACTS-based devices developed are effective in ensuring AC and DC bus voltage stabilisation and enhanced energy utilisation under load changes and wind velocity excursions. The use of direct random search and optimisation PSO/GA techniques for online dynamic Control Gain-Scheduling and Controller Gain Selection validated the effectiveness of the AI Evolutionary Computing MOGA and MOPSO Methods in maintaining AC and DC Bus voltage levels around 1pu and limiting transient over-voltages and inrush-type current conditions.

These two devices with the self-regulating dynamic error-driven and gain-scheduled controller are also effective in voltage stabilisation, power factor correction, power quality, efficient energy utilisation, feeder-loss reduction and minimal transient and inrush current conditions.

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