

An Optimal Energy Utilization Self Adjusting Variable Speed Drive Scheme for Large Locomotive Drives

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Abstract – The paper presents a novel GA/PSO self regulating diesel driven AC induction motor controlled drive system using the common AC-DC-AC bus interface for industrial applications and electric vehicle EV-locomotion. The proposed control scheme utilizes the dual regulation multi loop error driven controller using the novel modified proportional plus integral plus derivative PID structure with the added error rate compensating auxiliary loop. The EV-drive is fed from the AC-DC-AC interface of a six-pulse controlled rectifier –DC link and six-pulse voltage source inverter VSI using a coordinated dual action control scheme for firing angle control. The diesel engine is controlled to ensure dynamic of power demand with dynamic voltage and current tracking. A dynamic error driven control scheme is proposed to regulate the motor current to limit any inrush currents and overloading conditions, in addition to motor speed dynamic reference tracking. The Proposed tri loop dynamic error driven self regulated-tuned controllers are also utilized to ensure dynamic energy efficiency, control loop decoupling, drive stability and the unified system efficient energy utilization while maintaining accurate speed reference tracking. The paper presents soft-computing application of both Multi Objective Particle Swarm Optimization (MOPSO) and Genetic search MOGA optimization and search techniques for dynamic online gain-tuning to optimally adjust the settings of the proposed controllers.

Keywords: Diesel-Driven Generator Set, Induction Motor Drive, Electric Vehicles, Multi Objective Optimization MOO, Particle Swarm Optimization PSO and Genetic Algorithm

I. INTRODUCTION

Due to environmental concerns and increasing restrictions imposed on the exhaust emissions from internal combustion engines in the urban areas, a strong demand for the development of efficient electrical propulsion systems for automotive applications[1-2]. Electric vehicle is one of the solutions for the reduction of the fossil fuel consumption and pollutant emissions of gas, responsible for the green house effect [3-4]. By using diesel driven vehicle, it is expected that the fuel economy of a diesel vehicle can be enhanced using dual fuel injection engines capable of burning other types of bio-fuels and bio diesels [5]. The savings in fuel and flexibility will promote the new use of diesel engines in electric vehicle drives. It would also benefit national interests, as this would lead to a reduction in dependence on fossil oil supply [6] and promote the use of bio-fuels. Electric Vehicle drives and propulsion systems can utilize either AC or DC motor drives including efficient Permanent Magnet DC motors [6-8]. The induction motor has been selected as the electric vehicle drive motor for its competitive advantages of

being small, light, less expensive, more reliable and almost maintenance free [7-8]. Different classical PI, PID, fuzzy logic based, nonlinear, adaptive variable structure, model reference adaptive control, artificial neural networks, feed forward computed torque control strategies were proposed and utilized in speed regulation and position control applications [9-10] mostly using fixed gains and control settings. Nonlinear drive dynamics, mechanical inertia, friction load variations and parametric sensitivities due to saturation and temperature changes requires a flexible, fast and effective online regulation and gain adjusting/tuning methods. Several AI-related soft computing techniques, such as Genetic Algorithms GA and Particle Swarm Optimization PSO are emerging as valuable, robust, simple and effective tools in industrial process automation and on-line control adaptation [11-14]. All soft computing tools are flexible and reliable with strong universal property independent of gradient information and structured optimization tools. In this paper, a diesel engine powering an induction motor-EV drive propulsion system is fully studied. The scheme is controlled by a novel Modified PID control strategy that are dynamically regulated and self tuned using PSO and GA random search and optimization algorithms. The PSO and GA based self regulating algorithms are utilized to track any reference speed trajectory under varying parameter and load conditions. The coordinated control system comprises three different regulators used to track speed reference trajectory. The proposed novel coordinated control scheme has been validated for effective and accurate speed reference trajectory tracking and enhanced power utilization.

Genetic algorithm is an optimization method inspired by Darwin's reproduction and survival of the fittest individual [15]. 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.

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 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.

II. MULTI-OBJECTIVE OPTIMIZATION

The following definitions are used in the proposed Multi-Objective Optimization (MO) search algorithm [20-22]:

Definition 1: The general MO problem requiring the optimization of N objectives may be formulated as follows:

Minimize

$$\bar{y} = \bar{F}(\bar{x}) = [\bar{f}_1(\bar{x}), \bar{f}_2(\bar{x}), \bar{f}_3(\bar{x}), \dots, \bar{f}_N(\bar{x})]^T \quad (1)$$

$$\text{subject to } g_j(\bar{x}) \leq 0 \quad j = 1, 2, \dots, M \quad (2)$$

$$\text{Where: } \bar{x}^* = [\bar{x}_1^*, \bar{x}_2^*, \dots, \bar{x}_p^*]^T \in \Omega \quad (3)$$

\bar{y} is the objective vector, the $g_j(\bar{x})$ represents the constraints and \bar{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.

Definition 2 : A decision vector $\bar{x}_1 \in \Omega$ is said to dominate the decision vector $\bar{x}_2 \in \Omega$ (denoted by $\bar{x}_1 < \bar{x}_2$), if the decision vector \bar{x}_1 is not worse than \bar{x}_2 in all objectives and strictly better than \bar{x}_2 in at least one objective.

Definition 3 : A decision vector $\bar{x}_1 \in \Omega$ is called Pareto-optimal, if there does not exist another $\bar{x}_2 \in \Omega$ that dominates it. An objective vector is called Pareto-optimal, if the corresponding decision vector is Pareto-optimal.

Definition 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.

The Non-Dominated Sorting Genetic Algorithm (NSGA) is a multi-objective genetic algorithm that was developed by Deb, *et. al.* [23]. 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 Fig. 2. This process identifies non dominated solutions in the population,

at each generation, to form non dominated fronts [24], 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 [24]. 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.

In MOPSO [20-22], a set of particles are initialized in the decision space at random. 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 and position of the particle According to equations (4) and (5) respectively as follows:

$$V_{id} = \omega \times V_{id} + C_1 \times rand_1 \times (P_{id} - X_{id}) + C_2 \times rand_2 \times (P_{pd} - X_{id}) \quad (4)$$

$$X_{id} = X_{id} + V_{id} \quad (5)$$

Where P_{rd} , P_{pd} are randomly chosen from a single global Pareto archive, ω is the inertia factor influencing the local and global abilities of the algorithm, V_{id} 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 (4), each particle has to change its position X_{id} towards the position of the two guides P_{rd} , P_{pd} 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 3 shows the flow chart of the Multi-Objective Particle Swarm Optimization (MOPSO).

III. AC-DC-AC EV-DRIVE INTERFACE

The electric vehicle drive system is fed from a diesel drive generator set interfaced to an AC-DC-AC interface via a six-pulse controlled rectifier, DC link filter and the six-pulse voltage source inverter feeding the induction motor. The

AC-DC-AC drive scheme is regulated using dynamic self adjusting multi loop error driven coordinated GA/PSO self regulating/gain adjusting control scheme. Figures (3-7) show the proposed AC-DC-AC interface for the electric vehicle drive system with the diesel generator set source. The novel PSO and GA self tuned multi regulators and coordinated controller are used for the following purposes:

- 1) The Diesel generator set valve control regulator is for dynamic load matching as well as stabilization of the common AC bus. The Diesel generator set comprises three time de-scaled loops for power demand control with dynamic generator voltage and current tracking.
- 2) AC/DC power controlled rectifier regulator to regulate the DC voltage at the Diesel engine AC bus and ensure limited inrush conditions as well as dynamic DC power matching to reduce current transients and improve energy utilization.
- 3) The speed controller of the voltage source inverter to ensure reference speed trajectory tracking and optimized slip control for loss reduction using a current hysteresis control.

The unified AC-DC-AC interface scheme is fully validated using the Matlab/Simulink software environment under normal conditions, induction motor torque changes. Other excursion conditions in the diesel engine generator set are also introduced to assess the control system robustness, effective energy utilization and speed reference tracking.

The proposed control system comprises three sub-regulators or controllers named as a Diesel DC generator set value control regulator, the induction motor drive speed controller, and the AC/DC power converter regulator. Figures (4-7) depict the proposed multi-loop dynamic self regulating controllers based on Multi Objective Optimization search and optimization technique based on soft computing PSO and GA. The global error is the summation of the three loop individual errors including voltage stability, current limiting and synthesize dynamic power loops. Each multi loop dynamic control scheme is used to reduce a global error based on a tri-loop dynamic error summation signal and to mainly track a given speed reference trajectory loop error 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.

A number of conflicting objective functions are selected to optimize using the PSO algorithm. These functions are defined by the following:

$$J_1 = \text{Minimize} \{ |e_g|, |e_R|, |e_t| \} \quad (6)$$

$$J_2 = \text{Steady State Error} = |e_w(k)| = |\omega_{ref}(k) - \omega_m(k)| \quad (7)$$

$$J_3 = \text{Settling Time} \quad (8)$$

$$J_4 = \text{Maximum Over Shoot} \quad (9)$$

$$J_5 = \text{Rise Time} \quad (10)$$

The dynamic error driven controller regulates the controllers' gains using the Particle Swarm optimization PSO and GA to minimize the system total error, the settling time, the rising time, and the maximum overshoot. The proposed dynamic Tri Loop Error Driven controller, developed by the First Author, is a novel advanced regulation concept that operates as an adaptive dynamic type multi-purpose controller capable of handling sudden parametric changes, load and/or DC source excursions. By using the Tri Loop Error Driven controller, it is expected to have a smoother, less dynamic overshoot, fast and more robust speed controller when compared to those of classical control schemes. The proposed general PMDC Motor Drive Model with the novel Tri Loop Error Driven controller are fully validated in this paper for effective reference speed trajectory tracking under different loading conditions and parametric variations; such as temperature changes while driving a complex mechanical load with non-linear parameters and/or torque-speed characteristics.

IV. DIGITAL SIMULATION RESULTS

The induction motor driven Electric Vehicle AC-DC-AC scheme using the Diesel generation system performance is compared for 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 EV 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. The digital simulation results validated the effectiveness of both GA and PSO based tuned controllers in providing effective speed tracking 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 Artificial Neural Network (ANN) controller, the Fuzzy Logic Controller (FLC) and fixed type controllers. The self regulation is based on minimal value of absolute total/global error of each regulator. The control system comprises the three 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:

$$J_o = \alpha_1 J_1 + \alpha_2 J_2 + \alpha_3 J_3 + \alpha_4 J_4 + \alpha_5 J_5 \quad (11)$$

Where $\alpha_1 = 0.20$, $\alpha_2 = 0.20$, $\alpha_3 = 0.20$, $\alpha_4 = 0.20$, $\alpha_5 = 0.20$ are selected weighting factors. J_1, J_2, J_3, J_4, 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.

Figures (7-12) show the effectiveness of PSO and GA search and optimized control gains in tracking the induction motor EV motor three reference speed trajectories.

Table I shows the Induction Motor-Electric Vehicle dynamic behavior comparison using the Traditional controllers for the three selected reference tracks under normal conditions. In addition, Table II shows the Induction Motor-Electric Vehicle dynamic behavior comparison using the GA and PSO based Self Tuned Modified PID dynamic controller for the three selected reference tracks under normal conditions. Comparing the Induction Motor-EV dynamic response results of the two study cases, with GA and PSO tuning algorithms and traditional controllers with constant controller gains, ANN controller and FLC, it is quite apparent that the GA and PSO tuning algorithms highly improved the Induction Motor-EV system dynamic performance from a general power quality point of view. The GA and PSO tuning algorithms had a great impact on the system efficiency improving it from 0.8085 (constant gains controller), 0.8257 (ANN controller) and 0.8232 (FLC) to around 0.8694 (SOGA based tuned controller), 0.8831 (MOGA based tuned controller), 0.8867 (SOPSO based tuned controller) and 0.9030 (MOPSO based tuned controller) which is highly desired. The Motor Power Factor is improved from 0.8532 (constant gains controller), 0.8879 (ANN controller) and 0.8875 (FLC) to around 0.9175 (SOGA based tuned controller), 0.9354 (MOGA based tuned controller), 0.9261 (SOPSO based tuned controller) and 0.9416 (MOPSO based tuned controller). The Root Mean Square RMS of Motor current (PU) is improved from 0.85211 (constant gains controller), 0.8228 (ANN controller) and 0.8213 (FLC) to around 0.7531 (SOGA based tuned controller), 0.7306 (MOGA based tuned controller), 0.7427 (SOPSO based tuned controller) and 0.7209 (MOPSO based tuned controller). Total Harmonic Distortion THD of Motor Voltage $\times 100\%$ is improved from 0.2583 (constant gains controller), 0.2236 (ANN controller) and 0.2290 (FLC) to around 0.0613 (SOGA based tuned controller), 0.0505 (MOGA based tuned controller), 0.0623 (SOPSO based tuned controller) and

0.0534 (MOPSO based tuned controller). Total Harmonic Distortion THD of Motor Current $\times 100\%$ is improved from 0.2643 (constant gains controller), 0.2284 (ANN controller) and 0.2237 (FLC) to around 0.0721 (SOGA based tuned controller), 0.0699 (MOGA based tuned controller), 0.0613 (SOPSO based tuned controller) and 0.0430 (MOPSO based tuned controller).

V. CONCLUSION

The GA/PSO self adjusting-tunable gain multi regulation coordinated controllers are fully validated using the MATLAB-SIMULINK software environment. The EV-Induction motor drive system fed from a diesel driven generator set is fed to the controlled six-pulse rectifier for coordinated speed control and DC-bus dynamic stabilization. The EV-Drive locomotive scheme is fully validated for effective and accurate tracking of three different speed reference trajectories under motor mechanical load torque variations and prime mover excursions diesel engine fuel valve changes. The use of dynamic multi loop with decoupled time de-scaled error driven structure and PSO/GA adaptable self regulation is also validated. The Multi Objective Optimization MOPSO and MOGA techniques are utilized to adjust all proposed controllers' gains and settings to minimize the total absolute deviation error. The iterative search and optimization results show the effectiveness of both Multi Objective Particle Swarm Optimization (MOPSO) and MOGA techniques to maintain the system power quality. The proposed novel control schemes have been validated for effective dynamic speed reference trajectory tracking with enhanced energy utilization.

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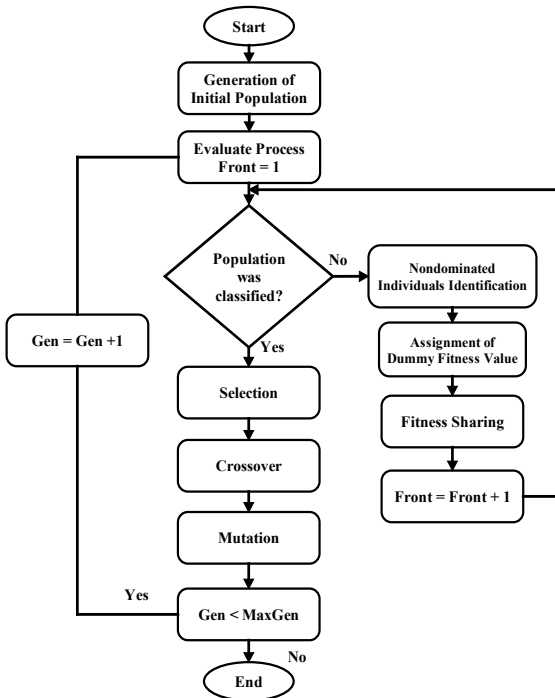


Fig. 1 Flow chart of NSGA

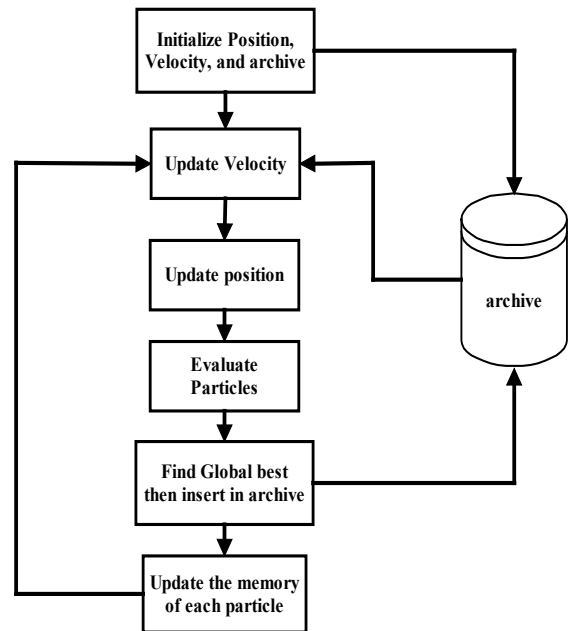


Fig. 2 Flow chart of the MOPSO optimization search algorithm

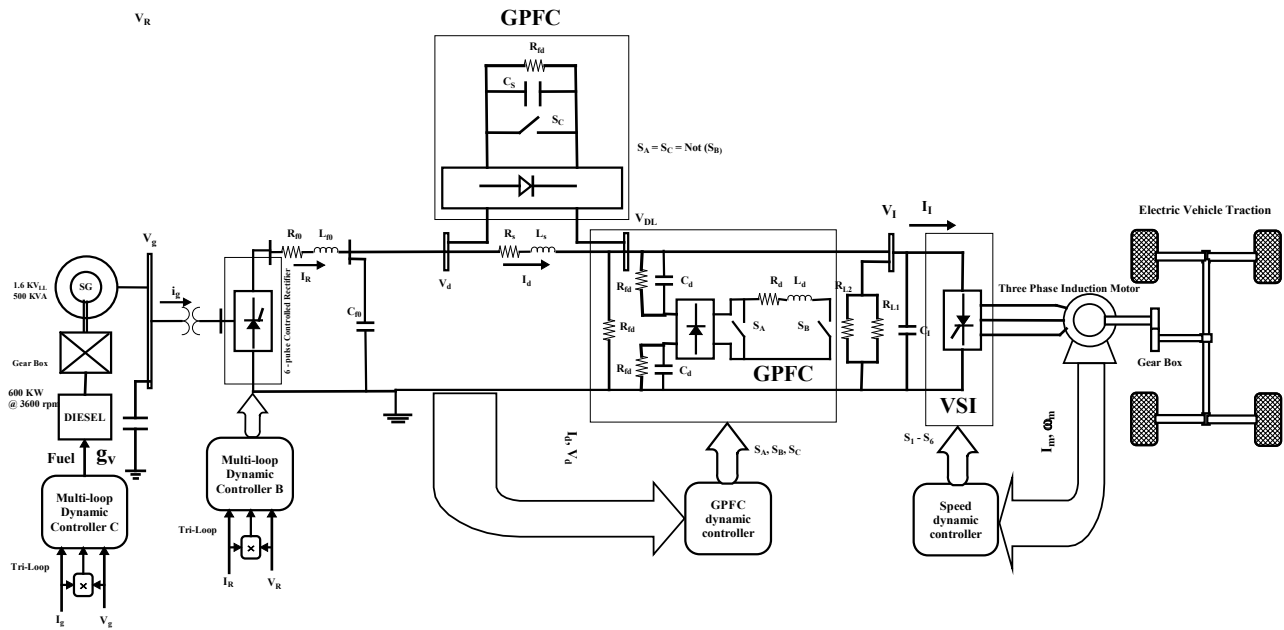


Fig. 3 Schematic diagram of a prototype Diesel Engine powered Induction Motor Electric Vehicle Drive System

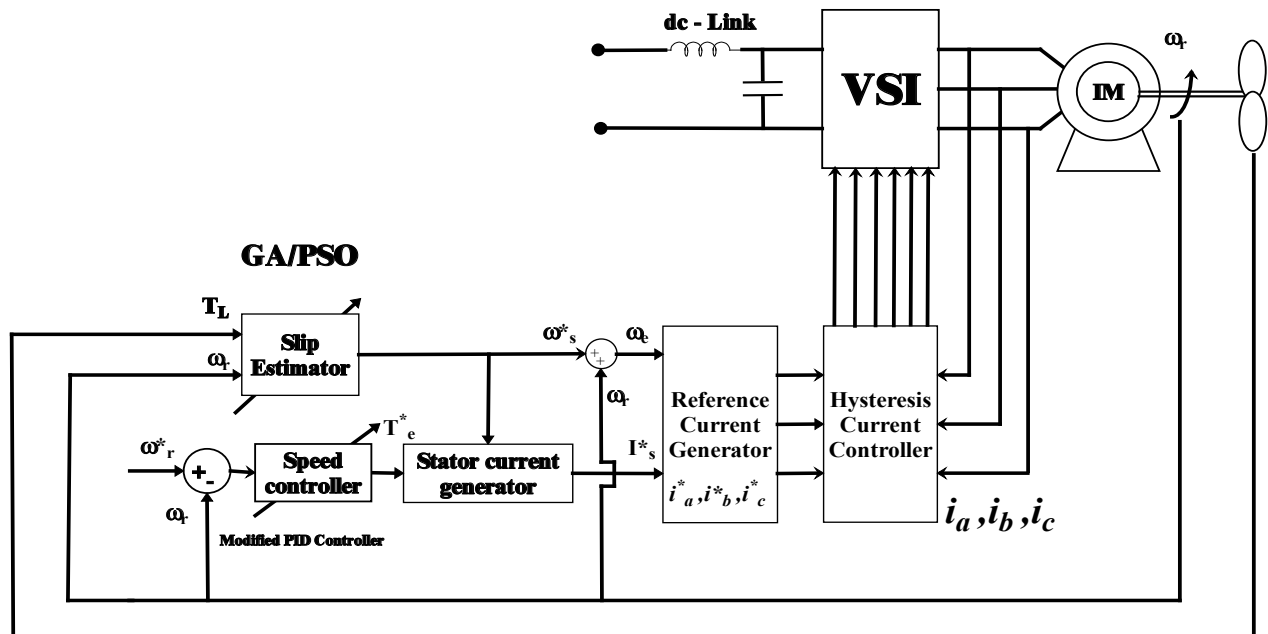


Fig. 4 The proposed drive system using GA/PSO

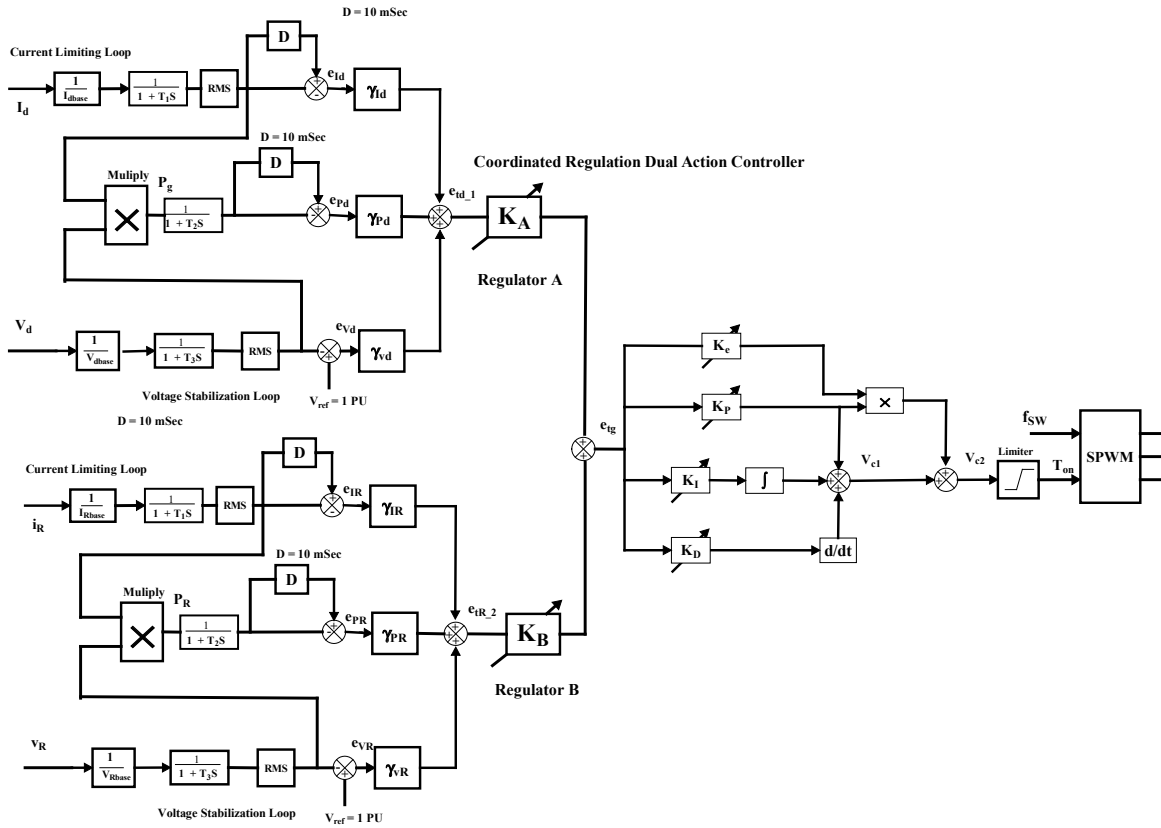


Fig. 5 Tri-loop error driven self regulating Modified PID dynamic controller for the common DC side - GPFC Scheme

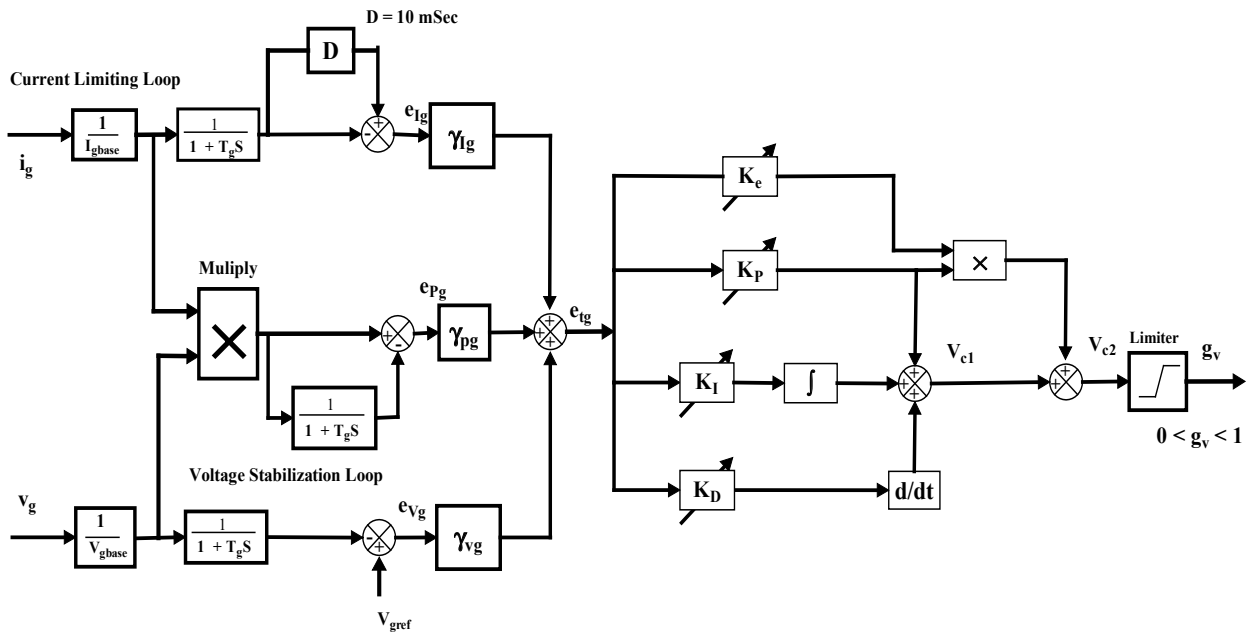


Fig. 6 Tri-loop error driven self-regulating Modified PID dynamic controller for the diesel engine generator set

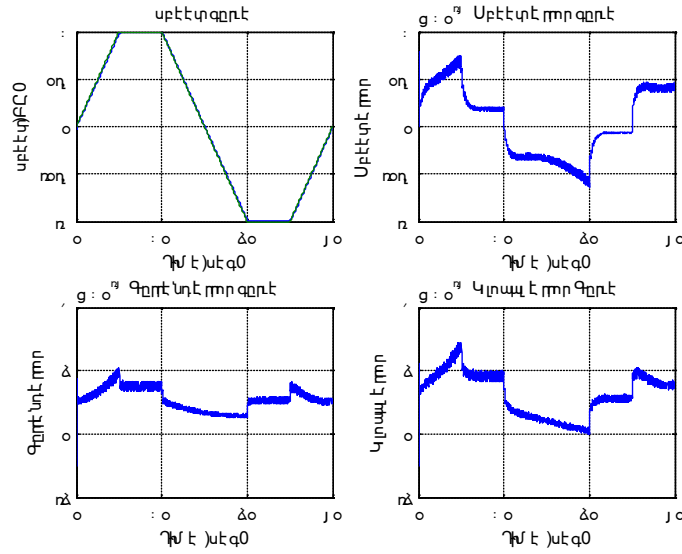


Fig. 7 Induction Motor Electric Vehicle Drive System dynamic response for the first speed track using GA

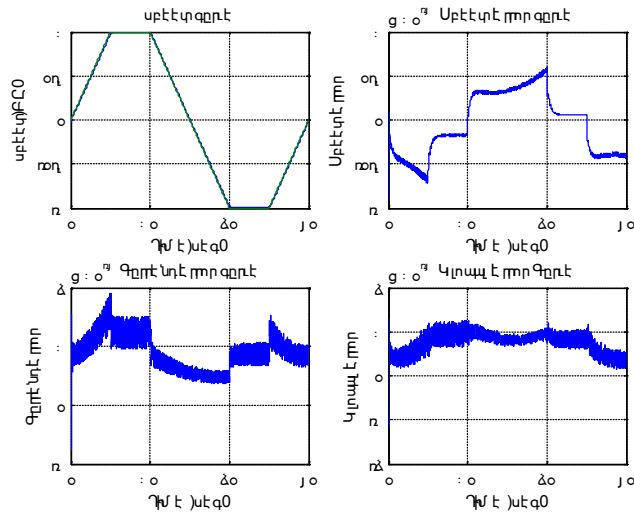


Fig. 8 Induction Motor Electric Vehicle Drive System dynamic response for the first speed track using PSO

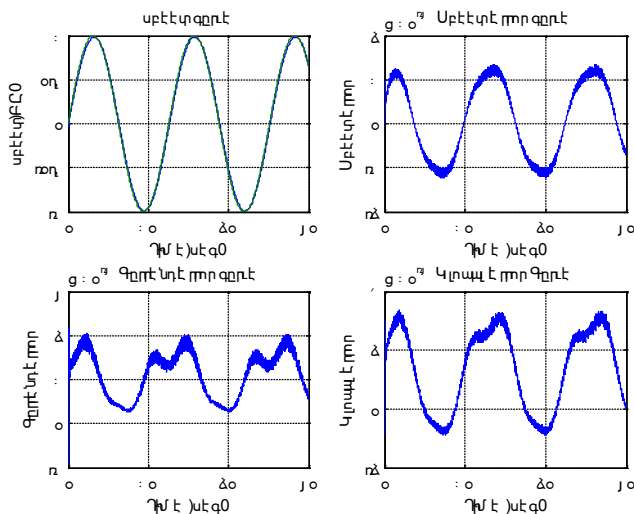


Fig. 9 -Induction Motor Electric Vehicle Drive System dynamic response for the second speed track using GA

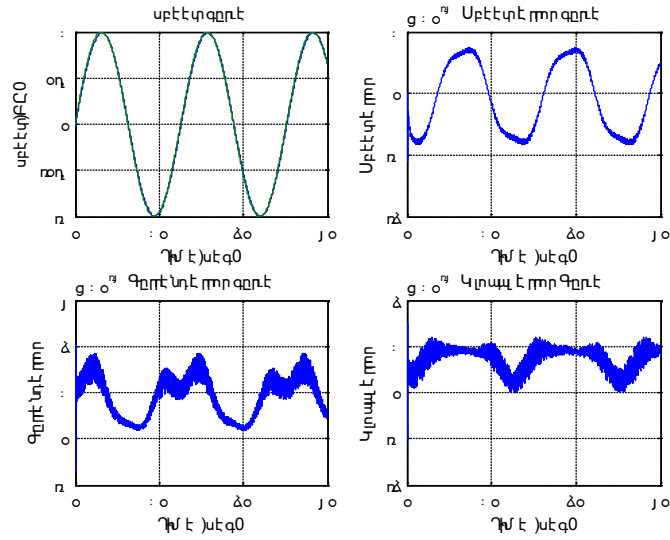


Fig. 10 Induction Motor Electric Vehicle Drive System dynamic response for the second speed track using PSO

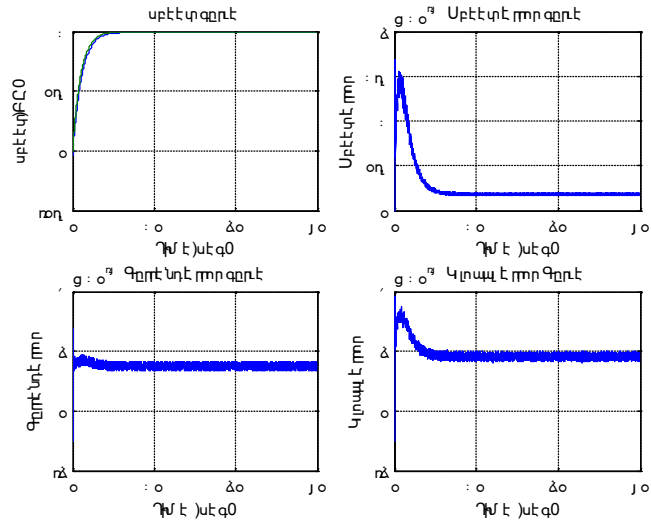


Fig. 11 Induction Motor Electric Vehicle Drive System dynamic response for the third speed track using GA

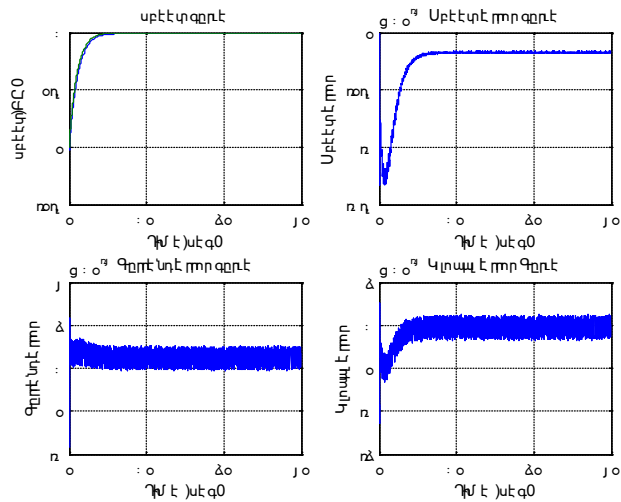


Fig. 12 Induction Motor Electric Vehicle Drive System dynamic response for the third speed track using PSO

TABLE I INDUCTION MOTOR-ELECTRIC VEHICLE DYNAMIC BEHAVIOR COMPARISON USING THE TRADITIONAL CONTROLLERS UNDER NORMAL CONDITIONS

	Modified PID dynam Controller			ANN Controller			FLC		
	First Speed Track	Second Speed Track	Third Speed Track	First Speed Track	Second Speed Track	Third Speed Track	First Speed Track	Second Speed Track	Third Speed Track
System Efficiency	0.8085	0.8038	0.8079	0.8257	0.8229	0.8292	0.8232	0.8272	0.8223
Motor Power Factor	0.8532	0.8543	0.8573	0.8879	0.8821	0.8821	0.8875	0.8839	0.8857
RMS of Motor current (PU)	0.85211	0.8434	0.8541	0.8228	0.8319	0.8208	0.8213	0.8257	0.8381
THD_DC_Bus_Voltage × 100 %	0.2545	0.2485	0.2533	0.2099	0.2160	0.2187	0.2167	0.2238	0.2228
THD_DC_Current × 100 %	0.2659	0.2535	0.2617	0.2113	0.2278	0.2395	0.2288	0.2356	0.2345
THD_Motor_Voltage × 100 %	0.2583	0.3008	0.2516	0.2236	0.2151	0.2298	0.2290	0.2298	0.2193
THD_Motor_Bus_Current × 100 %	0.2643	0.3188	0.2684	0.2284	0.2292	0.2276	0.2237	0.2268	0.2280
DC Voltage Over/Under Shoot (PU) × 10 ⁻¹	0.6295	0.6834	0.6343	0.5352	0.5190	0.5350	0.5950	0.6551	0.5251
DC Current – Over/Under Shoot (PU) × 10 ⁻¹	0.6897	0.6056	0.5441	0.6475	0.5989	0.5672	0.6449	0.6222	0.6761
Motor Voltage Over/Under Shoot (PU) × 10 ⁻¹	0.7266	0.5914	0.7027	0.4826	0.7337	0.5133	0.5073	0.7013	0.6582
Motor Current – Over/Under Shoot (PU) × 10 ⁻¹	0.4713	0.4325	0.7070	0.4908	0.5218	0.6346	0.5173	0.5748	0.4490
Motor Speed Over/Under Shoot (PU) × 10 ⁻¹	0.7364	0.6102	0.5606	0.5892	0.5327	0.5635	0.4991	0.6092	0.6654
NMSE_V _{DC-Bus} × 10 ⁻¹	0.5937	0.6281	0.4939	0.5470	0.6726	0.6407	0.5723	0.6055	0.6760
NMSE_ω _m × 10 ⁻¹	0.4472	0.6164	0.4444	0.5581	0.5237	0.7009	0.4335	0.6678	0.7309
Motor Speed Steady State Error × 10 ⁻¹	0.7369	0.6743	0.5653	0.5839	0.4954	0.6291	0.5284	0.7276	0.6549
Control System Total Error × 10 ⁻¹	0.5570	0.6605	0.5122	0.5657	0.7193	0.6415	0.4949	0.6900	0.6245
Motor Speed Rise Time	0.4704	0.4933	0.6178	0.6248	0.5441	0.6078	0.5693	0.4425	0.4373
Motor Speed Settling Time	0.5261	0.4328	0.5483	0.6414	0.4577	0.4398	0.6194	0.6182	0.4337

TABLE II INDUCTION MOTOR-ELECTRIC VEHICLE DYNAMIC BEHAVIOR COMPARISON USING THE GA AND PSO BASED SELF TUNED MODIFIED PID CONTROLLER UNDER NORMAL CONDITIONS

	SOGA			MOGA			SOPSO			MOPSO		
	First Speed Track	Second Speed Track	Third Speed Track	First Speed Track	Second Speed Track	Third Speed Track	First Speed Track	Second Speed Track	Third Speed Track	First Speed Track	Second Speed Track	Third Speed Track
System Efficiency	0.8694	0.8681	0.8631	0.8831	0.8825	0.8837	0.8867	0.8880	0.8871	0.9030	0.8950	0.8998
Motor Power Factor	0.9175	0.9215	0.9113	0.9354	0.9312	0.9339	0.9261	0.9376	0.9295	0.9416	0.9458	0.9454
Motor current (PU)	0.7531	0.7553	0.7568	0.7306	0.7312	0.7321	0.7427	0.7389	0.7417	0.7209	0.7330	0.7271
THD_DC_Bus_Voltage × 100%	0.0621	0.0819	0.0724	0.0699	0.0699	0.0766	0.0613	0.0643	0.0771	0.0530	0.0437	0.0586
THD_DC_Current × 100 %	0.0614	0.0760	0.0818	0.0751	0.0773	0.0713	0.0591	0.0581	0.0639	0.0593	0.0537	0.0547
THD_Motor_Voltage × 100 %	0.0613	0.0723	0.0742	0.0505	0.0627	0.0523	0.0623	0.0712	0.0726	0.0534	0.0603	0.0673
THD_Motor_Bus_Current × 100 %	0.0721	0.0819	0.0724	0.0699	0.0699	0.0766	0.0613	0.0643	0.0771	0.0430	0.0537	0.0586
DC Voltage Over/Under Shoot (PU) × 10 ⁻²	0.3581	0.4688	0.5993	0.4507	0.4075	0.4391	0.5600	0.5313	0.6213	0.5880	0.4751	0.5248
DC Current – Over/Under Shoot (PU) × 10 ⁻²	0.3469	0.4975	0.4706	0.5974	0.5949	0.4758	0.5737	0.5329	0.3288	0.3696	0.4828	0.3407
Motor Voltage Over/Under Shoot (PU) × 10 ⁻²	0.3996	0.4308	0.6087	0.4264	0.4071	0.4635	0.5909	0.3862	0.4869	0.4695	0.4301	0.4471
Motor Current – Over/Under Shoot (PU) × 10 ⁻²	0.6047	0.5657	0.6038	0.4711	0.5775	0.3705	0.3491	0.4455	0.4450	0.4794	0.6305	0.4352
Motor Speed Over/Under Shoot (PU) × 10 ⁻²	0.4074	0.5108	0.4918	0.3797	0.4802	0.4832	0.5912	0.5797	0.5957	0.5186	0.5049	0.5192
NMSE_V _{DC-Bus} × 10 ⁻²	0.3608	0.3781	0.4575	0.5032	0.4124	0.5729	0.4495	0.3384	0.5110	0.5026	0.3913	0.3560
NMSE_ω _m × 10 ⁻²	0.6192	0.4095	0.3923	0.3441	0.5174	0.4988	0.3586	0.5270	0.4666	0.3495	0.4453	0.4063
Motor Speed Steady State Error × 10 ⁻²	0.6166	0.5247	0.6021	0.5285	0.5773	0.4642	0.6341	0.3587	0.4930	0.4986	0.4173	0.4442
Control System Total Error × 10 ⁻²	0.3489	0.4983	0.5891	0.3740	0.3822	0.3500	0.5852	0.3705	0.6041	0.4890	0.6287	0.3663
Motor Speed Rise Time	0.3438	0.4471	0.4573	0.4537	0.4598	0.4461	0.6112	0.5374	0.6281	0.3795	0.5618	0.4452
Motor Speed Settling Time	0.4702	0.3408	0.5038	0.4447	0.5755	0.5763	0.4480	0.4075	0.4355	0.6300	0.4781	0.4434