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Metaheuristic Control Strategies Applied to Voltage Control

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***Abstract*— This paper involves the application of three metaheuristic control strategies, namely, the Ant Colony Optimization, Imperialist Competitive Algorithm and the Firefly Algorithm to voltage control. The Automatic Voltage Regulator considered different combinations of exciter and generator models. The exciter models used are the linearized exciter model and the IEEE Type DC1A Exciter model and the generator models consist of first order and fourth order synchronous generators. Proportional-Integral-Derivative (PID) controllers are implemented on MATLAB/Simulink 2015a and tuned using parameters obtained from the metaheuristic algorithms. The areas requiring considerable enhancement for the uncompensated system response included the peak overshoot, the settling time and the steady state error. A comparative analysis of the different tuned responses showed that all the proposed algorithms provided major improvements in terms of system response with the Firefly Algorithm showing the best overall performance.**

Keywords*— Automatic Voltage Regulator, Ant Colony Optimization, Imperialist Competitive Algorithm, Firefly Algorithm, DC1A, PID Introduction (Heading 1)

I. INTRODUCTION

Power system stability forms part of a crucial problem for the performance of a secure system. The analysis of an operational power system requires a convenient and correct model. For an efficient process, components need to be properly controlled and protected. Voltage stability is referred to as the capability of a power system to maintain steady voltages for every bus following disturbances from a given point of initial operation. It is dependent on the ability of the system to uphold or rebuild equilibrium of system's load demand and the load supply [1]. The terminal voltage level on the load side can be adjusted from the generator reactive power.

To address the control of the latter, an Automatic Voltage Regulator (AVR) is implemented. The five main components constituting the AVR are the regulator, exciter, generator, sensor and comparator. The main task of an AVR is to sense the generator output voltage and rectified by means of the exciter control unit to the desired direction. The reactive power reaches an altered equilibrium and hence the terminal voltage is raised to the desired position [2]**.** A PID controller can be defined as a drastic phase lead-lag compensator having a pole at zero and another at infinity. It is identified as the three-term controller. Ang et al. [3] published a research paper in the IEEE Transactions on Control Systems Technology presenting an analysis on the performance and modern methods of tuning PID controllers using tuning algorithms, patents, software packages and inclusion of hardware modules which are commercially used. The research mainly dealt with the incorporation of intelligent techniques for tuning the PID controller using software based systems. The performance characteristics were based on a high stability and a short transient leading to an enhancement in the quality and aiming for an optimal productivity offering the simplest and most efficient solution. During the past years, metaheuristic algorithms have been implemented in control problems due to its ability in finding solutions of a good quality in a favorable timescale.

Gaing [4] developed a design method to obtain the parameters of the PID controller of an Automatic Voltage Regulator with the application of the Particle Swarm Optimization (PSO) technique. The research exhibited the application of the PSO technique for the most efficient search of the parameters of the PID controller of the system. The simulation results were compared to the Genetic Algorithm and the recommended method yielded an improvement in the step response of the system based on the performance characteristics. The stability of the ACO was studied with Kalil et al. [5] presenting the Ant Colony Optimization (ACO) technique to enhance the stability condition for voltage and minimization of loss in transmission along with a better monitoring of the voltage profile. Yang [6] addressed multimodal optimization using Firefly Algorithm (FA). The nature based proposed algorithm was compared to the likes of traditional metaheuristic algorithms including the PSO and Genetic Algorithm.

The simulation results showed a superiority towards the Firefly algorithm and also that multi objective optimization problems can be solved using the FA with slight modifications. Atashpaz-Gargari and Lucas [7] published a paper to the IEEE Congress on Evolutionary Computation proposing an algorithm taking inspiration form the imperialistic competition. The modern algorithm was tested against functions of benchmark cost to show its capability in dealing with distinct cases regarding optimization. The algorithm was compared with the PSO and GA for one of the benchmark functions highlighting the speed of execution of the algorithm when applied in an optimization problem.

This work aims to make use of three intelligent algorithms namely, the Ant Colony Optimization, Imperialist Competitive Algorithm and the Firefly Algorithm to tune the PID controllers used for voltage control. Even though, it is

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one of the conventional controllers, the PID controller is still being given significant importance in power system control since it is relatively simple to implement and can be easily adapted to any control problem. We aim at determining the authority of these algorithms in this particular control issue and in comparison to each other. To the authors' best knowledge, this has not been investigated yet and this work can make an important contribution to research in this field.

II. AVR SYSTEM MODELLING

A. Generator

The first model consisted of a linearized first order generator while the second one involved a fourth order generator model to accurately comment on the system's behavior under a transient state. The transfer function of the models are given by (1) and (2).

$$G_{GEN1}(s) = \frac{V_t(s)}{V_F(s)} = \frac{K_{G1}}{1+\tau_{G1}s} \tag{1}$$

Where $G_{GEN1}(s)$ represents the transfer function of the 1st order generator, K_{G1} is the gain of the field of the generator set to 1 and τ_{G1} is the time constant of the generator normally varied between 1 and 2 seconds which is load dependent.

$$G_{GEN4}(s) = \frac{K_{G4}(1+\tau_{Z1}s)(1+\tau_{Z2}s)(1+\tau_{Z3}s)(1+\tau_{Z4}s)}{(1+\tau_{P1}s)(1+\tau_{P2}s)(1+\tau_{P3}s)(1+\tau_{P4}s)} K_5 \tag{2}$$

This choice for the model is to identify the effects of a high order synchronous machine on an AVR system. The parameters taken into consideration for the design and simulation of the operation of the synchronous machine were based on the simulation design proposed by Law [8]. $G_{GEN4}(s)$ represents the transfer function of the fourth order generator, K_{G4} is the gain of the field of the generator, K_5 is the gain dependent on load, τ_{z1} - τ_{z4} is the time constant coefficients of the generator for zeros and $\tau_{P1} - \tau_{P4}$ represent the time constant coefficients of the generator for poles. The model specifications included the assumptions that at synchronous speed the single turbine will maintain a constant speed and produce a constant torque. Additionally, the parameters set for the fourth- order model used for simulation was based on the works of Walton [9], which examined a systematic method to determine the parameters of synchronous machines.

B. Exciter

The simplified transfer function used in the linearized model of the automatic voltage regulator system considered for analysis is given in (3).

$$G_E(s) = \frac{V_F(s)}{V_R(s)} = \frac{K_E}{1+\tau_E s} \tag{3}$$

Where K_E represents the exciter gain and τ_E is the time constant coefficient of the exciter. For the design of the model, K_E is chosen to be 1 implying a separately excited dc rotating exciter and τ_E is taken as 0.4.

The amplifier may be represented by the transfer function containing time constant τ_A and gain K_A. to avoid any damage to the exciter, the regulator can be followed by a level limiter to prevent any output to exceed the practical limits. The transfer function is denoted in (4).

$$G_A(s) = \frac{V_R(s)}{V_e(s)} = \frac{K_A}{1+\tau_A s} \tag{4}$$

The time constant, τ_A, and gain, K_A, are chosen to be 0.1 and 10 respectively for the simulation.

The second excitation system considered for analysis constitutes of the IEEE recommended Type DC1A Excitation System Model [10]. This model represents the field controlled dc commutator exciters having voltage regulators continuously in action. This model is generally implemented and used to represent diverse system types with inadequate or incomplete detailed data or the unavailability of a simpler model when required.

C. Sensor

The measurement of the terminal voltage is carried out using a potential transformer where the signal is rectified and filtered [11]. The transfer function s given by (5).

$$G_S(s) = \frac{V_S(s)}{V_t(s)} = \frac{K_R}{1+\tau_R s} \tag{5}$$

Where, K_R denotes the sensor gain with a value of 1, τ_R is the time constant of the sensor representing the rectification and filter of V_t. A value of 0.01 is chosen for τ_R for the design and simulation of the model.

III. CONTROLLER DESIGN

A PID controller is adopted for this study as the technique for compensation for the AVR system. The PID controller parameters require optimal tuning for successful implementation and optimum performance. In this project, the parameters shown in (6) for tuning the controller would be identified by metaheuristic algorithms.

$$G(s) = K_P + K_I\frac{1}{s} + K_D s \tag{6}$$

Where K_P represents the proportional gain, K_I denotes the integral gain and K_D is the derivative gain. The three parameters of the PID controller must be mutually tuned to achieve an optimum performance. The decisive objectives for improvement in the control of the system are based on the performance characteristics of the step response of the models.

IV. OBJECTIVE FUNCTION

The objective of using metaheuristic control strategies is to minimize the error performance of the transient response. The latter displays damped oscillations in cases of practical control systems prior to attaining a steady state. The

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evaluation of the step response is usually carried out with the use of time domain parameters. The measures of performance include the peak overshoot, settling time, rise time and the steady state error. The minimization of the time domain parameters lead to an improvement in the step response [12]. The performance indices are obtained from the *stepinfo* command in MATLAB. A weighted sum of the objectives can therefore be derived and combined to formulate an objective function in order to minimize the error between the step response and the input step signal.

From the uncompensated responses, areas requiring major improvement included peak overshoot, settling time and the steady state error. However, rise time was also included in the objective function for further enhancement. The Integral Absolute Error (IAE) and the Integral Squared Error (ISE) are not considered in the formulation of the objective function as the errors are equally weighted independent of time [13]. The error between the reference signal and the step response is calculated as follows with the application of the Integral Time Absolute Error (ITAE) in the objective function.

$$ITAE = \int t \cdot |e(t)|\, dt \tag{7}$$

Where e (t) is the error signal at time t. The multiplication by the time weight t is so that the large initial error for the system response do not outweigh the errors encountered at the end.

V. OPTIMIZATION TECHNIQUES

A. *Ant Colony Optimization*

Experimental observations have shown that after a phase of transition being a few minutes, the ants choose the shortest branch from the nest to the source of food, out of two branches available to them. Furthermore, the probability of selection of the branch of the shortest length also increases with the length difference of the two branches. The materialization for the choice of this shortest length is due to a phenomenon known as *autocatalysis*, where ants communicate indirectly, also denoted by the term *stigmergy*, arbitrated by the exchange of information in modifying their local environment.

While making the transit from the nest to the food source, a chemical substance, known as the *pheromone*, is deposited by the ants. Therefore the probability of choosing a path will further increase for future ants based on the smell of the pheromone aggregate on the branch [14].

Based on the differential path length, the shorter branch will have the higher probability to be chosen, with the ants using the latter reaching the food source first. In their transit back to their nest the smell of the trail of pheromone will also increase the chance of choosing the shorter branch. In this occurrence, new pheromone will be deposited, hence increasing the probability of choice for the future ants. This process continues with the rate of deposition increasing until a convergence of the entire ant colony is observed in using the shorter path for their transit.

Dorigo et al. [15] formulated the ant colony optimization into a metaheuristic algorithm to be used for the optimization of problems. The optimization problem should however consist of a model, a search space and a set of constraints with a proper objective function. This model would be used in the definition of the pheromone model for the ant colony optimization. The probability of the ant choosing the city *j* at the city *i* is denoted by $P_{ij}^k(t)$ using the pheromone matrix $\tau = \{\tau_{ij}\}$ to construct potential optimal solutions. It is also noted that all values for τ are initially set to $\tau_{ij} = \tau_0$ for all (*i*, *j*) where $\tau_0 > 0$.

$$P_{ij}^k(t) = \frac{[\tau_{ij}(t)]^\alpha [n_{ij}]^\beta}{\sum_{i,j\,\epsilon\, T^k} [\tau_{ij}(t)]^\alpha [n_{ij}]^\beta}\ if\ i,j\ \epsilon\ T^k \tag{8}$$

The level of pheromone on the *i* to *j* path is denoted as $\Delta\tau_{ij}^k$ and given as:

$$\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{L^k}\ , if\ ant\ k\ used\ edge\ (i,j)\ in\ its\ tour \\ 0\ ,\quad otherwise \end{cases} \tag{9}$$

Where Q is a constant and the tour length created by the ant *k* is denoted by L^k.

However for this optimization problem, this definition is slightly altered for the objective function. Hence the pheromone level is defined in (10).

$$\Delta\tau_{ij}^k = \begin{cases} \frac{L^{min}}{L^k}\ , if\ i,j\ \epsilon\ T^k \\ 0\ ,\quad otherwise \end{cases} \tag{10}$$

L^{min} is the best cost obtained from the algorithm from N number of ants until the present iteration while L^k is the actual cost value found by ant *k*. To prevent a boundless increase in the pheromone trails and to clear the seldom used ones, pheromone evaporation is used. The model is shown in (11).

$$\tau_{ij}(t) = \rho\tau_{ij}(t-1) + \sum_{k=1}^{N} \Delta\tau_{ij}^k(t) \tag{11}$$

$\Delta\tau_{ij}^k$ is the pheromone quantity on each path, N represents the number on ants and ρ is the rate of evaporation which usually ranges from 0 to 1. Fig.1 shows the methodology used for the Ant Colony optimisation

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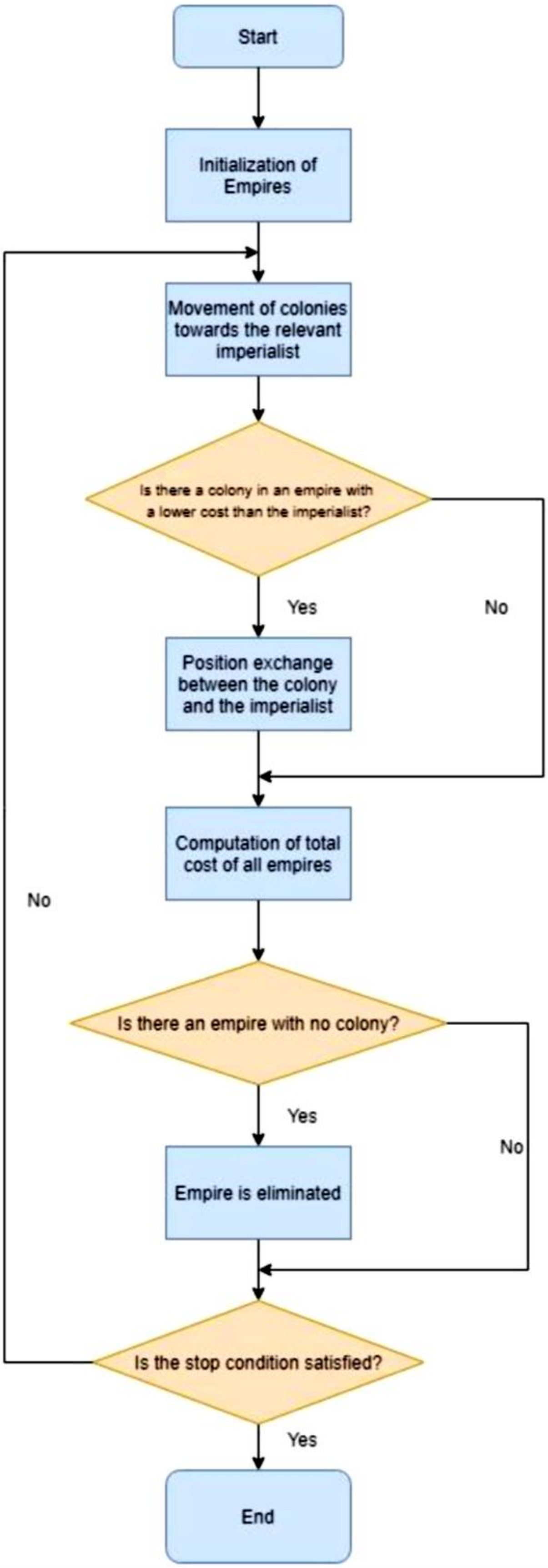

Fig. 1. Methodology for Ant Colony optimization

B. *Imperialist Competitive Algorithm*

The optimization method is proposed by a recent algorithm of evolutionary behavior taking inspiration from the imperialistic competition in search of a global optimization. The division of the countries are classified into two distinct categories namely the colonies and the states of imperialistic nature. The purpose of the evolutionary algorithm dwells on the competition of imperialists and the convergence of the following colonies towards a cost function minimum globally. The empires and the rest of the colonies are initialized from the initial population. On the basis of their potential and capacity, the colonies previously formed from the population are divided among the imperialists.

Subsequently, a movement of the colonies towards their corresponding imperialist empires. The power of the imperialist as well as the power of the colonies are required to form the total power of the empire. The Imperialistic Competitive Algorithm is initiated in the midst of all the empires. The elimination of any empire is led by the lack of capability in increasing its power or even being unable to avoid decreasing its power. A gradual power increase will be developed for the powerful empires and the opposite scenario for the weaker empires leading to an ultimate disruption and crash. The colonies moving towards their corresponding imperialist countries and the disruption structure among the population leads to a convergence. Another common situation arises when while moving towards its relevant imperialist, a colony can be at a position with a lower cost than that of its imperialist. Then, in the occurrence of such an event, the colony exchanges position with its imperialist. The running of the algorithm is unaffected, however, the other colonies move to the new locations. After this imperialistic competition, only the most powerful empire will remain and will control all the colonies. In this new world, ideally, all the colonies will be disposed with the same costs and positions with the imperialists being the same. Hence, there is no difference between colonies and the imperialist and following this condition, the algorithm is put to a halt.

C. *Firefly Algorithm*

More than two thousand species of fireflies can be observed around the world and most of them are responsible in producing rhythmic flashes of a short duration. However, these flashes are very particular in their pattern for each of the species. The light produced by the flashes are caused by a phenomenon by the name of bioluminescence. The rhythm of the flash and the rate of the latter are what englobes the signals that makes both sexes closer. Light intensity, *I*, follow the inverse square law at a distance *r*. It can therefore be deduced that the light intensity increases as the distance decreases as shown in (12).

$$I \propto \frac{1}{r^2} \tag{12}$$

Also, as the distance *r* increases, the air becomes weaker, hence creating a limit for how far most fireflies can be identified, usually being in the range of hundred meters during the night time. The flashing light is what is formulated, relating to a fitness function that can be optimized, hence developing the Firefly algorithm. In the development of the algorithm inspired by the fireflies and their unique pattern

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and characteristics of flashing lights, various rules have been considered and idealized.

For simplicity and further development in the algorithms, three main rules have been taken into consideration as described in [6] and [16], stating that one firefly will be attracted to another firefly regardless of their sex on the basis that the species are unisex. Another rule is that attractiveness and brightness follow a proportional relationship such that for any two fireflies which are flashing, the brighter one will attract the other, hence making the latter move towards the former. However, if there is no brighter firefly in sight, it will continue to follow a random movement. The brightness is proportional to the attractiveness and a decrease is noted as the distance increases. The third rule is that the prospect of the objective function of the optimization problem affects the fireflies' brightness.

The attractiveness, however, is relative and only judged by the fireflies. Hence, the attractiveness β changes with the distance between fireflies i and j, having a distance r_{ij} between them. The firefly's attractiveness can be defined as expressed below since it has a proportional relationship with the light intensity, I, observed by neighboring fireflies.

$$\beta = \beta_0 e^{-\gamma r^2}, \ \beta_0 \text{ is the attractiveness at } r = 0. \quad (13)$$

The distance between two fireflies can be defined as x_i and x_j for fireflies i and j respectively is the Cartesian distance defined as (14).

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k}\right)^2} \quad (14)$$

With $x_{i,k}$ being the kth component of the spatial coordinate x_i of the i^{th} firefly. In a 2D case, the following can be observed.

$$r_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \quad (15)$$

A firefly i moving towards a brighter firefly j has a movement mathematically defined as (16).

$$x_i = x_i + \beta_0 e^{-r_{ij}^2}\left(x_j - x_i\right) + \alpha\, \epsilon_i \quad (16)$$

The second term in this equation represents the firefly's attractiveness. The third term is α, a randomization parameter followed by ϵ_i which is a vector from a uniform distribution with random numbers. Fig.2 shows the methodology used for the Firefly Algorithm.

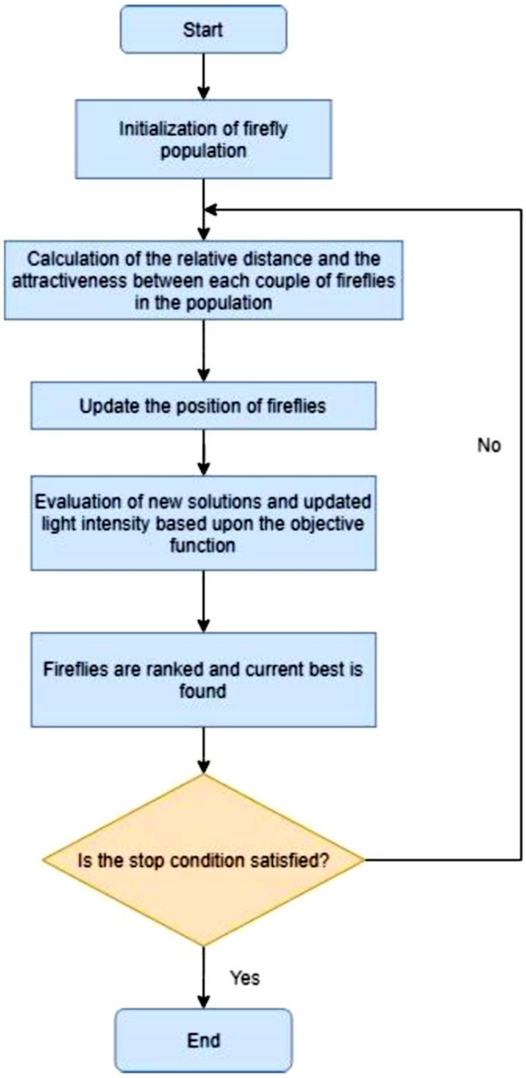

Fig. 2. Methodology for the Firefly Algorithm

VI. SIMULATION AND RESULT

All the Optimization techniques were simulated in MATLAB/ Simulink 2015a and the following results were obtained. The number of iterations were set to 75 and the same objective function was used for all the algorithms implemented. Each algorithm was run 5 times and the parameters delivering the best performance was selected as the simulation result. This activity was executed to obtain the optimal parameters for the controller as it is directly linked to the performance indicators. The PID parameters obtained from the algorithms are shown in Table 1. For every simulated model, it was observed that ICA and FA PID parameters were close, except for a high discrepancy in K_i by ICA for the Linearized model with a fourth order generator from FA and ACO. Figs. 3-6 present the step responses for the different models where the PID controller is subjected to three metaheuristic algorithms i.e. Ant Colony Optimization, Imperialist Competitive Algorithm and Firefly Algorithm. The uncompensated responses are also included to highlight the improvement brought by the algorithms. Table II

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summarizes the results obtained for the different models and algorithms implemented in terms of the performance indicators. ACO displayed satisfactory results, however, due to its limited range intensification, better solutions could not be found. It can be inferred that FA displayed the best performance for three out the four models considered. ICA displayed nearly alike results as FA for the fourth model considered involving the DC1A excitation system and a fourth order generator and the best performance for the third model. Therefore, it can be observed that ICA started delivering better performance with higher order systems with a faster execution speed.

TABLE I. PID Parameters computed by the algorithms

Linearized AVR Model with a first order synchronous generator			
PID Parameters	ACO	ICA	FA
K_p	0.4500	0.6190	0.5372
K_i	0.3000	0.4133	0.3709
K_d	0.1500	0.2415	0.1708
AVR model with a Type DC1A excitation system and a first order synchronous generator			
PID Parameters	ACO	ICA	FA
K_p	0.8500	1.2741	0.6799
K_i	0.1000	0.0866	0.0835
K_d	0.0500	0.2014	0.0464
Linearized AVR Model with a fourth order synchronous generator			
PID Parameters	ACO	ICA	FA
K_p	7.7889	8.5356	8.5356
K_i	2.2611	13.1511	2.2195
K_d	1.1556	0.8768	0.8130
AVR model with a Type DC1A excitation system and a fourth order synchronous generator			
PID Parameters	ACO	ICA	FA
K_p	9.1000	10.0000	10.0000
K_i	0.0500	0.1175	0.1164
K_d	0.3500	0.2827	0.2601

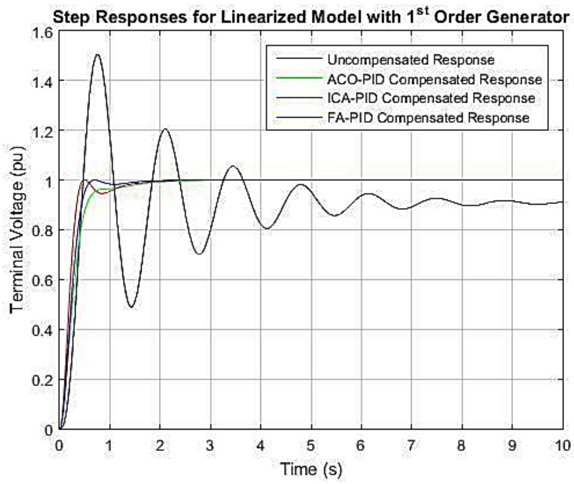

Fig. 3. Combined responses for Linearized AVR Model with a first order synchronous generator

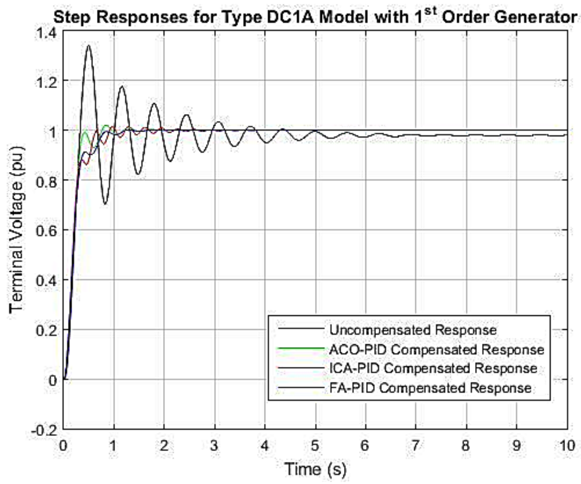

Fig. 4. Combined responses for AVR model of DC1A excitation system with a first order synchronous generator

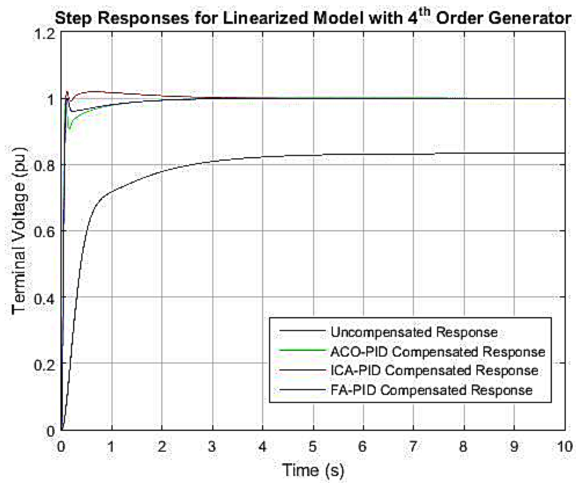

Fig. 5. Combined responses for AVR model of Linearized system with a fourth order synchronous generator

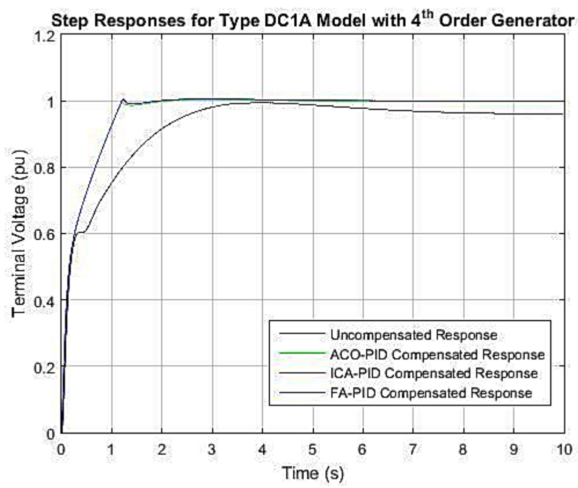

Fig. 6. Combined responses for AVR model of DC1A excitation system with a fourth order synchronous generator

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TABLE II. PERFORMANCE CHARACTERISTICS OF ALL SYSTEMS

Linearized AVR Model with a first order synchronous generator				
Performance Indicator	ACO	ICA	FA	Uncompensated
Settling time(s)	0.5616	0.5212	0.2798	2.2436
Peak Overshoot (%)	0.0010	0.1302	0.02168	65.1601
Steady State Error (%)	0.0001	0.0001	0.0001	-8.8106
AVR model with a Type DC1A excitation system with a first order synchronous generator				
Performance Indicator	ACO	ICA	FA	Uncompensated
Settling time(s)	0.4651	0.5754	0.4267	1.6271
Peak Overshoot (%)	2.0442	1.5619	0.1552	36.6262
Steady State Error (%)	0.03486	-0.0006	-0.0016	-1.9558
Linearized AVR Model with a fourth order synchronous generator				
Performance Indicator	ACO	ICA	FA	Uncompensated
Settling time(s)	3.5113	0.3257	3.2173	11.1892
Peak Overshoot (%)	0.4134	1.9627	0.0125	0
Steady State Error (%)	0.0334	-0.0031	0.0102	-16.6752
AVR model with a Type DC1A excitation system with a fourth order synchronous generator				
Performance Indicator	ACO	ICA	FA	Uncompensated
Settling time(s)	3.7932	3.8151	3.8125	18.6728
Peak Overshoot (%)	0.6369	0.5964	0.5931	3.5656
Steady State Error (%)	-0.256	-0.0235	-0.0272	-3.9612

VII. CONCLUSION

In this study, metaheuristic control strategies are applied to an AVR system. However, modifications were made for better understanding of the criteria of the controller parameter. The Type DC1A excitation system was additionally considered for the AVR model. Two distinct generator models were investigated, the first one having a first order transfer function while the second one had a fourth order transfer function. These two generators modelled with the two excitation systems made a combination of four contrasting AVR systems. The PID controller was chosen as the method for compensation in this study due to its far reaching acknowledgement in the voltage regulation industry in contrast to the other types of AVR controllers offering the simplest and most efficient solution in various control problems. Three metaheuristic control strategies were considered for the PID tuning of the models. ACO, ICA and FA were developed and implemented as control strategies for voltage regulation. To adapt the control strategies to the Optimization problem relevant in this work, an objective function was developed using the collective of the performance indicators to form a single cost to be minimized by the tuning algorithms. From the simulation results, reliable outcomes were achieved using the PID controller. The individual step response with the corresponding performance indicators comprising of the settling time, the peak overshoot along with the steady state error were analyzed for the selection of the finest performance executed by the algorithm. From the comparative analysis of the three algorithms, ACO showed good results but displayed a limitation in the search range exploitation to find the best solution. ICA showed a better performance in higher order systems. FA displayed the best performance results in three out of the four models investigated.

As recommendations for further works,

1. Other exciter models proposed by IEEE can be implemented and the corresponding responses investigated.
2. The objective function can be enhanced using other performance indices and tested.
3. More iterations can be run for the possibility of a better fitness value for the multi-objective problem.
4. The ‘Hybrid’ algorithm obtained by merging the two best performing metaheuristic algorithms can be tested.
5. The robustness of the solutions can be confirmed using other alternative exciter-generator models.

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