3 SRM Block Diagram

The position of rotor is sensed by the rotor position sensor and it provides its corresponding output to the error detector. Error detector compares reference speed given in RPM and the actual speed feedback from the motor itself to generate an error signal which is given to the controller block. The controller (PID or GA-PID or ACO-PID) gives control signal to the converter according to the error signal value. The speed of the motor is controlled by the converter through proper excitation of their corresponding windings.

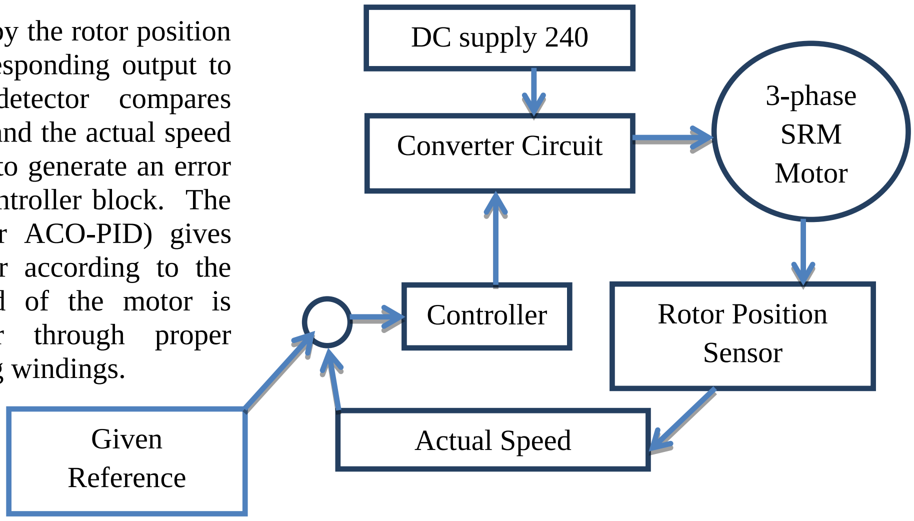

Fig.2 Block Diagram of SRM Speed Control

4 Genetic Algorithms

Genetic Algorithms were invented to try to mimic some of the processes observed with living being [3-5]. The idea with GA is to use the power of natural living ability for evolution to solve hard and very complicated Engineering optimization problems [13]. GA's process starts with no knowledge at all for the correct and accurate solution and depends entirely on responses it receives from the surrounding environment and its internal evolution operators such as reproduction, crossover and mutation to get to the best available solution.

The application of these three basic operations allows the creation of new and better individuals, which may be better than their old parents. This algorithm is repeated for many generations and at the end we stops when we reaches for individuals that represent the optimum solution to the problem or we stop at certain number of iterations we initially stated.GA starts with an initial and random chromosome & checks its fitness value. The fittest chromosome are taken as parents for further reproduction also to be crossed over & mutated again. The offspring or their children are checked for the fitness value & depending on it. We can decide either to be taken again or to be neglected from the population [7, 16, 17]. Genetics father is "John Holland" who invented this technique in the early 1970's [6]. GA's is an adaptive artificial search technique based on the evolutionary ideas of natural selection [7]. In order to use the "GA's" there are two important aspects to follow: chromosome coding and defining the evaluation criteria. Although it appears as a randomized process, GA's is not a completely random process. Instead it develops some historical information to direct the search into the region of better performance within the search space it has. The Basic techniques of the GA's are designed to simulate processes with natural living being which is necessary for evolution as found on the block diagram on Figure 3. Especially those who follows the principles of Charles Darwin "survival of the fittest" Since in nature, competition among individual's results in the fittest individuals dominating over the weaker ones and this is observed and proved its existence in history. GA's can give robust & adaptive response for a system with nonlinearity, parameter variation and load disturbance effect [3-5].

GA's is better than traditional techniques and more robust to sudden load changes and is a very adaptive technique. Unlike old AI systems, they do not break easily if the input changes or noise applied suddenly. Also in searching a large state-space, GA's may offer significant benefits over the typical search of optimization artificial techniques.

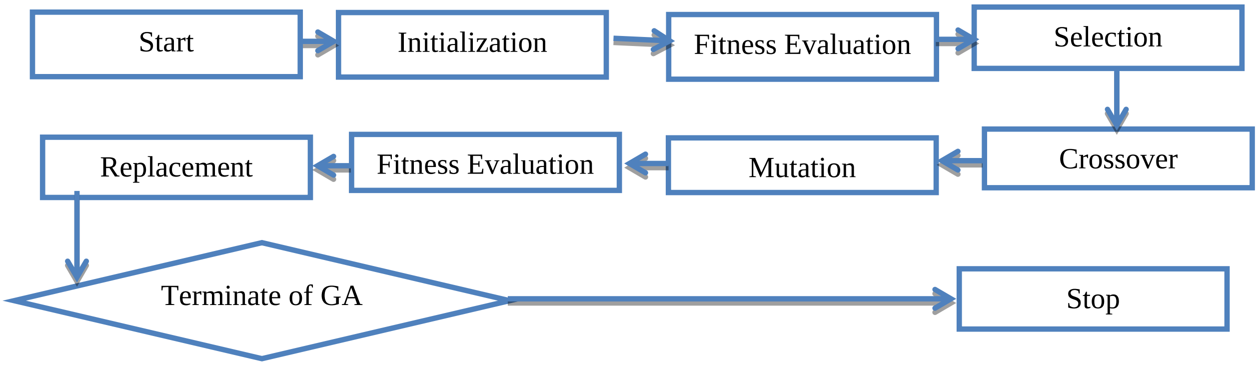

Fig.3 Block Diagram for GA Sequence

5 Ant Colony Optimization

Marco Dorigo and some of his colleagues invented the first ACO concept in the early 90's [8, 9, 10]. The development of these algorithms was inspired by the observation of ant colonies in nature. Ants are social insects with an ability to organize their food obtaining process very accurately. They live in colonies (groups) and their behavior is governed by the goal of colony survival rather than being focused on the survival of individuals. Ant algorithms are adaptive and robust to any complicated engineering problem. The behavior that

provided the inspiration for ACO is the ants "foraging behavior" and in particular, how ants can find the shortest path between food sources and their nest (Home). The main advantages of artificial ants are taken from their natural model. Which are (1) artificial ants exist in colonies of cooperating individuals; (2) they communicate indirectly by depositing pheromone on their way to any expected food sources [11, 12] (3) they use a sequence of local moves to find the shortest path from a starting position which is completely random, to a destination point they apply a stochastic decision policy using local information only to find the best solution. When searching for food supplies (Sources), ants initially searches the surrounding area or explores it which is near its nest

This is in completely random directions. While moving it leaves a small amount of pheromones behind it on the ground. This is in order for the other ants to smell it during this trip of finding food sources. While other ants search for food it chooses its way in a probability which is according to the amount of pheromones it finds. As soon as an ant finds a food source, it tries to know the quantity and the quality of these sources of food and carries some of it back to its home base. During the return trip the quantity of pheromone it was left over during the trip is evaluated again to try to know the shortest route to its nest. When it reaches its nest other ants will go on the same route to the food source which contains actual food as illustrated on figure 4. It has been shown that, this kind of communications is an indirect one which is built in every ant to get to its nest as soon as possible and in an organized manner also it is called "stigmergy effect" which enables them to find the shortest path between their home base and expected food source.

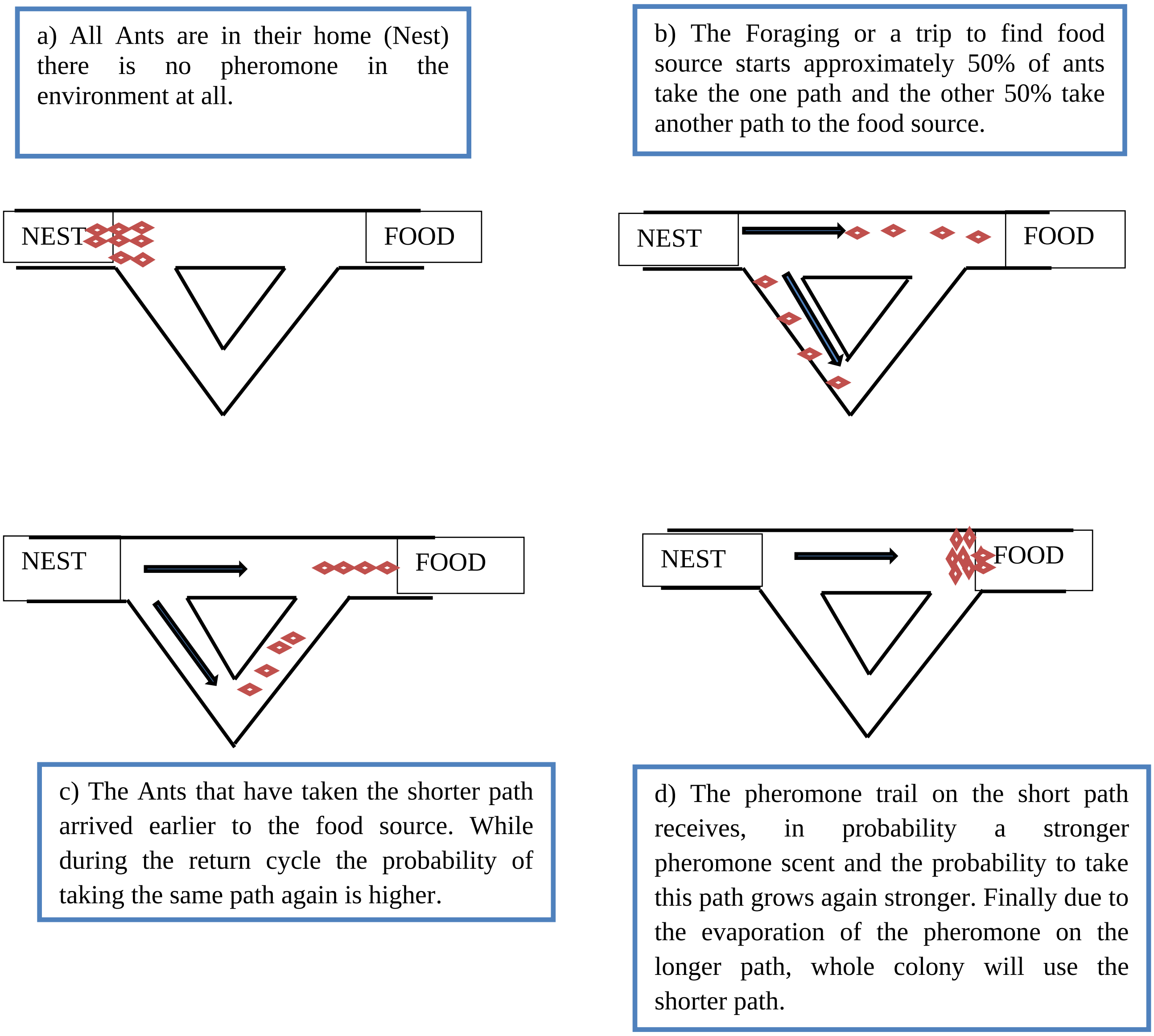

Fig. 4 Experimental setting that demonstrate the Shortest Path Finding Capability of Ant Colonies, between the ants nest and the only food source exist with two paths of different length.

6 Experimental Setup of the SRM Drive Using Matlab-Simulink

The experimental setup is shown on Figures 5, 6. This shows the PID controller optimized by GA's also the same PID controller optimized by ACO technique. We start the simulation by using a 3-phase 60KW SRM motor which is used on this research paper with motor features as found on table 1.

Also it is the same built-in Matlab motor model. Tables 2 and 3 shows the GA's and ACO controller's parameters used after several trials. the response of Kp, Ki and Kd parameters are summarized on table 4 which shows that using the proportional controller "Kp" will have the effect of reducing rise time of the output signal and will reduce the steady state error while the integral controller "Ki" will have the effect of eliminating the steady state error have the effect of eliminating the steady state error produced by the "Kp" parameter but will have the worst transient response on any system.

While the derivative controller "Kd" will have the effect of increasing the stability of the system, reducing the overall overshoot and improves the transient response of the system. Several simulations were carried out for controlling motor's speed with a different load torque disturbances to explore the effectiveness of the proposed controller's robustness in comparison with the conventional old PID controller.

The results were obtained for cases such as step variable (Input) speed of ranges starts from "1000-1500 RPM" which is our maximum RPM for such motor and under variable load torque "Nm".

Table 1
Matlab built-in Motor Features

Item	Features Description	Value
1	Rotor Pole number "Nr"	6
2	Stator Pole Number "Ns"	8
3	Turn on angle	40 degree
4	Turn off angle	75 degree
5	Number of Phase	3
6	Power in (KW)	60
7	Maximum (Reference) speed (RPM)	1500
8	Stator Resistance (Ohm)	0.05
9	Inertia (Kg.m.m)	0.05
10	Friction (N.m.s)	0.02
11	Source Voltage (Vdc)	240

Table 2
Genetic Algorithm Parameters

Item	Description	values
1	Proportional gain limits Kp	Ranges [0-100]
2	Integral gain limits Ki	Ranges [0-100]
3	Derivative gain limits Kd	Ranges [0-100]
4	Population type	Double vector
5	Population size	100
6	Creation Function	Uniform
7	Mutation rate	0.1
8	Mutation Function	Uniform
9	Selection method "Function"	Uniform
10	Crossover type	Arithmetic

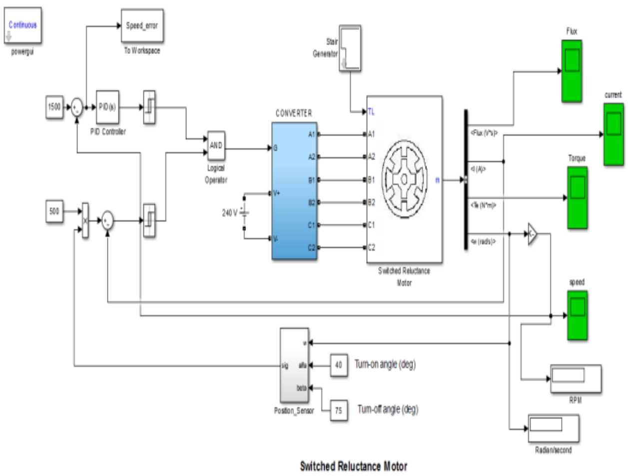

Fig.5 SRM motor speed control with GA-PID Controller.

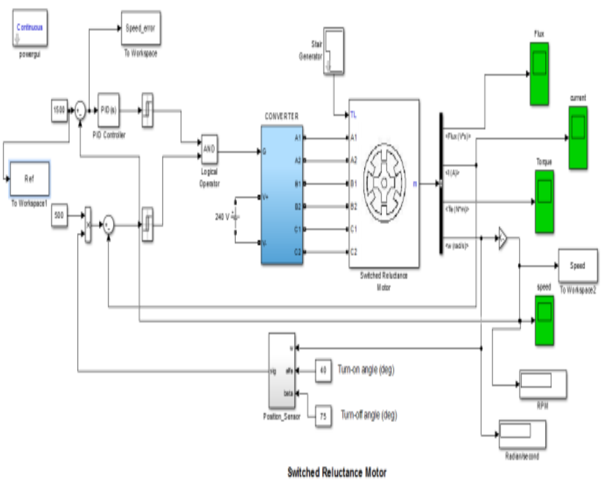

Fig.6 SRM motor speed control with ACO-PID controller

Table 3
Ant Colony Parameters

Item	Description	values
1	Number of Iterations	100
2	Number of Ants	300
3	Alpha	0.8
4	Beta	0.2
5	Evaporation Rate	0.7
6	Number of Parameters	3
7	Lower& upper limits	[000] & [111]

Table 4
Response of K_p, K_i and K_d

Item	K_p	K_i
Rise time	Decrease	Small change
Overshoot	Increase	Decrease
Settling time	Small change	Increase
Steady state error	Decrease	Eliminate
Item	K_p	K_i

7 Simulation Results

To explore the effectiveness of the proposed techniques, a Matlab-Simulink computer simulation has been carried out for the different proposed controllers. The conventional PID, GA-PID and ACO-PID controllers system [*i.e.* the maximum torque obtained, rotor's position, reference and actual speed values, speed error signal and change in the error signal, input values of torque, produced flux current] can be observed.

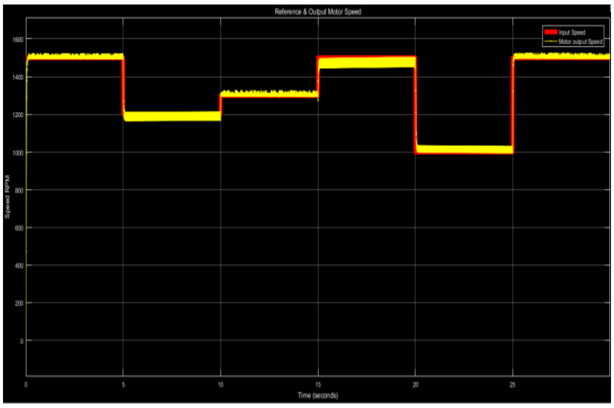

Fig.7 shows the variable step input (Speed) and the motor actual output speed after using Conventional PID controller.

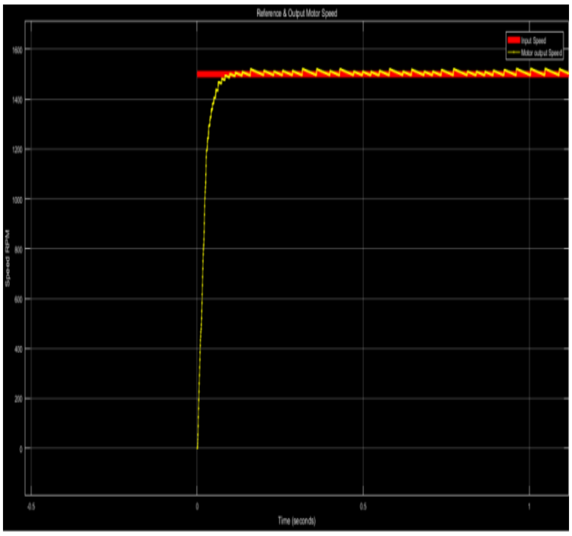

Fig.8 shows the delay on the output (Zoomed in) of the motor with reference step input when using conventional PID controller.

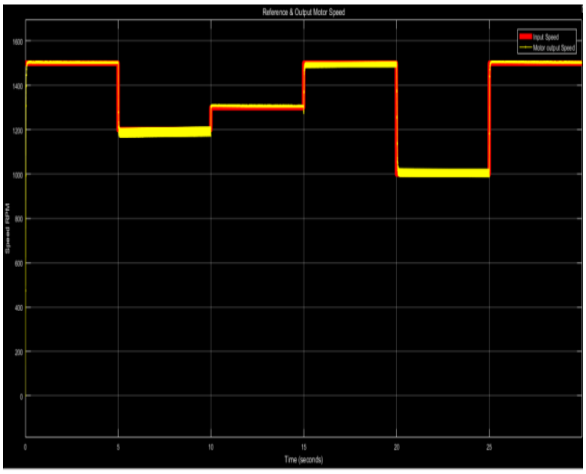

Fig.9 shows the variable step input (Speed) and the motor actual output speed after using the new artificial Genetic algorithm Technique.

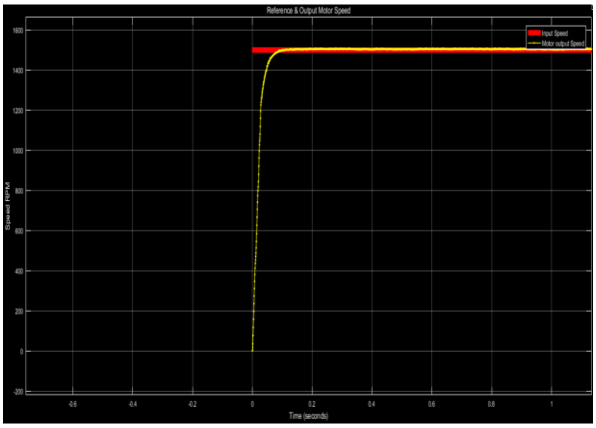

Fig.10 Shows the delay on the output (Zoomed in) of the motor with reference step input when using the Genetic algorithm

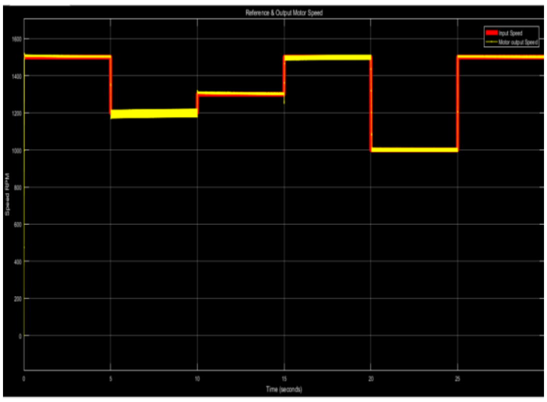

Fig.11 Shows the variable step input (Speed) and the motor actual output speed after using the Ant Colony technique.

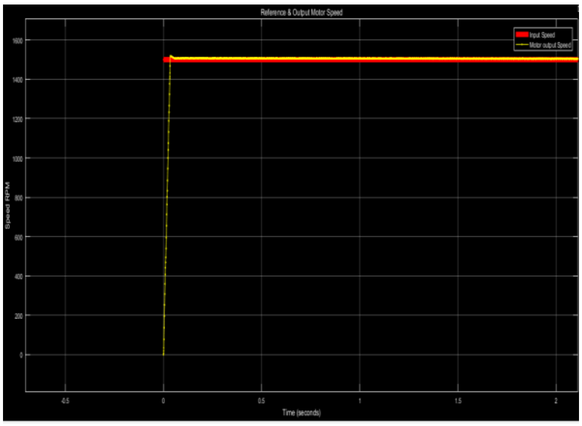

Fig.12 shows the delay on the output of the motor with reference step input when using the Ant Colony technique.

8 Future Works

The ACO and GA can be modified for future enhancement such that a new and updated research could and can be focused on each technique disadvantages in order to produce better solution by improving the effectiveness of getting the best solution and reducing its limitations. Research work has been carried out to get the maximum and optimal values for PID controller parameters automatically using GA and ACO artificial optimization techniques as found on figures 9, 10, 11 and 12. Simulation results demonstrate that the tuning methods proposed and used as found on both figures 10 and 12 have a better control performance compared with the conventional ones as found on figure 8 also they have a better steady state response, rise time, settling time, overshoot and a robust control with variable loads as found on table 5.

Table 5
Comparison between the conventional control method (PID) and Heuristic Intelligent artificial methods (GA & ACO)

Tuning Method	PID Parameters			Dynamic Performance Specifications		
ZN	Kp Proportional gain	Ki Integral gain	Kd Derivative gain	Tr Rise time	Ts Settling time	Mp Peak overshoot
	0.95	0.05	0.01	0.070 sec	0.10 sec	1.53 %
GA	282.9	26	2.346	0.060 Sec	0.080 Sec	0.53%
ACO	268.8579	65.86439	0.01	0.036 Sec	0.037 sec	1.2%

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