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Qualitative Analysis of Stochastic Operations in Dual Axis Solar Tracking Environment

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Abstract

This research reviews the major contributions to the solar tracking field from a normal mechanical turning single axis to double axis which continuously evolve to the application of different evolutional algorithm's methods in optimizing solar tracking system. This literature review shows that heuristic methods have outperformed other classical approaches in maximizing the performance of solar tracking system. Detailed discussion on solar tracker together with the evolution of artificial intelligent methods such as genetic algorithm simulated annealing and threshold acceptance is materialised in this paper. In this research, genetic algorithm has been identified with its superiority in searching for optimal solution due to its robustness. Both software and hardware have been developed to simulate related genetic algorithm results compared to different optimization search. Simulation results demonstrated the ability of GA to converge to best fitness value at 0.98021 with the axles X and Y pointing to +3 degree and +2 degree respectively in relation to sun's position compared to simulated annealing and threshold acceptance.

Key words: Genetic algorithm, solar tracking, simulated annealing, threshold acceptance.

Introduction

Stochastic optimization (SO) methods are optimization algorithms which incorporate probabilistic elements either in the problem data which includes the objective function, the constraints or in the algorithm itself through random parameter values or random choices[1]. The search space of a problem is determined by its structure. For instance, we can perceive the search space as the set of all feasible and non-feasible candidate solutions. Therefore, a point in this search space is a candidate solution to the problem, be it feasible or otherwise.

Hill climbing, simulated annealing[2-4], Tabu Search[5-7], Neural Networks[8-10] and Genetic Algorithms[11-13] are just some stochastic search algorithms that attempt to contain the combinatorial explosion problem at the price of completeness. Hill climbing, simulated annealing, tabu search and neural networks have the same characteristic of maintaining only one solution throughout the search process. This solution is repeatedly improved by exploration of the search space, making small beneficial jumps in the search space.

There are two types of solar tracker mounting available in the research field which is single axis solar tracker and double axis solar tracker. Single axis solar trackers can either have a horizontal or a vertical axle. The horizontal type is used in tropical regions where the sun rises very high at noon but the days are short. The vertical type is used in high latitudes where the sun does not rise high but summer days can be very long. The single axis tracking system is the simplest solution and the most common method used in the research industry[14]. Double axis solar tracker normally uses horizontal and vertical axles. The dual axis tracking system is used for concentrating a solar reflector toward the concentrator on heliostat systems. By tracking the sun, the efficiency of the solar panels can be increased by 30-40%.

Literature review shows that only few researchers cited some finding regarding GA based solar tracking system as follow:
Khlaichom[15] applied a closed loop control using genetic algorithm (GA) method for a two-axis (altitude over azimuth) solar tracking system. A sensor fabricated from poly crystalline solar cell converts solar radiation to voltage. In their algorithm, the decoder and counter receive signals from an optical encoder and convert it to the corresponding degree-position of the axle turns. Data is then transferred to a PC via an interface card for maximum tracking. The system tracks the sun with $+/-10^0$ in both axes. The tests and analysis explained that the solar tracking system using GA increases output voltage to 7.084% in comparison to non GA method.

Syamsiah Mashohor[16] evaluated the best combination of GA parameters to optimize solar tracking system for PV panels in terms of azimuth angle and tilt angle. Simulation results demonstrated the ability of the proposed GA system to search for optimal panel positions in term of consistency and convergence properties. It also proved the ability of the GA-Solar to adapt to different environmental conditions and successfully track sun positions in finding the maximum power by precisely orienting the PV panels.

However, recent researches for GA based solar tracking system are based on the traditional GA algorithm structure which is composed of four key processing which are initialization, evaluation, selection and recombination. Anyhow, most population-based, reproductive, optimization algorithms such as genetic algorithms had a critical problem called premature convergence problem[17-19].

This problem occurs when highly fit parents in a population pool breed many similar offspring in the early evolution time. If the highly fit individuals are in local optima areas, then newly generated offspring from the parents are near the local optima areas[20].

In this coming methodology and result section, an explanation of optimization variation for multiple heuristic approaches will be studied and shows the best genetic operations in preventing premature convergence problem.

Material and Methods

Few stochastic operations are used in this research to discuss optimization characteristic applied in solar tracking as shown below: i. Genetic Algorithm, ii. Simulated Annealing, iii. Threshold Acceptance

Genetic Algorithm: Genetic Algorithm is an adaptive search which is used for multi-objective optimization[21]. Optimization design has always been of great importance in solving real industry issue[22]. GA has better performance if it is compared to conventional search method which is applied to a single point in the search space. The point-to-point approach in the conventional search can result in danger of falling into local optima. GA on the other hand performs a multiple directional search by maintaining a population of potential solutions which is the result of data encoding.

The population-to-population approach attempts to make the search escape from the local optima which could lead to desirable global optima as shown in figure-1

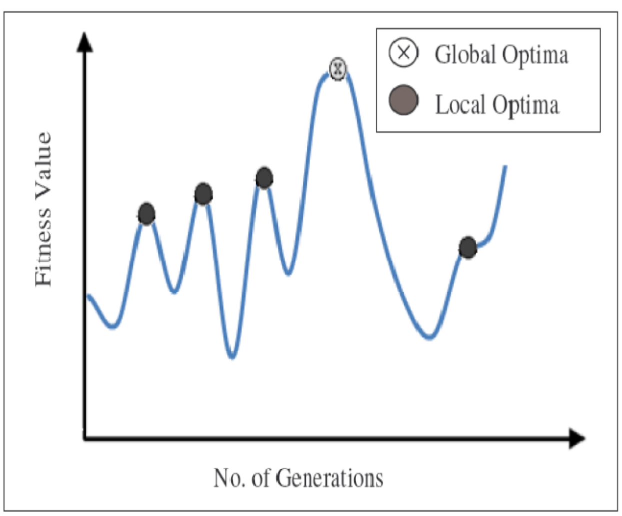

Figure-1
Global optima and local optima[23]

Simulated Annealing: SA is a global optimization technique that crosses over the search space by testing random mutations on an individual solution. A mutation with increasing fitness will be adopted while decreasing fitness value will be selected based on probability difference in fitness and decreasing temperature parameter. For example, It is accepted if the motion is moved to higher point. Otherwise, it is accepted only with probability *p(t)*, where t is time. The function *p(t)* begins close to 1 but gradually reduces towards zero, the analogy being with the cooling of a solid.

Initially, any moves are accepted but as the "temperature" reduces, the probability of accepting a negative move is lowered. Negative moves are essential sometimes if a local maximum is to be escaped. Likewise, too many negative moves would simply lead us away from the maximum point. Simulated annealing only deals with one candidate solution at a time and does not build up an overall picture of the search space. No information is saved from previous moves to guide the selection of new moves.

Threshold Acceptance: Threshold acceptance uses a similar approach like simulated annealing but instead of accepting new points that raise the objective with a certain probability, it accepts all new points below a fixed threshold. The threshold is then systematically lowered, just as the temperature is lowered in an annealing schedule. This is to avoid the probabilistic acceptance calculations of simulated annealing where it may locate an optimizer faster than simulated annealing.

Problem Formulation: The problem formulation is given to optimize the tracking angle based on the highest intensity location. End users could define X-Y tuning parameters, X-Y coefficients, generation number, mutation rate and crossover rate using the developed visual basic interface before running genetic algorithm program. The solar tracker XY axles will always move in random angles from minimum zero degree to maximum forty five degree in each positive or negative direction. Developed fitness function is as shown below:

$$K(x_i)= (1/ (\exp (A*(x_i)\wedge\alpha))) ,i = 0, i +1\ldots n$$
$$F(y_i)=(1/ (\exp (C*(y_i)\wedge \beta))), i = 0, i +1\ldots n$$
$$G(z_i) =[K(x_i) * F(y_i)] , i = 0, i +1\ldots n \qquad (1)$$

Where, x_i = X tracker rotation degree (°), y_i = Y tracker rotation degree (°), A = Controlling Parameter for X tracker, α = Tuning Parameter for X tracker, C= Controlling Parameter for Y tracker, β = Tuning Parameter for Y tracker, z_i = X-Y tracker rotation degree (°), n = Number of generation

Simulation: The simulation has been carried out using the standard testing parameters for different stochastic operations as shown in table-1, table-2 and table- 3.

Table-1
GA parameters for genetic algorithm

Simulation Parameter	Value
Maximum Generation	50
Population size, p_s	50
Chromosome length	8
Selection Method	Roulette Wheel
Crossover Rate, p_c	0.8
Mutation Rate, p_m	0.025

Table-2
Simulated annealing parameters

Simulation Parameter	Value
Maximum Iteration	50
Population size, p_s	50
Chromosome length	8
Temperature Update Function	Exponential Temperature Update

Table-3
Threshold acceptance parameters

Simulation Parameter	Value
Maximum Iteration	50
Population size, p_s	50
Chromosome length	8
Temperature Update Function	Exponential Temperature Update

Results and Discussion

For this result and discussion section, both software and hardware package have been developed to test its functionality according to parameters in table-1, table-2 and table-3. Dual Axis XY solar tracking prototype has been designed and developed to interface with visual basic simulator via RS232 communication protocol. Gathered results will be shown as below:

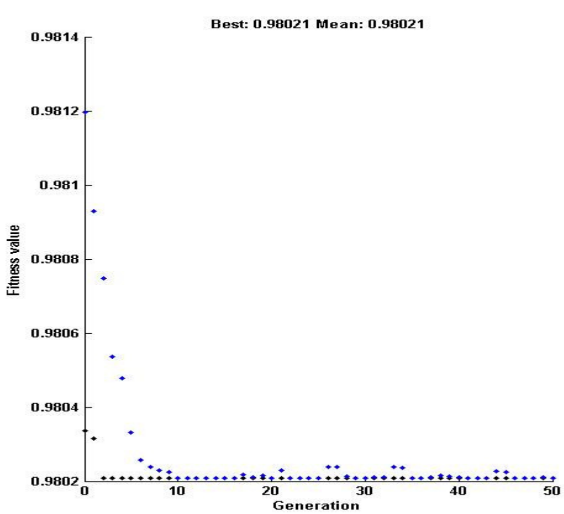

Figure- 2
Best fitness value- 0.98021 using genetic algorithm

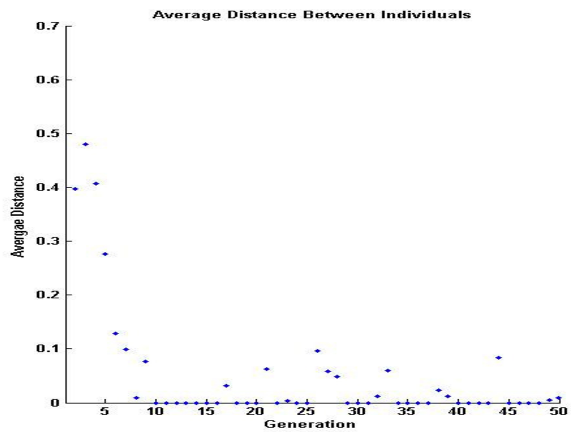

Figure -3
Average distance between individuals in each generation using genetic algorithm

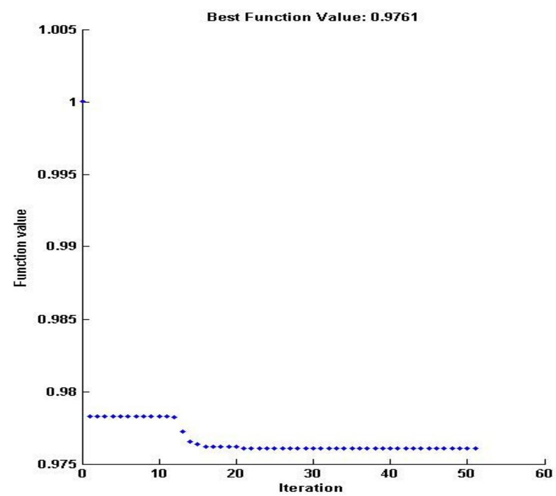

Figure- 4
Best fitness value- 0.9761 using simulated annealing

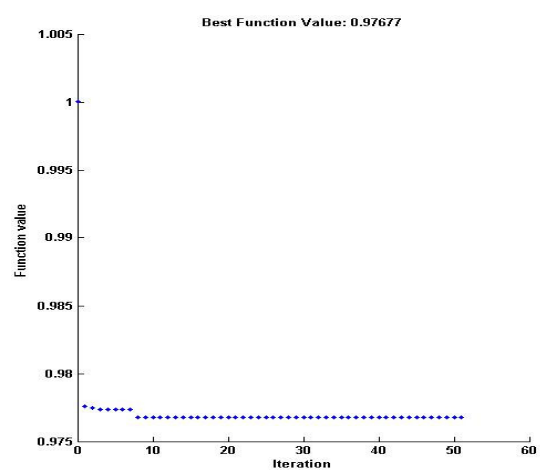

Figure- 5
Best fitness value- 0.97677 using threshold acceptance

Figure-1 indicates that convergence starts at 11th generation onwards where the best fitness value recorded is 0.98021. From figure-3, it could be observed that initial generation involves more activities in searching for optimum value which causes a larger distance split among each individual from 0th generation till 11th generation. Once the search space is narrowed down towards achieving global optimum value, distance between individuals is getting smaller and convergence moves to the vicinity of global minimum value which is 11th generation onwards till 50th generation as indicated in figure-3.

Figure-4 indicates that convergence starts at 21st generation onwards where the best fitness value recorded is 0.9761. It could be observed that convergence speed is much slower as compared to genetic algorithm operation which starts at 11th generation onwards. This is probably due to GA has better performance if it is compared to conventional search method such as SA which is applied to a single point in the search space. The point-to-point approach in the conventional search can result in danger of falling into local optima where we could observe that there is no much search space activities happen from 0 generation till 12th generation.

As for figure- 5, it indicates that convergence starts at 8th generation onwards where the best fitness value recorded is 0.97677 which is slightly better than simulated annealing as complied with theoretical explanation. Anyhow, there are no much robust searching activities happen in threshold acceptance as well since fitness value is nearly constant from 0th generation till 7th generation.

Comparison: From the result that we obtained, summary of optimal fitness value for various stochastic operations are as shown below:

Table-4
Comparison of fitness value among stochastic operations

Stochastic Operations	Fitness Value	Axle X Angle (°)	Axle Y Angle (°)
Genetic Algorithm	0.98021	+3	+2
Simulated Annealing	0.97610	+10	+11
Threshold Acceptance	0.97677	+8	+7

From table-4, it could be concluded that genetic algorithm is robust and is good at finding solution to a problem as compared to simulated annealing and threshold acceptance. It also complies with the theoretical result where simulated annealing and threshold acceptance are easily trapped into local optima as compared to genetic algorithm. This could be verified through its simulation result on the fitness value versus generation graph where genetic algorithm command the highest fitness value which is 0.98021 with axle XY angles at +3 and +2 degree as shown in figure-6. This fitness value is approximate to the optimal value at fitness value 1 with axles XY pointing to 0 degree in relation to sun position. This optimal value is verified through its manually measured intensity voltage at 10.05V with optimum angles XY point to 0 degree in relation to sun position.

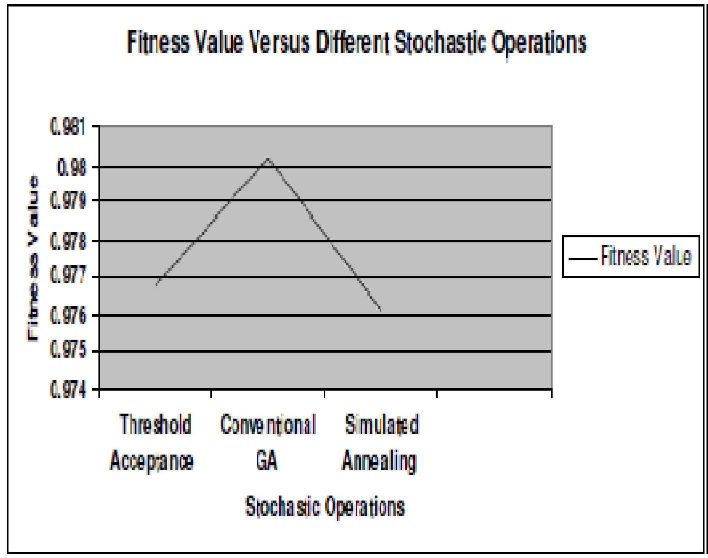

Figure-6
Fitness value versus different stochastic operations

Conclusion

In conclusion, it could be summarized that genetic algorithm produces better fitness value with the optimum angles which approximate the highest solar intensity voltage as compared to other stochastic operations. Genetic algorithm commands highest fitness value 0.98027 with axle XY angles pointing to +3 and +2 degree in relation to sun position. It could be concluded that this experiment is successfully producing practical result which is verified by theoretical understanding.

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