Optimization Techniques for Multi Cooperative Systems MCTR 1021
Mechatronics Engineering
Faculty of Engineering and Materials Science
German University in Cairo

Optimization of Solar Panel Installation in Homes

By

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Chapter 1

Introduction

Renewable energy systems have always seemed the solution for the energy problems available. Not only renewable energy is a clean source of energy with little to no emissions but also it is cheaper and most efficient type of energy. Being too good of an option, the number of homes installing solar systems and converting away from the inefficient conventional fossil fuel systems increased [1].

Chapter 2

Literature Review

[2] presents methods for sizing solar systems and electrical energy storage systems from an economic perspective. The most important finding suggested that it is preferable to size the storage first so that photovoltaic (PV) sizing can depend on the chosen storage size. The size model was tested in Finland, but it can be used to other contexts provided that the regional electricity price structures are taken into consideration. [3] describes a concise model for off-grid PV system sizing that takes into account the loss of load probability (LOLP). In relation to the specified value of loss of load probability, load curve, and period where optimal size will be calculated. The model provides the ideal system size in terms of the necessary number of PV modules, peak power, number of batteries, and cost of system. For the city of Osijek, the model is used to determine the ideal size of the off-grid PV installation. The best system size is established using the measured load curve for values of the loss of load probability ranging from 0.00 to 0.10 in steps of 0.01, as well as for 0.15. Further increase in LOLP value does not have justification in substantial investment cost reduction. The optimal size and operation of home solar PV systems combined with battery units are discussed in [4] using a two-stage adaptive robust optimization (ARO). User-defined bounded intervals with polyhedral uncertainty sets are used to describe the uncertainties of PV generation and load. The suggested approach establishes the ideal PV-battery system size while reducing operational costs in the event of worst-case realization of uncertainties. With 10% uncertainty in the parameters, 30 was discovered to be the ideal robustness level. Therefore, if uncertainties develop, these resilient settings result in the lowest value of additional expenditures, which increases the benefits to the PV-battery owner. The results in [5] show that energy consumption and cost of electricity are reduced significantly. Optimizing the running cost and cost of installation is an integral role to convert to such a system. To reduce the operating expenses of a model PV based micro grid, a backup power generation system is an essential component of micro grids, since a significant portion of the power generated is weather dependent. By enabling dependable and cost-effective resource use, optimization approaches allow for the justification of micro grid

investment costs. By fusing clever optimization algorithms with adaptive strategies, the study of multi-objective optimization problems demonstrates greater performance. In order to reduce energy costs, peak-to-average ratios (PAR), and peak load demands, users can manage and control the consumption patterns of their appliances through the use of smart grid technology. In [6], a general architecture of the home energy management system (HEMS) is designed in context of the smart grid with a novel scheduling mechanism for residential customers that is restricted and multi-restricted. The initial goal is reducing monthly electricity costs as much as possible. Minimization of the PAR and maximum peak load demand are the second and third goals, respectively. Due to the non-convex character of the issue, two potent binary type metaheuristic optimization algorithms—Grey wolf optimization (GWO) and particle swarm optimization (PSO)—are used to efficiently solve it. The results show that energy consumption and cost of electricity are reduced significantly. In order to reduce the oscillations around the global maximum peak power (GMPP), a new metaheuristic technique called the opposition based equilibrium optimizer (OBEO) algorithm is employed in [7]. The success of this method can be determined by comparing it to other methods like SSA, GWO, and PO. The OBEO method outperforms all other methods, according to the results of the simulation. The gains demonstrated by the suggested technique include an increase in PV system performance, quick and accurate tracking, and very little oscillation. However, [8] was inspired by the idea of smart home systems and developed an optimization method to organize energy needs, minimize cost and maximize efficiency. The appliances are powered by a combination of grid electricity and solar energy that is stored in the storage units. An optimization engine for Integer Linear Programming-based Home Energy Management (ILPHEM) is used in the suggested management system. Based on updated real-time input data for the minimum household payment, ILPHEM schedules appliance requests and storage utilization. To avoid partial shading, [9] discussed a geographic information systems (GIS) planning system for rooftops. The goal of this work was to create a reinforcement learning (RL) model based on geographic information systems GIS for the best design of rooftop photovoltaic systems while taking into account the unpredictability of future situations during the course of building lifespans. In order to do this, an RL model was created to optimize the economic return of the rooftop PV installation in various locations and potential future scenarios. GIS was also used to establish the spatial data for the rooftop PV installation. [10] discussed some variables that were crucial in the installation phase. Direct normal incident (DNI), direct horizontal incident (DHI), global horizontal incident (GHI), ambient temperature, wind speed, and ground albedo are the primary variables that affect the performance of solar panels. All of these variables were retrieved from the National Renewable Energy Laboratory (NREL) database, which spans more than 20 years. Investigating the three U.S. locales with various climatic conditions allows us to evaluate the accuracy of the optimization platform used in this study [9]. In [11], one of the most important factors was discussed which is the temperature of the solar panel. Solar panels generate electricity from light not heat. High temperatures degrade the solar panels efficiency up to 25%. Optimizing the temperature of the solar panel will yield to more energy and hence better efficiency.

Chapter 3

Methodology

3.1 Problem Formulation

Objective1	Variables	Constraints
Maximizing the energy output of a PV power plant Objective Function: $Energy = \sum_{i=1}^{m}(Power_i * n_i) * 0.9$	The power output of the different types of solar panels installed: Power(watts) The number of each solar panel type installed: Number of panels type(n_i) Maximum loss in efficiency allowed due to temperature: 0.9	The power output should be maximized to at least reach an acceptable power output that is constrained by the minimum power requirements to operate all essential electrical devices

The cost is the most important problem when converting to solar energy. Many people just are afraid to switch to solar energy when they look at the large initial cost of conversion. However, prices of electricity rise with time as inflation occurs and so do the bills.

Objective2	Variables	Constraints
Minimizing Cost $Cost = \sum_{i=1}^{m}(C_i * n_i)$	The number of each solar panel type installed: Number of panels type(n_i) The cost of each solar panel type: C_i	The cost should be less than the budget provided by the user as an input

Objective3	Variables	Constraints
Minimizing area containing no solar panels. $AreaWasted = \frac{A_0 - \sum_{i=1}^{m}(n_i * A_i)}{A_0}$	The number of each solar panel type installed: Number of panels type(n_i) Area of roof A_0 The area of the panel of type A_i	the value of the percentage of area wasted value should be contained to be less than 0.1 (10%)

The equation subtracts the area of solar panels installed from the overall available area and is then divided by the overall area to obtain a percentage of the area wasted.

Solar panels produce energy from light, not temperature. Therefore, the performance of a solar panel varies according to its temperature. The optimum temperature at which maximum output from the panel is generated is found to be 25°C. Monthly, we see different regional maximum temperatures in each region. Since the installation takes place in Egypt, no problems may be faced during the winter period as per temperature (disregarding shady winter days). We target to choose solar panels that will remain as close to the optimum 25°C. Each solar panel has a certain value specification called the temperature coefficient. The temperature coefficient describes the percentage decrease in the value of the maximum power generated by the panel corresponding to a 1°C increase in the temperature of the panel. The regional maximum temperature describes the maximum ambient temperature in which the panel operates. But this is different from the temperature of the panel itself which depends on multiple factors. According to the mounting of the panels on the roof, it is said that the temperature of panels directly mounted on the roof gets 15 percent hotter than mounting with at least a 150 mm air gap. As a result, there are multiple cooling methods available in the market which include both air- and water-cooling systems. However, the cost should not increase so an equation was developed that generates the types of panels that will be appropriate.

Objective4	Variables	Constraints
Minimizing the temperature of solar panels $EfficiencyDrop = \sum_{i=1}^{m} \frac{T_r+20-25*M_T}{m}$	The ambient temperature of the regionT_r The temperature coefficient of the panels of its type M_T	Given the assumption that a maximum 10 percent loss in power is generally accepted[1][3] ,this will be the constraint governing whether the choice of panels acceptable.

The last constraint would be the number of types allowed to be installed, and in this case only 5 types will be allowed. $n_{type} <= 5$ Combining all objectives: $Objective = Cost + AreaWasted + Temperature - Power$

$$Objective = \sum_{i=1}^{m}(C_i*n_i)+\frac{A_0-\sum_{i=1}^{m}(n_i*A_i)}{A_0}+\sum_{i=1}^{m}\frac{T_r+20-25*M_T}{m}-\sum_{i=1}^{m}(Power_i*n_i)*0.9$$

3.2 Solution Representation

The solution for the optimization problem will be a combination of the different solar panels used (which may be multiple types), the quantity of each type, and the type used as a binary solution.

An example of a possible solution may be in the following form: 140 square meters of space. 40 of which will be tier 2 Panasonic 250-watt panels. 100 meters will consist of 200-watt tier 1 LG. Although this combination of panels has different wattage sizes and specifications, it will generate the highest possible power within the constrained cost, space, and temperature.

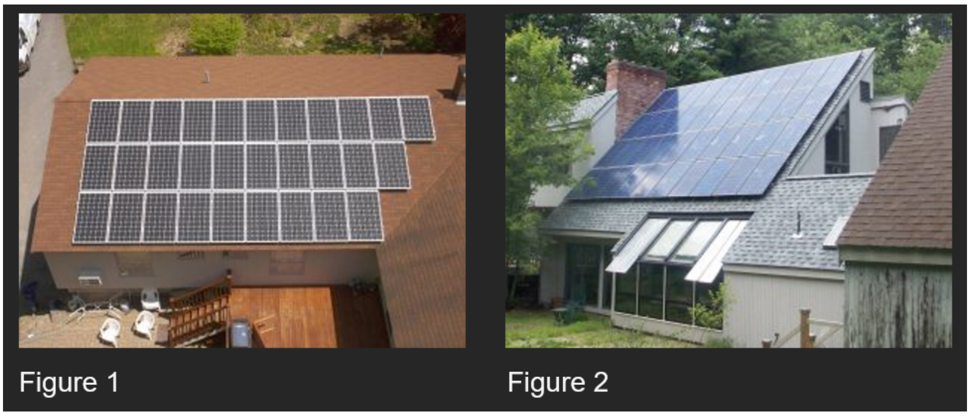


Figure 3.1: Solar Panel installation

The difference is clearly seen in the installation of solar systems in both houses as in figures 1 and 2. The house in figure 1 has a vertical column on the left that contains no panels aka wasted space. Meanwhile as seen in the house corresponding to figure 2 most space is used which results in an optimum alignment hence increasing the efficiency of the system.

3.3 Simulated Annealing (SA) Optimization Technique

3.3.1 SA Pseudocode

Figures/WhatsApp Image 2022-12-01 at 14.53.50.jpeg

Figure 3.2: SA Pseudo Code

The solution to our optimization problem consists of 2 arrays, solA and solB. solA is an arithmetic array containing the quantity of the panels used while solB is a binary array containing only 5 ones which decide which type of panels are to be used. Once multiplied together we obtain the final solution.

3.3.2 Case Studies

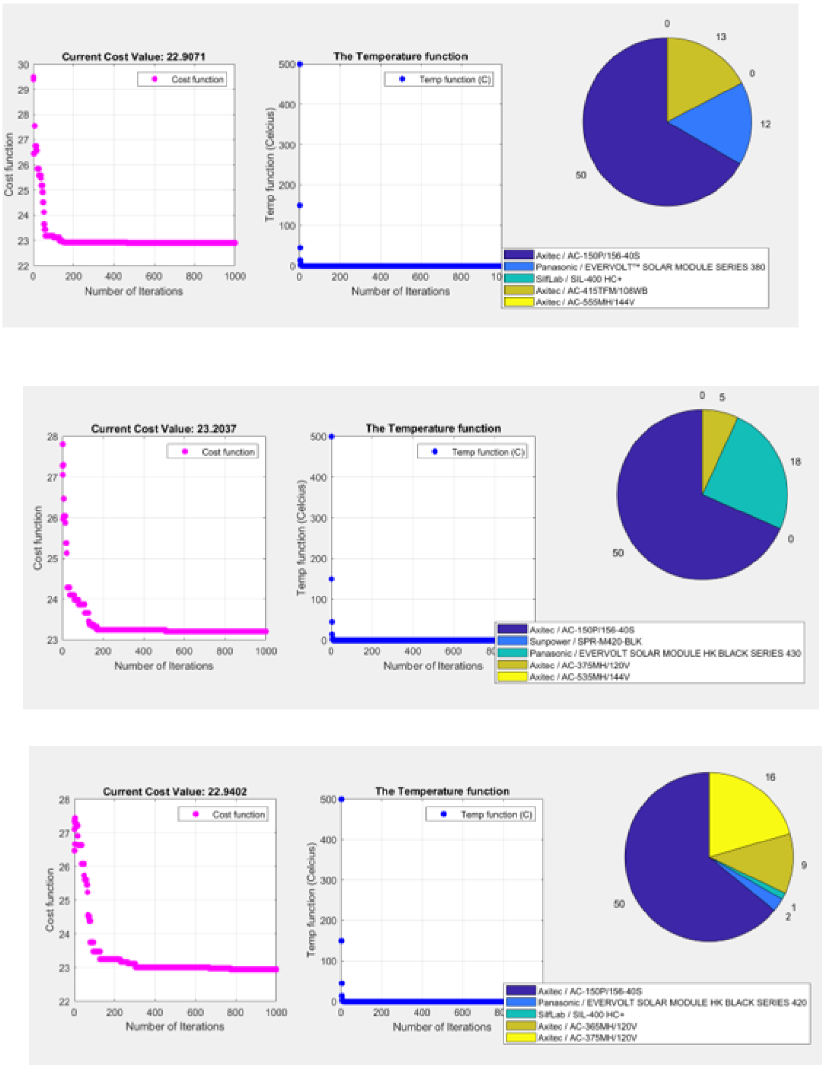


Figure 3.3: Case Study 1

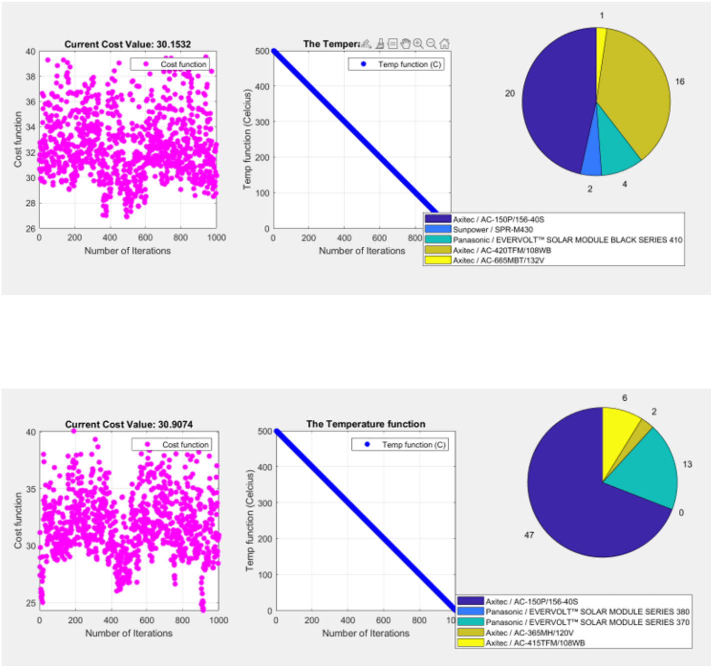


Figure 3.4: Case Study 1

The 5 previous figures (figures 3.3 and 3.4) are the results for 5 consecutive runs of the SA algorithm with the exact same inputs. The inputs were as follows: 35°C ambient temperature, area available was 150m, a budget of 25000, a power requirement of 5000 KW, 15% allowable energy loss and 10% allowable waste in area. For the previous inputs 2 runs were performed using linear cooling while 3 runs were performed using geometric cooling with alpha equal to 0.3. In the 2 linear cooling runs it is clear that the code does not converge as can be seen by the frequent spikes in the fitness value. This is due to the large area under the linear cooling curve which is translated to high exploration. This problem is resolved when we switch to a geometric cooling rate. Convergence is clear. In this run it was decided to go with a low value of alpha (0.3). This greatly favors exploitation however, getting stuck in a local minima is very likely. As the budget requirement was low compared to the area, we can see a similarity in the results where the Axitec /AC-150P/156-40S solar panels were chosen in high quantities due to their cheap price and hence making them more suitable for the low budget test case. All 5 runs are virtually identical however all the results are different, displaying the stochastic nature of the SA algorithm.

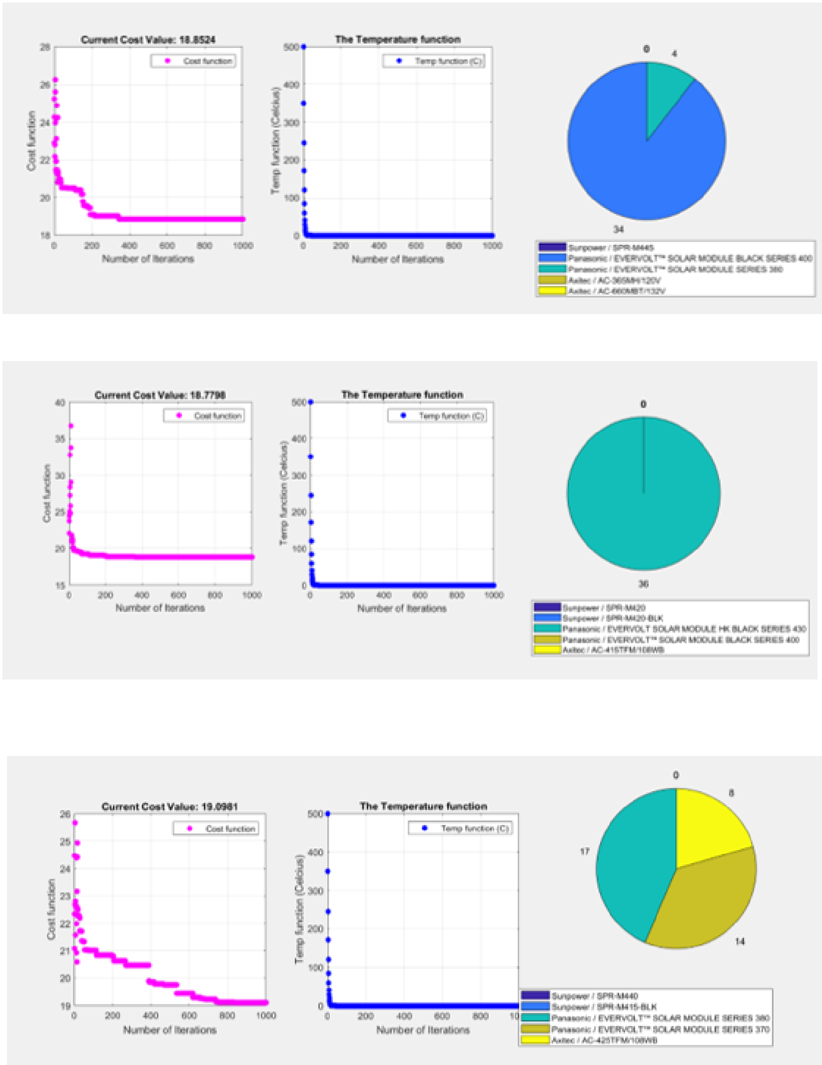


Figure 3.5: Case Study 2

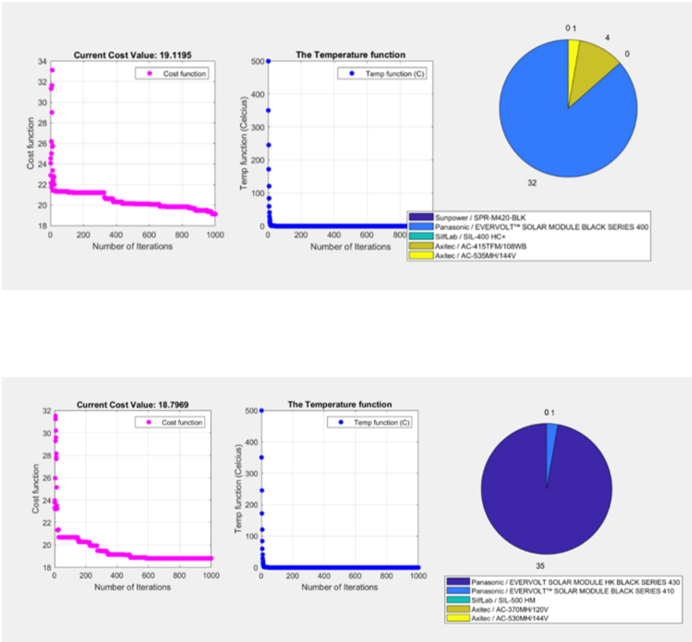


Figure 3.6: Case Study 2

In the previous graphs (figures 3.5 and 3.6), the inputs were as follows: 35°C ambient temperature, an area available was 70m squared, a power requirement of 4.5 KW, 15% allowable energy loss, and 10% allowable waste in the area. Using a geometric cooling rate and an initial temperature of 500, an initial cost of 40000$ was inputted. After running the code 5 times, it is shown that the Panasonic / EVERVOLT SOLAR MODULE HK BLACK SERIES 430 and Panasonic / EVERVOLT SOLAR MODULE HK BLACK SERIES 420, which are relatively expensive panels, were the most selected panels and in higher quantities than the other panels, which because of the high budget were not selected in high quantities. In the fourth test run, it can be observed that because of the high budget provided, only 1-panel type was selected out of the 5 that can be selected. The factors that determined the selection of this panel Panasonic / EVERVOLT SOLAR MODULE HK BLACK SERIES 380 were not dependent solely on the cost, but other factors like the power requirement. The choice of any Panasonic panel in the database has a very good temperature coefficient however that factor did not contribute to the choice. Also, there are more expensive panels with higher output power that were neglected because of the hard-constrain area of installation.

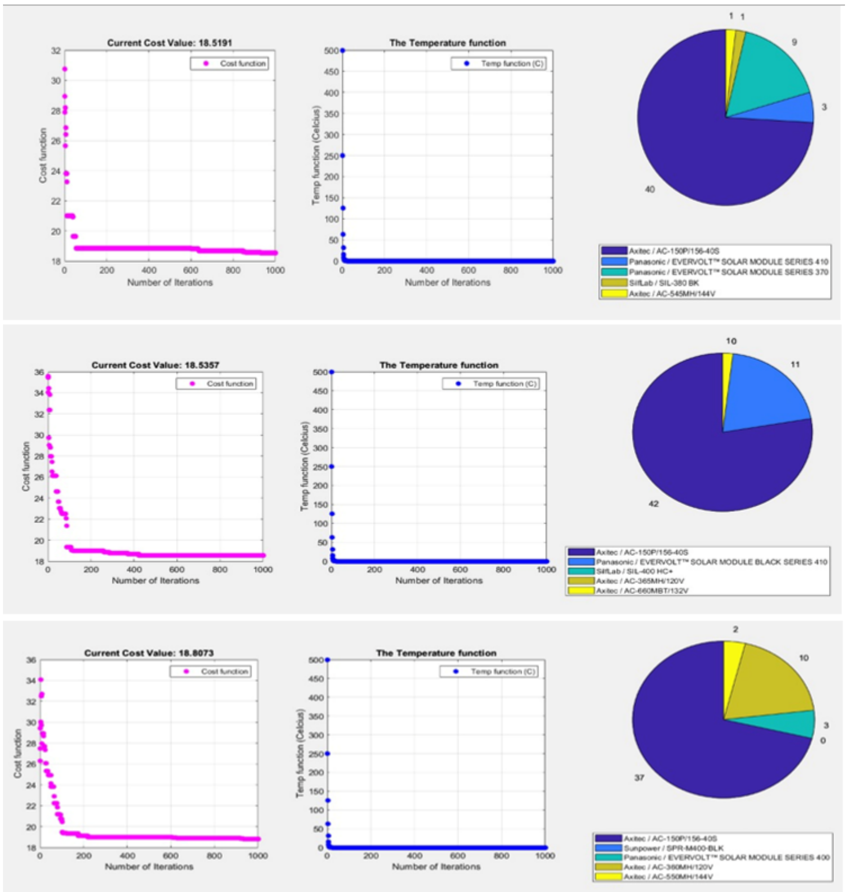


Figure 3.7: Case Study 3

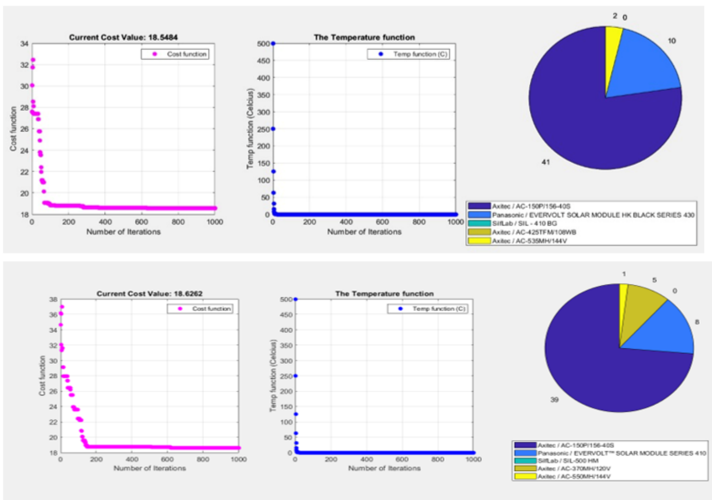


Figure 3.8: Case Study 3

The five previous runs of the SA algorithm (figures 3.7 and 3.8) were made by the same requirements. The ambient temperature of the system was 25 degrees Celsius. The area available for installation was 70 square meters. The power required from the system was 4.5 kilo watts. The budget of the installation was 15000 USD. The cooling rate used in these runs was geometric cooling rate with an alpha of 0.5. The results contained large numbers of cheap AX-ITEC 150P panels, because the low cost compared to other projects with similar power required and space provided. Also, meeting the relatively low energy requirement per area was easily attained using this cheap panel. The temperature coefficient didn't play a major role since the ambient temperature of the system is the same as the temperature at which most solar panels operate at maximum efficiency. A smaller alpha in geometric cooling makes the solution to exploit faster. As shown in the results the near optimum solution is reached by the 100th to 150th iteration.

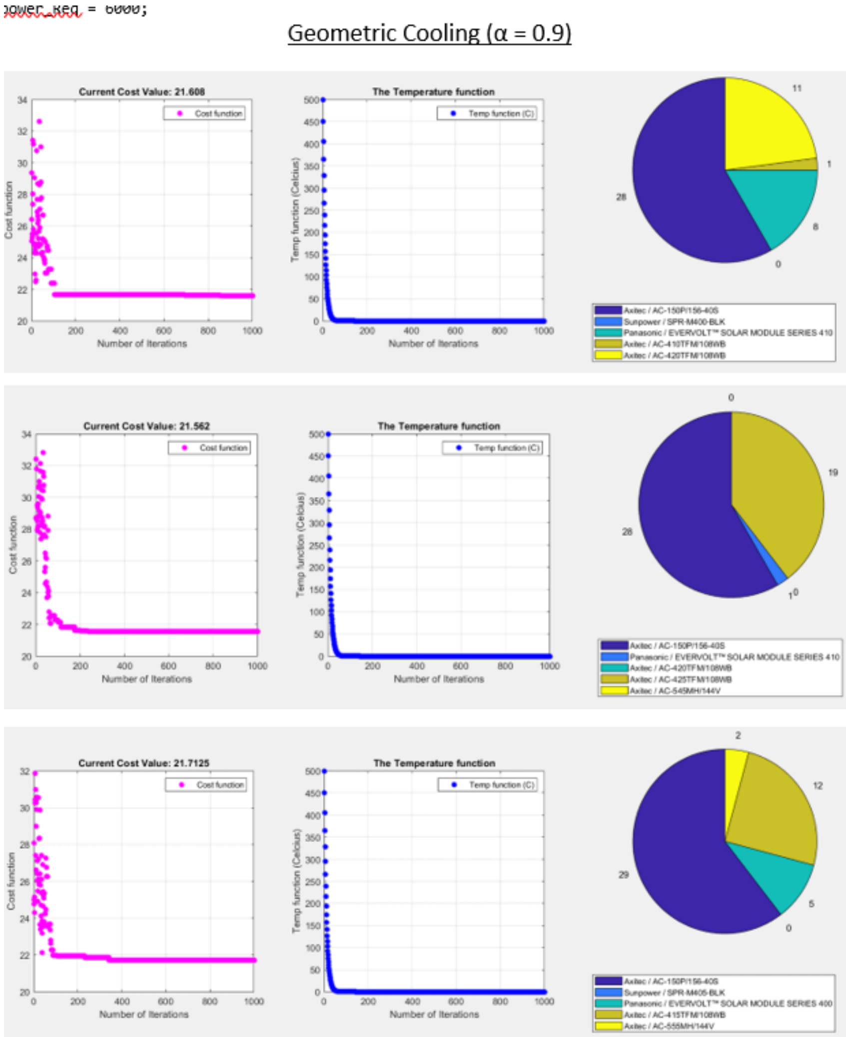


Figure 3.9: Case Study 4

Linear Cooling

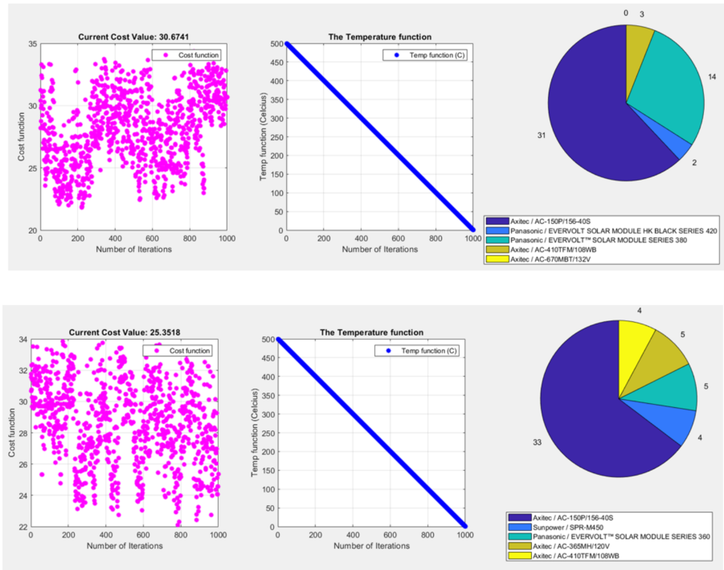


Figure 3.10: Case Study 4

The five previous runs (figures 3.9 and 3.10) were made on the same set of inputs. The inputs were an available area of 70 square meters, a budget of 20000 USD, minimum required power of 6kW, an ambient temperature of 35°C, allowable area loss of 15%, and allowable power loss of 10%. The first 3 runs were performed using geometric cooling with = 0.9, and the remaining 2 runs were performed by using linear cooling. As observed from the previous results, “Axitec / AC-150P/156-40S” is the most chosen solar panel type, because it is the cheapest and least area consuming panel, although not generating much power. For this case study, Panasonic / EVERVOLT™ SOLAR MODULE SERIES 380, Axitec / AC-415TFM/108WB, Axitec / AC-420TFM/108WB, and Axitec / AC-425TFM/108WB were chosen, for generating high power for a reasonable low cost.

3.3.3 SA Literature Comparison

Power	Cost range	Area m2
2 kW	$5,060 – $6,300	13
3 kW	$7,590 – $9,540	19
4 kW	$10,120 – $12,600	25
5 kW	$12,650 – $15,750	30
6 kW	$15,180 – $18,900	38
7 kW	$17,710 – $22,050	44
8 kW	$20,240 – $25,200	50
9 kW	$25,300 – $31,500	62
10 kW	$30,360 – $37,80	75

Figure 3.11: Literature Cases

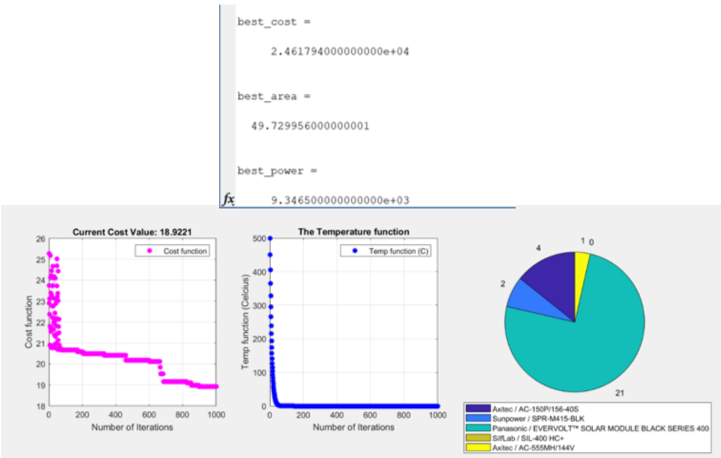


Figure 3.12: Literature Case 1

Testing Inputs from the Literature Review (figure **??**): Using an ambient temperature equal to 25, power equal to 7KW, a budget of 26,200$, an average area of 50 square meters, 15% allowable energy loss, and 10% allowable waste in the area. The result showed a saving of 590$, 0.271 square meters, and excess power equal to 2.340 KW.

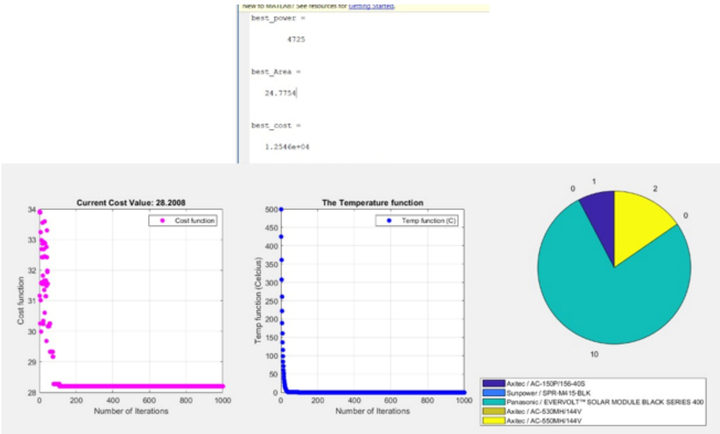


Figure 3.13: Literature Case 2

The inputs of this run (figure 3.13) of the SA optimization algorithm are real life values that we aim to optimize and improve upon. The power requirement was 4KW. The ambient temperature was 25 degrees Celsius. The budget for this application is 12600 USD. The solution generated better results than required within the same area. The power generated was 4.8kw. The cost was 12550 usd. So within the constrained the cost decreased and the power output increased. The panels used in this solution are Axitec / AC-150P/156-40S (1), Axitec / AC-550MH/144V (2), and Panasonic/ EVERVOLT SOLAR MODULE BLACK SERIES 400 (10)

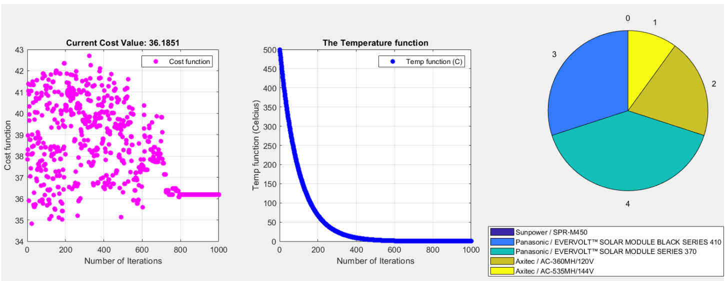


Figure 3.14: Literature Case 3

Testing the inputs from the literature case study for the SA algorithm which are: the required power is 3kW, the budget is 9540 USD, the area is 19 square meters, and the ambient temperature is 25 degrees Celsius. The choice of the Panasonic and Axitec solar panel types were the best choice to achieve the required power.

3.4 Genetic Algorithm (GA) Optimization Technique

```
Decision Variables: Cost,Power,Cof,Area
Objective function: f(x)
Initialize: num_Gen,Pop_size,Pe,Pc,Pe,Best_sol,sol_initA,sol_initB

for i =1 to Pop_size:
        While sol_init not feasible:
                Obtain sol_initA(i) and sol_initB(i)
                Obtain fitness
                Check and update feasibility
for i = 1 to num_Gen:
        for j=1 to Pe*Pop_size (number of elites):
                old elites survive to the new generation: Gen_newA(j) = Gen_oldA(j)
                                                          Gen_newB(j) = Gen_oldB(j)

        for j = pe*Pop_size +1 to (Pe+Pc)*Pop_size (number of cross-overs):
                While solution not feasible:
                        Select to Random Parent from old generation: Parent1, Parent2
                        Generate 2 new children for arithmetic sol: Gen_newA(j)=α*parent1(j) +
                        (1-α)*parent2(j)
                        Generate 2 new children for binary sol: Gen_newB(j) =1 point cross-over for
                        parents
                        Check and update feasibility

        for j = (Pe+Pc)*Pop_size+1 to Pop_size (number of mutants):
                While solution not feasible:
                        Generate new arithmetic mutant member: Gen_newA(j) = Gen_oldA(j) + Noise
                        Generate new Binary mutant member: Bit swapping
                        Check and update feasibility
        Plot results and visulisation
Output Best_Sol
```

Figure 3.15: GA Pseudo Code

3.4.1 GA Case Studies

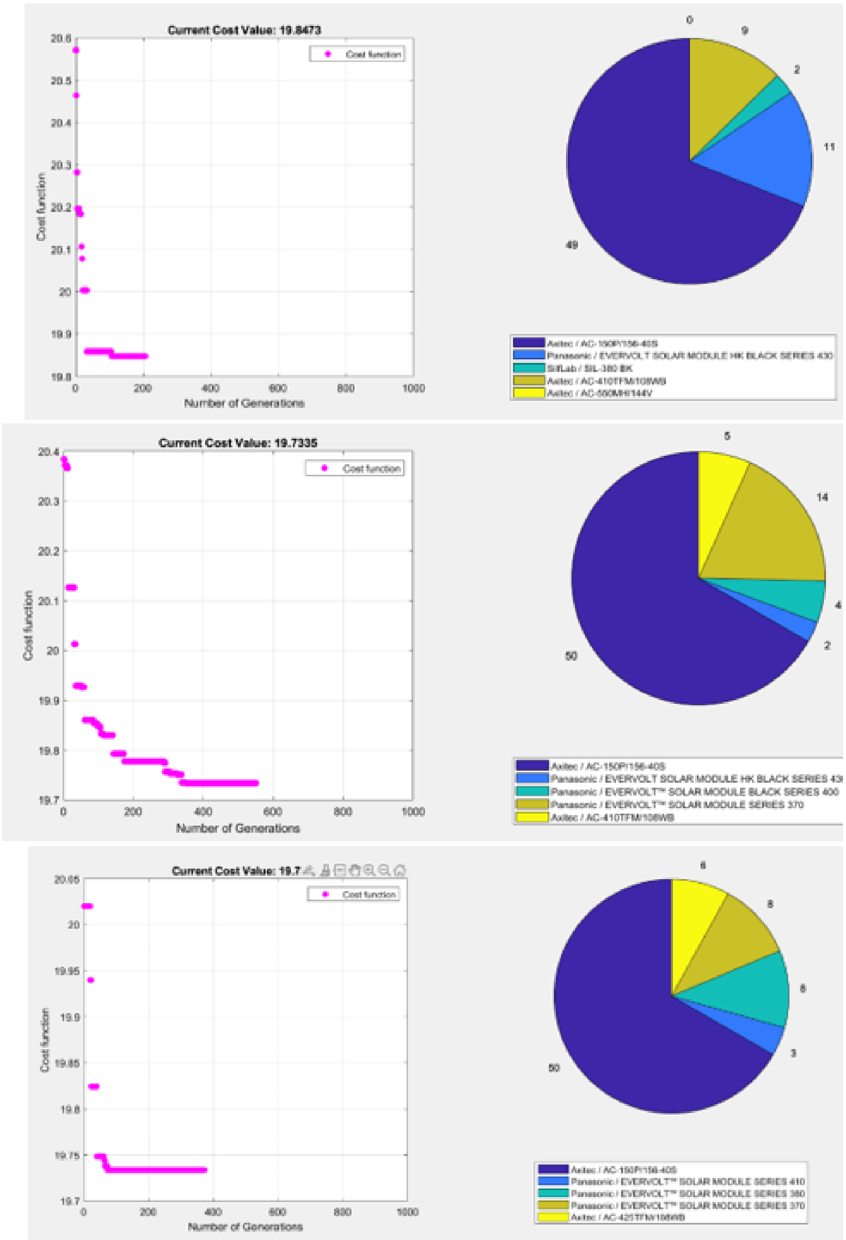


Figure 3.16: Case Study 1

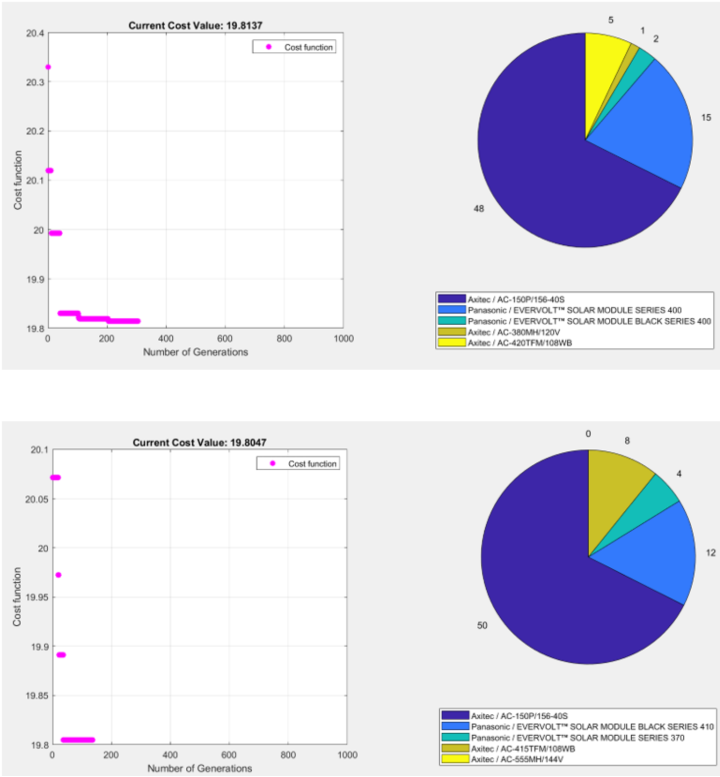


Figure 3.17: Case Study 1

These are 5 consecutive runs (figures 3.16 and 3.17) for the same input with an ambient temperature of 35°C, area available 110 meters squared, a budget of 25000, power required of 10KW, allowable area waste 10% and allowable 15%. The elite ratio used is 0.1, cross-over ratio 0.8, and mutation ratio of 0.1. Due to the low ratio of mutation exploration is limited. The high cross-over allows exploitation around the previous solutions. Due to the low budget an high quantity of Axitec /AC-150P/156-40S solar panels are used. The stopping criteria was experimented with where the first two runs were terminated after no improvement in the best solution after 100 iterations. The 2nd two runs had experimenting criteria had a stopping criteria of 200 similar results while the result for the last run showed a stopping criteria of 300 similar best solutions. The algorithm was edited to stop iterating when the cost function stays the same for 100 iterations.

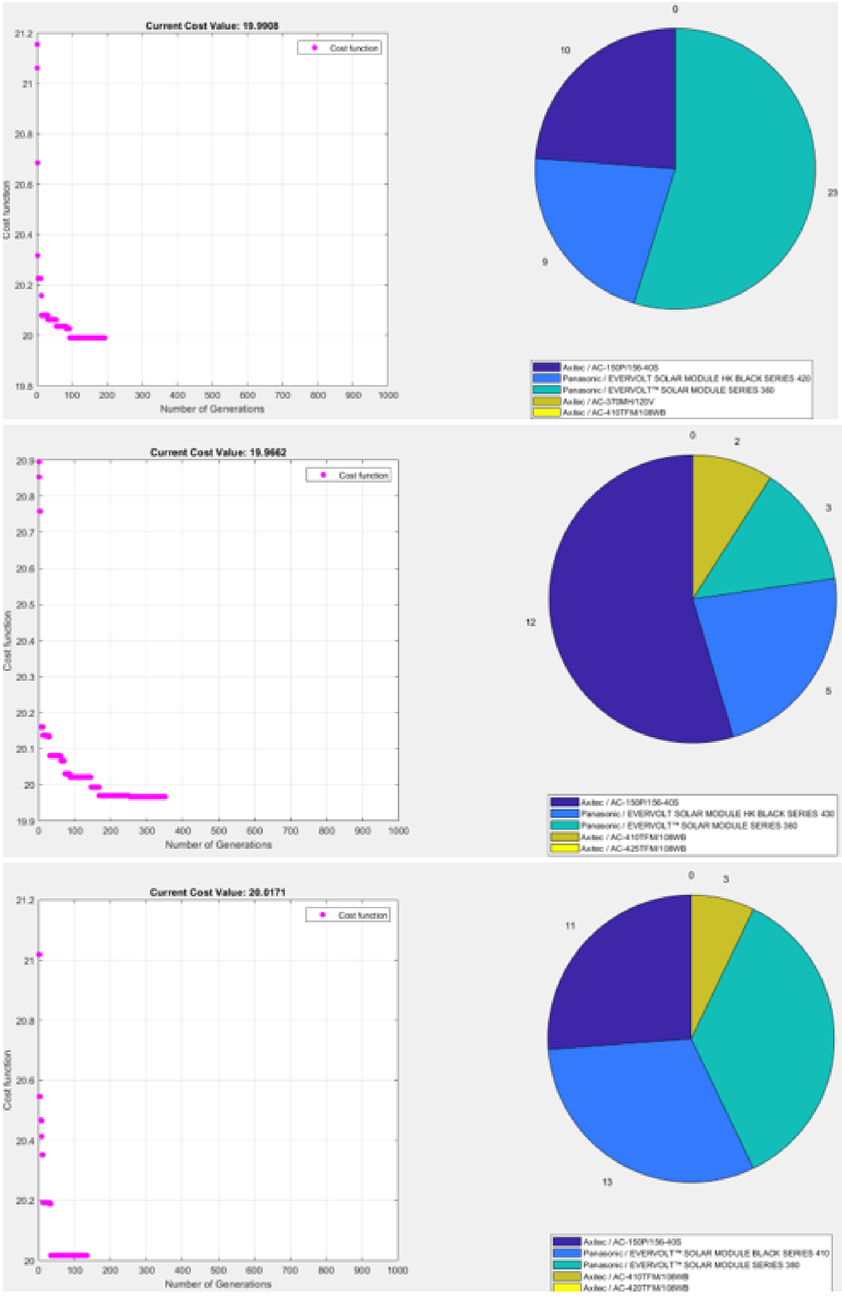


Figure 3.18: Case Study 2

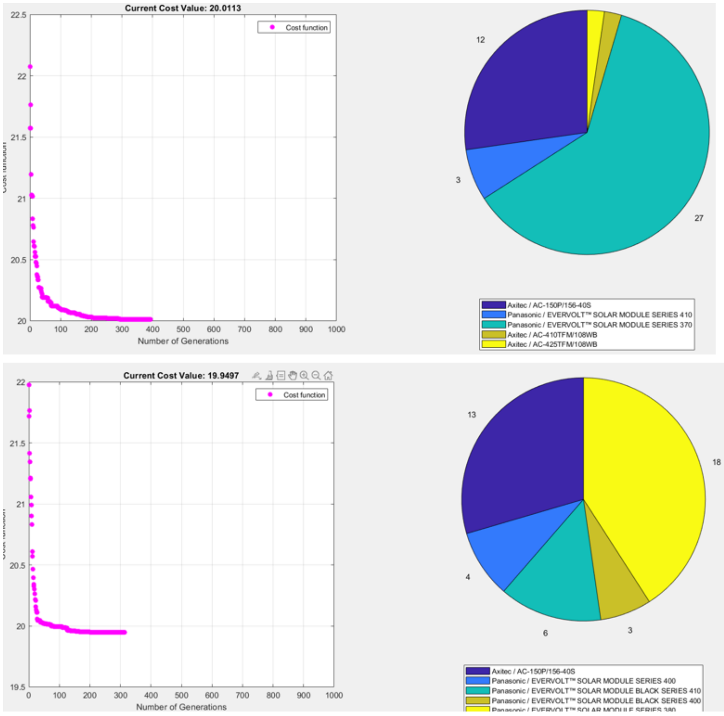


Figure 3.19: Case Study 2

The five previous runs (figures 3.32 and 3.19) were made on the same set of inputs. The inputs were an available area of 70 square meters, a budget of 20000 USD, minimum required power of 6kW, an ambient temperature of 35°C, allowable area loss of 15%, and allowable power loss of 10%. The elite ratio is 0.2, the crossover ratio is 0.4 and the mutant ratio is 0.4. As observed from the results, the algorithm converged quickly to a near optimal solution with different collection of panels.

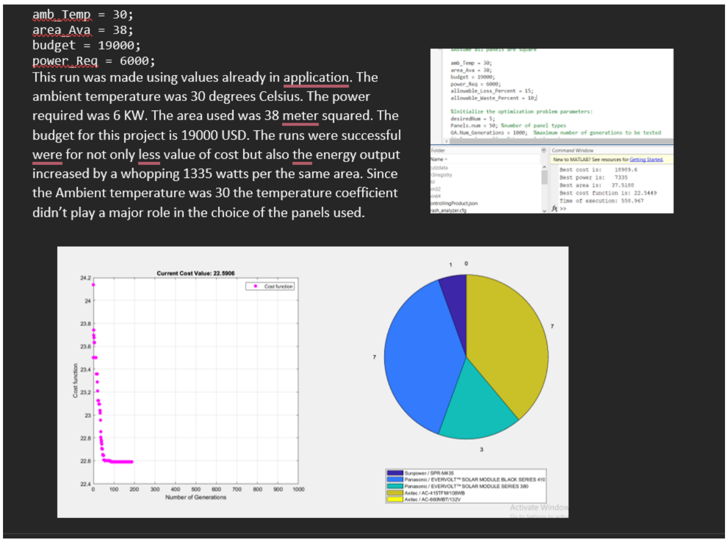


Figure 3.20: Case Study 3a

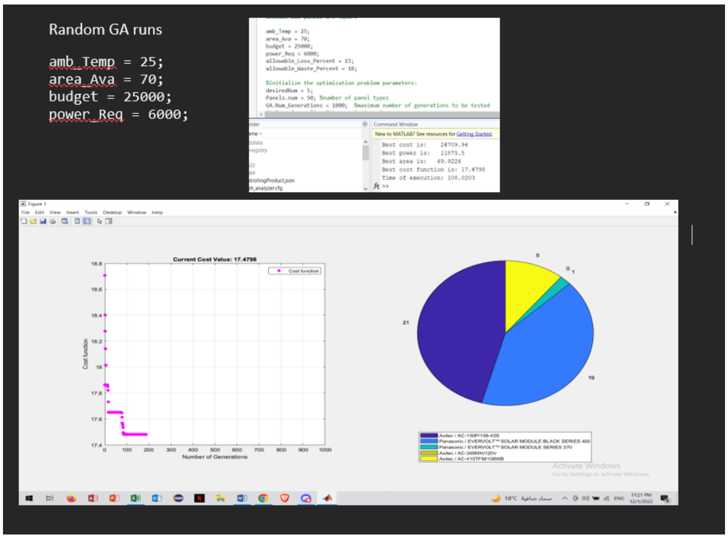


Figure 3.21: Case Study 3b

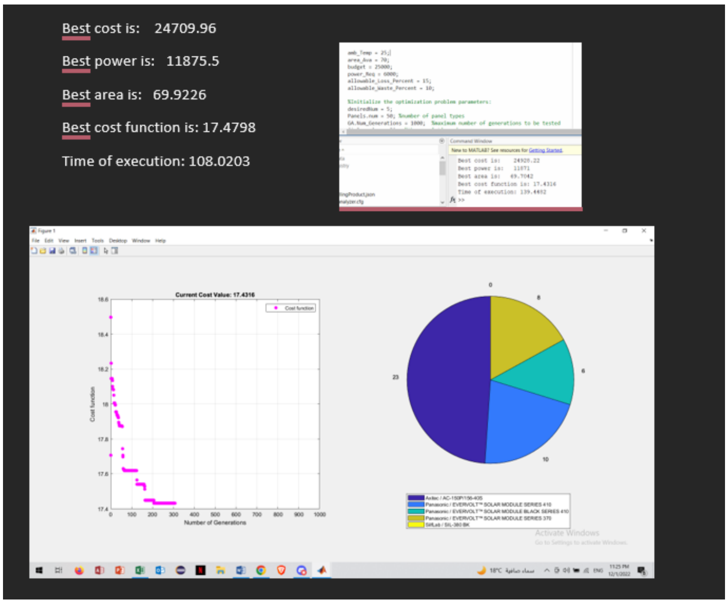


Figure 3.22: Case Study 3b

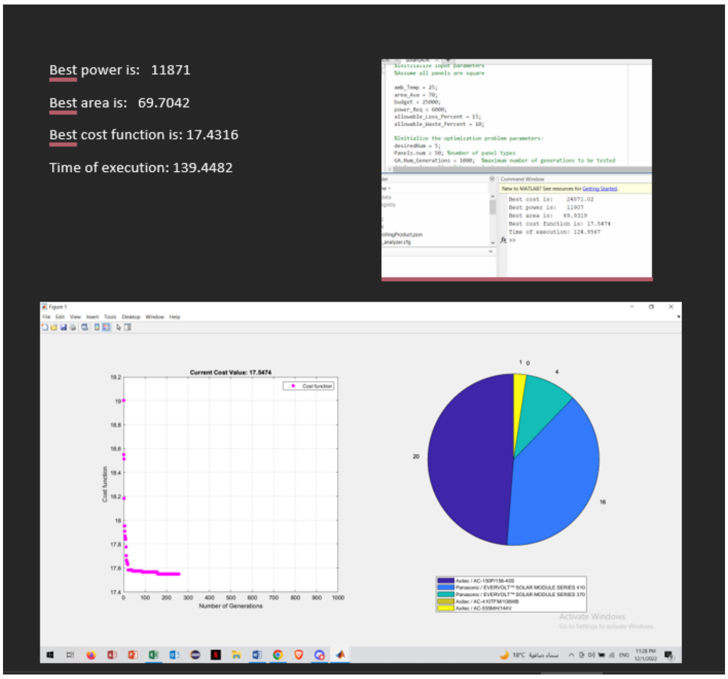


Figure 3.23: Case Study 3b

When comparing running the two algorithms the SA algorithm complete run of 1000 iterations took an average of 6 minutes. The computational time for the initial solution was low. Comparing this with the GA algorithm. The initial solution took a much longer time than the SA algorithm. For only approximately 300 iteration the running time was 4 minutes. There for computational time for GA algorithm is clearly much higher. In return the average objective function value for the SA algorithm was above 20 while for the GA algorithm all objective function values were 19 or lower and hence reaching more optimum solutions.

The run was made using random values for the area, cost, and power generated. The ambient temperature was given by 25 degrees Celsuis. As a result the temperature coefficient plays no role in the choice of the panels. The area given is 70 meters squared. The power required is 6kW. The budget needed for this project is 25000 USD. The results vary slightly in the cost function. The power generated was 5871 more than the required power which is a huge benefit. The results on the different types of panels vary greatly because of the stochasticicity of the code.

Run 1: stopping criteria 100

This was too small of a stopping criterion which means the algorithm did not explore enough and stopped early without finding a better solution.

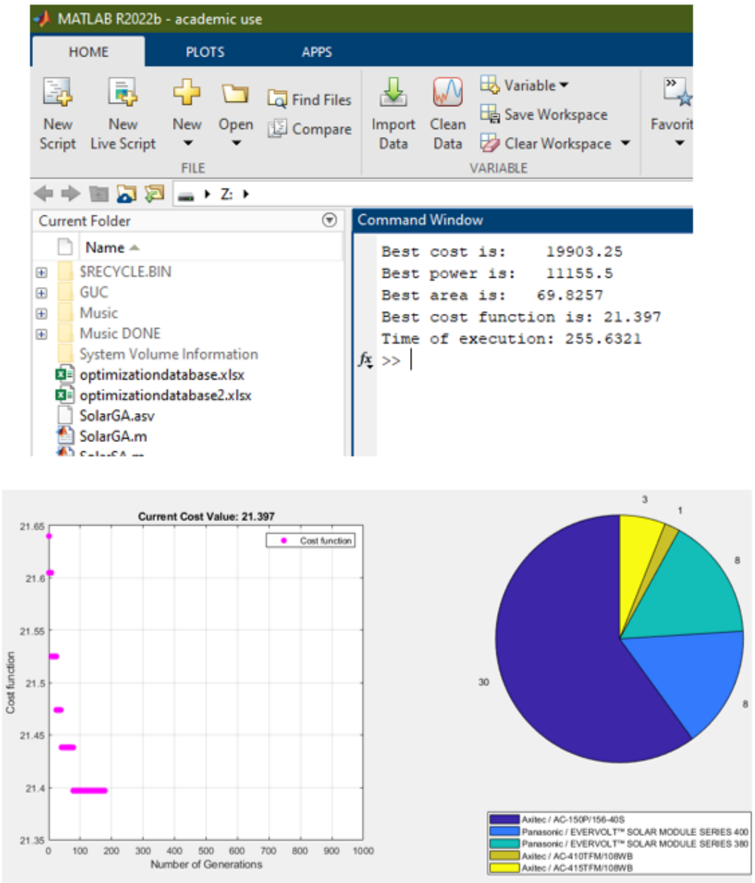


Figure 3.24: Case Study 4 1st run

Run 2: stopping criteria 200

This was a good a stopping criterion which means the algorithm explored enough and stopped when finding a consistent good solution.

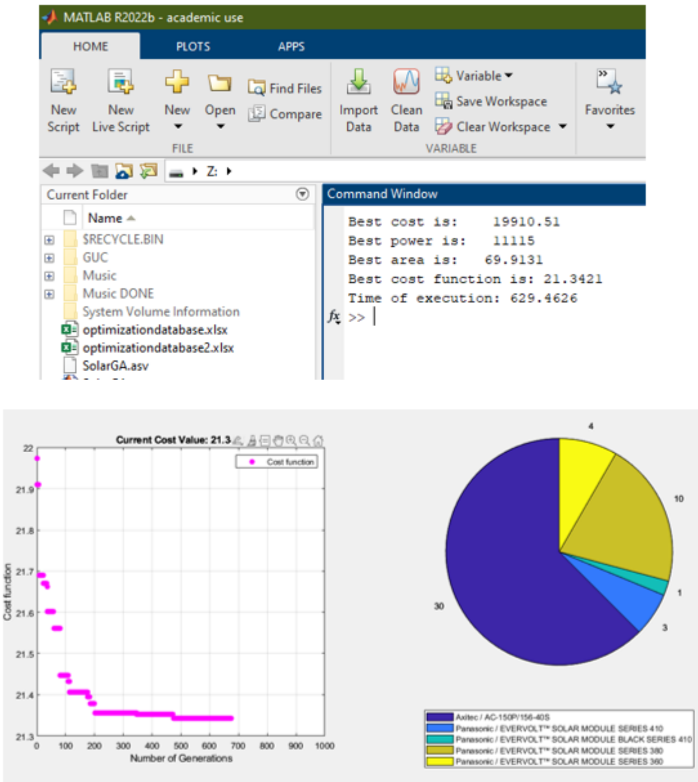


Figure 3.25: Case Study 4 2nd run

Run 3: stopping criteria 200

This was a good a stopping criterion which means the algorithm explored enough and stopped when finding a consistent good solution

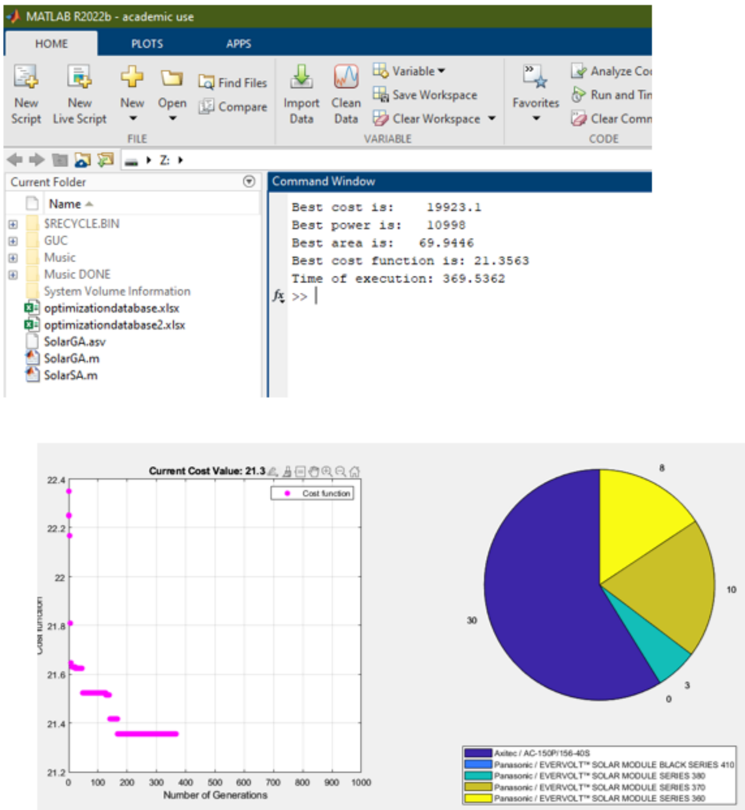
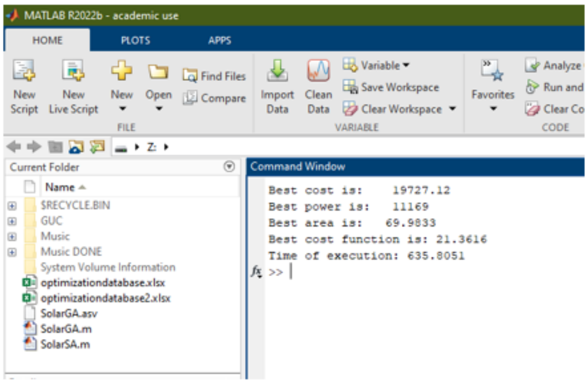


Figure 3.26: Case Study 4 3rd run

Run 4: stopping criteria 200

This was a good a stopping criterion which means the algorithm explored enough and stopped when finding a consistent good solution



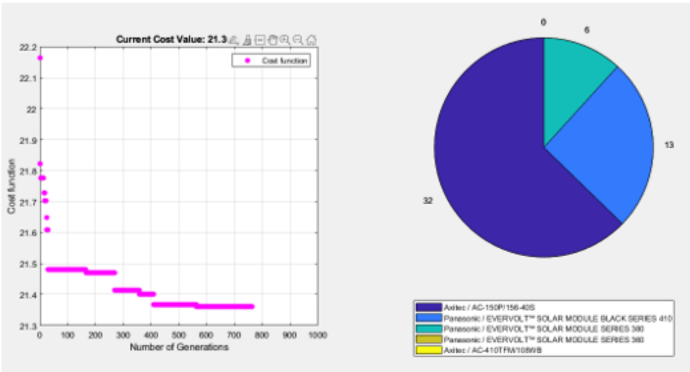


Figure 3.27: Case Study 4 4th run

Run 5: stopping criteria 200

This was a good a stopping criterion which means the algorithm explored enough and stopped when finding a consistent good solution

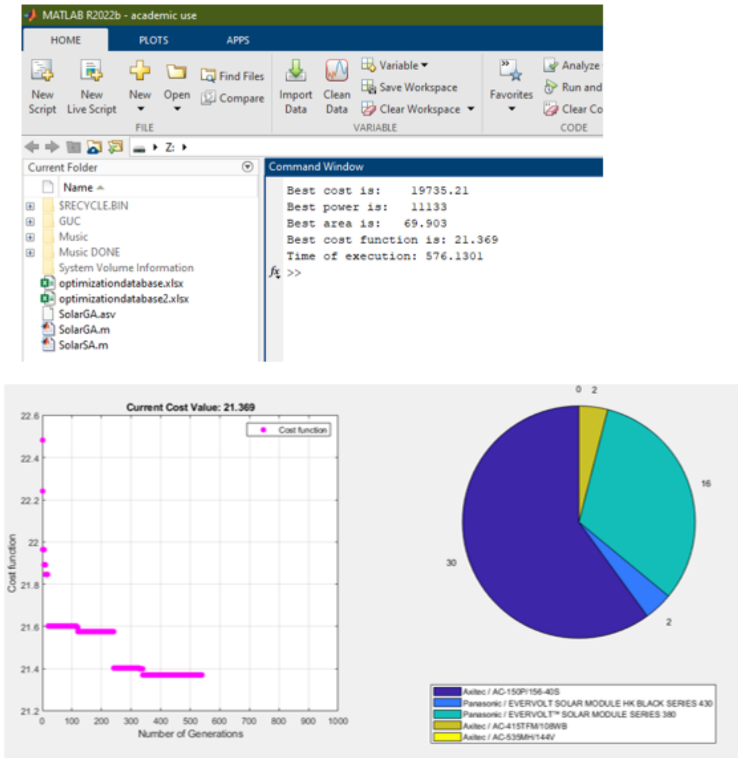


Figure 3.28: Case Study 4 5th run

The inputs and constraints were as follows: 35°C ambient temperature, 70m2 area available, 4.5 KW power required, 20000$ budget, 15% allowable energy loss, and 10% allowable waste in the area. Number of generations is 1000 and population size is 50. Elite ratio is 0.1 and crossover ratio is 0.6 with an alpha of 0.6 and mutation ratio 0.3 with a noise scale of 0.5. With this combo of ratios, the code should favour exploration a little more over exploitation. In our inputs we restrained the budget to a low one and a high power required and due to this almost in all runs Axitec/ AC-150P/156-40S was being chosen in excess as it has lowest cost with a decent power output that can satisfy our requirements out of all the solar panels available. On average the operation time is higher than simulated annealing but gets a better solution than simulated annealing as seen by the best function of the tests taken. The algorithm makes certain that all the solution is feasible. The algorithm is a complete one as it guarantees to find a solution if a solution exists, or determines if no solution exist.

3.4.2 GA Literature Comparison

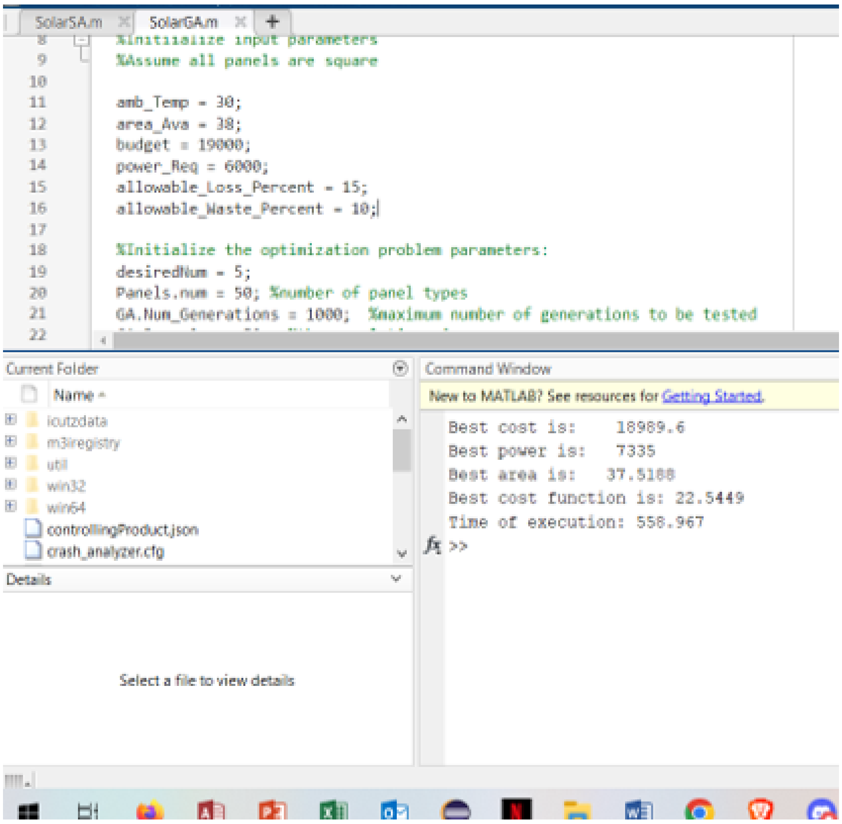


Figure 3.29: Lit comparison 1

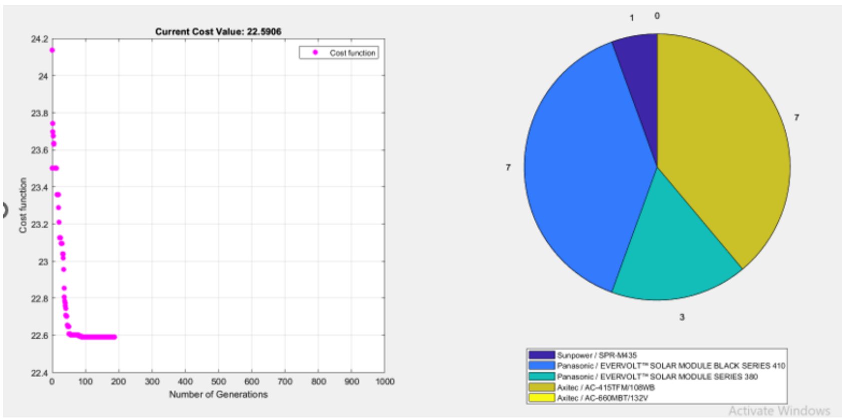


Figure 3.30: Lit Comparison 1

These are the results (figures 3.29 and 3.30) when tested with real life inputs from previous literature. The inputs were an area of 38 meters squared, a budget of 19000 USD and the power required was 6KW. As can be seen it the previous photos the GA algorithm was able to obtain a combination of panels using slightly less are and money and produce more power.

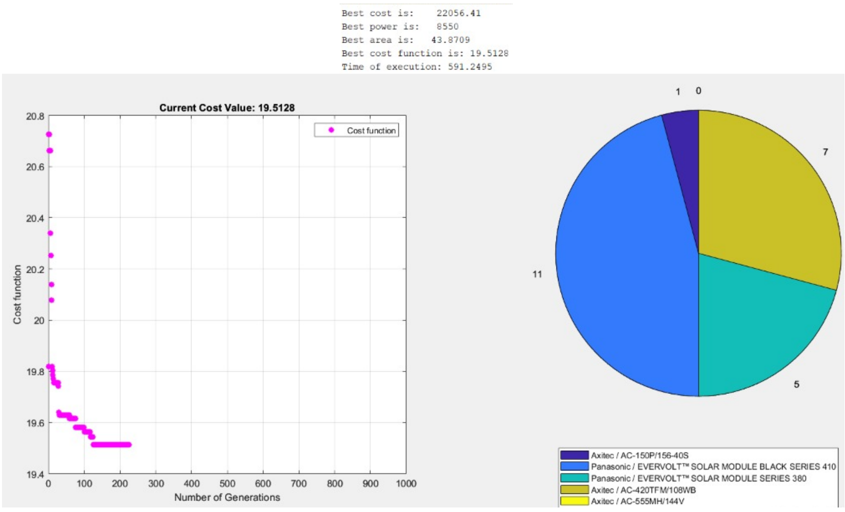


Figure 3.31: Lit Comparison 2

This run was made according to real life values. The ambient temperature was given to be 25 degrees Celsius. The area to be installed upon is 44 meters squared. The power needed to be generated is 7kW. And the cost to be paid for this project is 22100 USD. Since the ambient temperature is 25 the temperature coefficient played no role in choosing the type of panel. The area wasted was negligible. The cost was decreased by 1000 USD. The power generated increased by 1550 Watts from the required Power.

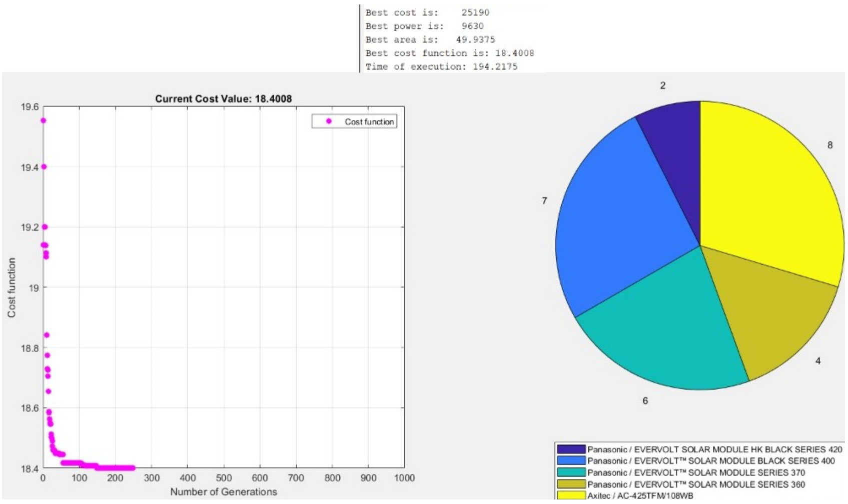


Figure 3.32: Lit Comparison 2

This run was made according to real life values. The ambient temperature was given to be 25 degrees Celsius. The area to be installed upon is 50 meters squared. The power needed to be generated is 8kW. And the cost to be paid for this project is 25200 USD. Since the ambient temperature is 25 the temperature coefficient played no role in choosing the type of panel. The area wasted was negligible. The cost was not decreased. The power generated increased by 1630 Watts from the required Power.

3.5 Grey Wolf Optimization (GWO) Technique

```
Decision Variables: Cost, Power, Cof, Area
Objective Function: f(x)
Initialize: Num_Generations, Pop_size, Pop_init, Pop_initA, Pop_initB, Cost, Alpha, AlphaB, Beta, BetaB, Delta, DeltaB

for i=1 to Pop_size:
        while (Pop_init not feasible):
                Obtain Pop_initA(i) and Pop_initB(i)
                Obtain Fitness
                Check and update feasibility

for i=1 to gen to Num_Gen
        Save the best solution as the alpha: GW.Alpha = GW.Pop_current(member_index(1),:);
                                             GW.AlphaB = GW.Pop_currentB(member_index(1),:);

        Save the second best solution as the beta: GW.Beta = GW.Pop_current(member_index(2),:);
                                                    GW.BetaB = GW.Pop_currentB(member_index(2),:);

        Save the third best solution as the delta: GW.Delta = GW.Pop_current(member_index(3),:);
                                                   GW.DeltaB = GW.Pop_currentB(member_index(3),:);

        Initialize D_alpha, D_beta, D_delta, x1, x2, x3, xAvg, omegaB
        Update the new generation with the alpha, beta, and delta

        for i=4 to Pop_size (the remaining population (omegas))
                while (omega(i) not feasible)
                        Calculate a, A, and C
                        if abs|A|<1
                                for j=1 to Panels.num (each omega)
                                        Calculate corresponding D_alpha, D_beta, D_delta, x1, x2, x3, xAvg
                        elseif abs|A|>=1
                                for j=1 to Panels.num (each omega)
                                        Calculate corresponding D_alpha, D_beta, D_delta, x1, x2, x3, xAvg
                        Perform bit swapping on binary solution
                        Check and update feasibility

        Plot best results and visualization
Output Best results
```

Figure 3.33: GWO Pseudo Code

3.5.1 GWO Case Studies

Figure 3.34: Case Study 1

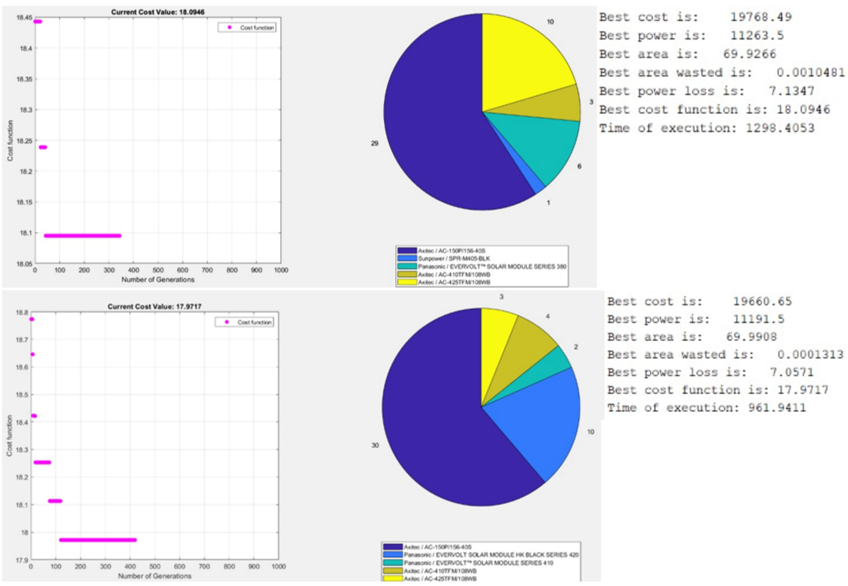


Figure 3.35: Case Study 1

The five previous runs (figures 3.34 and 3.35) were made on the same set of inputs. The inputs were an available roof area of 70 square meters in an ambient temperature of 25 degrees, the budget was 20000 USD, the power required was 4.5kW, an allowable area waste of 10%, and an allowable power loss of 15%. The code was designed to terminate after 300 iterations with no better found solution (stopping criteria). As noticed from these runs, only one run was able to find a better solution among the other runs which was a cost function of 17.99. Axitec 150P was greatly used in all runs, because it is the cheapest solar panel type that can give this amount of power in that area. The average time of execution was about 1300s, because the solutions were exhausting to find for these set of inputs.

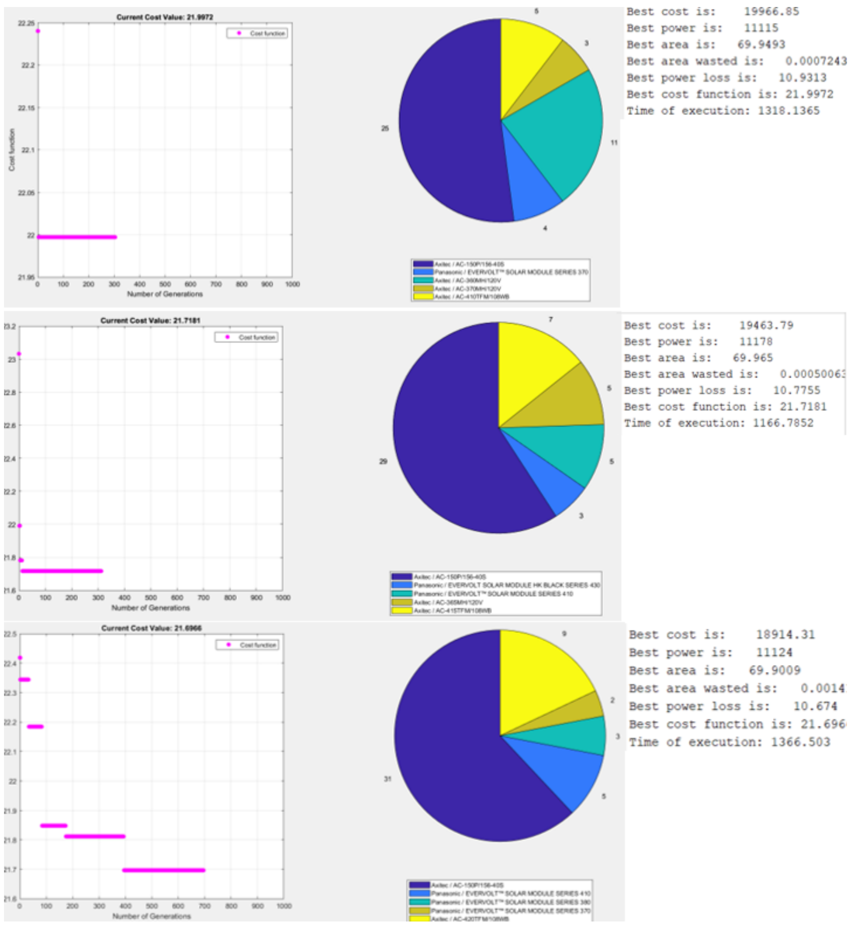


Figure 3.36: Case Study 2

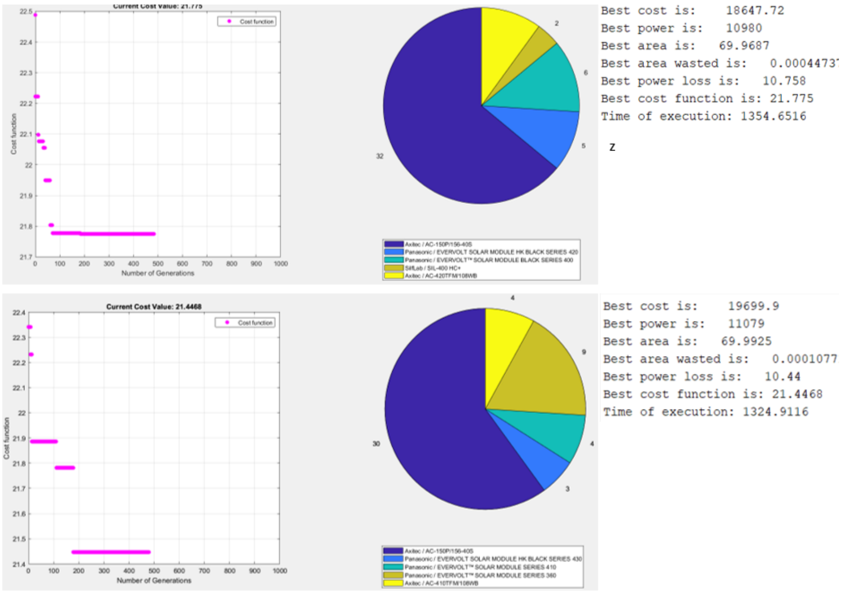


Figure 3.37: Case Study 2

For the previous set of runs (figures 3.36 and 3.37), the inputs were the same as the previous case except for the power which was 6kW and an ambient temperature of 35 degrees. The results were pretty much similar where Axitec 150P was greatly used for its cheap price and average power output.

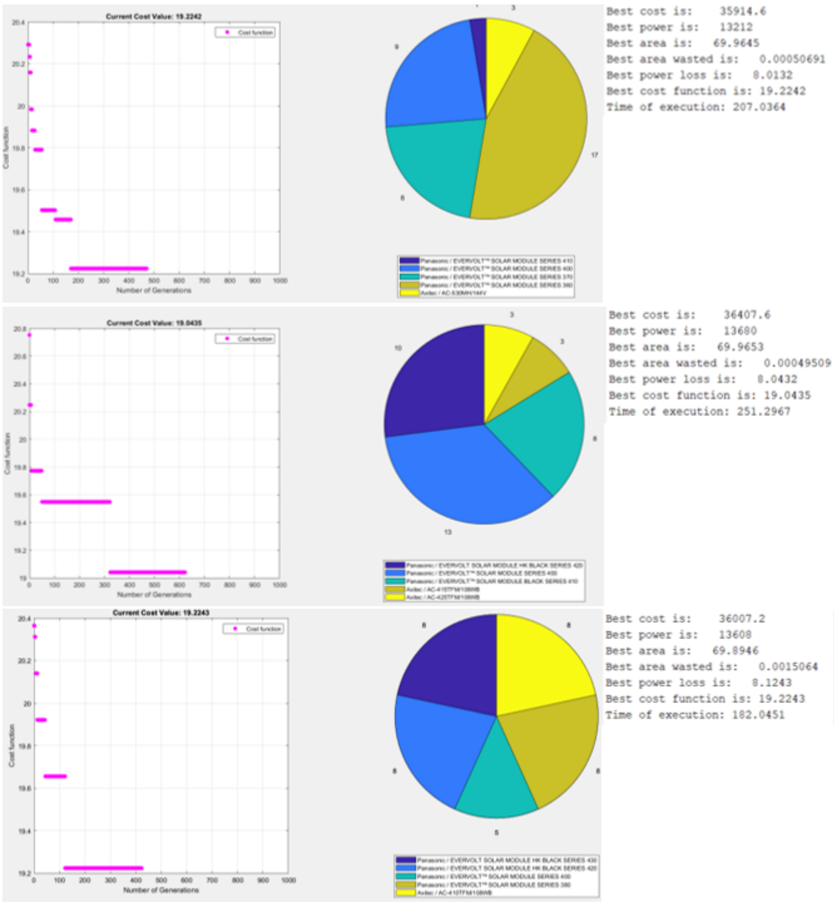


Figure 3.38: Case Study 3

Figure 3.39: Case Study 3

The inputs for the last 5 runs (figures 3.38 and 3.39) were the same as the first case study except for the budget which was 40000 USD and the ambient temperature was 35 degrees. The results were different this time since there was much more budget than the previous 2 cases. Panasonic solar panels were greatly used from all types, because its cost was balanced with the amount of power it can give, and the algorithm was able to use the whole budget, which made it choose the reliable expensive panels. The average time of execution was very fast (about 3min) compared to the previous cases, because the search for a solution was not as exhausting as the previous runs, since any type of panel could be a solution easily. The population size for all these 3 cases was 50.

Figure 3.40: Case Study 4

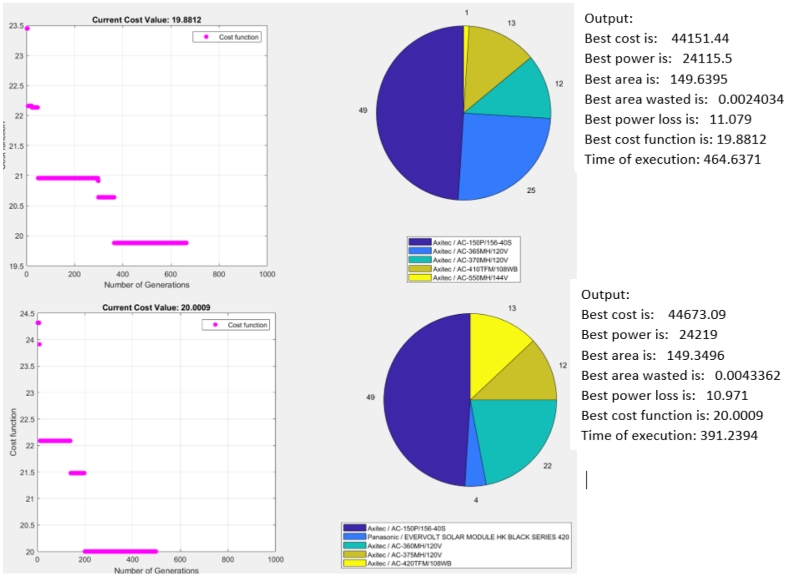


Figure 3.41: Case Study 4

For the previous five runs (figures 3.40 and 3.41), the inputs were an available area of 150 square meters in an ambient temperature of 35 degrees, a budget of 45000 USD, a required power of 6kW, an allowable area waste of 10%, and an allowable power loss of 15%. Once again, the Axitec 150P was greatly used in all runs, because the ratio of the area to the budget was not changed, although the values were changed to the double from the second case study. A population size of 30 was chosen (figure 3.40) to test the difference in speed, which was clear that it was almost slower the double, when compared to the population size of 50 (figure 3.41).

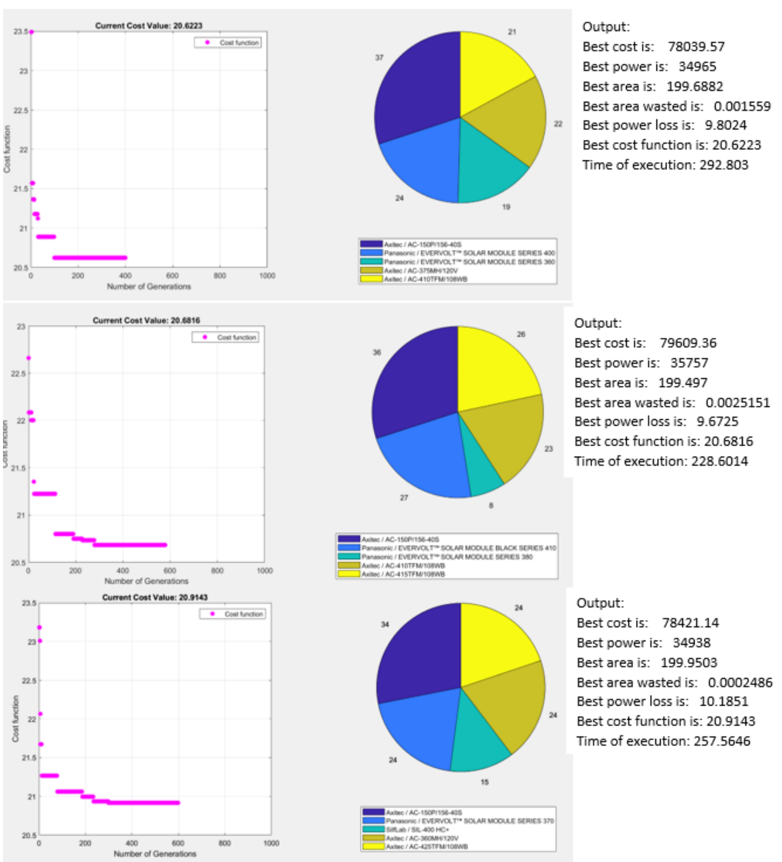


Figure 3.42: Case Study 5

Figure 3.43: Case Study 5

For this case study (figures 3.42 and 3.43), the inputs were the same as the previous case (case 4) except for an area of 200 square meters, a budget of 80000 USD, and a required power of 20kW. Since the area was enormous, a large number of solar panels per type were used and again the most used type was the Axitec 150P and the rest of the used panel types had an overall balanced number of panels among each other. The population size for this case study was 50, and the search was not exhausting, because there were many available easy solutions for the algorithm to find, unlike when the inputs are extremely hard.

3.5.2 GWO Literature Cases

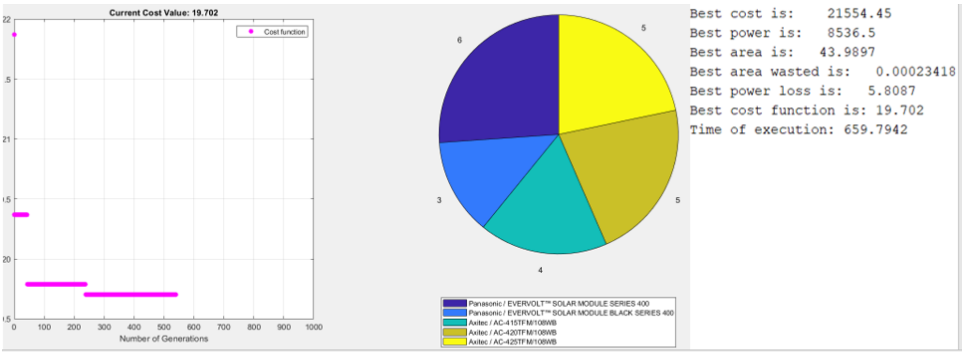


Figure 3.44: Literature Case 1

These are the results (figures 3.44) when tested with real life inputs from previous literature. The inputs were an area of 38 meters squared, a budget of 19000 USD and the power required was 6KW. As can be observed from the previous run, Panasonic solar panels were the most chosen, because the required power output was high for the small area, and the budget was mostly used for reaching that solution.

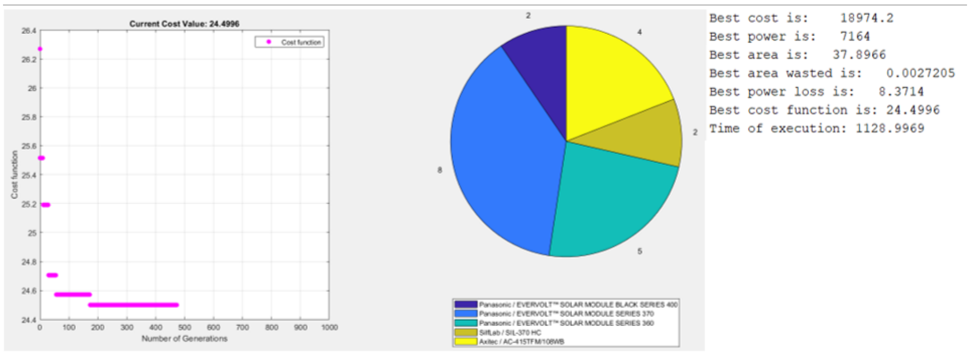


Figure 3.45: Literature Case 2

The previous run (figure 3.45) was made from another real life values. The available installing area was 44 square meters in an ambient temperature of 25 degrees, the power required was 7kW, and the available budget was 22100 USD. About 550 USD was saved and the power generated was increased by almost 1.6kW from the required power. For the required area, the cheap panel type was not used, since it would have made it harder to reach the required inputs.

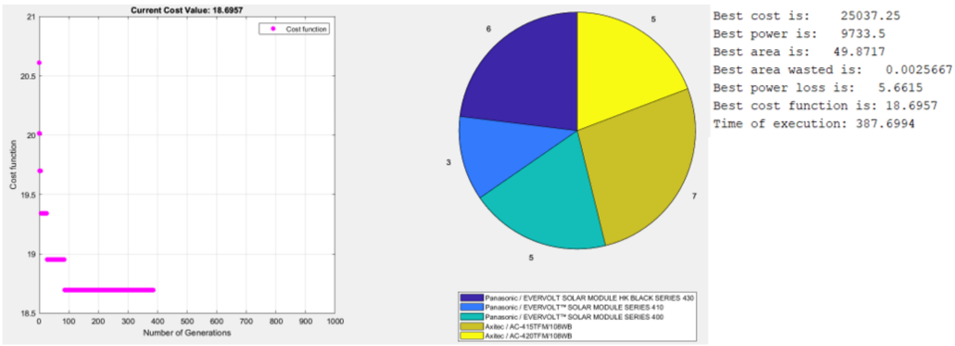


Figure 3.46: Literature Case 3

For this literature case (figure 3.46), the real life values were an area of 50 square meters in an ambient temperature of 25 degrees, a required power of 8kW, and a budget of 25200 USD. Most of the area was used, whereas only about 200 USD were saved. The power generated was more than the required by 1.7kW, which is great. Panasonic and Axitec solar panels were used to be able to reach the required power for the area available, and no cheap panels were used again.

3.5.3 Comparison of GWO to SA and GA Algorithms

The GWO Algorithm had a fast execution time only when the inputs were easy and not exhausting, executing in an average of 3min while using a stopping criteria, which was terminating when the solution does not change for 300 generations. The GWO takes an average of 20min when the inputs are hard which makes it very exhausting. The SA takes much time to find an initial solution of about 5min and a total of 8min, when the inputs are hard, and it finds an initial solution almost immediately when the inputs are not very constrained, which is about 3min in total. The GA algorithm is very exhausting when the inputs are hard, where it takes about 14min in total, and using the same stopping criteria used in the GWO, it takes about 5min, while the easy inputs takes a little bit less time of about 4min in total.

The GWO algorithm does not reach the optimal solution, since it sometimes gets stuck in a local minima, and does not normally reach the optimal solution. The SA Algorithm does not always reach the optimal solution, because only one solution is found per iteration, but it is proven that it converges quickly to a near optimal solution when the geometric cooling parameter ranges from 0.75 to 0.99. The GA Algorithm always reaches the optimal solution almost quickly, since it is a population-based algorithm that depends on elites from the previous generations.

In conclusion, based on the previous runs, the GWO algorithm does not reach the optimal solution like the GA algorithm, but it can reach a near optimal solution quicker than SA and GA when the inputs are not exhausting.

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