Optimizing the Installation of Solar Panels for Homes using Meta-Heuristic Optimization Techniques

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***Abstract*—Renewable energy systems have always seemed the solution to the energy problems available. Not only is renewable energy a clean energy source with little to no emissions but it is also cheaper and most efficient. The number of homes installing solar systems and converting away from inefficient conventional fossil fuel systems increased in recent years; therefore, in this paper, 4 meta-heuristic optimization techniques were implemented, 3 of which are population-based and one trajectory-based (Simulated Annealing), which output good results although it's not a population-based. The population-based techniques used were Genetic Algorithm(GA) which produced the best fitness value but at the expense of time, Grey-Wolf(GWO), which has low complexity and thus converges very fast, and Meta-Verse (MVO), which proved to be superior compared to the others using less time and giving near-optimal resul**

***Index Terms*—textbfIndex Terms- component, formatting, style, styling, insert**

I. Introduction

Renewable energy or free energy as labeled by many engineers is the future. Not only sustainable, renewable energy answers all doubts and uncertainties about alternate forms of energy such as fossil fuels. Solar energy is one of the most prominent energy sources in the world. The number of homes installing solar converting away from nonrenewable sources of energy has risen exponentially. To maximize the benefit of renewable energy optimization must be done. Optimization aims to generate a near-optimum solution for the renewable energy system that maximizes power output per area used. Optimization of the installation of solar panels for homes is one of the most important areas of application because of the high initial cost. Optimization aims to not only lower the cost required for the installation but also increase the power output per unit area and minimize losses of energy output. Of course, some constraints limit the benefits of our optimization these include: Area of installation (hard constraint), cost of installation, the temperature of an area of installation, and the power output of panel type. By optimization, we aim to improve, improvise, and overcome all obstacles hindering the switch to solar by not only lowering the initial cost of installation but also increasing the power produced and limiting losses of power.

II. Literature Review

[1] 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 in other contexts provided that the regional

electricity price structures are taken into consideration. [2] describes a concise model for off-grid PV system sizing that takes into account the loss of load probability (LOLP). About the specified value of loss of load probability, load curve, and a 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 the 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 for substantial investment cost reduction. The optimal size and operation of home solar PV systems combined with battery units are discussed in [3] 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 the 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 [4] 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 microgrid, a backup power generation system is an essential component of microgrids 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 microgrid investment costs. By fusing clever optimization algorithms with adaptive strategies, the study of multi-objective optimization problems demonstrates greater performance.

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 [5], a general architecture of the home energy management system (HEMS) is designed in the context of the smart grid with a novel scheduling mechanism for residential customers that is restricted and multi-restricted. The initial goal is to reduce 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 the cost of electricity are reduced significantly. 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 [5].

The success of this method can be determined by comparing it to other methods like SSA, GWO, and P and O. 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, [6] 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, [7] 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 building lifespans. 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.

[8] 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 [9], one of the most important factors was discussed which is the temperature binary-type panel. Solar panels generate electricity from light, not heat. High temperatures degrade the solar panel's efficiency by up to 25%. Optimizing the temperature of the solar panel will yield more energy and hence better efficiency.

III. Methodology

A. Problem Formulation

To apply an optimization technique, a fitness or objective function is obtained with variables and constraints. The algorithms in MATLAB choose from a database of panels with different types, sizes, power output, cost, area, and temperature coefficients. The objectives are:

- Maximizing the energy output of a PV power plant
- Minimizing the initial Cost to be spent on the PV system
- Minimizing area containing no solar panels
- Minimizing the temperature of solar panels

The optimization problem is selected to be a minimization problem, therefore the energy output is mathematically manipulated to increase as the function decreases. Table I shows all the variables used in the objective function.

Symbol	Name
n_i	number of each solar panel type installed
C_i	cost of each solar panel type
A_0	Area of roof
A_i	The area of the panel of type
m	number of panels in the array
T_r	The ambient temperature of the region
M_T	The temperature coefficient of the panels of its type

TABLE I
VARIABLES USED IN OBJECTIVE FUNCTION

The first variable, 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 inside the house where the panels should be installed to operate.

$$Power = \sum_{i=1}^{m} (Power_i * n_i) * 0.9 \tag{1}$$

In Equation 1, the power output of the different types of solar panels installed is power(watts). The constraint is a maximum loss in efficiency allowed due to the temperature being 0.9.

The second variable is cost shown in Equation 2, which is the most important problem when converting to solar energy. Many people are just 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. The constraint on the cost is that it should be less than the budget provided by the user as an input.

$$Cost = \sum_{i=1}^{m} (C_i * n_i) \tag{2}$$

The third variable is the area, which needs to be minimized, as shown in Equation 3. 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. The constraint is the value of the percentage of area wasted value which should be contained to be less than 0.1 (10%).

$$AreaWasted = \frac{A_0 - \sum_{i=1}^{m} (n_i * A_i)}{A_0} \tag{3}$$

The fourth variable is the temperature of solar panels which needs to be minimized shown in equation 4. The optimum temperature at which maximum output from a solar panel is generated is found to be 25°C. Since the installation takes place in Egypt, no problems may be faced during the winter period as per temperature. It is targeted 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 which 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. Given the assumption that a maximum 10 percent loss in power is generally accepted. [10] [11], this will be the constraint governing whether the choice of panels is acceptable. The last constraint would be the number of types allowed to be installed, and in this case, only 5 types will be allowed. $n_{type} <= 5$

$$EfficiencyDrop = \sum_{i=1}^{m} \frac{(T_r + 20 - 25) * M_T}{m} \tag{4}$$

The total objective function is shown in Equation 5

$$Objective = Cost + AreaWasted + Temperature - Power \tag{5}$$

B. 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. Note that the dimensions of the solar panels are assumed to be of type square (length equals its width). The algorithms have stopping criteria if the fitness value didn't change for 200 generations.

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.

C. Simulated Annealing Algorithm(SA)

The first algorithm implemented was a trajectory-based meta-heuristic technique, Simulated Annealing. The technique is based on using the cooling relation in temperature to control the exploration and exploitation of the solution. In the SA Algorithm, an initial solution is obtained for both arithmetic and binary solutions, then the solution feasibility is checked and updated. In the optimization loop, a new feasible arithmetic solution was generated based on the previous solution with added noise. Then, a binary solution was generated from the previous solution by bit-swapping. After the fitness is calculated, if the change in the fitness is less than 0, the better solution is accepted. If the change in fitness is greater than 0, a random number is generated and compared with a probability. If the probability is greater than the random number, the worse solution is accepted, or else rejected. Finally, update the SA parameters.

D. Genetic Algorithm(GA)

Next, a population-based meta-heuristic technique was implemented. In the literature, population-based approaches maintain and improve multiple candidate solutions, often using population characteristics to guide the search. In the GA Algorithm, an initial solution is obtained for both arithmetic and binary solutions, then the solution feasibility is checked and updated. In the optimization loop, a certain percentage of the population will be elites (best cost function of the previous generation). Then, 2 random parents were chosen from the previous generation to create 2 children using the Whole Arithmetic Recombination Cross-over Technique. For the binary solution, a one-point cross-over technique was used. Finally, the arithmetic solution in the mutants was generated by adding noise to the previous solution. The new binary mutants were generated by bit swapping technique.

E. Grey-Wolf Algorithm(GWO)

After implementing the GA, which takes a lot of time to converge to a solution, the GWO algorithm was implemented as it should converge to a solution faster than the GA, but at the expense of memory. The GWO wasn't guaranteed to reach a solution better than the GA but was much faster. In the GWO Algorithm, an initial solution is obtained for both arithmetic and binary solutions, then the solution feasibility is checked and updated. In the optimization loop, the best three solutions are saved as alpha, beta, and delta, respectively. For the rest of the population, each omega (arithmetic solution) will be calculated based on 2 random numbers and some other parameters depending on all three elites (alpha, beta, and delta). The binary omegas will be generated using bit swapping. The best results were plotted.

F. Multi-Verse Optimization Technique(MVO)

The third population-based technique implemented was the Multi-Verse optimization algorithm. This algorithm exploits faster than any other algorithm implemented and is based on three concepts in cosmology: white hole, black hole, and wormhole. The mathematical models of these three concepts are developed to perform exploration, exploitation, and local search, respectively. In the MVO Algorithm, MVO parameters are initialized, and an initial solution is obtained for both arithmetic and binary solutions, then the solution feasibility is checked and updated. In the optimization loop, update the wormhole existence probability and the traveling distance rate. Then, for each solar panel, a random number (r1) is generated and compared with the normalized fitness of the population. If the random number is smaller than the normalized universes, the jth parameter (Uij) in the solution is taken as it is. Then, a random number (r2) is generated and compared with the wormhole existence probability, if the r2 was smaller than the WEP, then 2 random numbers will be generated and the new solution will be generated accordingly.

Test 1	Test 2	Test 3
A = 38 m^2	A = 49 m^2	A = 50 m^2
Budget = 19000 USD	Budget = 22100 USD	Budget = 25200 USD
Power = 6 KW	Power = 7 KW	Power = 8 KW

TABLE II
TEST CASES THAT WERE APPLIED ON THE ALGORITHMS

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

Fig. 1. Literature Cases for the installation showing the cost, power, and the area used.

IV. RESULTS AND DISCUSSION

According to [4], the cases which were applied to the industry were tested on the 4 algorithms. Figure 1 shows the reference values which were inputted to the algorithms. The expected results should be equal to or better as in more power outputted, less cost saved, and/or less wasted. 3 test runs were applied and are shown in Table II along with an allowable loss in power equals no more than 15%, loss in an area no more than 10%, and an ambient temperature $= 25^oC$. The results show 2 graphs, the first being a graph of the fitness or cost function across the number of iterations in the case of the SA and the population on the x-axis in the case of the population-based techniques, and the other plot is a pie chart showing the type and number of each panel type being used.

A. SA Results

In all 3 tests, geometric cooling was used with the rate of alpha = 0.3. As seen in Figure 2, the best objective function reached after the first test converging was 21.9522 with types of panels used between 9 Panasonic and 11 Axitec. After observing the outcome, the results showed an improvement in giving excess power of 1236 W. The second test showed the best fitness function of value 21.7453, and excess power of 2040 W along with 9 Panasonic and 17 Axitec panels. The third test showed the best fitness function of 18.7431 and excess power of 1236 W with 12 Panasonic and 13 Axitec.

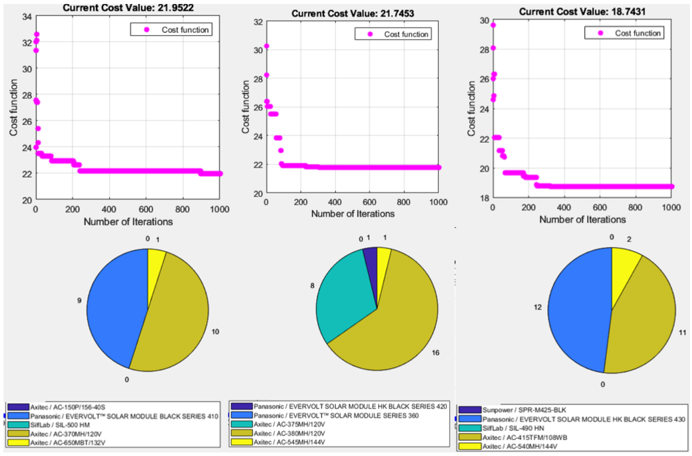

Fig. 2. Literature Cases for the installation showing the cost, power, and the area used on the SA Algorithm

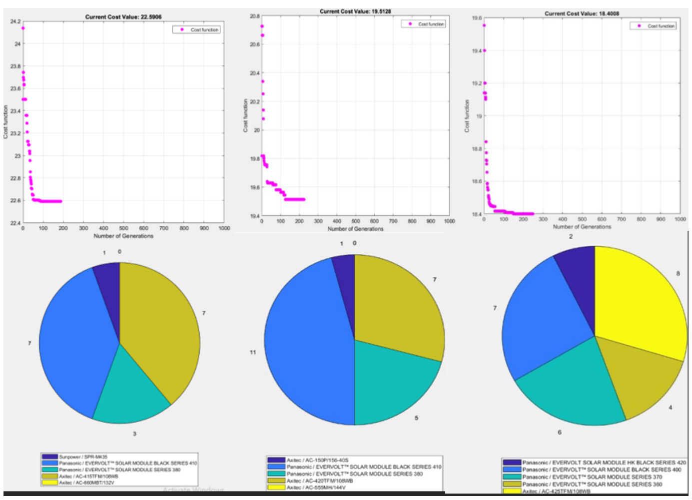

Fig. 3. Literature Cases for the installation showing the cost, power, and the area used on the GA Algorithm

The average execution time of the algorithm was about 10 minutes.

B. GA Results

As seen in Figure 3, the best objective function reached after the first test converging was 22.5906 with types of panels used between 1 Sunpower, 10 Panasonic, and 7 Axitec. After observing the outcome, the results showed an improvement in giving excess power of 1335 W. The second test showed the best fitness function of value 19.5128, and excess power of 1550 W along with 16 Panasonic and 8 Axitec panels. The third test showed the best fitness function of 18.4008 and excess power of 1630 W with 15 Panasonic and 12 Axitec panels. The average execution time of the algorithm was about 7.5 minutes.

C. GWO Results

As seen in Figure 4, the best objective function reached after the first test converging was 24.996 with types of panels used

Fig. 4. Literature Cases for the installation showing the cost, power, and the area used on the GWO Algorithm

between 2 Silflab, 15 Panasonic, and 4 Axitec. After observing the outcome, the results showed an improvement in giving excess power of 1164 W. The second test showed the best fitness function of value 19.702, and excess power of 1536 W along with 9 Panasonic and 15 Axitec panels. The third test showed the best fitness function of 18.6957 and excess power of 1733 W with 15 Panasonic and 12 Axitec panels. The average execution time of the algorithm was about 12 minutes.

D. MVO Results

As seen in Figure 5, the best objective function reached after the first test converging was 21.323 with types of panels used between 11 Panasonic and 9 Axitec. After observing the outcome, the results showed an improvement in giving excess power of 1362 W. The second test showed the best fitness function of value 19.7071, and excess power of 1532 W along with 9 Panasonic and 14 Axitec panels. The third test showed the best fitness function of 18.7388 and excess power of 1684 W with 8 Panasonic and 18 Axitec panels. The average execution time of the algorithm was about 8 minutes.

E. Comparison between Algorithms

4 optimization techniques were tested in total, 3 of them population-based. The computational time of the SA algorithm ranged from 3 to 8 mins, the time varying according to the complexity of the test case and constraints. For low complexity test cases, initial solutions were obtained almost immediately, while for some higher complexity cases this value increased up to 5 mins. However, as the SA algorithm is not a population-based algorithm, it did not yield the best results reaching near-optimal solutions, and also not as good as those yielded by some of the other algorithms tested. The fitness values for the majority of literature cases tested were about the mid-twenties with a few exceptions. It was identified that the use of linear cooling resulted in a greater emphasis on exploration due to

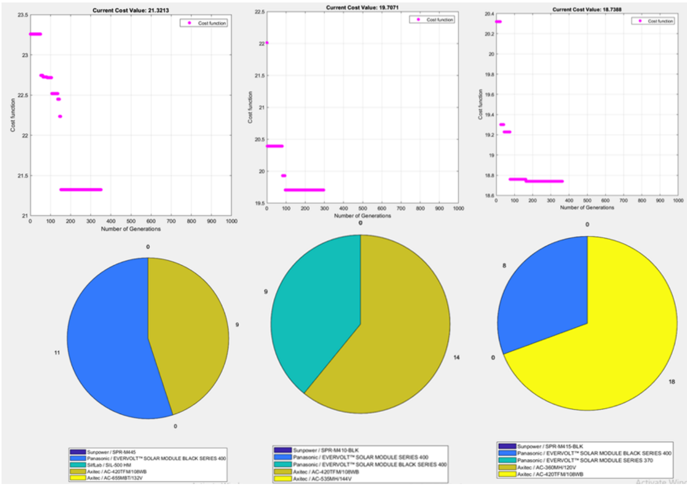

Fig. 5. Literature Cases for the installation showing the cost, power, and the area used on the MVO Algorithm

the increased area under the graph, while geometric cooling yielded better results with cooling parameters ranging from 0.75-0.99. The GA is very exhausting regarding computational time and power with run-time varying from 4 mins for low-complexity test cases and reaching 14 mins for test cases of greater complexity. When applying stopping criteria which terminates the algorithm when the elite solution is unchanged for approximately 200 generations, the run time is considerably reduced to about 5 mins with the code terminating after a total of between 400 to 600 generations instead of continuing the 1000 generations. Results for the GA algorithm were far superior to those of the SA algorithm. The worst fitness value obtained for the literature cases was about 22.5 with other literature test cases obtaining fitness values approaching 18. The mixture of elites, crossovers, and mutations provided a good balance between exploration and exploitation which resulted in such outstanding results. The GWO algorithm, another population-based algorithm, was tested. It showed the largest variation in computational time between low and high-complexity test cases. Some simple cases took an average of 3 mins and as the complexity of constraints increased so did run time reaching an unprecedented 20 mins even after applying stopping criteria of 200 and 300. It was noticed from the results that the algorithm struggled to continuously produce feasible solutions when constraints were tight which caused inflation in the run time. Apart from the long run time, the results were respectable with the GWO producing results slightly better than the SA algorithm but not quite as good as those obtained from the GA. The fitness values for the literature test cases ranged between 19.5 and 20.5. However, it was also noticed that convergence occurred quickly, not allowing enough exploration and hence resulting in the algorithm occasionally getting stuck in local minima. MVO was the final optimization algorithm and the third population-based technique. The results of the MVO algorithm were similar in value to that of the GWO algorithm with average fitness values also ranging between 19.5 and 21.5. It was observed that specific solutions in some test cases were frequently visited in almost all runs. It was also observed that solutions obtained from all 3 previous algorithms utilized approximately 4 or all 5 different types of solar panels while the MVO solutions utilized 3 and in some instances only 2. However, even though the results from the MVO algorithm were fairly similar to those of the GA and GWO algorithms, it far surpassed them in computational time, with the running time being consistently between 3 and 4 minutes using the above-mentioned stopping criteria. This did not vary much with an increase in the complexity of the test cases.

V. Conclusion

In conclusion, the GA algorithm produced the best fitness values with the GWO and MVO coming close seconds. The SA performed relatively well considering it is not a population-based algorithm. However, when considering run time, MVO was superior with GA and SA almost identical and the GWO was acceptable until the complexity was increased.

Future Recommendations

Using the true dimensions of the solar panels and visualizing the installation of these panels over the desired roof area and also increase the solar panel library. Implementation of recent different algorithms.

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