Journal of Mathematical Problems, Equations and Statistics

E-ISSN: 2709-9407
P-ISSN: 2709-9393
JMPES 2023; 4(1): 86-92

www.mathematicaljournal.com
Received: 01-11-2022
Accepted: 14-12-2022

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Using the Lagrange equation to plot the most useful capacity of the photovoltaic age in economic analysis

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Abstract
The Lagrange equation is a standard method for solving this limited optimization issue. The Lagrange equation is applied in a time-consuming and customary manner in order to recall the nonlinear functions of dependability restrictions that occur as a result of paying attention to various scenarios. The approach of Lagrange has been successfully applied to several optimization problems. Where, for high-quality customization of PV devices and batteries, value features were minimized using the Lagrange equation to achieve the highest level in the world with little computing complexity. Where the analytical comparisons between the outcomes and the change in the overall performance of the simulation were examined, and where the results were favorable. Using the Lagrange equation and the Mahtematica software, high-quality results were achieved. Two locations for which samples were acquired from the Faculty of Science at American Harvard University were compared with an explanation of the obtained findings.

Keywords: Lagrange equation, photovoltaic age, economic analysis

1. Introduction

The science of economics refers to the discipline that was believed to investigate the interdependent links between phenomena; the study of the causal linkages between economic events [17]. Recently, several population-based search and optimization approaches have been successfully applied to a wide range of power and energy applications [3, 5, 6]. The GAM is one of the most well-known and efficient population-based algorithms; it was designed to emulate the evolutionary principle of natural genetics [2, 7]. Thanks to the probabilistic crossover and mutation process, GAM may examine unique features that aren't present in the existing population. Despite the modest population number, the whole accessible space is scanned. GAM is superior to earlier search algorithms because it is less susceptible to being trapped by local minimums and provides a more optimum global solution [11, 15]. Numerous bio-inspired optimization strategies [9] have been used to seek a suitable answer to difficult engineering difficulties. In lieu of the global optimal solution, the objective of these approaches is to find a sufficient "good" answer effectively based on the problem's features, making them an attractive option for large-scale applications. GAM accomplishes both local exploration and global exploitation, resulting in a robust and efficient method for finding a near-optimal solution that has been used in a variety of optimization applications. Recent reports [2-10] detail the GAM technique's potential for building renewable energy systems. Several software tools [7, 16] are accessible for the design of a PVL system. The majority of these tools, on the other hand, simply identify and simulate a single design option; they do not provide a diversity of design alternatives [13]. In addition, the impacts of nonlinearity and optimization in system models, as well as alterations to main design factors, are necessary to examine the efficacy of these simulation and optimization tools when applied to particular applications [8, 14].

Das *et al.* [18] made an additional possible development in boosting the efficiency of PV systems. They claimed that multi-junction solar cells may produce three times as much energy as conventional systems [19]. Priority number one for scientists at the time was to produce as much electricity as possible, regardless of cost [19]. As the environmental consequences and fast depletion of other conventional resources came to light, the economic issues assumed a greater significance. Solar energy, on the other hand, is very efficient but exceedingly costly to harness. According to Borenstein [20], one of the main issues with solar panels is their price, which inhibits the market from anticipating their use.

Although solar cells are still fairly, their costs are reducing and their utilization on larger sizes is increasing [21]. One-third of the world's energy is used by the building sector, which releases the equivalent amount of greenhouse gases [22]. PVL systems are seen as a viable addition to the current energy infrastructure since they are steady, simple to install, provide regular yearly returns, and may be used to power electric appliances, lights, heaters, heat pumps, and even electric automobiles. Consequently, PVL systems may be used in buildings alone or in conjunction with other energy sources [23].

The research problem is how to determine an appropriate method for determining economic analysis in the photovoltaic energy process and how to use the data obtained from Harvard University in the United States to analyze and extract these data using the Lagrange equation to achieve positive outcomes in our work. This study aims to evaluate the precision and relative performance of Lagrange capacity planning strategies. Examining the best SPVL system compromise between reliability and installation cost. Lagrange is more effective than classic Lagrange relaxation optimization in locating global optimum solutions.

2. Preliminaries

2.1 Economic Analysis Levels: The economic study is segmented as follows

1. Analysis of the Macroeconomic Environment: John Maynard Keynes' method of macroeconomic analysis refers to the treatment of economic aggregates and macro variables, keeping in mind that aggregates (total variables) do not represent the sum of changes in the behavior of businesses and individuals (the economic units that make them) [25].
2. Microeconomic Analysis Microeconomic analysis focuses on the behavior and actions of individual fundamental economic units concerning the production or consumption process, as well as investment and saving. It is irrelevant whether the fundamental economic unit is a person or a project. Microeconomic analysis has evolved via marginal theory and neoclassical theory, it should be highlighted [26].
3. Misoeconomie is a technique of analysis that demonstrates the peculiarities of assessing the conditions of the main industrial groupings that are the focus of Keynesian macroeconomic analysis and dominate the neoclassical microeconomic analysis [26].
4. Global Economic Analysis Global economic analysis is a contemporary style of economic analysis that considers national economies to be interdependent components of a single global economy. This theory relies on the extensive growth of productive forces, the expansion of multinational corporations, the growing interdependence between nations, and the significance of each region's efficiency in producing the commodities and services it consumes [24].
5. Comprehensive economic analysis: dependent on mathematical equations and examining all components that fluctuate simultaneously [25].
6. Static analysis: This analysis examines economic phenomena at a particular point in time [25].

2.2 Economic Analysis Benefits

The economic analysis seeks to accomplish the following goals:

1. The economic analysis demonstrates the outcomes of different options and gives the most effective ways for selecting among them.
2. Economic analysis enables economic decision-makers to foresee possible future developments.
3. The statistical analysis offers reliable instruments for formulating economic policies based on the principles of scientific analysis; so increasing the likelihood of economic success at the project, national, and global levels.
4. Economic analysis facilitates the evaluation of economic and system performance.
5. Economic analysis evaluates the efficacy of economic initiatives to allocate resources to meet consumer demands.
6. Economic analysis aids in the development of governmental policy.
7. Economic analysis enables the understanding of the role of economic institutions in the allocation of societal resources [24, 26].

2.3 Tools for Economic Analysis

The genders reported marital partnerships. Verbal Justification: To clarify economic linkages, variables, and phenomena, it utilizes verbal reasoning. Utilizing statistical analysis to interpret numeracy. For the goal of expressing economic relationships and phenomena, you define graphs. The first mathematical symbol: The use of mathematical reasoning in defining economic linkages and variables is crucial [25, 26].

2.4 Analysis of SPV Generation Reliability

Before establishing a PV system, one of the most important factors to consider is the potential solar generation in the chosen location. Due to the intermittent character of solar radiation, power reliability analysis has been recognized for a long time as a crucial step in the planning and design of any power system [2, 12].

In the simulation, the total loss of load hours (LMF1) during a specified period is treated as the reliability index (usually one year). LMF1 is a useful measure of system performance for a certain load profile. When LMF1 is set to 0, the load will always be fulfilled during the duration of the simulation. A greater LMF1 suggests that the client is more likely to lose power. The abbreviation LOLH1 stands for the following: [1].

$$\text{LMF1} = \sum_{m=1}^{k}\sum_{n=1}^{k}\ell(m,n)$$

$$\begin{cases} 0 & \text{if } \left(\Re(m,n) - K(m,n)\right) + 1 < K_{\min} \\ \Re(m,n) - \frac{K(m,n) - K_{\min} + 1}{\Re(m,n)} & \text{if } K(m,n) < K_{\min}, K(m-1,n-1) < K_{\min} \\ 1 & \text{if } \left(\Re(m,n) - K(m,n)\right) - 1 \geq K_{\min} \end{cases} \tag{2.1}$$

Where K(m,n) is BTY's capacity condition during the m-day and n-hour, R(m,n) is the load consumed during the m-day and n-hour, the system deficit during the day hours, and K min is the minimum battery discharge capacity.
The quantity of solar radiation determines the current output of a PVL generator. After considering the load profile, the output current of a PVL generator may be utilized to determine the charge/discharge current of BTY. Positive and negative signs indicate distinct SPVL operating modes: a positive sign indicates that PVL generation exceeds load, while a negative sign indicates an SPVL generation shortfall.

2.5 Function of the Objective
To determine the optimal size for an SPVL system, a restricted optimization problem must be addressed. The optimal approach will strike a compromise between system power availability and system installation expense. The objective of optimal capacity planning is to lower the total installed cost of the SPVL system while achieving its dependability criteria. The cost of an SPVL system's installation might serve as the objective function:

$$\mathfrak{H} = \mathfrak{H}_{PV} * PV + \mathfrak{H}_{\varkappa} * BTY + \mathfrak{R}_{\mathcal{L}} - 1 \tag{2.2}$$

where $\mathfrak{H}$ is the entire cost of installing a solar power system, $PV/\,BTY$ is the solar array and battery capacity, and $\mathfrak{H}_{PV}$, $\mathfrak{H}_{\varkappa}$ are the PV (\$/wh) and BTY (\$/wh) unit costs respectively, and $\mathfrak{R}_{\mathcal{L}}$ is the initial cost of installing the system [1].

2.6 Function with Restriction
After the LMF1 has been built, a nonlinear function can be employed to combine several PV and battery sizes. A limited function was developed for eight distinct values of LMF1, 5, 15, 35, 75, 200, 260, 300, and 500 hours with respect to diverse dependability needs and load profiles [2, 9].
It is essential for an SPVL planner to have alternatives when addressing various system faults. A polynomial regression approach may be utilized to generate unique limiting functions with distinct LMF1 values. Saber shown [14]. that if a polynomial equation has more than 10 orders, the regression coefficient matrix would be skewed, which means that even modest data variations result in substantial parameter estimate mistakes.

3. The Optimization Model's Methodology
3.1 Lagrange Equation Methodology
The Lagrange multiplier approach is a well-known and widely used technique for constrained optimization. The six-order polynomial constraint function illustrated below can define the capacity combination of PV/BTY under specified system reliability requirements:

$$\aleph = \ell(PV + 2, \mathrm{BTY} + 1) = PV - (ƛ_1 BTY + ƛ_2 BTY^2 + ƛ_3 BTY^3 + ƛ_4 BTY^4 + ƛ_5 BTY^5 + ƛ_6 BTY^6 + ƛ_7 BTY^7 + ƛ_8 BTY^8 + ƛ_9 BTY^9 + ƛ_{10} BTY^{10}) \tag{3.1}$$

After integrating the objective cost function $\mathfrak{H}$ and the constraint function $\aleph$ in terms of an indeterminate multiplier, the constrained optimization problem can be written as follows:

$$\mathfrak{R} = \mathfrak{H} + \varkappa\aleph - 1 \tag{3.2}$$

The optimal point is when the partial derivative of R with respect to each of the independent choice variables, PV, BTY, and $\aleph$, equals zero. In Lagrange calculations, analytical derivatives are utilized; they may not be efficient when working with discrete variables, but an approximation function is employed to obtain the derivative. In several engineering applications, extremely complicated iteration processes have been developed to trade off various multipliers of Lagrange by employing the Lagrange equation approach. The restricted optimization problem, on the other hand, has difficulty locating the multiplier of Lagrange's crucial points and rapidly reaches a local optimum.

3.2 Purpose of the Lagrange technique
The renewable energy planning problem has an economic objective and demands a long-term system performance evaluation to determine the optimal system reliability and cost balance. The Lagrange method is utilized to determine the optimal size of solar and battery storage systems by reducing the cost or fitness function. Selection, crossover, and mutation are three essential Lagrange phases for simulating natural evolution processes. When the convergent criterion is satisfied, the optimal solution enforces the selection of crossover and mutation processes, so creating the subsequent generation. The ability to influence the random search for a Lagrange by picking the healthiest chromosomes from a population is one of the most essential aspects of computer simulation. If any of the initial population's chromosomes break the system's constraints, the Lagrange optimization procedure is repeated until a new cell is selected. In this work, the suggested Lagrange approach was created using Mathematica and the roulette-wheel random selection, single-point crossover, and mutation operators, followed by elite replacement. Only the results of the best experiment case are presented here. Regarding varying degrees of dependability, the Lagrange model provides the optimal size. In order to determine the appropriate capacity of PV and BTY, binary coded Lagrange was developed. Input data include hourly data per year, solar radiation on the horizontal surface, ambient air temperature, and load power consumption. Following parameters are utilized in the Lagrange simulation:
1) the population size is 5000;
2) Crossover frequency: 0.98;
3) mutation frequency: 0.02.

4. Reliability Analysis and Optimal Simulation

4.1 Simulation of Reliability

The optimal sizes of an SPVL system were investigated and compared at two selected American weather stations. Using actual meteorological data from a weather station for a specific two-year period, a three-dimensional (3D) curve on the left side of Figure 1 illustrates the potential PV/BTY capacity combinations associated with distinct LMF1 values. On the right side of Figures 1(b) and 2, eight predefined values of LMF1, 5, 15, 35, 75, 200, 260, 300, and 500 hours are selected and represented by multicolored two-dimensional curves.

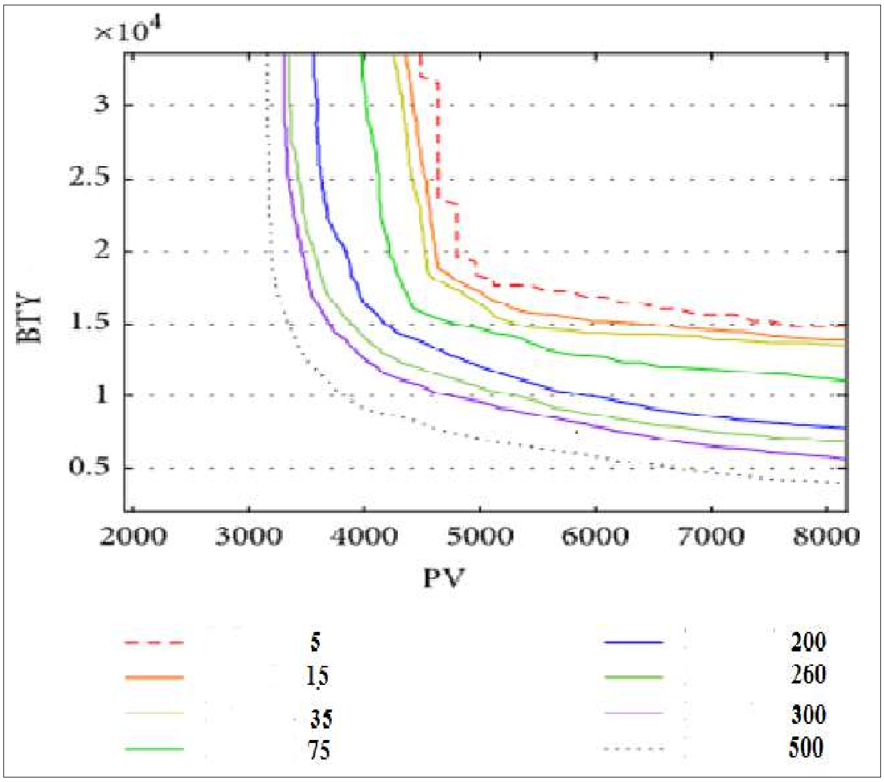

Fig 1: Curves of 2D using Lagrange equation

a) Curves of 2D using Lagrange equation

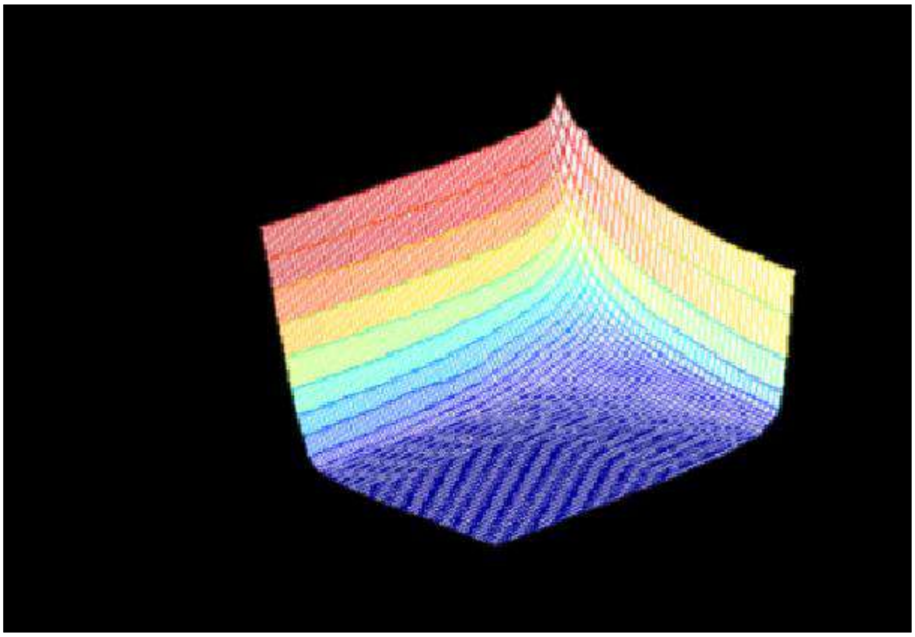

Fig 2: Curves of 3D using Lagrange equation

b) Curves of 3D using Lagrange equation
c) Fig 3.1 The capacity demonstration with various LMF1 needs using Lagrange Equation

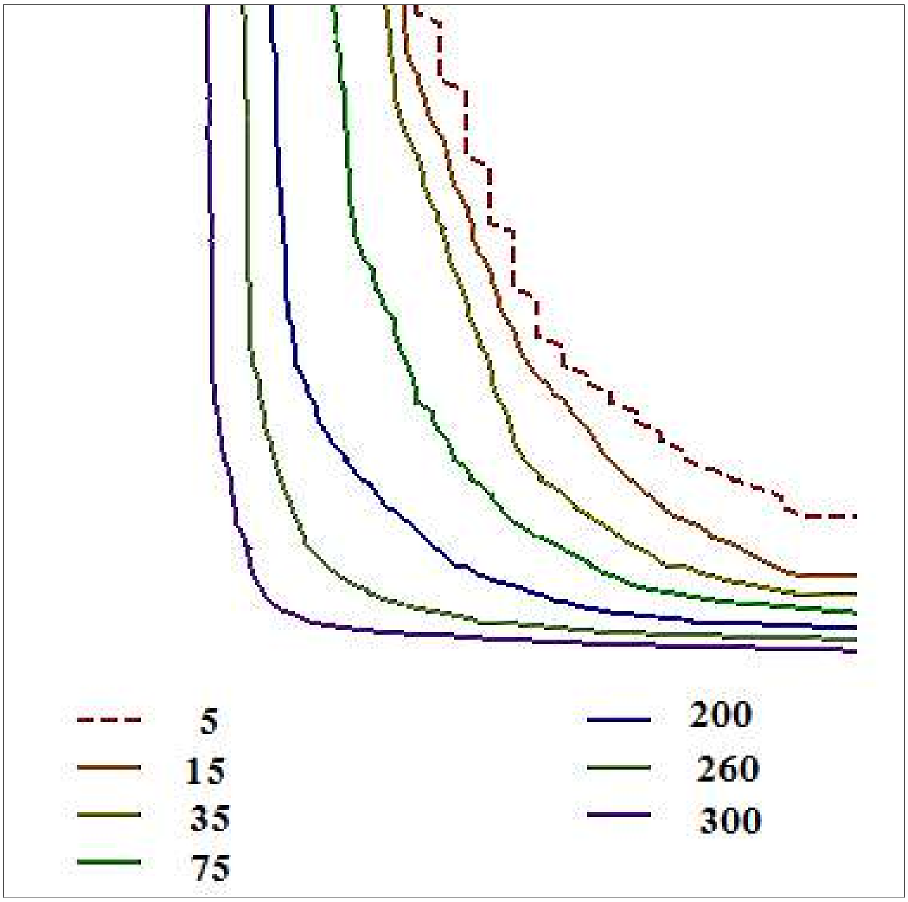

Fig 3: capacity allocations at two locations for various requirements.

Each 2D curve illustrates the fluctuating PV/BTY size trend in the context of a persistent system deficit. By plotting the 2D trade-off curve, the several permutations of PV/BTY capacity that provide the same degree of power supply dependability may be clearly seen. When the Lagrange varies between 5 and 500 hours, the installed PV and BTY capacity reduces substantially. Solar radiation differs based on location. To show the effect of location, meteorological data were reproduced from two different weather stations.

4.2 Simulation of optimal Size

The optimal planning solution for an SPVL system occurs at the inflection point of the LMF1 curve. By analyzing the link between PV and BTY capacity in terms of LMF1, the optimal state of capacity allocation may be determined. Due to the fact that the unit cost of a PV component is significantly greater than that of BTY, the total installation cost of PV has a large effect on the final optimal cost. Two years of actual solar radiation/temperature data were simulated. The real load is the electricity consumption of a Harvard University of Science laboratory. Table 4.1 compares the best PV/BTY allocation for 16 unique LMF1 at two independent locations. Where Eight samples were collected from two distinct sites within the Harvard College of Science, and the sites were compared as follows:

Table 1: The Lagrange equation for two sites different are compared.

Lagrange equation						
LMFI	Site (1)			Site (2)		
	PV (Wp)	BTY (W)	Cost ($)	PV (Wp)	BTY (W)	Cost ($)
5	2435.5487	1934.3563	1738.2655	2823.477	1899.383	1527.183
15	2653.4332	1997.2655	17938.285	2699.861	1901.44	1599.284
35	2296.386	2026.4927	1945.271	2606.8632	1897.834	1636.3279
75	2573.6433	1834.2374	1857.5439	2978.928	1989.034	1577.294
200	2644.1733	1736.8376	1982.119	2986.286	2011.194	1478.7634
260	2759.4823	1936.3481	1694.278	2879.696	1886.209	1798.284
300	2639.1924	1818.2863	1786.3933	2488.291	1738.293	1683.194
500	2158.1851	1478.2281	1799.2864	2809.337	1791.376	1566.182

Therefore, the time of site (1) is 8.2797, but the time of site (2) is 15,68473.

Table 4.1's cells indicate that the unreasonable installation cost solution has been identified. Because the Lagrange equation tends to become trapped at a local optimal solution and the Lagrange equation reaches a global solution, it frequently yields subpar results. Table 4.1 indicates that the cost of the first location is less than that of the second. This is owing to the restricted capacity of the test system at the first site and the inadequacy of the search area; the bigger the system capacity and load profile, the broader the search for potential solutions for both locations. Therefore, the suggested Lagrange model can produce a solution that is near to optimal. Statistically, the Lagrange equation technique performs marginally better for the amplitude mapping of SPVL systems, as shown in Figure 4.1. Consequently, the Lagrange equation search strategy may be examined in further detail. The data suggest that local inference has a major effect on the Lagrange equation procedure. A solution based on superior heuristics can help the Lagrange equation improve its performance by reducing the likelihood of early convergence.

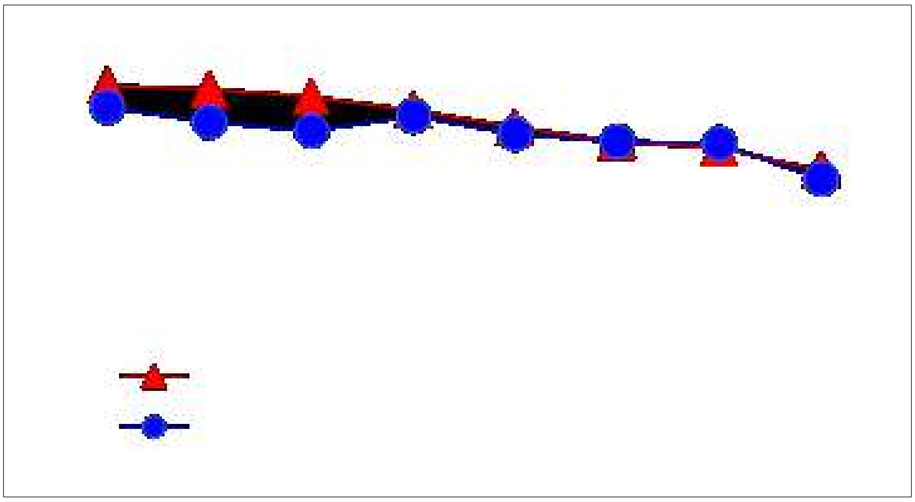

Fig 4: The Lagrange of site (1) and Lagrange of site (2) are compared

Table 1 demonstrates that the Lagrange equation may be solved effectively in a shorter amount of time. In the use of complicated optimization-constrained circumstances, such as solar allocation planning, where establishing the global optimal solution is difficult, GA is unquestionably superior. Due to the probabilistic nature of the solution development, the Lagrange equation is not constrained by optimum in the local neighborhood; compared to conventional optimization methods of comparable computing complexity, it may discover the optimal system configuration on a global scale.

5. Conclusion

The optimal capacity planning of the system using the Lagrange equation is examined. Two sites for which samples were acquired from the Faculty of Science at the American Harvard University were compared with an explanation of the obtained results. To compare performance, the overall installation cost of a system with a set of load and system resilience criteria should be kept to a minimum. The simulation results indicate that the Lagrange equation is marginally more effective at determining the optimal capacity planning method for a vast search space. In terms of expense and duration, the outcomes of the first site are much superior to those of the second site. Where the time of second site is 8.2797 seconds and the time of second site is 15,68473 seconds. In terms of execution time, the Lagrange equation proves to be highly competitive.

6. References

1. Bazmi A, Zahedi G. Sustainable energy systems: Role of optimization modeling techniques in power generation and supply-a review, Renewable & Sustainable Energy Reviews. 2011;15(8):3480-3500.
2. Poonam G. A comparison between memetic algorithm and genetic algorithm for the cryptanalysis of simplified data encryption standard algorithm. International Journal of Network Security & Its Application. 2009;1(1):34-42.
3. Marchand A, Gendreau M, Blais M, Emiel G. Fast near-optimal heuristic for the short-term hydro-generation planning problem. IEEE Trans. Power Syst. 2018;33(1):227-235.
4. Baños R, Manzano-Agugliaro F, Montoya FG, Gil C, Alcayde A, Gómez J. Optimization methods applied to renewable and sustainable energy: a review, Renewable and Sustainable Energy Reviews. 2011;15(4):1753-1766.
5. El-Arini MMM, Othman AM, Fathy A. A new optimization approach for maximizing the photovoltaic panel power based on genetic algorithm and Lagrange multiplier algorithm. International Journal of Photoenergy; c2013. p. 12. Article ID 481468.
6. Ismail MS, Moghavvemi M, Mahlia TMI. Characterization of PV panel and global optimization of its model parameters using genetic algorithm, Energy Conversion and Management. 2013;73:10-25.
7. Mellit A, Kalogirou SA, Hontoria L, Shaari S. Artificial intelligence techniques for sizing photovoltaic systems: a review, Renewable and Sustainable Energy Reviews. 2009;13(2):406-419.
8. Arabali A, Ghofrani M, Etezadi-Amoli M, Fadali MS, Baghzouz Y. Genetic-algorithm-based optimization approach for energy management, IEEE Transactions on Power Delivery. 2013;28(1):162-170.
9. Tang C, Liu S, Jian J, Ou X. A multi-step doubly stabilized bundle method for nonsmooth convex optimization. Appl. Math. Comput. 2020;376:125154.
10. Bernal-Agustín JL, Dufo-López R. Simulation and optimization of stand-alone hybrid renewable energy systems, Renewable and Sustainable Energy Reviews. 2009;13(8):2111-2118.
11. Helseth A, Fodstad M, Mo B. Optimal hydropower maintenance scheduling in liberalized markets. IEEE Trans. Power Syst. 2018;33(6):6989-6998. 11.
12. Toledo OM, Filho DO, Diniz ASAC, Martins JH, Vale MHM. Methodology for evaluation of grid-tie connection of distributed energy resources—case study with photovoltaic and energy storage, IEEE Transactions on Power Systems. 2013;28(2):1132-1139.

13. Azizipour M, Afshar MH. Adaptive hybrid genetic algorithm and cellular automata method for reliability-based reservoir operation. J. Water Resour. Plan. Manag. 2017;143(8):04017046.
14. Bakhshi R, Sadeh J, Mosaddegh HR. Optimal economic designing of grid-connected photovoltaic systems with multiple inverters using linear and nonlinear module models b ased on Genetic Algorithm, Renewable Energy. 2014;72:386-394.
15. Feng Z, Niu W, Cheng C, Lund JR. Optimizing hydropower reservoirs operation via an orthogonal progressive optimality algorithm. J Water Resour. Plan. Manag. 2018;144(3):04018001.
16. Seki T, Yamashita N, Kawamoto K. New local search methods for improving the lagrangian-relaxation-based unit commitment solution, IEEE Transactions on Power Systems. 2010;25(1):272-283.
17. Liu S. A simple version of bundle method with linear programming. Comput. Optim. Appl. 2018;72(2):391-412.
18. Das N, Wongsodihardjo H, Islam SJRE. Modeling of multi-junction photovoltaic cell using matlab/simulink to improve the conversion efficiency. Renew. Energy. 2015;74:917-924.
19. Das N, Wongsodihardjo H, Islam S. A preliminary study on conversion efficiency improvement of a multi-junction pv cell with mppt. In Smart Power Systems and Renewable Energy System Integration; Springer: Berlin, Germany; c2016. p. 49-73.
20. Berinstein P. Alternative Energy: Facts, Statistics, and Issues; Oryx Press: Westport, CT, USA; c2001. p. 1-190.
21. Burns JE, Kang JS. Comparative economic analysis of supporting policies for residential solar pv in the united states: Solar renewable energy credit (srec) potential. Energy Policy. 2012;44:217-225.
22. Nejat P, Jomehzadeh F, Taheri MM, Gohari M, Majid MZA. A global review of energy consumption, CO2 emissions and policy in the residential sector (with an overview of the top ten CO_2 emitting countries). Renew. Sustain. Energy Rev. 2015;43:843-862.
23. Nižetić S, Papadopoulos A, Tina G, Rosa-Clot MJE. Hybrid energy scenarios for residential applications based on the heat pump split air-conditioning units for operation in the mediterranean climate conditions. Energy Build. 2017;140:110-120.
24. Li Jiayuan. why economic growth did not translate into increased happiness: preliminary results of a multilevel modeling of happiness in China, Social Indicator Research, and. 2015;128(1):241-263.
25. Li Lulu, Shi Lei. Economic growth and subjective Well-being: analyzing the formative mechanism of Easterlin Paradox, The Journal of Chinese Sociology; c2019.
26. Nili F, Babazadeh Khorasani B, Shadkar M. Analyzing Dependency of Subjective Well-Being in Developing Countries to Macroeconomics Factors. Journal of Economic Research. 2015;50(1):21-28.