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# Solar Panel Stand Alone Microgrid Allocation System

*Sistema de asignación de microrred para paneles solares*

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## ABSTRACT

This research developed two methods for selecting optimal electrical components from n suppliers, considering a dual-objective optimization process and a single-objective genetic algorithm. The main objectives of the problem are to minimize overall system costs (operating and maintenance costs) and maximize overall system efficiency. Two methods are proposed to determine the best supplier selection for the initial microgrid configuration: 1) an optimization algorithm that allows for the design of a multi-objective process comparing the main characteristics of the components and thus selecting the best options from different suppliers, and 2) the Genetic Algorithm for the Solar Panel Microgrid Allocation System, which focuses on cost minimization. The genetic algorithm is developed to obtain, through multiple iterations, a result that minimizes the implementation and operating costs of a microgrid. Its purpose is to minimize the total implementation cost prorated according to the component's lifespan and its annual maintenance cost.

**KEYWORDS:** optimization; microgrid; solar panel.

## RESUMEN

En la presente investigación se desarrollaron dos métodos para seleccionar componentes eléctricos óptimos de n-proveedores, considerando un proceso de optimización de doble objetivo y un proceso de algoritmo genético de un solo objetivo. Los principales objetivos considerados en el problema son minimizar los costos generales del sistema (costo de operación, costo de mantenimiento) y maximizar la eficiencia general del sistema. Se proponen dos métodos para determinar la mejor selección del proveedor para la primera configuración de microrred: 1) un algoritmo de optimización que permite diseñar un proceso multiobjetivo que compara las principales características de los componentes y, por lo tanto, selecciona las mejores opciones entre diferentes proveedores, y 2) el Algoritmo Genético del Sistema de Asignación de Microrredes de Paneles Solares, que se centra en la minimización de los costos. El algoritmo genético se desarrolla para obtener a través de múltiples evoluciones un resultado que minimice el coste de implementación y operación de una microrred, cuyo propósito es minimizar el coste total de implementación prorrateado según la vida útil del componente y su coste anual de mantenimiento.

**PALABRAS CLAVE:** optimización; microrred; paneles solares.

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## I. INTRODUCTION

Currently, there's an increasing need for electrical energy, posing a significant challenge to mitigate climate change primarily caused by emissions from fossil fuel consumption [1].

Fifty years ago, the United States was self-sufficient in petroleum for electricity generation. Today, it imports over half of its petroleum and consumes 25% of the world's supply [2]. Oil is a finite resource and will inevitably become less available, especially as a sustainable energy source [2], [3].

The rapid increase in global energy demand is mainly responsible for the quick depletion of fossil fuel reserves and the rise in emissions from conventional power sources [4].

Earth offers a variety of natural alternatives for electricity generation, including photovoltaic, concentrated solar energy, wind energy, fuel cells, and more. Climate change concerns have not only captured the attention of governments worldwide but also prompted in developed nations significant research investment into devising or enhancing green energy strategies.

Statistics reveal a gradual increase in global energy consumption, with a 1.0% rise in 2015 and a 1.1% increase in 2014, while the average over the past decade stands at 1.9%. These figures highlight the collective efforts of governments and citizens towards energy conservation. The power grid consists of three main segments: the generating station, the transmission network, and the distribution network; with special attention given to the distribution network, also referred to as the load center. Load centers are classified as public or private, and as either small or large areas.

This study specifically targets public or private buildings. According to Dan Arvizu, director of the National Renewable Lab, buildings account for 38% of total energy consumption, with 71% of this being electricity. Notably, hotels on average consume more energy than commercial buildings, with annual power consumption ranging from 250 to 350 kWh/m² for hotels and 30–152 kWh/m² for commercial buildings.

Moreover, larger-scale lodging facilities have distinct operational characteristics, requiring greater load capacities due to increased air-conditioning requirements and broader comfort amenities. Annual energy consumption figures for large hotels typically range between 450 and 700 kWh/m²) [5]. Building energy supply comes from either external electricity supplied by a city's electric company or is self-supplied through a microgrid. A building microgrid is designed to generate enough energy for internal consumption through renewable sources.

The project's objective is to achieve complete self-sufficiency by installing green energy generation components, predominantly solar photovoltaic and/or wind power. Initially, a solar-based microgrid design was developed based on load requirements, geographic solar irradiation data, and general electrical component specifications such as solar panels, regulators, batteries, and inverters.

Subsequently, two methods are proposed to select the best supplier for the initial microgrid configuration. The first method employs an optimization algorithm to design a multi-objective process that evaluates key component characteristics and selects optimal options from various providers. The second approach focuses on cost minimization employing a Solar Panel Microgrid Allocation Genetic Algorithm which iteratively evolve solutions to minimize the implementation and operation costs of the microgrid.

### *A. LITERATURE REVIEW*

#### *Microgrid*

A microgrid represents an independent energy system comprising distributed energy sources, including demand management, storage, and generation, alongside loads capable of operating with or separately from the primary power grid. Its fundamental aim is to ensure local, dependable, and cost-effective energy security for both urban and rural communities, while also offering solutions for commercial, industrial, and governmental consumers [4].

A microgrid is also defined as a network of interconnected distributed energy resources, controllable loads, and critical loads, operating at low voltage. These microgrids have the flexibility to function in either grid-connected or island mode, depending on the operational conditions of the main grid. The advantages extend to utilities and the broader community, encompassing the reduction of greenhouse gas emissions and alleviation of stress on transmission and distribution systems.

In essence, microgrids serve as scaled-down versions of conventional power grids, incorporating power generation, distribution, and control elements such as voltage regulation and switch gears. However, they distinguish themselves from traditional grids by facilitating closer proximity between power generation and consumption, leading to efficiency improvements and decreased transmission losses.

Moreover, microgrids seamlessly integrate with renewable energy sources like solar and wind power. They possess dynamic control capabilities over energy sources, enabling autonomous and self-healing operations. During normal, peak usage, or primary grid failure periods, microgrids can operate autonomously, isolating their generation nodes and power loads from disturbances without compromising the integrity of the main grid.

Microgrids are interoperable with existing power systems, information networks, and infrastructure, capable of supplying power back to the main grid during grid failures or outages. Such a comprehensive definition underscores the significant imperative to establish self-sufficient energy buildings by harnessing renewable energy sources for electricity generation.

### *Genetic Algorithm*

Genetic algorithms (GA) serve as optimization tools adept at exploring optimal solutions for intricate problems characterized by discontinuities, multimodality, and other complexities. These algorithms are utilized for system optimizations across one or more objectives, resulting in a set of solutions where each outperforms another in at least one tested objective [6].

Operating on principles akin to natural genetics, genetic algorithms represent adaptive search and optimization methodologies distinct from traditional engineering design problem-solving approaches. Leveraging fundamental concepts borrowed from biological genetics, these algorithms are engineered to construct robust search algorithms, demanding minimal problem-specific information [7].

A typical constrained, single variable optimization problem can be outlined as follows:

$$\text{Maximiz e } x\text{: } f(x)$$

subject to the constraint: $x\text{min} <= x <= x\text{max}$

In tackling such problems with genetic algorithms, the variable $x$ is typically encoded within string structures. Binary-coded or floating-point strings may be employed, with the length of the string determined based on the desired solution accuracy [7].

According to Michalewicz [8], a genetic algorithm employed as an evolutionary procedure for a specific problem must encompass the following components:

- A generic representation for potential solutions, akin to the system modeling described in the preceding section.
- A mechanism for generating an initial population of potential solutions.
- An evaluation function, serving as the environment, to assess solutions based on their fitness.
- Genetic operators, such as crossover and mutation, which modify the composition of offspring.

### *Genetic Algorithm and Microgrids*

The widespread adoption of hybrid energy generation, reliant on renewable sources, is increasingly prevalent. Utilizing renewable energies can alleviate the impact of greenhouse gases, aligning with the requirements outlined in the Kyoto Protocol, particularly in reducing $CO_2$, NO, $NO_2$, and other pollutants like particulate matter. Implementing systems with multiple energy sources, termed hybrid systems, to power specific applications can enhance reliability and energy security compared to single-source systems [9].

The demand for more adaptable electrical systems, driven by evolving regulatory and economic landscapes, alongside the imperative for energy efficiency and reduced environmental impact, is propelling the advancement of microgrids. These microgrids are anticipated to assume a greater role in future electric power systems [10].

Koutroulis *et al.* [7] utilized genetic algorithms to optimize component sizes within a standalone hybrid energy system comprising PV panels, wind turbines, and a battery bank. Rajkumar *et al.* [11] proposed an optimization methodology for PV/Wind/battery hybrid systems. Mohamed and Koivo [10] proposed an approach utilizing genetic algorithms to ascertain the optimal operating strategy for a microgrid, incorporating a wind turbine, PV array, diesel generator [12], microturbine, fuel cells, and storage battery, with a focus on residential applications.

The capacity of the energy sources was assumed to remain constant, with the genetic algorithm employed to determine the optimal configuration of these various sources in order to minimize the cost function. Shrestha and Goel [13] proposed a sizing method for standalone PV systems, utilizing energy generation simulation for different combinations of PV panels and batteries, ensuring reliability metrics such as loss of load hours are met.

Kellogg *et al.* [14] introduced a design approach for hybrid PV/wind generator systems, employing an energy balance method utilizing hourly wind speed, solar radiation, and consumer power demand data to calculate the difference between generated and demanded power over a 24-hour period. The number of PV modules and wind generators are iteratively adjusted to achieve an average power difference of zero. Markvart [15] suggested considering seasonal variations in PV and wind generator power generation in the design methodology.

Chedid and Rahman [16] proposed determining the optimal sizes of PV panels, wind generators, and batteries by minimizing the total system cost function using linear programming techniques. Dalton *et al.* [5] conducted an analysis comparing various energy approaches for a large building, including photovoltaic, wind energy, and standalone grid energy, as well as combinations of renewable energy sources such as photovoltaic/wind and photovoltaic/grid. The study identified the most economically viable renewable energy system component for large-scale accommodation, demonstrating that wind energy conversion systems without batteries yielded the optimal net present cost. Delgado and Dominguez [6] presented a case study on renewable energy systems based on energy cost and reliability, with a focus on the methodologies employed.

The Universal Generating Function and Monte Carlo Simulation methods were compared in terms of their efficiency in achieving optimal results within the shortest timeframe. Ismail *et al.* [9], Mohamed and Koivo [10], Moghaddam *et al.* [17], and Koutroulis *et al.* [7] devised various genetic algorithms aimed at optimizing renewable energy utilization within microgrids. These algorithms encompassed combinations of photovoltaic solar panels, wind turbines, microturbines, and fuel cells, catering to both hybrid and standalone generating systems.

Kumar Basu [18] conducted a comparative analysis on a 14-bus radial microgrid, assessing two groups of Distributed Energy Resources (DERs) with different configurations—one group solely comprised of Diesel Generators (DGS) and the other featuring a mix of DGS and Micro Turbines (MTs). The evaluation aimed to determine the most economically viable technology deployment strategy from an owner's investment perspective, with the objective of minimizing fuel costs and optimizing economic parameters such as Net Present Value (NPV), Pay Back Period (PP), and Internal Rate of Return (IRR).

Abdelkader *et al.* [1] formulated an optimization approach targeting the Total Cost of Electricity (TCE) and the Loss of Power Supply Probability (LPSP) simultaneously. Utilizing a multi-objective Genetic Algorithm, the developed system was sized considering storage dynamics to achieve an optimal configuration, leading to various economic analysis scenarios revealing minimal LPSP alongside low TCE.

Yousefi *et al.* [19] modeled a hybrid Combined Cooling, Heating, and Power (CCHP) microgrid system, determining optimal component sizes through a multi-objective optimization approach. This system comprised fossil fuel-fired Internal Combustion Engines (ICE) and solar photovoltaic/thermal (PV/T) panels, offering two configurations—an entirely fossil fuel-based CCHP system and a hybrid CCHP microgrid incorporating both renewable and non-renewable CHP components. Employing Genetic Algorithm (GA), the optimal sizing problem for the CCHP microgrid was solved, highlighting the effectiveness of this meta-heuristic optimization algorithm based on the principles of natural selection.

## II. METHODOLOGY

### *A. MODEL DEVELOPMENT*

The general configuration of the microgrid model based on solar energy stand alone is presented in Figure 1.

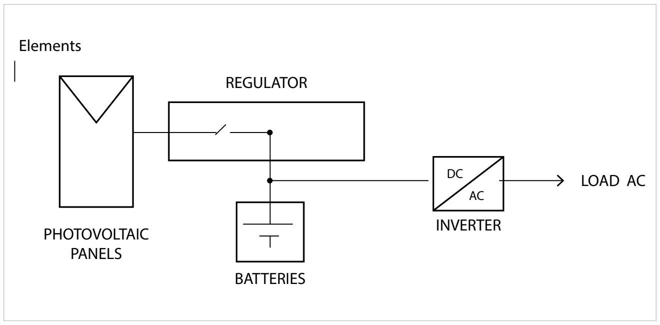


Figure 1. General configuration of a stand-alone microgrid solar panel.

As an initial phase of this investigation, a solar energy-based microgrid was conceptualized using data pertaining to load requirements, geographic solar irradiation information, and general specifications of electrical components including solar panels, regulators, batteries, and inverters. Based on this information, a particular microgrid configuration (refer to Figure 2) was chosen, taking into account the specific quantities of solar panels, batteries, regulators, and inverters.

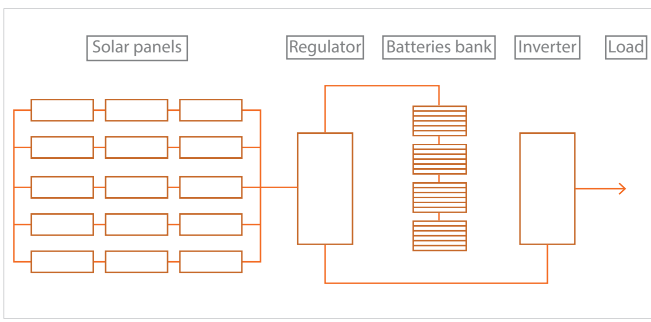


Figure 2. Solar panel stand-alone microgrid.

### B. SOLAR PANEL MICROGRID ALLOCATION SYSTEM GENETIC ALGORITHM

Throughout this research, a key aspect involves acquiring a stand-alone solar panel microgrid to develop algorithms for component replacement and supplier selection based on the offerings of current market suppliers. Presently, a genetic algorithm has been formulated with the aim of iteratively evolving solutions to minimize the cost associated with the implementation and operation of the microgrid. The objective is to reduce the total implementation cost over the component's useful life while considering its annual maintenance expenses. This scenario focuses on a stand-alone solar panel microgrid comprising 15 solar panels, one regulator, four batteries, and one inverter.

Although this methodology can be applied to any number of suppliers, the specific example herein pertains to seven suppliers of electrical components. Tables 1 to 4 present the data considered in this instance, encompassing information sourced from various suppliers regarding electrical components such as solar panels, regulators, batteries, and inverters.

TABLE 1
SOLAR PANELS

| SOLAR PANEL | S1 | S2 | S3 | S4 | S5 | S6 | S7 |
|---|---|---|---|---|---|---|---|
| Initial cost ($) | 220 | 222 | 280 | 200 | 250 | 300 | 350 |
| Maintenance cost ($) | 50 | 80 | 70 | 80 | 85 | 110 | 130 |
| Inom (Amps) | 4.71 | 4.89 | 4.96 | 4.45 | 5.02 | 4 | 4.18 |
| Vnom (Volts) | 18.04 | 17.4 | 17.1 | 19.1 | 16.93 | 18 | 18 |
| Isc (Amps) | 5.04 | 5.32 | 5.89 | 5.02 | 5.32 | 5 | 5 |
| Voc (Volts) | 21.92 | 21.7 | 21.62 | 21.98 | 21.7 | 18.1 | 19 |
| G (Kw/m²) | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| Area (m²) | 0.65 | 0.7 | 0.55 | 0.65 | 0.7 | 0.55 | 0.5 |
| Useful life (years) | 20 | 20 | 18 | 15 | 20 | 15 | 13 |

TABLE 2
REGULATOR

| REGULATOR | S1 | S2 | S3 | S4 | S5 | S6 | S7 |
|---|---|---|---|---|---|---|---|
| Initial cost ($) | 687 | 750 | 690 | 750 | 810 | 900 | 1000 |
| Maintenance cost ($) | 100 | 105 | 100 | 110 | 120 | 200 | 240 |
| Useful life (years) | 20 | 18 | 20 | 16 | 20 | 15 | 16 |
| Efficiency (%) | 97.5 | 97 | 98 | 96 | 95 | 94 | 93 |

TABLE 3
BATTERIES

| REGULATOR | S1 | S2 | S3 | S4 | S5 | S6 | S7 |
|---|---|---|---|---|---|---|---|
| Initial cost ($) | 1600 | 1400 | 1500 | 1600 | 1200 | 1800 | 2000 |
| Maintenance cost ($) | 160 | 140 | 180 | 160 | 180 | 200 | 300 |
| Discharge Eff (%) | 0.8 | 0.85 | 0.8 | 0.85 | 0.7 | 0.6 | 0.8 |
| Chemical Eff (%) | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 | 0.9 |
| Useful life (years) | 20 | 8 | 12 | 18 | 16 | 8 | 7 |

TABLE 4
INVERTER

| REGULATOR | S1 | S2 | S3 | S4 | S5 | S6 | S7 |
|---|---|---|---|---|---|---|---|
| Initial cost ($) | 1600 | 1600 | 1800 | 1400 | 1500 | 1900 | 2000 |
| Maintenance cost ($) | 160 | 160 | 180 | 150 | 200 | 300 | 400 |
| Efficiency (%) | 95 | 95 | 94 | 92 | 92 | 90 | 92 |
| Useful life (years) | 15 | 16 | 15 | 12 | 10 | 8 | 8 |

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# III. RESULTS

## A. NUMERICAL RESULTS

A multi-objective genetic algorithm (GA) was devised to identify the optimal components from a pool of n suppliers. The study incorporated two main objectives: firstly, maximizing the average solar panel efficiency, and secondly, minimizing the total annualized cost of components. The objectives aimed to maximize the average solar panel efficiency within the constraint of a nominal efficiency threshold (13%), while simultaneously minimizing the overall annualized cost of components.

$$\text{Average Solar Panel Efficiency (Ftss1)} = \sum_{i=1}^{n} \frac{Eff_{pi}}{n} \quad (1)$$

$$\text{Annualized Component Cost (Ftss2)} = \sum_{i}^{n} \frac{C_i}{Ul_i} + Cm_i \quad (2)$$

$$Eff = \frac{I_{nom} \cdot V_{nom}}{G \cdot A} \quad (3)$$

Subject to:
Ftss1 >= X
Ftss2 >= Budget

where $Eff$ = solar panel efficiency; $G$ = irradiance kWh/m$^2$; $A$ = area of solar panel m$^2$; $I_{nom}$ = nominal current, $V_{nom}$ = nominal voltage; $C_i$ = cost of element $i$; $Ul_i$ = useful life in years of component $i$; $Cm_i$ = maintenance cost of element $i$.

After running 30 iterations the algorithm shows through a Pareto set (Figure 3) different options of supplier combinations. It is evident that higher solar panel efficiency solutions are located in the upper right corner while lower cost solutions are found in the lower left corner.

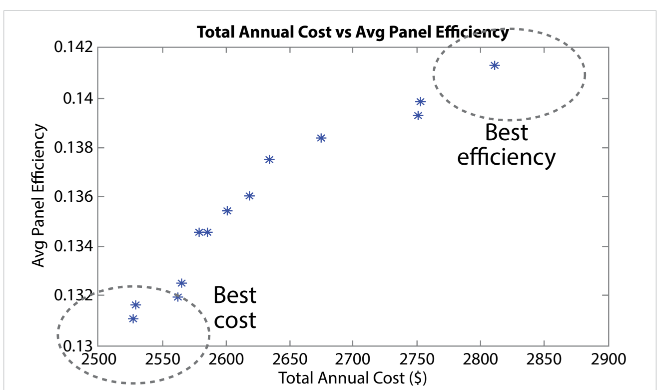


Figure 3. Pareto Optimal Solution for microgrid configuration.

## B. SINGLE OBJECTIVE

$$\text{Annualized Component Cost (Ftss2)} = \sum_{i}^{n} \frac{C_i}{Ul_i} + Cm_i \quad (2)$$

Subject to:
Ftss2 >= Budget

where $C_i$ = cost of element $i$; $Ul_i$ = useful life in years of component $i$; $Cm_i$ = maintenance cost of element $i$.

After running the genetic algorithm, several evolutionary populations were created and evaluated according to the objective considered in Figure 4.

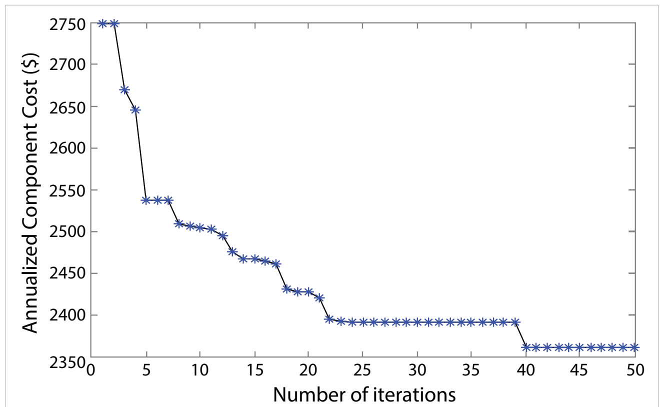


Figure 4. Genetic Algorithm evolutionary Pareto set.

Approximately, 40 evolutions were necessary to obtain a potential best solution in the solar panel stand-alone microgrid based on seven different suppliers to complete the configuration of 15 solar panels, one regulator, four batteries and one inverter.

# IV. CONCLUSIONS

This work focuses on microgrid solar panel stand-alone component selection based on two different methodologies. The microgrid configuration is based on customer load needs. The current configuration was defined according to a database considering primarily customer load needs and actual components traits.

On the first hand, we have a two objective optimization process to determine the best first configuration based on solar panel efficiency and total cost of components. After running this process a Pareto Optimal Solution was obtained for microgrid configuration showing different options according to total cost and efficiency. On the other hand, a genetic algorithm was designed to de-

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termine the best supplier combination for the first microgrid configuration system. Several generations were evaluated throughout the process. In summary, both methodologies are valuable for identifying the optimal initial microgrid investment configuration, or for other processes that involve new equipment and multiple supplier offers.

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