

Optimization and design of isolated microgrid systems with the daily energy balance method

by

Eduard Plett

B.S., Wichita State University, 2002

M.S., Kansas State University, 2004

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

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KANSAS STATE UNIVERSITY
Manhattan, Kansas

2024

Abstract

A state-of-the art alternative or supplement to the legacy electric power delivery system – the electric power grid – is the microgrid, a decentralized, local group of interconnected loads and distributed power sources that can operate in conjunction with or independently of the main grid, in a cooperative group or as stand-alone entities. The focus of this dissertation is the optimization and design of stand-alone, also called islanded or isolated, microgrids.

Microgrids typically include various power sources such as engine generators, solar panels, wind turbines, fuel cells, and energy storage devices such as batteries. Given the high variability of power demand of loads, and the high variability of generated power by different types of energy sources; considering the completely different cost structures for different microgrid components, a major technical challenge is designing an optimal microgrid system, that is, determining the optimal combination of components for a reliable, stable, cost-effective and environmentally friendly microgrid system.

Virtually all currently existing optimization approaches use extensive simulations to attempt to select configurations that match the generated and consumed power for each hour over the course of the project lifetime. This approach requires detailed system data, is computationally inefficient and slow; is not easily adaptable to different systems, different consumer profiles and different locations; requires expensive and complex software to operate; and in general is not very suitable for making practical engineering decisions.

The novel method presented in this dissertation is uniquely different from all existing approaches in that it does not attempt to match power quantities. Instead, this method aims to achieve a balance between generated and consumed energy over the course of a day.

To determine the amount of energy that can be generated by different sources, new and revised equations were developed that calculate the expected amount of energy generated by solar and wind power systems. In addition, new equations were developed to calculate the expected amount of energy that needs to be stored in batteries for reliable operation. A Generalized Reduced Gradient (GRG) and a genetic algorithm (GA) were then used to determine the optimum combination of components that minimize cost and maximize reliability.

Unlike some other approaches, this method allows a high degree of customization. Various power profiles and various components can be selected, and multi-objective optimization operators produce optimization results according to the preferences of the user. The equations and results are easily verifiable and provide a high degree of confidence in the obtained solutions. This method is much more computationally efficient than other methods, and can be implemented on widely available computation platforms such as MS Excel. In short, this method is much more engineer friendly compared to all other approaches.

To verify the validity of this method, the developed models and equations were tested with real-life production data of operational generator, wind, and solar power systems. The optimization algorithms were then run with power demand data of real-life small, medium, and large individual users, as well as with demand data for a community of multiple users. For all systems, the resulting configurations were then benchmarked to configurations determined by a specialty software tool called HOMER. In all cases the obtained solutions by the new method were superior in terms of reliability and economic as well as environmental costs, hereby confirming the validity of this method as well as its superiority to competing approaches.

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Chapter 1 - Introduction

1.1 Problem Description

1.1.1 Isolated Microgrids

In general, electric power systems can be divided into two broad categories: macro-grids and micro-grids. The legacy configuration is the macro-grid, where most consumers and producers are connected in a large network, covering large geographical areas, sometimes entire countries or even continents, spanning hundreds if not thousands of miles. The power generation is centralized, anchored by large coal, nuclear or hydroelectric power plants. The power plants and consumers are interconnected utilizing high-voltage, long-distance power transmission lines.

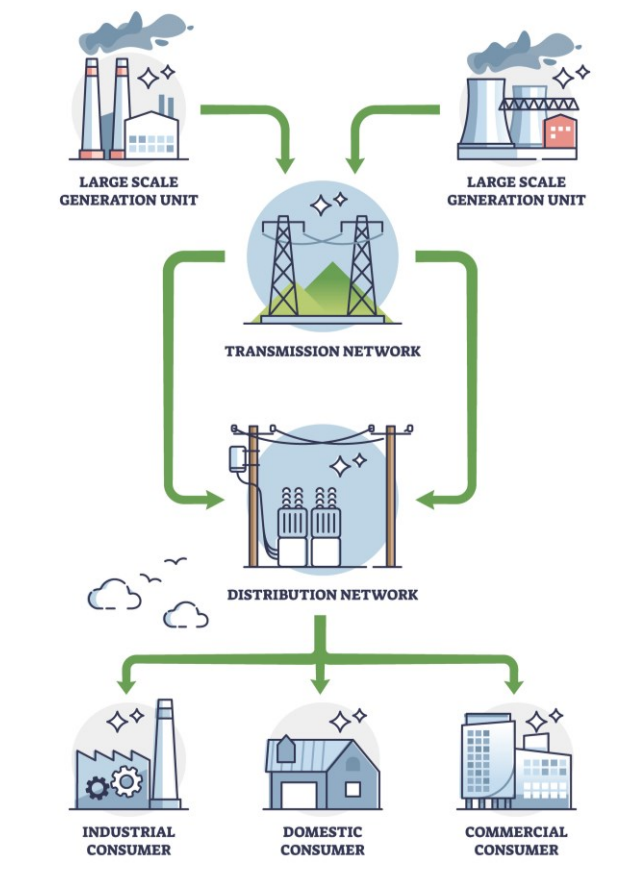


Figure 1.1. A diagram of a macro-grid

(Source: stock.adobe.com)

Due to the size of the systems and redundancy of components, macro-grids are typically more efficient, more economical, more stable, and more reliable than stand-alone systems. However, macro-grids are susceptible to potentially crippling large-scale outages due to natural or man-made disasters. They also carry a substantial environmental liability due to their reliance on non-renewable energy sources.

A micro-grid is a localized group of interconnected loads and energy sources most commonly limited to a certain geographic area, such as remote settlements (e.g., in Alaska), literal islands (e.g., Puerto Rico), drilling platforms, etc., where connecting to the macro-grid is either impractical, cost prohibitive or simply impossible. Power generation is decentralized, often using renewable energy sources such as solar, wind, and small-scale hydro power plants. Electricity is distributed locally, reducing the need for long-distance transmission lines.

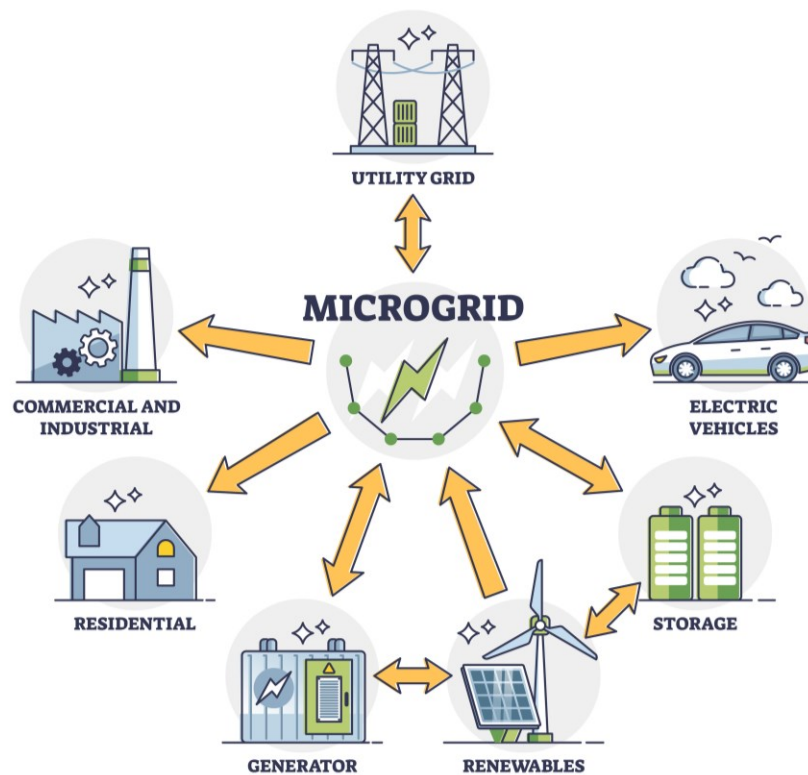


Figure 1.2. A diagram of a micro-grid

(Source: stock.adobe.com)

Micro-grids provide energy independence and security, offer improved resilience and reliability for remote or disaster-prone areas, facilitate an increase in renewable energy generation, and offer potential cost saving through local generation and reduced transmission costs. However, micro-grids often have higher initial costs, limited capacity compared to macro-grids, and require complex management and control systems to balance supply and demand and to provide a reliably continuous service.

Fairly recently, a substantial body of research has been done to try to merge the two systems. Localized groups of consumers and producers are connected into micro-grids, but with the flexibility of connecting to a cooperatively-run macro-grid.

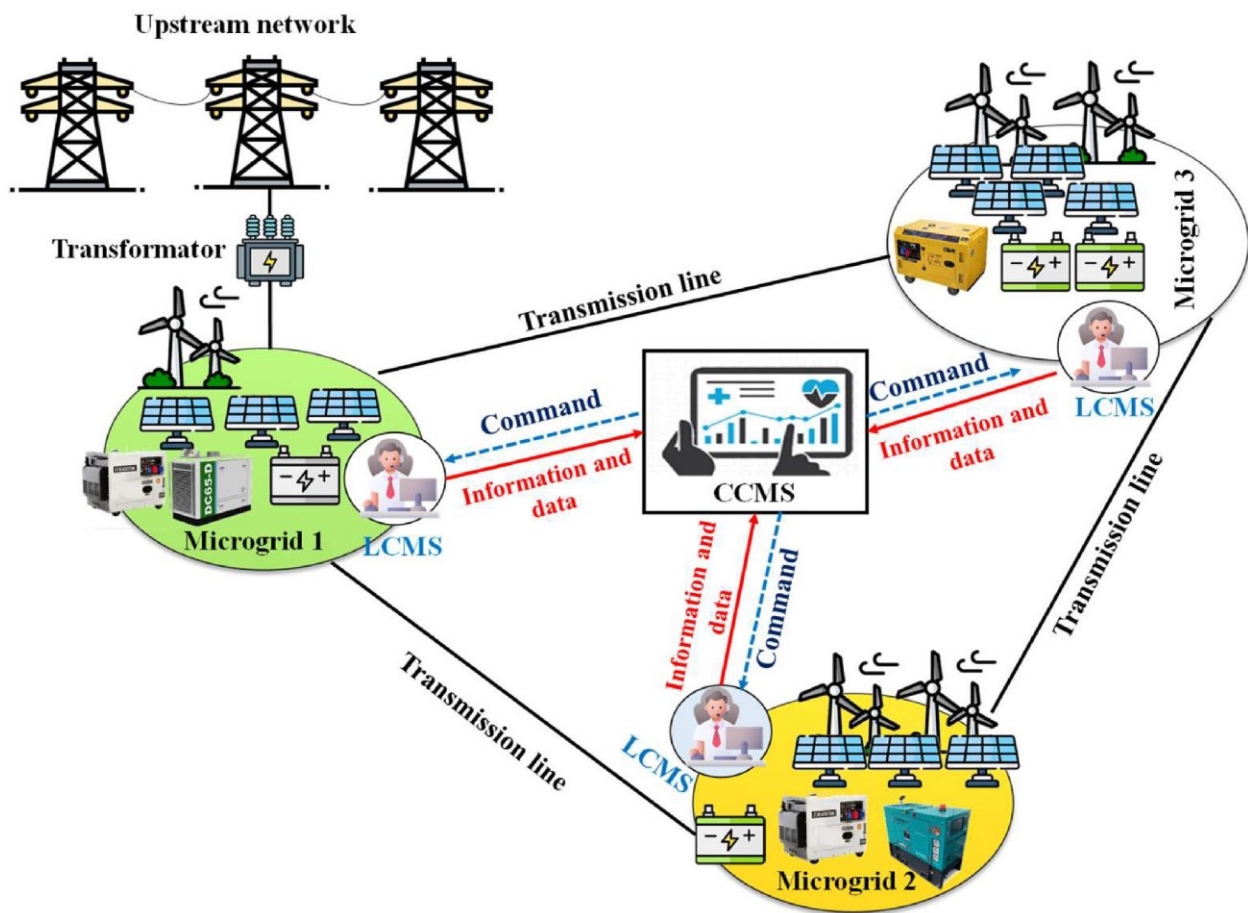


Figure 1.3. A diagram of a collaborative microgrid

(Source: [1])

Each sub-system of the cooperatively-run microgrid can provide service and operate independently when the macro-grid fails (in the so-called “islanded” mode), but each unit can still be connected to the macro grid and is able to have continuous service and reap the benefits of economy-of-scale when operating cooperatively in the grid-connected mode.

Unlike cooperatively-run microgrids which are currently still mostly experimental systems, isolated or stand-alone microgrid systems have already proven themselves in practice and are particularly beneficial for providing electricity in remote areas where connection to a macro grid is not feasible. Often, they include only one load, or a small number of loads, for applications such as remote weather stations, off-grid residences, etc. Typically, these systems combine renewable energy sources like solar photovoltaics (PV), wind turbines, and hydro-power turbines with conventional power sources such as diesel and propane generators, augmented with storage options such as fuel cells and batteries.

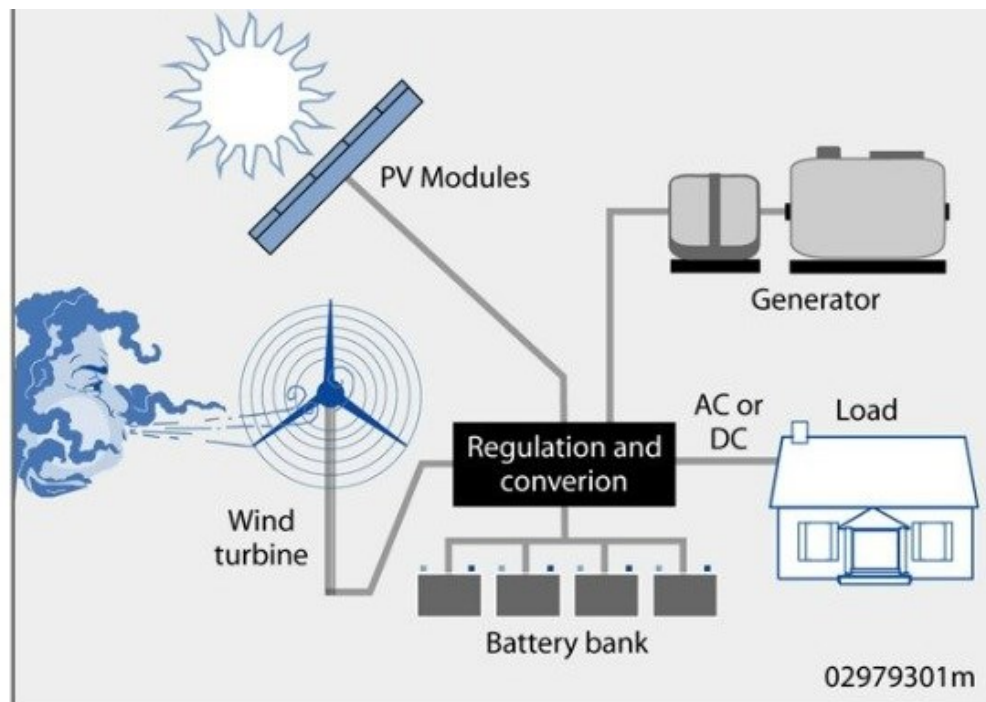


Figure 1.4. A diagram of an isolated microgrid

(Source: [2])

1.1.2 Isolated Microgrid Applications

As discussed earlier, microgrid systems are particularly beneficial for providing electricity in remote areas where connection to a macro grid is not practical or feasible. They come in various sizes, which can be loosely grouped as follows:

- Small-sized systems (1-20 kWh/day). Examples include remote weather stations, cell towers, etc.
- Medium-sized system (20-100 kWh/day). Examples include off-grid houses, remote ranches, etc.
- Large scale (>100 kWh/day). Examples include remote settlements, literal islands, etc.

There are a multitude of other applications, but two specific applications served as motivation for this research and will be highlighted below.

The first application are field power units. Field power units are compact and portable sources of electricity, which can be quickly set up to provide power for various needs. For example, field power units power communication equipment, radar systems, surveillance devices, and other critical electric needs for the military. They also supply power for medical equipment, communication devices, lighting, water purification systems, and other needs for disaster relief agencies. They are indispensable to operate data collection, communication, and instrumentation equipment for remote research stations. They are also a common sight at construction sites where they power lights, power tools, etc. They service cell towers, fiber-optic networks stations, rural water stations, and other remote infrastructure equipment. They provide power for lights on stages, a sound system, and other needs for outdoor events such as music festivals, concerts, or sporting events.



Figure 1.5. A picture of a field power unit

(Source: stock.adobe.com)

While field power units have been around for a long time, traditionally they were powered exclusively by engine generators. However, in recent years field unit manufacturing companies have started augmenting engine generators with batteries, solar panels, and wind turbines. A critical design aspect is to determine the optimum size and ratio of each of these components such that the cost per kWh is minimized. But so far there has been virtually no research done in this area.

The second major application for microgrid systems is providing power for off-grid dwellers. People living in remote areas without access to the power grid are a small minority in the US, but they still exist, particularly in western states such as Idaho, Montana, Wyoming and, as already mentioned, Alaska. Living off-grid is much more commonplace in other parts of the world, particularly in parts of Africa, Asia and South America, where the power grid is not as developed as in North America and Europe.



Figure 1.6. A picture of an off-grid ranch in Wyoming

(Source: Adobe Firefly)

In addition, in recent years an off-grid movement has gained momentum as people in the so-called developed countries seek alternative ways of living that prioritize self-sufficiency, sustainability, and independence from traditional utilities, and who then voluntarily go off grid. Whatever the reason for living off-grid, an electrical engineer might be tasked with designing a well-balanced power system for off-grid dwellers such that reliability is maximized, fuel consumption is minimized, and overall costs are minimized.

While there has been some research (surveyed in section 1.2) done in this area already, it is by and large strictly simulation-based academic exercises, and not much help for practical engineering decisions. There is a need for more research in this area to better understand microgrid systems, so that practical engineering methods and tools could be developed for designing optimum microgrid systems for off-grid applications.

1.1.3 Isolated Microgrid System Components

As discussed earlier, a microgrid typically consists of 4 key components, which will be discussed in greater details below:

- A single load device or several load devices which consume electric power.
- Dispatchable (controllable) power sources such as diesel, natural gas, or propane generators.
- Storage devices such as batteries, electric vehicles, flywheels, compressed air, fuel cells, etc.
- Renewable sources of electricity production, such as solar panels, wind turbines, hydro-turbines, etc.

While renewable energy sources such as wind and solar currently receive the bulk of research time and money, internal combustion engine generators (diesel, natural gas, or propane powered) are often the heart of a practical (functioning beyond simulation) system.



Figure 1.7. A picture of a large industrial generator

(Source: stock.adobe.com)

Unlike renewable sources, which depend on uncontrollable and unpredictable weather factors such as sun irradiation and wind speed, engine generators provide reliable, stable, and dispatchable, i.e., precisely controllable, power in large quantities. However, engine generators are not environmentally friendly, as they are a major source of air pollution (carbon monoxide, carbon dioxide, nitrogen oxide, etc.), as well as noise pollution. In addition, they have by far the largest operating costs of any available power sources, burning through tons of expensive fuel while in operation. They are also quite inefficient, especially when running with a low load, and burn fuel even when idling.

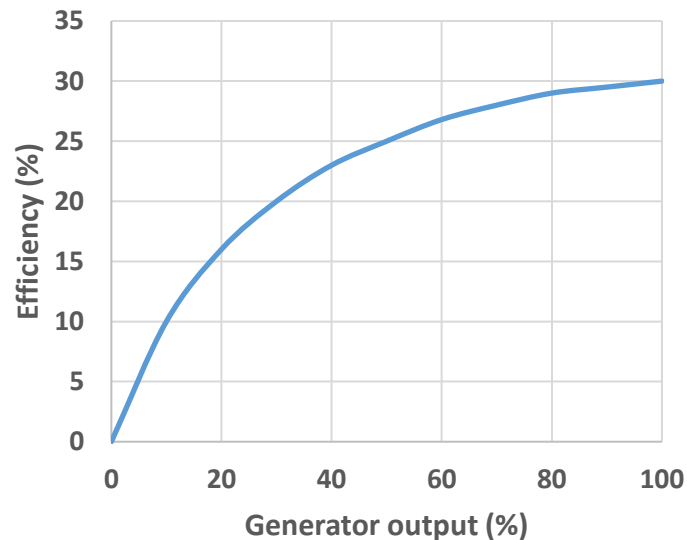


Figure 1.8. A typical efficiency curve of a diesel generator

The loads in a typical system vary greatly throughout the day, week, month, year, with the effect that the generator must be oversized to cover the peak load, while running inefficiently the rest of the time.

For example, given the power demand curve below, the minimum size of the generator needs to be at least 20 kW, but for large stretches the generator is loaded to quite a bit less than 50%.

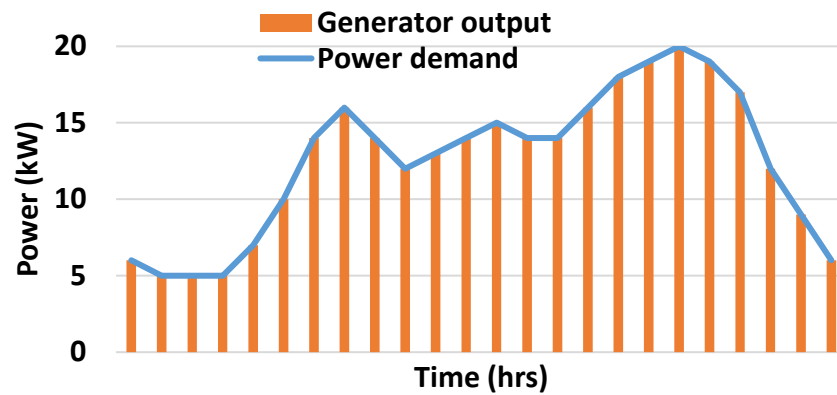


Figure 1.9. An example of an isolated microgrid supplied only by a generator

To improve the efficiency of a system employing engine generators, a common strategy is to add some storage devices, e.g., batteries.



Figure 1.10. A picture of a large energy storage unit

(Source: stock.adobe.com)

Now the generator can be sized smaller, and the batteries can be used to supply additional power in times of high demand. In times of low demand, the generator can be used to replenish energy stored in the batteries, so that most of the time the generator operates in the most efficient region.

This strategy, called *peak-shaving*, de-couples energy production and consumption, allowing the generator to be sized according to the average demand instead of the peak demand. By increasing the size of the storage unit *load-leveling* can be achieved, resulting in a fairly flat demand curve for the generator.

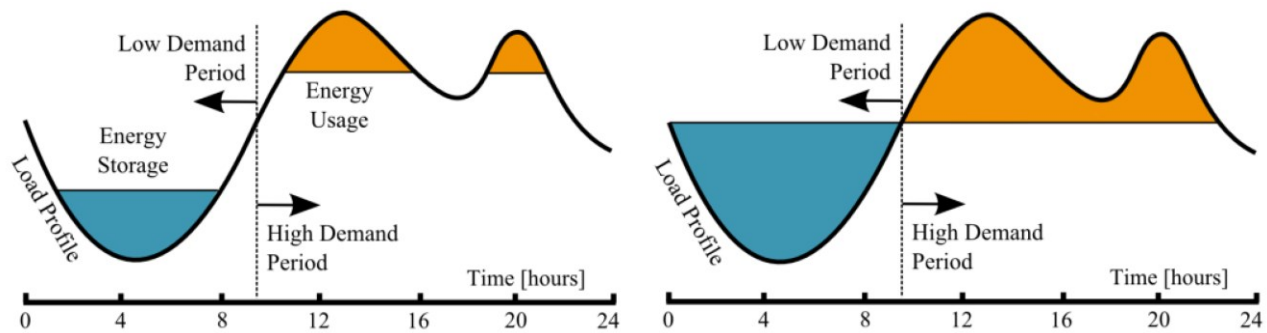


Figure 1.11. Peak-shaving (left) and load-leveling (right) schemes

Source: [3]

For the same example above, the generator can now be sized much smaller, with a rated power of only 12.5 kW. While still running all the time, the generator is now operating in the most efficient region, charging batteries in times of low demand, while the energy stored in batteries can be used to supplement the generator power in times of high demand (see figure below).

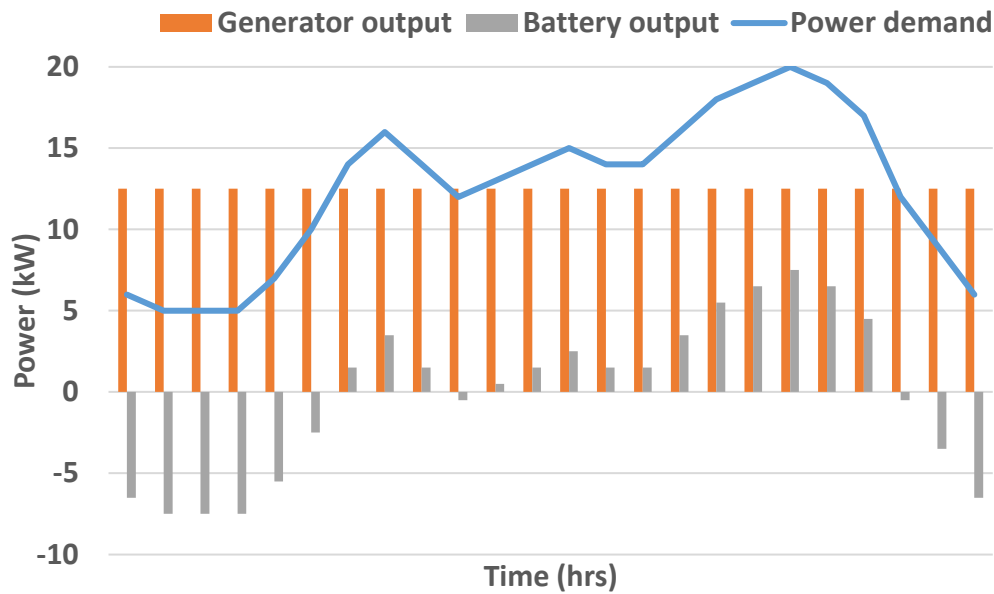


Figure 1.12. An example of an isolated microgrid supplied by a generator plus batteries

Once storage devices are part of the micro-grid, the next logical step is to add renewable energy sources such as wind turbines and solar panels to recharge batteries when these resources are available. Depending on the size of the components, the usage of an engine generator can be greatly reduced or even completely eliminated.



Figure 1.13. A picture of a renewable power system at K-State Salina consisting of 24 kW of PV panels and a 10-kW wind turbine

For the same example as before, by adding solar and/or wind power sources, the size of the generator can be reduced even more (to 10 kW), and the run time of the generator can be halved.

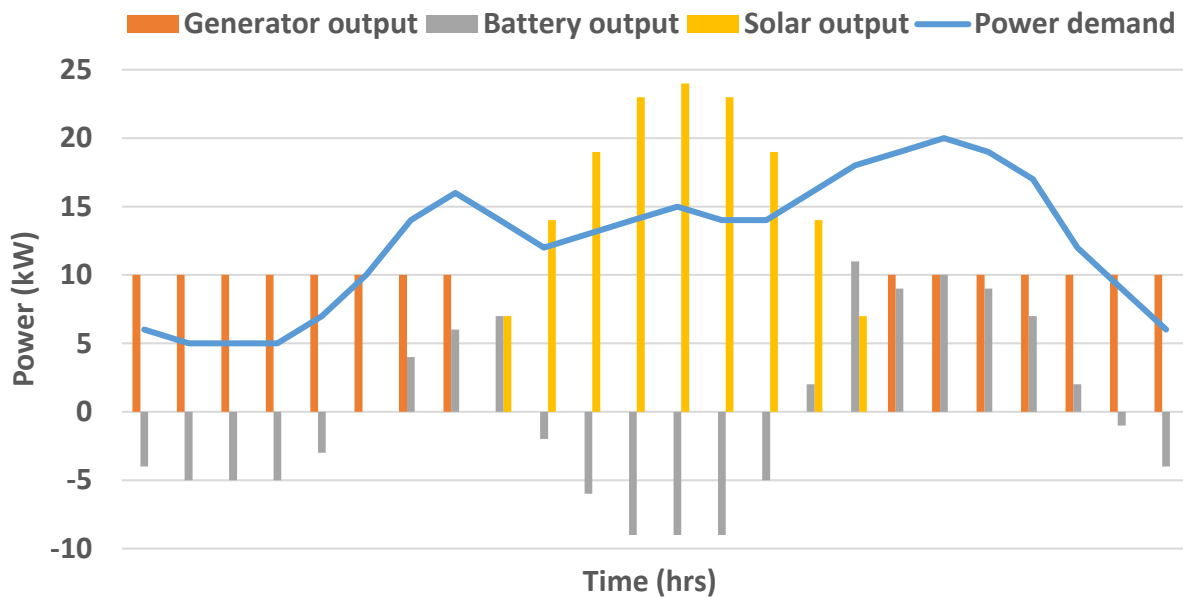


Figure 1.14. An example of an isolated microgrid supplied by a generator, PV panels and batteries

1.1.4 The Isolated Microgrid Design Dilemma

To summarize the discussion above, the same load can be supplied by either only a generator, or a generator and batteries, or a generator, solar power and some batteries, or any other combination of sources. But which is the “best”, or optimal combination? What is the optimal size of generators, solar panels, wind turbines and batteries such that power-less days are eliminated, fuel consumption is minimized, and the overall costs are minimized?

On the surface, it appears the most desirable solution for a microgrid system would be one where the usage of engine generators is completely eliminated, and the entire power demand is covered by renewable energy sources. However, while renewable energy sources require no fuel, and therefore have low operating costs, the upfront investment costs are often higher than engine

generators. In addition, renewable energy sources suffer from reliability concerns as they depend on highly variable and unpredictable energy sources such as solar radiation and wind speed.

Therefore, a practical solution for designing a microgrid system typically requires finding compromises between high investment costs (renewable energy components) and high operating costs (internal combustion engines), while considering reliability as well as a host of other technical, practical and financial design requirements of a project.

The problem can then be formally stated as follows: given the variability of power demand and power availability of different energy sources and loads, considering completely different cost structures of microgrid components - what combination of components would result in the most efficient, reliable, stable, “green”, etc., isolated microgrid power system?

1.2 Literature Survey of Current Research Efforts

1.2.1 General Research in Microgrids

Microgrids in general have been at the center of substantial research efforts for several years already, but there still remain a host of technical and economic problems to be resolved.

The technical side includes developing more advanced energy storage systems [4]; improving control [5], dispatch strategies, and load management [6]; designing resilience and protection schemes [7]; and improving stability and power quality [8]. Some of these technical challenges have been addressed by research done by the SPECS group at K-State.

For example, [9] discusses the challenges and solutions related to stability in microgrids with low inertia. As renewable energy sources like wind power and solar power become more common, traditional synchronous generators are being replaced, leading to a decrease in system inertia. This reduction in inertia makes it more difficult to regulate frequency and voltage, which

are crucial for stable microgrid operation. To address these issues, energy storage systems (ESS) combined with virtual synchronous generator (VSG) control are proposed. This approach helps to control power output and improve the stability of the microgrid. Various control strategies and techniques to limit fault currents and maintain synchronization during transient events are also explored.

In [10], the authors explore how converting critical loads to smart loads can enhance the stability and power quality of nanogrids. Nanogrids, defined as small-scale power systems typically serving a single load or a single building, often face challenges due to low inertia and power fluctuations. Smart loads can adjust their power consumption to match supply, thereby limiting voltage and power oscillations. This reduces stress on energy storage systems and minimizes the need for large battery banks. Several case studies demonstrating how smart loads improve the performance of nanogrids under various conditions are presented.

In [11], the authors discuss how voltage source inverters (VSIs) can be optimized to provide ancillary services in microgrids. These services include negative-sequence compensation and harmonic compensation, which are essential for maintaining power quality and stability. This study highlights a novel pulse-width modulation (PWM) technique that maximizes the utilization of the DC-bus voltage in grid-interactive two-level VSIs. By injecting a common-mode component into the PWM references, the proposed method increases the maximum active and reactive power that the VSI can deliver while providing ancillary services. This approach helps to keep the inverter operating within its linear modulation region, enhancing its performance and reliability.

In [12], the authors explore how inverters can autonomously manage microgrids, ensuring stable operation both when connected to the main grid and when operating

independently. A novel control strategy allows inverters to switch between grid-forming (GFM) and grid-following (GFL) modes without external communication. GFM mode allows inverters to create voltage and frequency references which are essential for microgrid operation. GFL mode enables inverters to synchronize with the main grid. Using dual parallel control pathways, the proposed method enhances the reliability and flexibility of the microgrid.

On the economics side, some major challenges are reducing the capital, operation, and maintenance costs; ensuring cost and power availability and fairness in a microgrid; and solving various regulatory and financing issues [13]-[15]. Some of these challenges, in particular providing cost reduction, power availability and fairness, have been addressed by research done by the BIC group at K-State.

For example, in [16] and [17], a novel double auction mechanism for energy trading between buyers and sellers within a microgrid is proposed to reduce operation costs. The auction is conducted iteratively, allowing adjustments without needing private information from agents. A central controller manages the auction, aiming to maximize both individual benefits and overall social welfare.

In [18] and [19], game theory is applied to optimize energy trading between agents in microgrids. The interactions between various agents in a microgrid, such as consumers, producers, and storage units, are modeled using multi-agent systems. Using game theory, equilibrium points are found where no agent can improve their own benefits by changing the strategy unilaterally. This approach ensures that all participating agents maximize their individual payoffs at the equilibrium points as well as maximize the system-wide efficiency.

While utilizing some elements of the previous research efforts, this dissertation takes it in a different direction. It is still concerned with the technical aspects as well as economic aspects

of microgrids, but the overall goal is determining appropriate methods and tools to design the most efficient isolated microgrid system.

1.2.2 Research in Isolated Microgrid Design and Optimization

There are surprisingly few practical guidelines for an engineer who is tasked with designing a microgrid power system. The various approaches can be loosely grouped as follows:

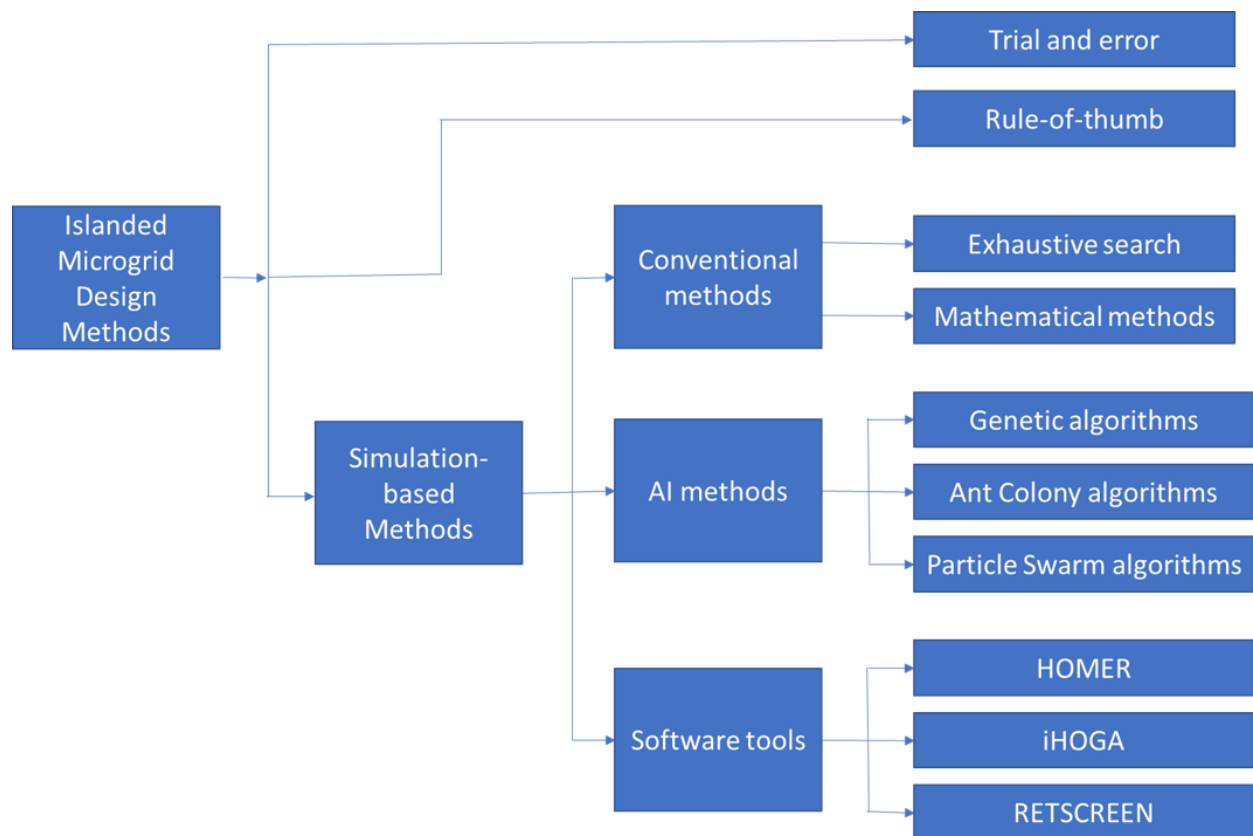


Figure 1.15. Microgrid optimization techniques classification

Currently most practical microgrid system design guidelines fall in the “trial and error” or “rule of thumb” categories. The trial-and-error method begins with an educated guess. The configuration is tested to see if it functions properly. If not, the experimentation continues until a working solution is found. This is typically an extremely time-consuming endeavor.

The rule-of-thumb approach uses some experimentally determined rules. For example, to choose the correct size for a battery, one source suggests the following design guideline: compute the load-ratio, defined as the total watt-hours divided by the continuous running watts of the load. Depending on the load-ratio, determine the battery ratio according to the following table [20]:

Table 1-1. Battery-ratio vs load-ratio guidelines

Load-ratio	Battery-ratio
1-5	5
5-10	4
10-15	3
15-20	2.5
>20	2

Then, based on the load ratio, multiply the battery-ratio by the total watt-hours to determine the necessary battery bank capacity. For example, if the required energy is 1710 Wh, and the continuous running power is 670 W, then:

$$\text{Load ratio} = \frac{1710}{670} = 2.5$$

Based on the table above, the battery ratio is 5, and the total capacity of the battery bank is:

$$E_B = 5 \times 1710 = 8.55 \text{ kWh}$$

As is to be expected, this approach is vague and imprecise, and might not always result in a working system, and even less likely in an optimal system. Unfortunately, there is usually not much consideration about determining an optimal configuration. Typically, the engineer is simply directed to design each subsystem (generator, solar, wind, battery) independently according to some rules-of-thumb, and if in doubt, oversize everything, especially the engine

generator, so that it can pick up the slack if the rest of the equipment turns out to be too small for proper operation.

To summarize, trial-and-error approaches are extremely time-consuming, and do not guarantee that an optimal solution will be found. Rule-of-thumb guidelines, even if they are available, are too vague, and may not provide a good solution to a specific problem either.

More scientific and repeatable is the simulations-based approach. In the most basic version, candidate solutions are selected by doing an exhaustive search of all possible combinations. For each selected solution, a simulation is run to determine if a solution is capable of supplying the power demand over each time frame, typically for each hour over the project's lifetime. For each solution, its desirability in respect to reliability, cost, fuel consumption, or other performance criteria is computed. The optimal solution can then be chosen from the list of feasible solutions.

The exhaustive search method, involving the search of all possible valid combinations, usually provides a workable solution, and several publications report using it, for example in [21]. Another exhaustive search approach is also used in [22], where the authors build a matrix with all possible combinations of numbers of solar panels and numbers of wind turbines according to a lengthy algorithm. For each combination, the generated power is computed. Then for each acceptable (in terms of power generated) combination the levelized cost of energy is determined, which allows the user to pick the optimal configuration. For a case study discussed in this paper, the result was presented in the form of a table below. For this case, the optimal configuration was found to be 95 PV panels and 7 wind turbines, resulting in the minimum levelized cost-of-energy (LCOE) equal to \$0.74.

Table 1-2. Cost of energy vs number of components solution table

Number of components	Levelized cost of energy (LCOE)
141 PV + 1 Turbine	0.859 \$/kWh
130 PV + 2 Turbines	0.85 \$/kWh
125 PV + 3 Turbines	0.812 \$/kWh
118 PV + 4 Turbines	0.797 \$/kWh
107 PV + 5 Turbines	0.792 \$/kWh
103 PV + 6 Turbines	0.759 \$/kWh
95 PV + 7 Turbines	0.741 \$/kWh

In [23], the process is similar, but the selection for candidate solutions is greatly simplified. It starts by selecting a combination with no generator output and using the maximum size of a solar system to still satisfy the load requirements. Then in each iteration, the size of the generator is increased, while the size of the solar system is decreased. An array is used to keep track of costs for each valid combination. When the costs for all valid combinations are found, the combination with the minimum cost is selected as the winning configuration.

Another subcategory of the conventional design method is the probabilistic optimization, which utilizes uncertainty parameters in the problem formulation or the solution process. For example, [24] computes the loss-of-power probability for different combinations of system components and determines an optimal solution vector satisfying both high reliability and low cost. To avoid over-sizing or under-sizing the system, every possible solution in the search space is considered, and the solutions are returned in the form of vectors.

For a case study presented in the paper, the optimization algorithm returned the solution vectors as seen in the figure below. For this example, the optimal vector is #187, corresponding to 57 MW of solar power, 187 MW of wind power, and a battery storage system of 63 MWh.

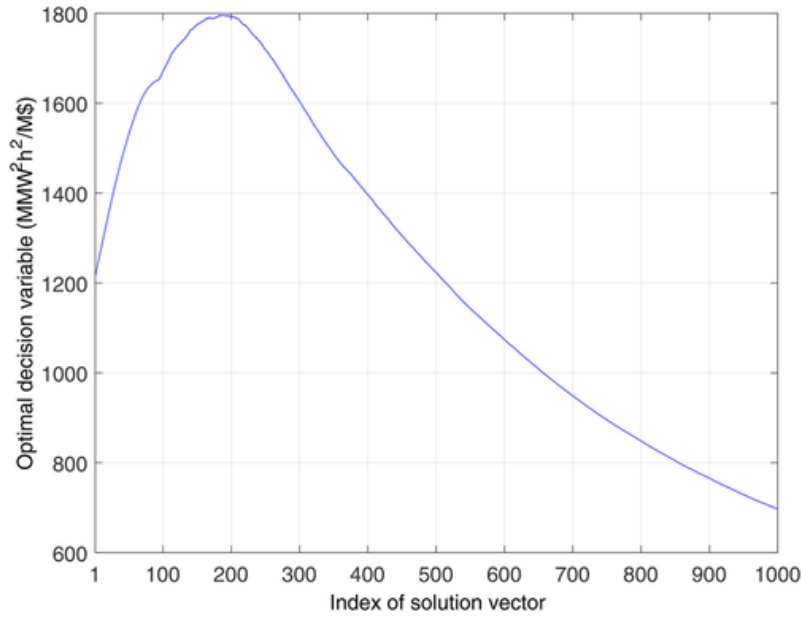


Figure 1.16. A graphical representation of a solution vector

(Source: [24])

In [25], the authors attempt to determine the optimal configuration of a microgrid system while also considering the uncertainties of solar irradiation and wind speed. They are using the Latin Hypercube Sampling (LHS) method to generate samples in the search space. The Weibull distribution is used to fit the wind speed data, while Gaussian distributions are used to fit the irradiation data and temperature data. Several types of optimization algorithms are then implemented and solved in MATLAB.

Usually faster and more efficient than exhaustive search methods, the meta-heuristic (artificial intelligence) methods are another option. While still relying on simulations, these algorithms use various bio-inspired techniques for a more efficient selection process. Some of the research efforts utilizing heuristic methods will be highlighted below.

For example, in [26] the authors use genetic algorithms from the MATLAB optimization toolbox striving to minimize both investment costs and operating & maintenance costs of a microgrid system while minimizing the carbon emissions of a diesel generator.

In [27] the authors propose two competing algorithms to find the minimum cost of energy. The first is also a genetic algorithm like above, while the second uses a Monte Carlo algorithm. In addition, both algorithms try to optimize the margin of safety (MOS).

In [28] the authors use a Particle Swarm algorithm to determine the optimal parameters for the design of a microgrid system for a remote area in Bangladesh.

In [29] and [30] the authors use a new gradient-based Particle Swarm algorithm (called “tunicate” swarm algorithm) to determine the optimum equipment sizing for a microgrid power system.

In [31] the authors develop an Ant Colony algorithm to optimize the size and configuration of a stand-alone microgrid system consisting of wind, solar, fuel cells, batteries, and diesel generators. The authors conduct three case studies and compare their results with results from competing GA algorithms.

In [32] the authors introduce a novel fuzzy-logic based optimization algorithm called modified cuckoo search (MCS). It is a multi-objective algorithm designed to optimally size a microgrid system to obtain the lowest cost of energy and the lowest probability of loss of service. The authors also compare MCS with other similar optimization algorithms.

In [33] the authors used a novel approach called Dragonfly algorithm (DA) to perform multi-objective optimization for designing a microgrid system for a remote settlement in Egypt. As in the previous examples, the authors also compare it with other competing algorithms such as NSGA and MODE.

In [34], the author presents another method for optimizing the size of a microgrid system. As before, the objective is to minimize the total cost of the system, but the author uses a Harmony Search algorithm, which is an optimization technique inspired by musical improvisation, to find the optimal solution. The author then applies the proposed method to a case study of an isolated island in Korea, and compares the results with other optimization methods, such as genetic algorithms and particle swarm optimization algorithms.

There are quite a few more references that could be included in this category, but they all seem to suffer from a common problem. They are all strictly simulation based and rely on hourly power consumption and power production data over a whole year (or even the entire lifetime of the project) to determine the feasibility & validity of found component combinations. This results in an extremely large search space, requiring an enormous overhead computational load, and requiring the usage of special simulation and computational software tools such as MATLAB.

In addition, most of the presented applications are hypothetical in nature and seem to serve strictly as a validation tool for a novel or re-designed analytical or meta-heuristic algorithm, without much concern about an actual microgrid system design problem at hand. Correspondingly, the system models are at best sketchy and incomplete, at worst inaccurate or sometimes completely missing. The actual case study data is often hidden or omitted altogether, making it impossible to test the algorithms, or to re-create and re-run the case studies. And even in the rare occasions when all the information is present, it is still difficult to test the algorithms, and adapt them for another engineering problem, because special software packages might be required which are often expensive and / or not widely available outside of the academic world.

In short, simulation-based optimization techniques usually result in a workable system, but these approaches require detailed system data, are typically computationally very expensive, have slow convergence rates, are often too specific to a particular problem, and are therefore by and large of very little value for making practical engineering decisions when designing microgrid systems.

Besides analytical and meta-heuristic algorithms, typically designed and tested for individual case studies, there are also several software packages, some even of commercial quality, specifically designed for microgrid power system optimization. Some examples are HOMER, iHOGA, RETScreen, Hybrid2, TRNSYS, INSEL. The first two (HOMER and iHOGA), are specifically designed to simulate and solve microgrid power system problems and will be discussed in more detail below.

The most popular optimization software package is called HOMER (Hybrid Optimization of Multiple Electric Renewables). HOMER was originally developed in 1993 for the Department of Energy (DOE) to help determine the tradeoffs of different energy production configurations. Several years later it was made available to the general public and has been steadily improved and adapted to new developments in the power industry.

Currently it is available as a free version called HOMER QuickStart, as well as 3 paid packages called HomerPro for stand-alone microgrids, HomerGrid for grid-tied systems, and HomerFront for large utility-scale hybrid systems. [35]

As an alternative to MATLAB / Simulink, HOMER software combines engineering calculations and economics calculations in one simulation and optimization package. It can simulate the performance of power systems and suggest optimal configuration choices. According to HOMER Pro's User Manual, it uses two optimization algorithms. The original

exhaustive, iterative search algorithm simulates all possible system configurations. The new HOMER Optimizer uses a “proprietary” algorithm to search for the optimal system more efficiently. [36]

To get started, the user provides a range of input variables such as load demand, fuel cost, various component costs, lifetime of the project, interest rates, etc. Then the HOMER software simulates, optimizes, and performs sensitivity analysis for possible combinations of components, and sorts solutions according to optimization choices such as lifecycle cost or net present cost as shown in the block diagram below [37]:

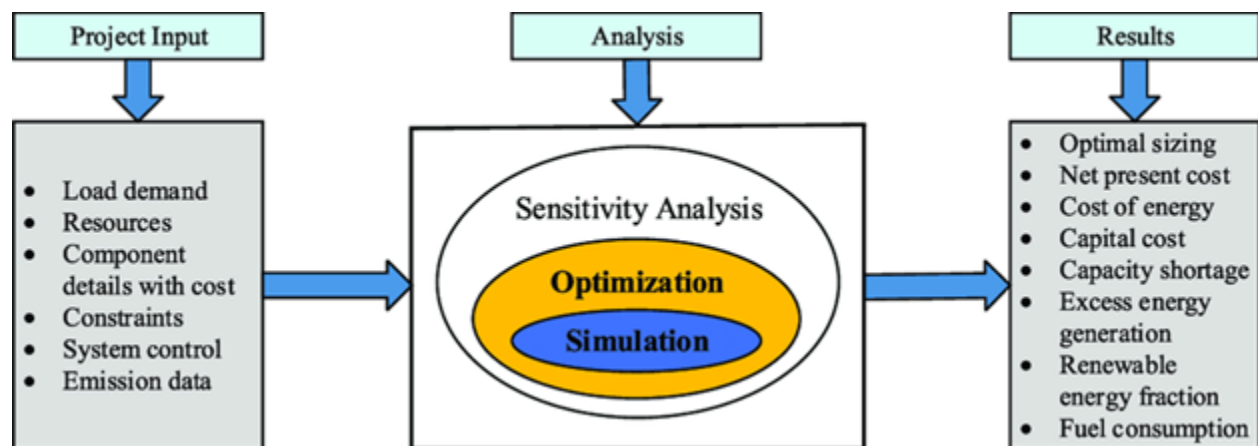


Figure 1.17. HOMER block diagram.

(Source: [37])

The results can be viewed in various formats, such as tables, charts, and maps, and can also be exported to other applications. Below are typical output screens after HOMER finishes its calculations:

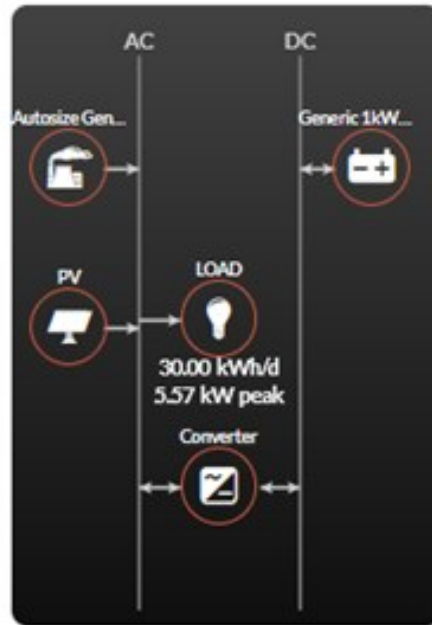


Figure 1.18. HOMER output tree

(Source: [37])

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel	
	6	6.8	4.0	6	CC	\$13,486	\$3,143	\$0.37	\$62,998	2,030	Details
	6		4.6	6	CC	\$6,878	\$5,339	\$0.53	\$90,980	3,748	Details
	6	24.5			CC	\$27,642	\$7,663	\$0.86	\$148,347	5,245	Details
	6				CC	\$3,100	\$10,458	\$0.97	\$167,841	7,118	Details

Figure 1.19. HOMER output table

(Source: [37])

In research circles HOMER seems to be quite popular for case studies and system analyses. For example, [37] investigates the potential of microgrid power systems to address electricity access issues in Rwanda where 47% of the population still lacks access to the power grid. The study aspires to identify the most suitable configuration to provide reliable and cost-effective electricity to off-grid dwellers. HOMER is used to simulate four (4) different

configurations, with the conclusion that for Rwanda, a hydro/solar/battery combination is the most cost-effective solution.

Similarly, [38] explores the viability of different types of microgrid power systems for supplying electricity remote areas in India. Various combinations of renewable energy sources, including solar, wind, diesel, biomass and hydro, are analyzed in this prefeasibility study and recommendations are made based on HOMER simulations.

In [39], ways to achieve a zero-emission electric power system for the Gran Canaria by 2040 are explored. The study uses HOMER to analyze six (6) different combinations of photovoltaic (PV), offshore wind, pumping storage, and mega-batteries to supply electric energy to the island. The most economical solution is then presented, consisting of 3700 MW of PV, 700 MW of offshore wind, 607 MW of pump storage, and 2300 MW of battery capacity to supply the necessary electric power to the island.

In [40], the feasibility of replacing diesel-based power systems with hybrid renewable energy systems (HRES) in remote areas of Northern Canada are examined. The study uses HOMER to simulate and optimize different HRES configurations, including combinations of photovoltaic, diesel generators, and battery storage systems. It determined that a PV-Diesel-Battery combination was the most effective, reducing fuel consumption by up to 22% and lowering the levelized cost of electricity compared to the existing diesel-only systems.

More examples could be listed here, but generalizations can already be made. HOMER is quite a powerful, polished software package especially useful for prefeasibility studies of large microgrid power systems. While performing quite well, HOMER has some limitations: it is not easily customizable for specific problems because actual power demand data cannot be imported, and the user can only use broadly defined user profiles. HOMER also uses “black box” code, so

the user does not have an easy way to double-check or verify HOMER's calculations. HOMER only performs single-objective function optimization, the smallest time frame is 1 hour, and the algorithm is relatively slow, especially when performing sensitivity analysis.

The second optimization software package considered in this dissertation is called iHOGA (Improved Hybrid Optimization by Genetic Algorithm). It was developed by the University of Zaragoza in Spain. The functionality is quite similar to HOMER, but it also allows multi-objective optimization and sensitivity analysis using genetic algorithms, with advertised faster convergence times than HOMER.

Like HOMER, it is available in a paid version called PRO+, as well as a free educational (EDU) version. Compared to HOMER, there are substantially more input parameters available, but it has an extremely cluttered feel and is not nearly as clear, focused, and well organized as HOMER.

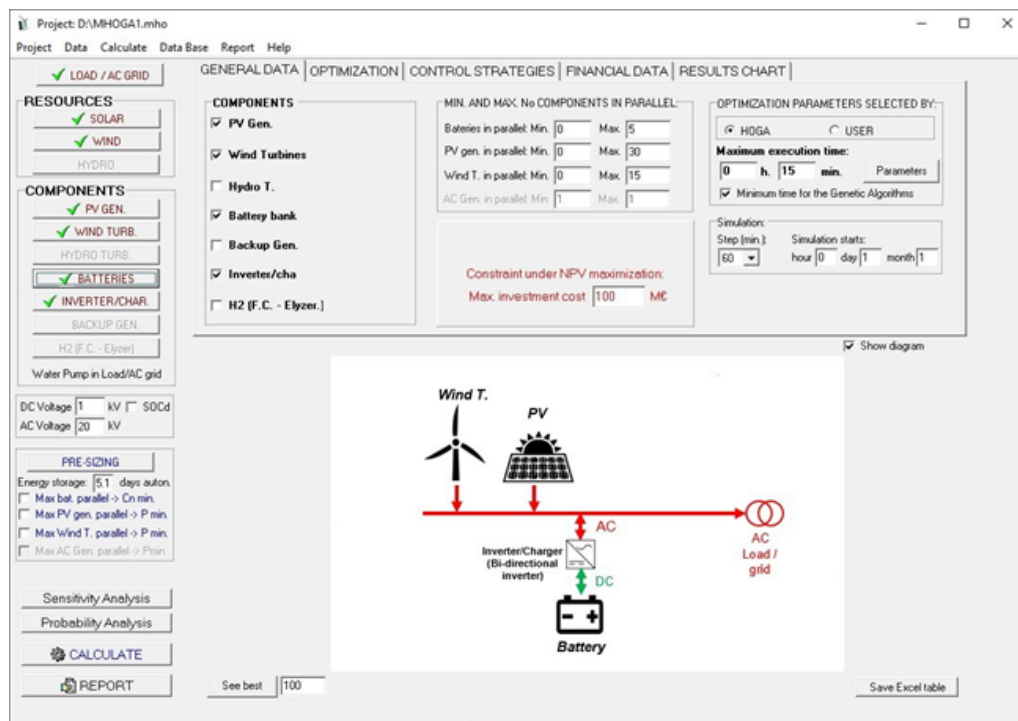


Figure 1.20. iHOGA front panel

(Source: [41])

Similar to HOMER, there are also several research studies utilizing iHOGA. For example, [41] presents a method for designing a microgrid energy system for a small town near Portland, Victoria, Australia. The study utilizes iHOGA to determine the optimal configuration of the system components to ensure that the system meets the town's energy demands efficiently. The characteristics of the selected system are then analyzed and discussed.

In [42], iHOGA is used to select an appropriate combination of components and determine the optimum control strategy to ensure reliable operation at minimum cost for a village in rural India.

In [43], the study attempts to minimize costs, enhance system reliability, and reduce environmental impact of a microgrid power system for an island in Columbia. The study uses the iHOGA simulation tool to model different scenarios and optimize system configurations.

There are also several papers that compare and contrast HOMER and iHOGA. For example, [44] compares the performance of the two simulation tools in designing microgrid power systems in Romania. The paper reports that iHOGA achieved a higher renewable energy share (92%) compared to HOMER (81%), and that the cost of electricity was also lower for iHOGA as compared to HOMER.

Additional comparative studies were conducted in [45]-[49], and the conclusions are quite similar. They report that the systems come up with comparable results, but that HOMER comes up with slightly higher cost-of-energy estimates than iHOGA. But while iHOGA allows multi-objective optimization, and usually converges faster due to a more efficient algorithm, it is much more complex and time consuming to install and run due to an antiquated licensing mechanism and a cluttered user interface. As one paper [47] put it: "The differences between the interface and practicality of each software is significant, since the time consumed to prepare a

simulation in HOMER takes a couple of minutes, while the time consumed to develop an equivalent simulation in IHOGA takes a couple of hours.”

To summarize, commercial simulation software tools are more useful in designing practical microgrid power systems than analytical or heuristic optimization approaches. However, as mentioned earlier, some of them (e.g., iHOGA) are much too complex and cluttered to be of practical use - an engineer might need more time to learn the intricacies of the software package than it would take to figure out an optimal design by a simple trial-and-error approach.

In addition, the software packages are often quite restrictive (e.g., HOMER only allows single-objective optimization, with a minimum time step of 1 hour), are not easily customizable (e.g. HOMER does not allow importing real demand data), have no straightforward way to re-create or verify a solution since the algorithms are unknown, and are quite slow in getting a solution. Lastly, they are often quite expensive to purchase, and cumbersome to install and run due to complex licensing schemes.

1.3 Objectives and Goals of this Dissertation

To summarize the main points made in section 1.2, there are trial-and-error, rule-of-thumb, and simulation approaches that are used to design and optimize microgrid systems. But trial-and-error approaches are extremely time-consuming, and do not guarantee that an optimal solution will be found. Rule-of-thumb guidelines, if they are available, are often too vague, and may not provide a good solution to a specific problem.

More scientific and repeatable is the simulations-based approach. Exhaustive search optimization techniques typically result in a workable system, but these approaches are inefficient, computationally expensive and are characterized by slow convergence rates.

Meta-heuristic (artificial intelligence) methods are usually faster and more efficient than conventional methods. But they are also strictly simulation based and need hourly power consumption and power production data over a whole year or lifetime to determine the feasibility & validity of found component combinations. This results in an extremely large search space, requiring a large overhead computational load, and requiring the usage of special simulation and computational software tools such as MATLAB.

In addition, most of the examples used are hypothetical in nature and seem to serve strictly as a validation tool for a novel or re-designed analytical or meta-heuristic algorithm, without much concern for an actual microgrid system design problem at hand. Correspondingly, the system models are at best sketchy and incomplete, at worst inaccurate or sometimes completely missing. The actual case studies data is often hidden or omitted altogether, making it impossible to test the algorithms, or re-create and re-run the case studies. And even in the rare occasions when all the information is present, it is still difficult to test the algorithms, and adapt them for another problem, because special software packages might be required which are often expensive and / or not widely available outside of the academic world.

Commercial software simulation tools like HOMER and iHOGA are more useful in designing practical microgrid systems than analytical or heuristic optimization approaches. However, some of them (e.g., iHOGA) are much too complex and cluttered to be of practical use - an engineer might need more time to learn the intricacies of the software package than it would take to figure out an optimal design by a simple trial-and-error approach.

In addition, the software packages are quite restrictive (e.g., HOMER only allows single-objective optimization, with a minimum time step of 1 hour), are not easily customizable (e.g. HOMER does not allow importing real demand data), have no straightforward way to re-create

or verify a solution since the algorithms are unknown, and are quite slow in obtaining a solution. Lastly, they are often quite expensive to purchase and cumbersome to install and run due to complex licensing schemes.

Therefore, seeing the need for practical methods and tools to help engineers design efficient microgrid power systems, the overarching goal and objective of this research was improving existing and developing new optimization tools and techniques.

And the objective of this dissertation is to inform the readers about the progress made in the research area of optimization and design of isolated microgrid systems, and to present unique and novel solutions to the microgrid system design dilemma.

1.4 Accomplishments and Achievements Presented in this Dissertation

In line with the goals and objectives outlined above, this dissertation presents the following accomplishments and achievements:

- Developed a brand-new microgrid system design method called “Daily Energy Balance” method (DEB). This method is uniquely different from all existing approaches in that it does not attempt to match power quantities for each hour. Instead, this method aims to achieve a balance between generated and consumed energy over the course of a day. As a result, this method is more efficient, much faster, more customizable, and in general more engineer friendly as compared to any other available microgrid system design approaches, and it can operate on any available computation platform.

- Developed new and revised models and equations to accurately determine the amount of daily energy that can be generated by generators, solar panels, and wind power systems.
- Developed new models and equations to determine the daily battery capacity requirements based on the daily average power and peak power consumption, as well as the daily average energy generation capability of different microgrid sources.
- Adapted two optimization algorithms, the Generalized Reduced Gradient (GRG) and a genetic algorithm (GA), to determine the optimum combination of components that minimize cost and maximize reliability of isolated microgrid power systems.
- Employed unique multi-objective optimization operators to enable tailoring of the optimization results according to the preferences of the user.
- Extensively tested and verified the developed models and equations with real-life production data of already operational wind and solar power systems.
- Designed and optimized (with the new DEB method) small, medium, large and community-sized isolated microgrid systems using real-life power demand data.
- Compared and benchmarked the resulting configurations with configurations determined by HOMER. In all cases the new DEB method outperformed HOMER, obtaining more reasonable solutions which were less costly, more reliable, and also more environmentally friendly, hereby confirming the validity of the new method as well as its superiority to competing approaches.

1.5 Organization of this Dissertation

The dissertation is organized as follows:

- Chapter 2 introduces, describes, and models technical parameters that are relevant to the optimization of microgrid systems. In particular, power demand of different types of customers, and the power generating and energy storage ability of various hybrid system components are explained and quantified via equations. Several of the equations are new and derived explicitly for the purpose of this dissertation. The most important equations are verified with data from existing real-life power systems. Also, the reliability of various microgrid system components is discussed in this chapter.
- Chapter 3 introduces, describes, and models economic parameters that are relevant to the optimization of microgrid systems. In particular, the Net Present Cost (NPC) of various microgrid system components is determined, and equations for calculating them are presented. Also discussed is Levelized Cost of Energy (LCOE), which is of utmost importance when optimizing microgrid systems. Equations to compute LCOE are presented and discussed.
- Chapter 4 contains a survey of some commonly used optimization techniques, including various mathematical approaches as well as machine-learning approaches, for single-objective, as well as multi-objective problems. Some of the most commonly used techniques in each category are described, and pseudo-codes, flowcharts, and illustrations are used to explain each technique.
- Chapter 5 introduces the novel Daily Energy Balance (DEB) method for designing and optimizing isolated microgrid power systems. First, the principle of operation of the method is discussed. Then the input parameters are presented, along with the

equations necessary for the proper operation of this method. The chapter also contains a detailed problem formulation for this design method.

- In chapter 6, the DEB method is tested and verified. Different types of microgrid systems, of varying sizes and with varying power demand profiles, are designed with the DEB method. All solutions are verified with the kW-counting procedure to ensure viability of each solution. The solutions are also compared to designs by HOMER. Conclusions and suggestions for future work are made.

1.6 Summary of Chapter 1

Chapter 1 introduced different types of microgrid systems, described several common applications for microgrid systems, and stated the dilemma of designing an efficient microgrid system. Current design approaches in this area were described via a literature survey, the objectives and goals of this research and this dissertation were stated, and the achievements and accomplishments of this dissertation were presented. Lastly, the organization of this dissertation was explained.

Chapter 2 - Mathematical Modeling of Technical Parameters for Microgrid Systems

In general, mathematical modeling is a process of developing mathematical equations that describe the behavior and performance of a certain system. In this chapter, some of the most important technical parameters will be introduced, and equations will be derived and tested that describe the interaction of various components in a microgrid system. In particular, power demand of different types of customers, and the power generating and energy storage ability of various hybrid system components will be explained and quantified via equations. Several of the equations are new and were derived explicitly for the purpose of this research. The most important equations will be verified with data from existing real-life microgrid power systems. Also, the reliability of various microgrid system components will be discussed in this chapter.

2.1 Power Demand

The electric power demand is the amount of electric power that is needed or requested by the load at a given time. Electric power demand is usually measured in watts (W) or kilowatts (kW) for small systems, and in megawatts (MW) or gigawatts (GW) for large or very large systems.

Electric power demand is one of the most important parameters to consider when designing an electric power system. The system must always balance the supply and demand of electricity to ensure reliability, stability, and efficiency. If the demand exceeds the supply, it could result in blackouts or brownouts. If the supply exceeds the demand, it could result in inefficient operation and wasted energy resources.

One of the biggest challenges when optimizing an electric power system is to predict the demand. It is typically highly variable, and depends on the type of customer, the time of day, the season, the weather, the location, etc.

All customers can be grouped into three major groups: residential, commercial, and industrial; and the power demand of different types of customers varies throughout the day depending on the activities and habits of the customers. For example, residential customers tend to use quite a bit more electricity in the morning and evening when they are at home, compared to a low demand at night. Commercial customers have a distinct increase in demand during business hours, while industrial customers typically have a mostly uniform demand around the clock.

The power demand also varies with the seasons depending on the weather and temperature. For example, residential and commercial customers tend to use more electricity in the summer for cooling and in the winter for heating, while industrial customers might use more electricity in the winter for lighting.

The power demand also varies with location and the availability and cost of electricity and other energy sources. For example, in areas with no easy access to natural gas, customers use more electricity for heating. In regions with low electricity cost, power-hungry industries might cluster and drive up the demand [50].

2.1.1 Load Profiles

To visualize power demand, charts called load profiles are used to show how the electric power demand varies over time, such as by hour, by day, or by season. As discussed above,

different types of customers have different load profiles, which need to be considered when optimizing a microgrid system.

Below are some typical residential, commercial and industrial demand profiles:

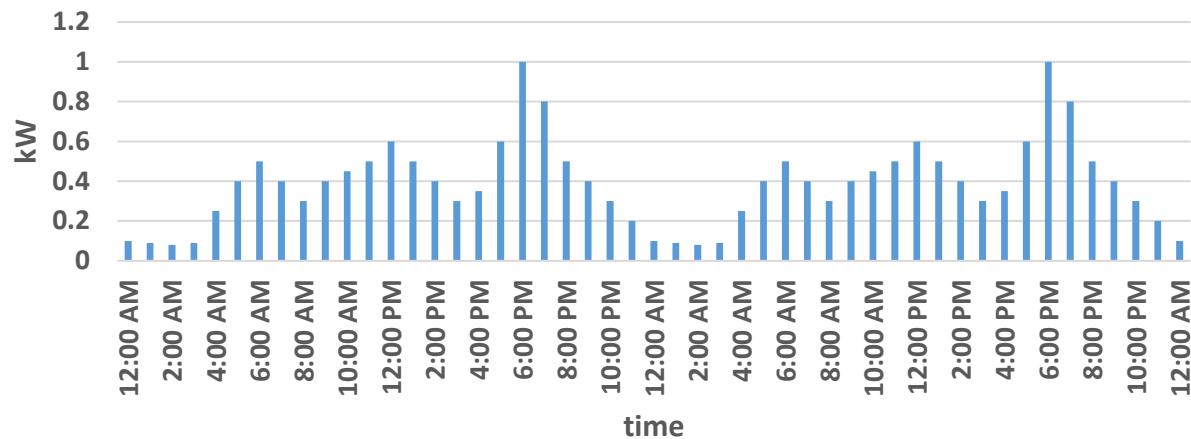


Figure 2.1. A typical load profile for residential customers

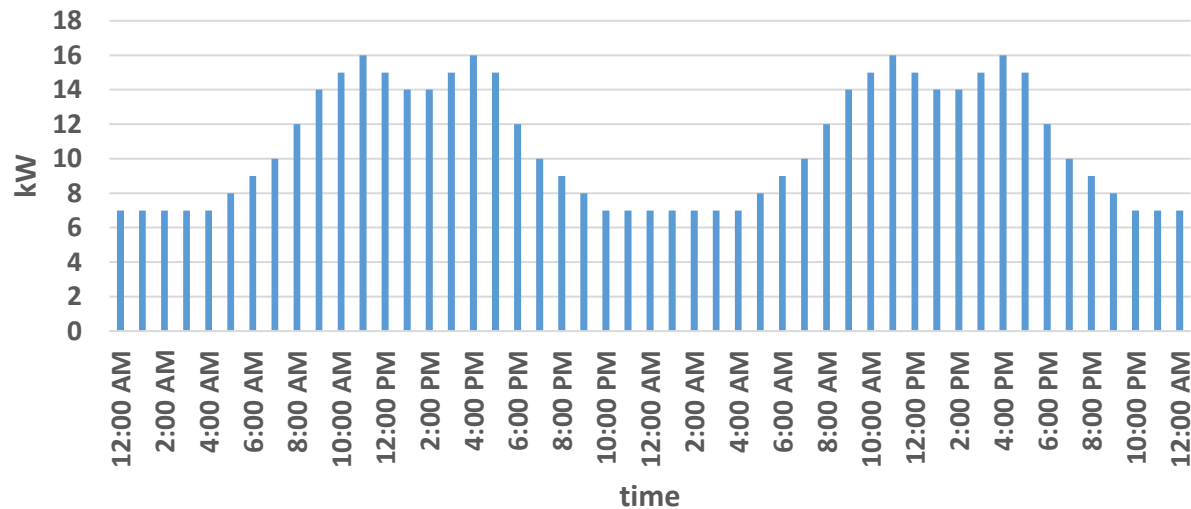


Figure 2.2. A typical load profile for commercial customers

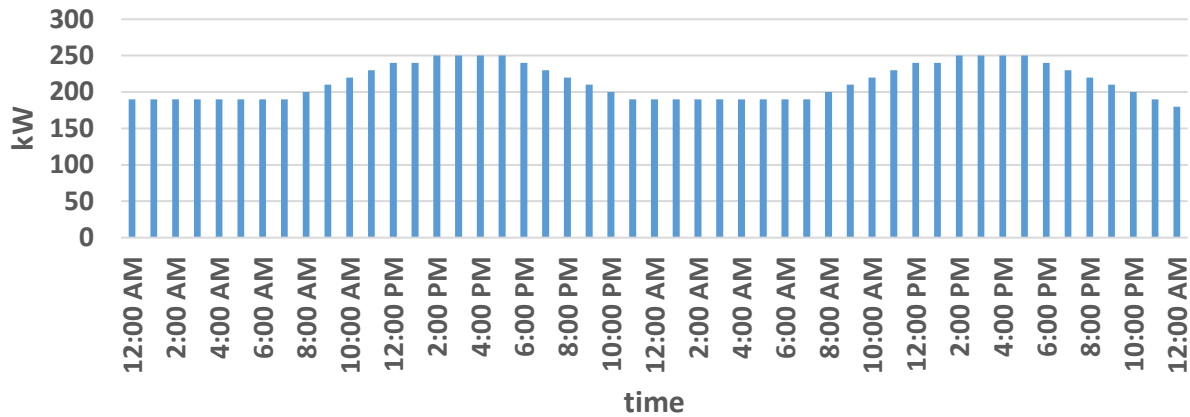


Figure 2.3. A typical load profile for industrial customers

As discussed earlier, residential customers tend to have a pronounced increase in demand during the morning hours as well as in the evening when people are at home. Commercial customers have a distinct increase in demand during business hours, while industrial customers typically have a mostly uniform demand around the clock.

A community load profile is typically a combination of all 3 types of customers, with pronounced but relatively consistent increases in the morning and again later in the afternoon and evening, and a substantial dip at night [51]-[53].

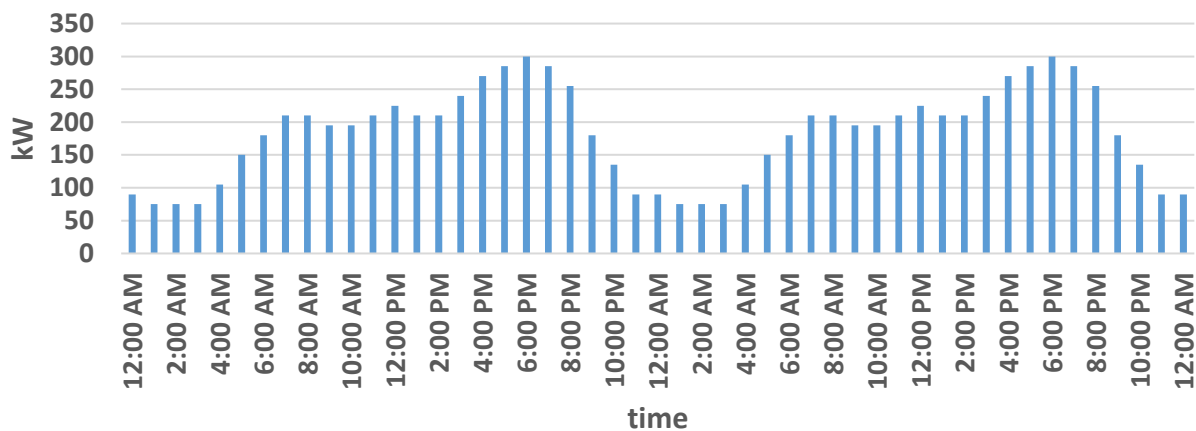


Figure 2.4. A typical load profile of a community

2.1.2 Peak Demand

Load profiles are useful for visualizing peak demand and average demand. The peak demand is the highest amount of electric power consumed at any given time. It is usually specified over a time frame, e.g. daily, monthly, seasonal or yearly.

$$P_{PEAK} = \max_T[P(t)]$$

Peak demand quantifies the power system's capacity, as it indicates the maximum amount of electricity the system must be able to supply at any given time.

2.1.3 Average Demand

The average demand is the aggregated amount of electricity used per unit of time.

$$P_{AV} = \frac{1}{T} \int_0^T p(t) dt$$

The average demand reflects the overall energy consumption and efficiency of the system or the customer, as it indicates how much electricity is used over a period of time.

2.1.4 The Load Factor

The ratio of average demand over peak demand is called the load factor, which quantifies how well a system, or a customer, utilizes the available capacity.

$$Load\ Factor = \frac{P_{AV}}{P_{PEAK}} \times 100\%$$

A higher load factor means a preferable constant and stable demand, while a lower load factor means a more variable demand with typically higher peak demands [54].

2.2 Power Output of Microgrid System Components

The output of a power system is the amount of electricity that the system can produce and deliver to the load. It is usually measured in watts (W) or kilowatts (kW) for small-scale systems, and in megawatts (MW) or gigawatts (GW) for large-scale systems.

The power output of a conventional macro-grid system is relatively constant with some daily and seasonal variation corresponding to variation in power demand. However, the power output of a microgrid can vary greatly depending on the type and configuration of the system, as well as the availability and variability of the different energy sources such as solar panels and wind turbines.

The power output of a microgrid system is hard to predict, but it can be estimated by using mathematical models and equations that describe the behavior and interaction of each component and/or the storage system under different scenarios. In the following section, the power output of individual microgrid system components will be discussed in more detail, and equations will be derived and tested.

2.2.1 Power Output of Engine Generators

The power output of internal combustion engine generators depends on several factors such as the size of the engine, the type of fuel, the number of cylinders, the compression ratio, and the efficiency. They come in sizes ranging from a few kW to low MW.

The power output of internal combustion engine generators is easily controllable and can be varied, depending on the load, between 0 and 100% of its rated value. However, for efficiency reasons the generator should be operated between 50% and 80% of its rated capacity [55].

2.2.2 Power Output of Solar Panels

The power output of solar panels is highly variable and depends on several factors, such as the location, the time of day, the weather conditions, the orientation and tilt of the panels, and the efficiency of the system components.

The most crucial factor that affects the output of a solar panel is the solar irradiance, which is the amount of solar energy that reaches a given area per unit of time. Solar irradiance varies by location, time of day, season, and latitude. Generally, solar irradiance is higher near the equator and lower near the poles, and higher at noon and lower in the morning and evening.

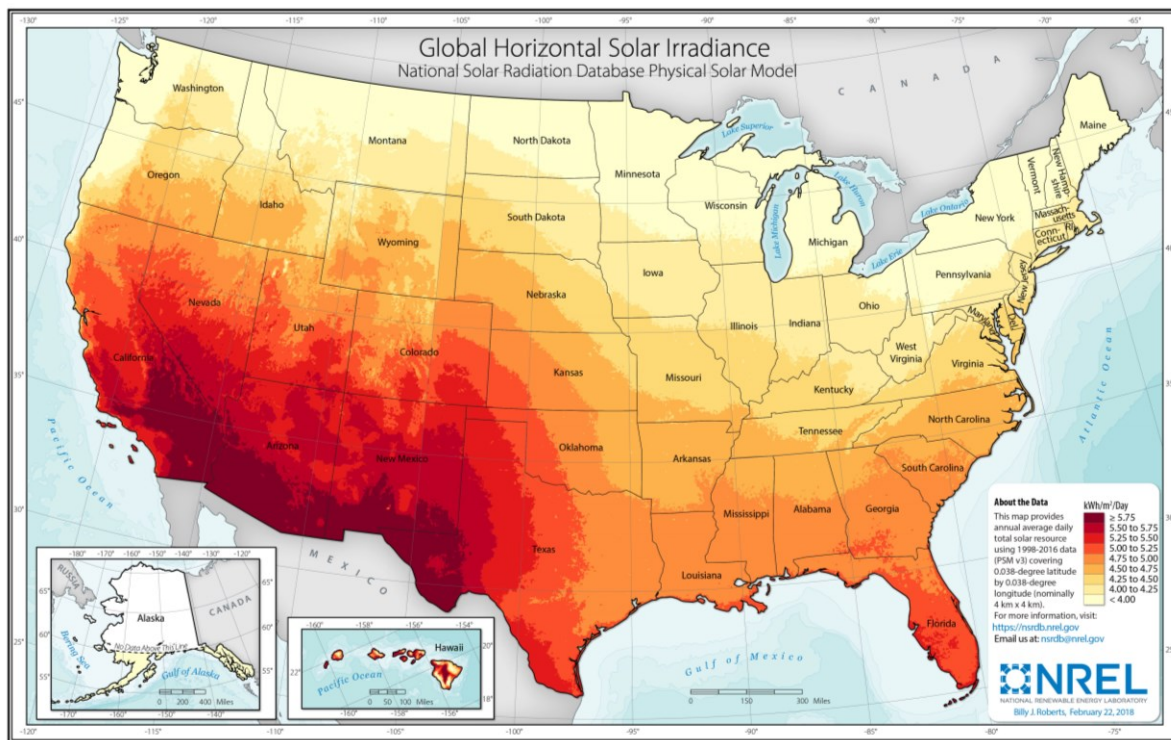


Figure 2.5. The average daily irradiance map of the US

(Source [56])

The second most important factor affecting the output of solar panels is the area subjected to irradiance. For example, according to the Global Solar Atlas [57], the daily average solar

irradiance in Salina, KS, is about 5.0 kWh/m²/day. This means that on average, each square meter of surface receives 5.0 kWh of solar energy per day. To convert this value to average power, it is divided by 24 hours obtaining approximately 208 W/m²/hour. However, this value varies greatly depending on the time of day and the weather conditions. For example, according to Solcast [58], the estimated solar irradiance in Salina on September 26, 2024, at noon was about 800 W/m². This is much higher than the average value because the sun was shining brightly and directly overhead.

The last factor that influences the power output of a solar system is the efficiency of the solar panels, i.e. the ratio of generated electric power over the available solar power. The efficiency of most commercial solar panels is 17% to 20% [59], which means that at most only 20% of the solar energy that reaches the panels is actually converted into electricity.

In addition, there are also system losses such as shading, dust, wiring resistance, temperature, inverter efficiencies, etc., that reduce the performance of a solar system. A typical value for system losses is 10 % - 30 % [60], which means that typical system efficiency is between 70 and 90 %.

To summarize the discussion above, the power output of a solar system can be computed with the following equation:

$$P_s(t) = I(t) \times A \times \eta_{PV}$$

where I is the solar irradiance measured in watts per square meter (W/m²), A is the area of the solar panels in m², and η_{PV} is the efficiency of the solar panel.

If instead of an area, a solar panel with rated power P_R is given, the actual power output of the panel can be calculated with the following equation:

$$P_s(t) = P_r \times \frac{I(t)}{I_{stc}} \times \eta_{SYS}$$

where $I(t)$ is the actual irradiation at time t , and I_{STC} is the irradiation at the standard test condition (STC) equal to $1,000 \text{ W/m}^2$, and η_{sys} is the efficiency of the solar system.

If it is desired to model a solar system while also considering the effects of the ambient temperature, then the following equation can be used:

$$P_s(t) = P_r \times \frac{I(t)}{I_{STC}} \times \eta_{sys} (1 - \alpha_T (T(t) - T_{STC}))$$

where α_T is the temperature coefficient, $T(t)$ is the ambient temperature, and T_{STC} is the temperature at the standard test condition (STC) which is equal to 25°C .

Besides equations, there are also online tools such as NREL's PVWatts Calculator [61], which considers quite detailed information such as panel orientation, tilt angle, shading, temperature coefficients, etc., to get a fairly accurate estimate of how much electric power a solar system can produce at a given location and time period.

2.2.3 Power Output of Wind Turbines

Similar to solar power, the power output of a wind turbine is also highly variable and depends on several factors, such as the wind speed, the air density, the sweep area of the blades, and the efficiency of the wind turbine.

The wind speed is the most crucial factor that affects the output power of a wind turbine. The available wind power is directly proportional to the cube of the wind speed. This means that if the wind speed doubles, the available wind power increases eightfold.

However, the actual output power of a wind turbine is not necessarily directly proportional to the cube of the wind speed. Wind turbines do not produce any power when the wind speed is too low or too high for them to operate. The cut-in speed is the minimum wind speed required for a wind turbine to start generating power, and the cut-out speed is the

maximum wind speed beyond which a wind turbine will shut down to prevent damage.

According to [62], the cut-in speed is typically around 3 to 5 m/s, and the cut-out speed is around 25 m/s for most wind turbines.

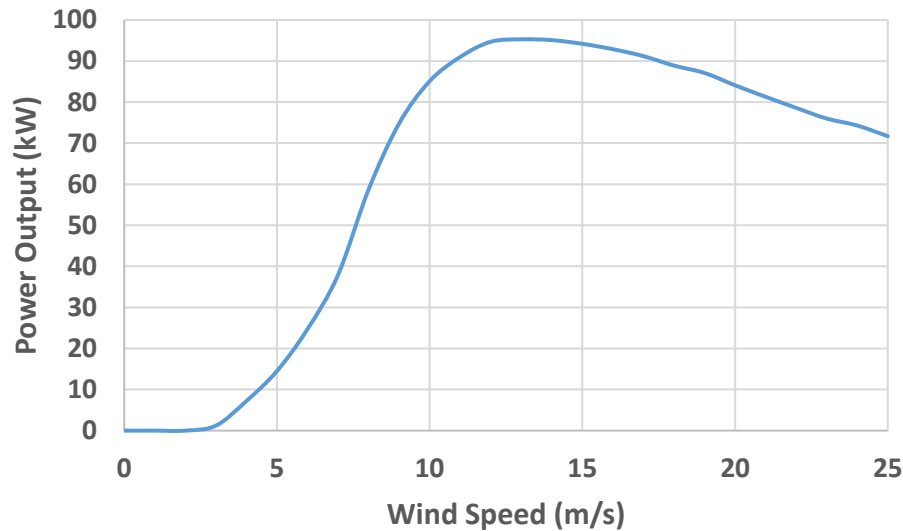


Figure 2.6. A typical wind turbine power output vs wind speed plot.

The wind speed is a highly variable and often unpredictable parameter. To determine current wind speeds for any place on the planet, various apps can be used, for example [63].

There are also various maps that show average wind speed data for different regions and countries. Some of them are created by the National Renewable Energy Laboratory (NREL), a U.S. Department of Energy research laboratory that focuses on renewable energy and energy efficiency. NREL wind maps illustrate the average wind speeds at various heights above the surface level. They are derived from NREL's Wind Integration National Dataset (WIND) Toolkit, which is a collection of meteorological and power data for more than 126,000 sites in North America. Below is one of the maps generated by NREL.

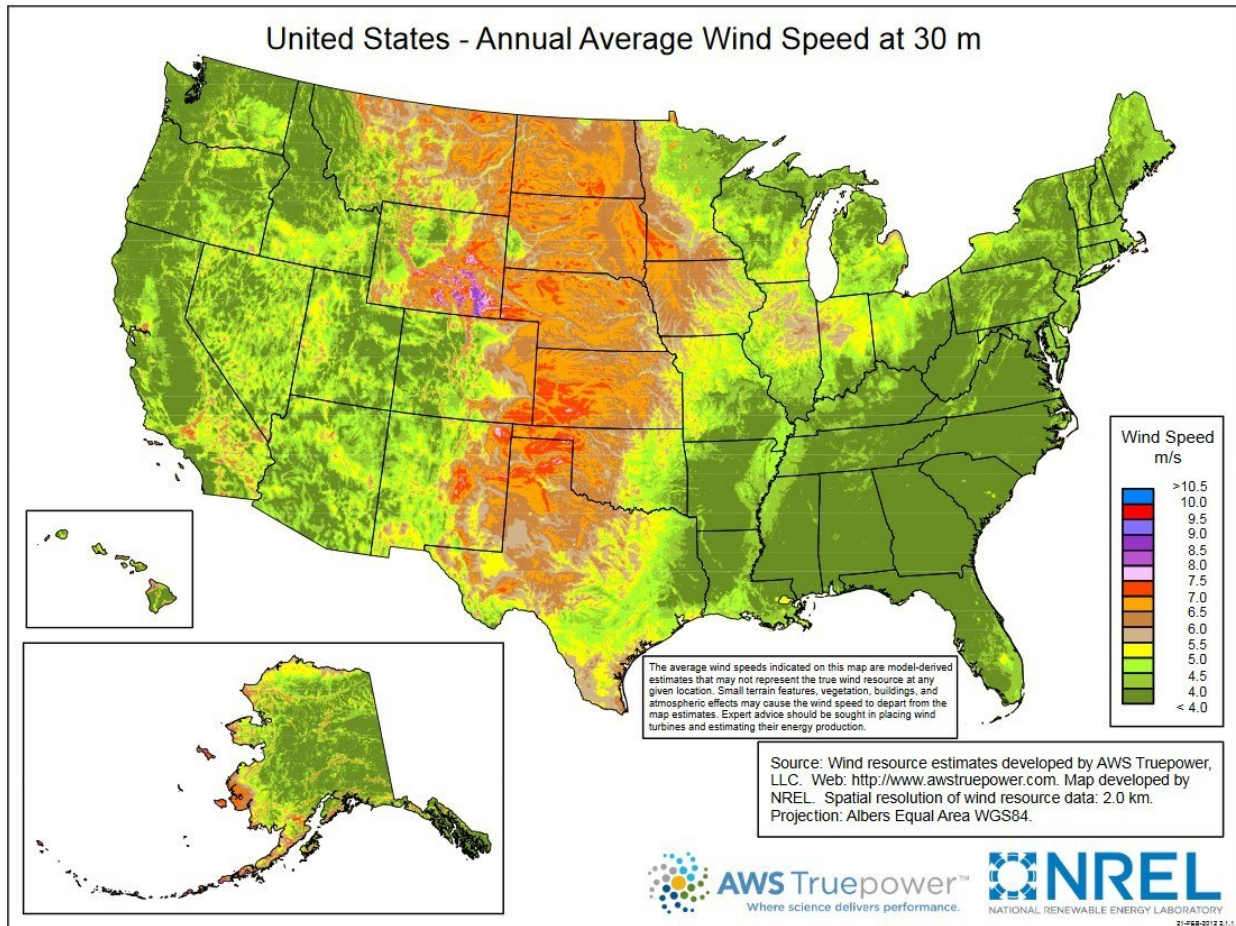
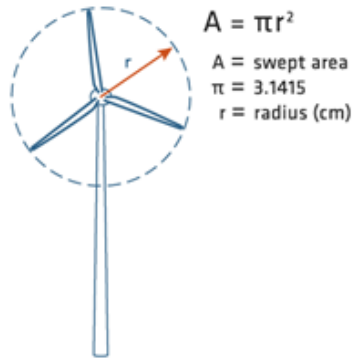


Figure 2.7. The annual average wind speed map of the US

(Source: [64])

The second most important factor that affects the output power of a wind turbine is the size and shape of the blades. The available wind power output is directly proportional to its sweep area, which depends on the construction of the turbine as shown in the figures below:

Horizontal Axis Turbine



Vertical Axis Turbine

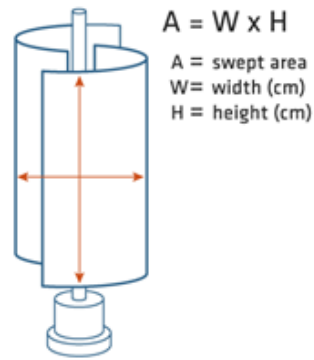


Figure 2.8. Wind turbine area calculations illustration

(Source: [65])

The power output of a wind turbine also depends on the air density, which is the mass of air per unit volume. The higher the air density, the more mass of air hits the turbine blades per second, and the more kinetic energy is transferred to the turbine. The standard value of air density at sea level and 25°C is 1.225 kg/m³, but it varies with temperature, pressure, and humidity of the air as seen in the figure below:

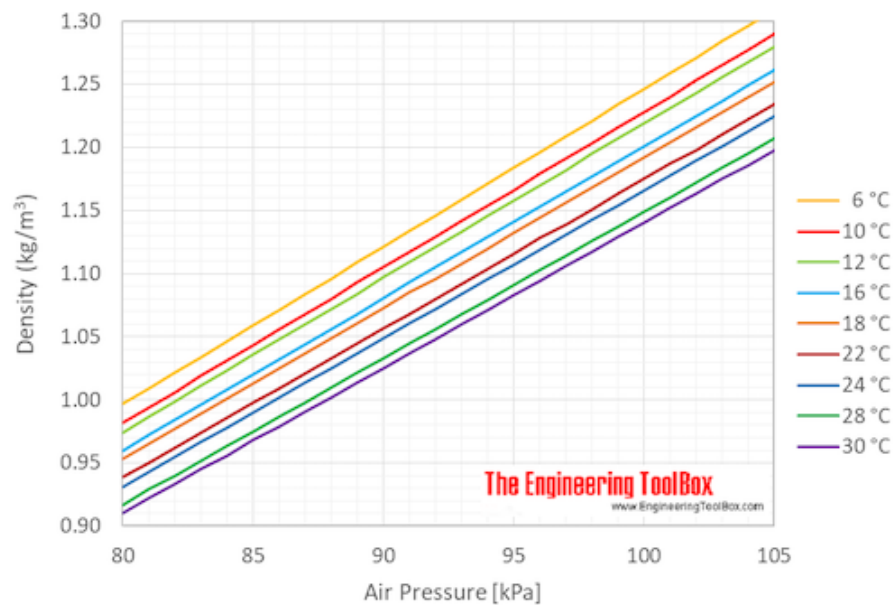


Figure 2.9. Air density vs temperature and air pressure plots

(Source: [66])

Lastly, the output power of a wind turbine also depends on the efficiency of the turbine, which varies with different wind speeds and other factors, such as friction, turbulence, and blade design. The efficiency of a turbine is not constant but has a range of wind speeds where it is highest, and it decreases when the wind speed is too low or too high.

The Betz limit of efficiency is the maximum theoretical efficiency that a wind turbine can achieve. It was proposed by Albert Betz, a German physicist, in 1919. The Betz limit states that no wind turbine can capture more than 59.3% of the kinetic energy of the wind. Intuitively this makes sense, because if the turbine extracted all the energy from the wind, the wind speed behind the turbine would be zero, and no more wind could flow through the turbine. Therefore, there must be some pressure left behind the turbine for the wind to keep moving.

The Betz limit can also be derived from the conservation of mass and the momentum of the air stream flowing through an idealized actuator disk that represents the turbine as shown in the figure below:

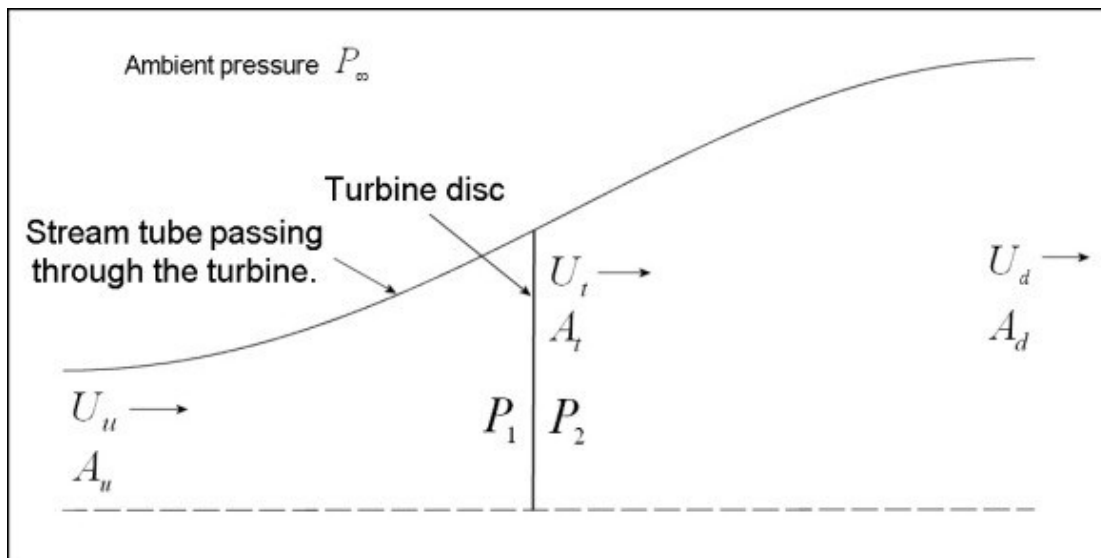


Figure 2.10. Idealized actuator disc representing a wind turbine

(Source: [67])

The actuator disk is assumed to have no drag or thickness and reduces the wind speed and pressure uniformly across its area. The power output of this turbine is equal to the force exerted on the disk by the wind speed at the disk. The turbine's efficiency is equal to the power output divided by the power available in the wind. It can be shown that the maximum efficiency occurs when the wind speed behind the disk is one-third of the wind speed before the disk. The efficiency at this point is $16/27$, or 59.3%. This is the Betz limit of efficiency.

The Betz limit is a theoretical upper bound for any wind turbine, regardless of its design or type. However, as already mentioned, there are other factors that lower the efficiency of a wind turbine, such as friction, turbulence, blade design, and operating conditions. The typical efficiency of modern wind turbines ranges from 35% to 45% as show in the figure below:

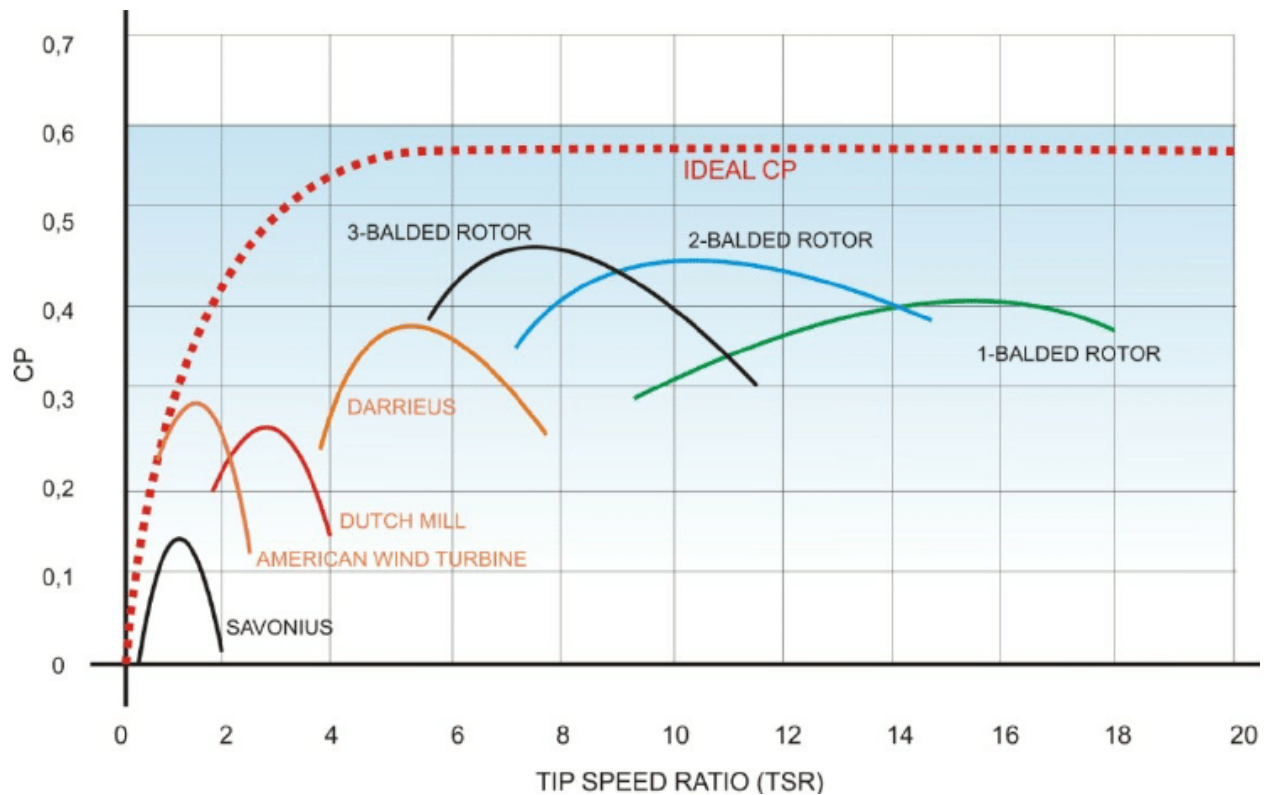


Figure 2.11. Efficiencies of turbines with different blade designs

(Source: [68])

To summarize the discussion above, to calculate the theoretical power output of a wind turbine, the following equation can be used [69]:

$$P_w(t) = \frac{1}{2} \times C_p \times \rho_a \times A \times v^3(t)$$

where C_p is the efficiency coefficient, ρ_a is the air density in $\frac{kg}{m^3}$, A is the sweep area of the turbine in m^2 , and v is the wind speed in $\left(\frac{m}{s}\right)^3$.

However, this assumes that the rated power is the maximum achievable power for an ideal turbine. In reality, the power output of wind turbines is non-linear, and only parts of the power curve exhibit cubic properties.

To determine the actual wind turbine power output, many sources, e.g. [70]-[73], suggest a simple linear interpolation according to the following equation:

$$P_w(t) = \begin{cases} 0 & V(t) < V_{ci} \\ Pr \times \left(\frac{V(t) - V_{ci}}{V_r - V_{ci}} \right) & V_{ci} < V(t) < V_r \\ Pr & V_r < V(t) < V_{co} \\ 0 & V(t) > V_{co} \end{cases}$$

Some sources, e.g. [74], suggest a more complex, exponential interpolation without specifying what exponent should be used:

$$P_w(t) = \begin{cases} 0 & V(t) < V_{ci} \\ Pr \times \left(\frac{V^k(t) - V_{ci}^k}{V_r^k - V_{ci}^k} \right) & V_{ci} < V(t) < V_r \\ Pr & V_r < V(t) < V_{co} \\ 0 & V(t) > V_{co} \end{cases}$$

Some other sources, e.g. [75], suggest a quadratic interpolation,

$$P_w(t) = \begin{cases} 0 & V(t) < V_{ci} \\ Pr \times \left(\frac{V^2(t) - V_{ci}^2}{V_r^2 - V_{ci}^2} \right) & V_{ci} < V(t) < V_r \\ Pr & V_r < V(t) < V_{co} \\ 0 & V(t) > V_{co} \end{cases}$$

while other sources, e.g. [76], use a basic cubic interpolation,

$$P_W(t) = \begin{cases} 0 & V(t) < V_{ci} \\ Pr \times \left(\frac{V^3(t) - V_{ci}^3}{V_r^3 - V_{ci}^3} \right) & V_{ci} < V(t) < V_r \\ Pr & V_r < V(t) < V_{co} \\ 0 & V(t) > V_{co} \end{cases}$$

and several other sources, e.g. [77]-[79], use a much more complex version of the same cubic relationship.

$$P_W(t) = \begin{cases} 0 & V(t) < V_{ci} \\ V^3(t) \times \left(\frac{Pr}{V_r^3 - V_{ci}^3} \right) - Pr \times \left(\frac{V_{ci}^3}{V_r^3 - V_{ci}^3} \right) & V_{ci} < V(t) < V_r \\ Pr & V_r < V(t) < V_{co} \\ 0 & V(t) > V_{co} \end{cases}$$

To verify which of the equations gives the best approximation, the actual power curve of several wind turbines along with the results of calculations with different power equations were plotted. First, the power curve of a small (1-kW) wind turbine was plotted utilizing data from [80].⁹

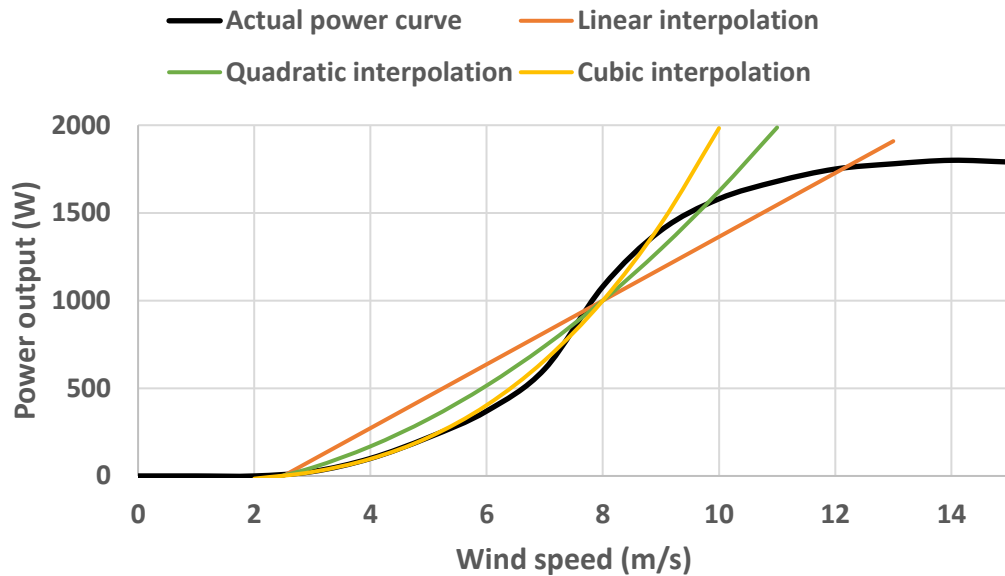


Figure 2.12. The power curve and results of approximations for a 1- kW wind turbine

For this turbine, it is clear that the linear as well as quadratic interpolation do not give a good approximation. Instead, the best approximation is the cubic interpolation. For further verification, a power curve for a Bergey Excel 10 wind turbine, using data from [81], was plotted.

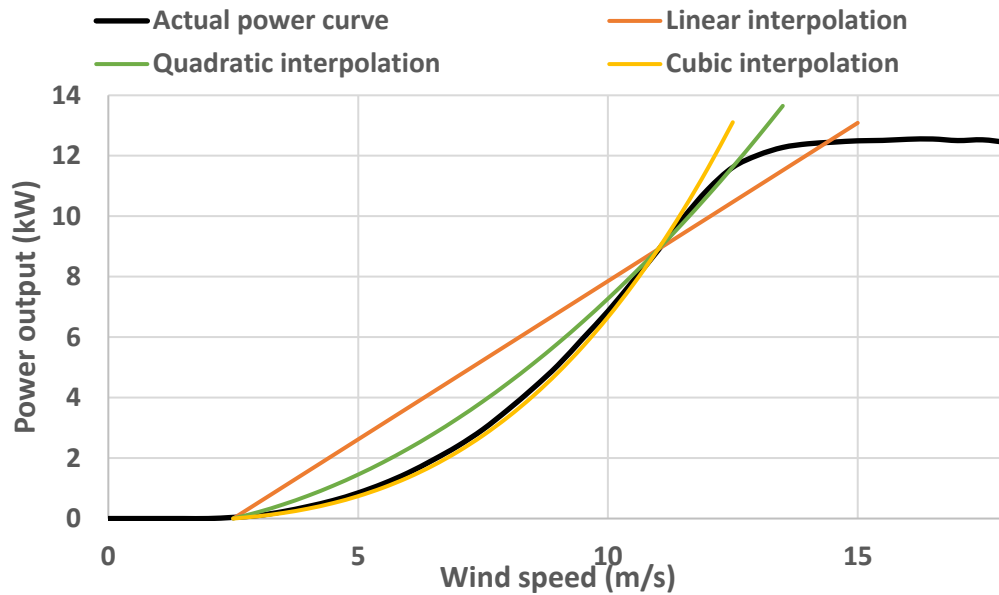


Figure 2.13. The power curve and results of approximations for a 10-kW wind turbine

It appears that for this turbine, the cubic interpolation is also the best fit. Note that the 2 cubic equations resulted in the same numbers; in fact, they are the same equation in a different form. Furthermore, also note that the following simplified equation also results in a good approximation for low wind speeds and will be used with the new DEB method:

$$P_W(t) = P_R \times \left(\frac{V(t)}{V_R} \right)^3$$

Besides equations, a fairly accurate estimate of how much power a wind power system can produce can be obtained with wind turbine calculators, for example [82].

2.2.4 Power Output of Batteries

Rechargeable batteries are unique components in a microgrid system in that they can be a load (receiving power) as well as a source (supplying power), depending on the needs of the system at any given time.

In either case the power input & output of a battery is governed by the equation:

$$P_B(t) = V(t) \times I(t)$$

where V is the voltage of the battery system, and I is the current supplied or delivered by the battery.

Theoretically, the power output of a battery can be very large over a short time frame; in practice there are limitations associated with the maximum charge / discharge current ratings which limit the amount of power that can be absorbed or provided by a battery.

This power delivering or absorbing capability of batteries is represented by the “C rating,” defined as [83]:

$$Cr = \frac{1}{t}$$

where t is the length of time that the battery can be completely charged or discharged safely.

Another way to represent the same idea is with the following equation [84]:

$$Cr = \frac{I}{Qr}$$

where Qr is the rated energy capacity of the battery in Ah, and I is the charge / discharge current.

For example, if a 100-Ah battery has a 1 C rating, it can provide 100 A for 1 hour. A battery with the same capacity but with a $\frac{1}{20}$ C rating could provide only 5 A over 20 hours, while the same capacity battery with a 10 C rating could provide 1000 A for 6 minutes.

Different types of batteries have different C ratings. A rule of thumb is LiFePO4 batteries have a limit of 0.5-1C, while lead-acid batteries have a limit of 0.1-0.3C [85].

To summarize the discussion above, the power supplied (or used) by batteries is governed by the following equation:

$$P_B(t) \leq V(t) \times Qr \times Cr$$

where V is the voltage of the battery system, and Qr is the rated capacity of the battery, and Cr is the battery's C-rating.

Besides equations, the power supplied (or consumed) by the battery can also be estimated by using battery calculators, for example [86] or [87].

2.3 Energy Output of Microgrid System Components

Electric energy supplied by a power system is closely related to the power generated. Specifically, it is equal to the power generated over a period of time.

$$E(t) = \int_1^t P(t)dt$$

In the conventional electrical power industry, the time period is typically 1 hour, and the energy is measured in kWh. However, for a microgrid system, the power output is often cyclical, so frequently the relevant energy quantity is kWh per day, per month, per season, or per year. For this research, the energy per day is of utmost importance and will be primarily considered here.

2.3.1 Energy Generated by Engine Generators

The energy output of an internal combustion generator is highly flexible and could range from zero to its maximum daily output of

$$E_G(max) = P_{RATED} \times 24 \text{ hrs}$$

In practice the energy produced by the generator is usually less, and all other optimization methods calculate the produced energy as the sum of the power delivered during each hour of the day:

$$E_G(day) = \sum_{h=1}^{h=24} P(h)$$

As mentioned before, for efficiency reasons it is desirable to run the generator at 50-80% of its rated power, and turn it off and use alternative power sources in times of low demand. So the DEB method uses a different equation, where the run-time of the generator is also an optimizable parameter:

$$E_G(day) = P_{RATED} \times 0.8 \times RunTime$$

2.3.2 Energy Generated by Solar Panels

As already discussed in section 2.2.2, the power output of a solar power system is cyclical throughout the day with a distinct peak during the noon hours, and the power generated during each hour can be computed using irradiation data:

$$P_S(h) = I(h) \times A \times \eta_{PV}$$

Most other optimization methods use either the equation above, or an alternative equation also introduced in section 2.2.2 which uses the rated power of solar panels:

$$P_S(h) = Pr \times \frac{I(h)}{I_{stc}} \times \eta_{SYS}$$

The total energy produced by solar panels is then calculated as a summation of the power generated during each hour of the day:

$$E_S(day) = \sum_{h=1}^{h=24} P_S(h)$$

However, these equations require that the irradiation data for each hour is known. In addition, as already discussed, summation calculations are computationally expensive and time-consuming.

The DEB method uses a much more efficient method to calculate the amount of energy generated by solar panels during the day by utilizing the concept of peak-sun-hours (PSH). A peak-sun-hour is defined as one hour in which the intensity of solar irradiance reaches an average of 1kW of energy per square meter [88]. The following illustration shows the idea behind this concept:

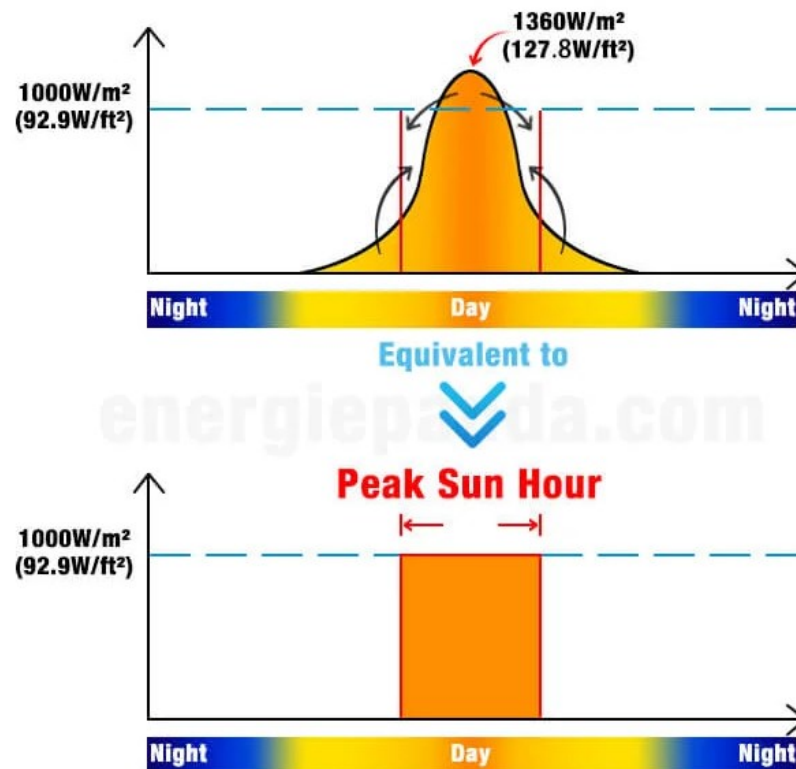


Figure 2.14. Peak-sun-hour illustration

(Source: [89])

The number of peak-sun-hours is determined by integrating the solar irradiance over a period of time (usually a day), then dividing it by the standard test condition (STC) irradiance of 1,000 W/m²:

$$PSH(t) = \frac{\int_0^t I(t)}{I_{STC}}$$

The number of peak-sun-hours varies by location, weather condition, and season. To obtain an estimate of how many peak-sun-hours a certain location receives, various sources could be used. For example, there are tables [89] and maps [90] that show the peak-sun-hours for a specific geographic location.

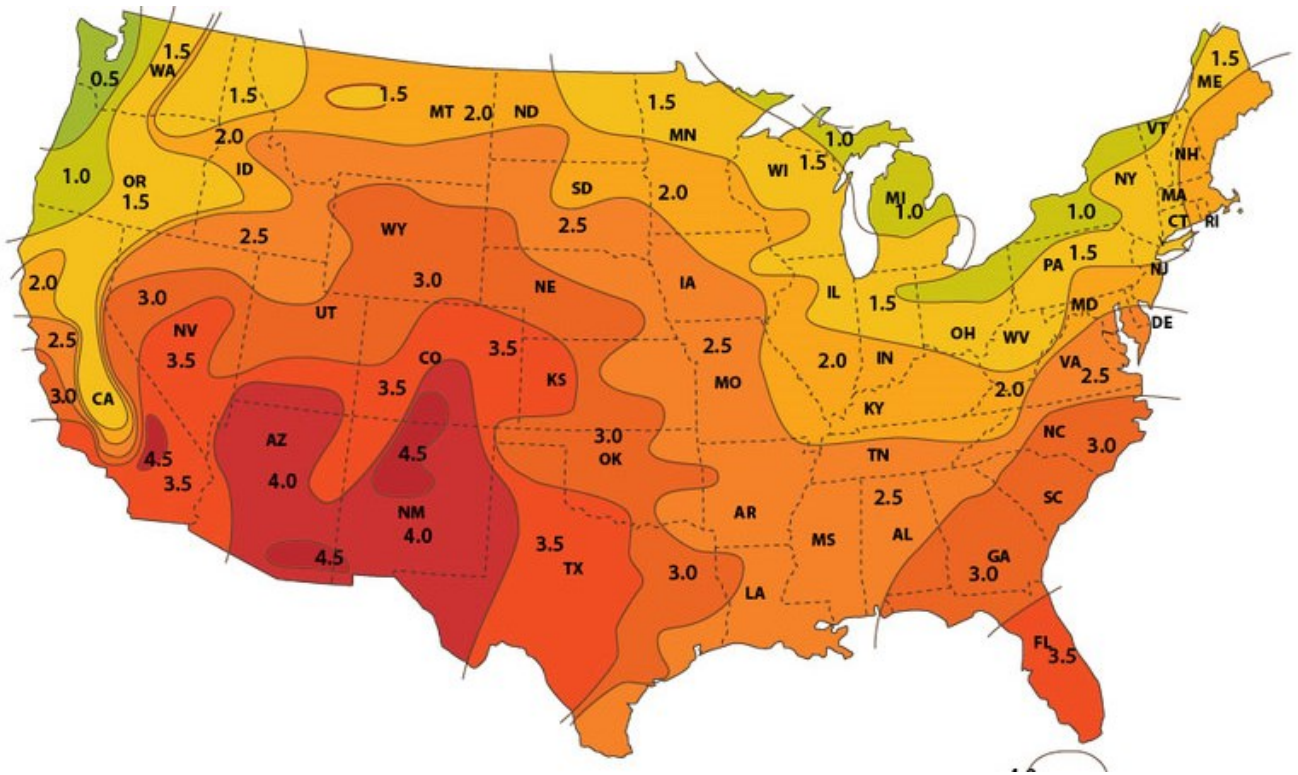


Figure 2.15. Winter peak-sun-hours map of the US

(Source: [90])

There are also several calculators where peak-sun-hours for a specific location can be estimated using historical data, e.g. in [91] and [92]. Using these calculators, it can be

determined that the yearly average peak-sun-hours for Salina, KS, are approximately 5.33 hours per day.

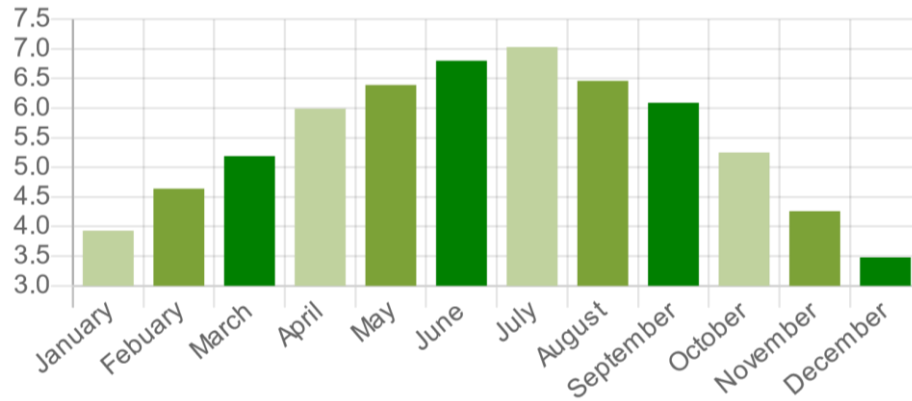


Figure 2.16. Monthly peak-sun-hours chart for Salina, KS

(Source: [92])

Using the number of peak-sun-hours for a specific location, the approximate energy output of a solar panel with a rated power output can then be calculated as follows:

$$Es(day) \cong P_{RATED} \times PSH \times \eta_{SYS}$$

where a typical system efficiency is $70\% < \eta_{SYS} < 90\%$

To employ this equation for the DEB optimization method, it was critical to verify that the equation above is a reasonable approximation. To verify it, first a 915 W portable solar generator with an estimated efficiency of 80% was used. Using the equation above, the expected power generated per day in the month of October in Salina, KS, is:

$$Es(day) = 915W \times 5.25 \text{ hrs} \times 0.8 = 3843 \text{ Wh}$$

The actual power produced was only marginally (3 Watts) less:

$$Es(day) = 80\% \text{ of } 4.8 \text{ kWh battery} = 3840 \text{ Wh}$$

For further verification, a fully functional solar system on K-State Salina's campus was used, which consists of 74 Canadian-Solar 325-W ground-mounted solar panels with a total nominal output power rating of about 24 kW.

The output of the solar system can be monitored via a link [93], and the energy production per day, per month, per year, or per lifetime can be monitored, recorded and plotted as shown in the figure below.

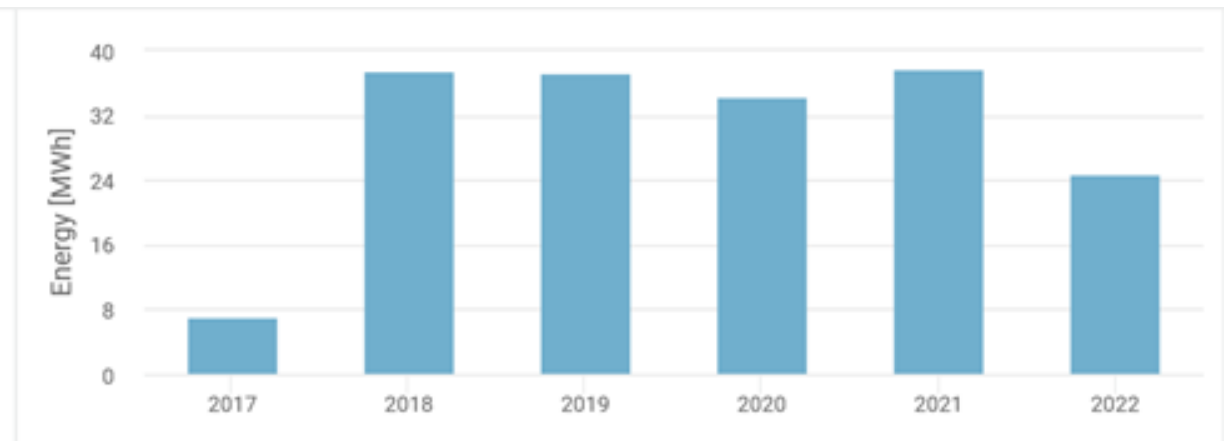


Figure 2.17. Energy production chart for K-State Salina's solar system

Note that in 2017 and 2022, the system was operational for only part of the year, but the energy production for fully-operational years, 2018-2021, averaged about 37 MWh. Using the average PSH of 5.33 and an efficiency of 80%, the predicted energy output of the solar system is:

$$Es(year) = 24 \text{ kW} \times 5.33 \text{ hrs} \times 365 \times 0.8 = 37,353 \text{ kWh}$$

Again, the predicted energy production is very close to the actual production numbers (within 1%), confirming the validity of the PSH-based energy equation.

2.3.3 Energy Generated by Wind Turbines

The energy production of a wind power system is also a function of power generated over a period of time. The period could be an hour, a day, a week, or a month, but as discussed in section 2.2.3, the wind speed is highly variable and difficult to predict. For example, below is a plot of the average wind speed in miles-per-hour for Salina, KS, for a specific day (June 15, 2024), according to [94]:

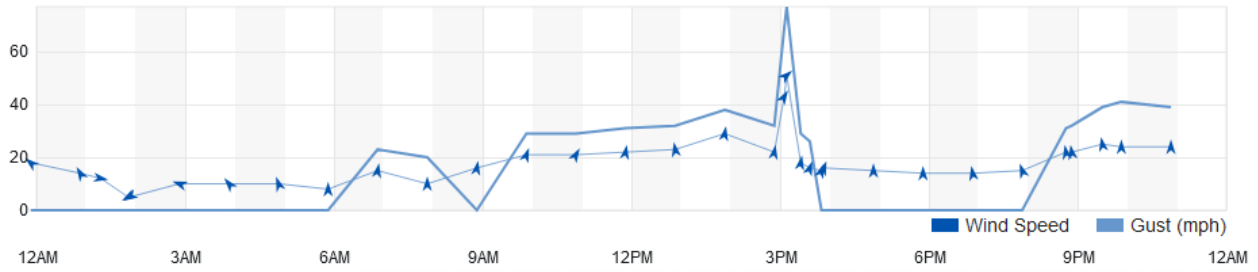


Figure 2.18. Hourly wind speed averages chart for Salina, KS, on June 15, 2024

Other optimization methods use the hourly wind speed averages to calculate the generated energy per day by accumulating the generated power for each hour using any of the power equations presented in section 2.2.3, e.g.:

$$E_W (day) = \sum_{h=1}^{h=24} P(h) = \sum_{h=1}^{h=24} P_{RATED} \times \left(\frac{V_{ave}(h)}{V_{rated}} \right)^3$$

But as discussed already, this equation requires detailed wind speeds over the course of a day. In addition, this method again requires extensive and time-consuming calculations. For the DEB method, it was more desirable to calculate the generated energy based on daily, monthly or even yearly average wind speeds, which are available from different sources. For example, below is a plot of the average daily wind speed in miles-per-hour for Salina, KS, for a whole month (June of 2024), with the peak wind speeds (gusts) also given in [95]:



Figure 2.19. Daily wind speed averages chart for Salina, KS, in June 2024

(Source: [95])

There are also tables, plots, or maps that give the expected monthly or yearly average wind speeds. For example, according to [96], the monthly average wind speed in June 2024 for Salina, KS, was between 5 and 6 m/s.

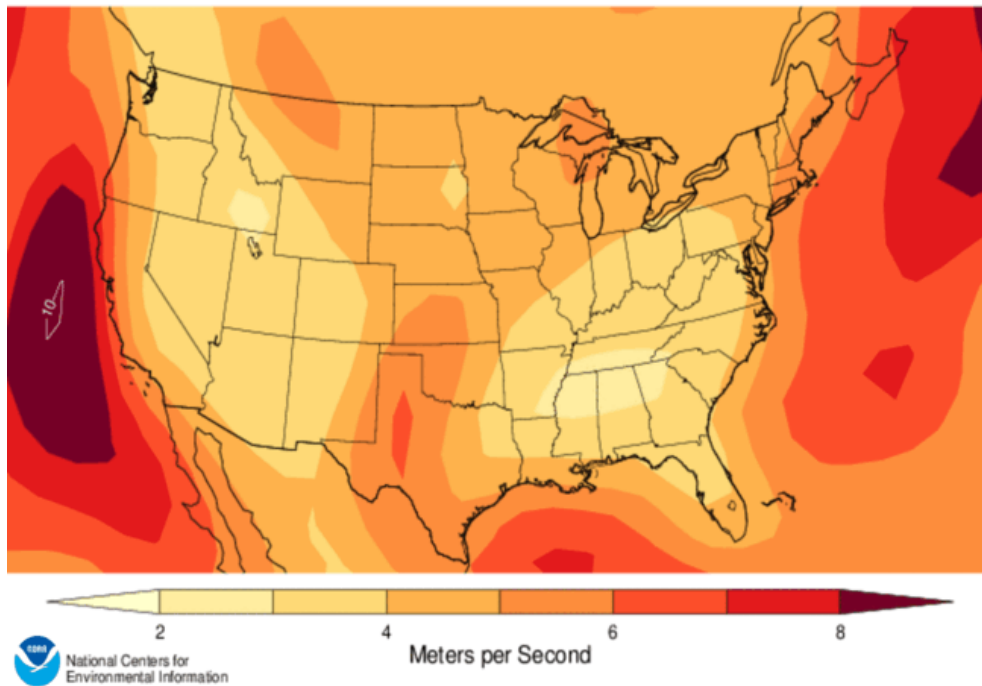


Figure 2.20. Monthly average wind speed map of the US for June 2024

(Source: [96])

However, the generated energy cannot be directly computed from the average wind speed. For example, given a wind turbine with a nominal (rated) output of 10 kW @ 12 m/s (27

mph), if the wind has a constant wind speed of 5 m/s (11.2 mph) for a day, the expected energy output of the wind turbine per day would be:

$$E_W(day) = 10 \text{ kW} \times \left(\frac{5 \text{ m/s}}{12 \text{ m/s}} \right)^3 \times 24 \text{ hrs} = 17 \text{ kWh}$$

However, if the wind speed is zero for the first 12 hours of the day, then 10 m/s (22.4 mph – double the speed above) for the rest of the day, then the average speed per day is still 5 m/s, yet the energy output per day is four times as much:

$$E_W(day) = 10 \text{ kW} \times \left(\frac{10 \text{ m/s}}{12 \text{ m/s}} \right)^3 \times 12 \text{ hrs} = 69 \text{ kWh}$$

The conclusion is that commonly used wind energy generation equations are only useful when the wind speed is constant during a specific time period. However, the wind speed is usually *not* constant, so the estimated energy is significantly less than the actual energy produced.

A large body of work in this research was done trying to determine an equation describing the relationship between average wind speed and the expected energy output. The closest approximation determining the expected energy production of wind turbines per day was found to be:

$$E_W(day) \cong 2 \times P_{RATED} \times \left(\frac{V_{ave}}{V_{rated}} \right)^3 \times 24$$

Again, this is a critical equation for the DEB method, and it had to be verified before it could be used for microgrid design and optimization. Therefore, the equation above was verified with two separate wind power systems. The first was the 1-kW wind turbine already presented in section 2.2.3. It is rated 1 kW @ 8 m/s [80]. According to the equation above, given a 5 m/s average wind speed in Salina, KS, the expected energy production per year is:

$$E_W(year) = 2 \times 1 \text{ kW} \times \left(\frac{5 \text{ m/s}}{8 \text{ m/s}} \right)^3 \times 8760 \text{ hrs} = 4,277 \text{ kWh}$$

This number closely aligns with the expected energy production according to the data sheet of the turbine (4,450 kWh per year at 5 m/s), confirming the validity of the wind energy equation.

The second test was performed with a real-world 10-kW Bergey Excel wind turbine that is located on K-State Salina's campus. According to the wind turbine specification found in [81], the expected yearly output of the turbine is:

$$E_W(year) = 2 \times 8.9 \text{ kW} \times \left(\frac{5 \text{ m/s}}{11 \text{ m/s}} \right)^3 \times 8760 \text{ hrs} = 14,644 \text{ kWh}$$

Using historical data available at [97], the actual output of the turbine for the years 2018-2022 was as follows:

Table 2-1. Yearly production data of the K-State Salina's wind turbine

Year	2022	2021	2020	2019	2018		Average
Output (kWh)	15564	14018	13996	14703	13500		14356

Again, the actual average energy output of the wind turbine is very close (within 2 %) of the predicted number calculated via the wind energy equation, further confirming the validity of the equation.

2.3.4 Energy Stored in Batteries

As already discussed, storage systems are a critical component in a microgrid because it allows peak-shaving and load-leveling. However, batteries are also some of the more expensive parts of a microgrid, so all optimization approaches attempt to select the appropriate size - not too big and not too small - of the battery bank to minimize costs. In this section, first the battery

sizing approaches used by other optimization methods will be discussed, followed by approaches used by the DEB method.

2.3.4.1 Battery Capacity and State-of-Charge (SoC) Equations

The maximum amount of energy that can be stored in batteries is a product of its output voltage and its rated capacity Q (measured in Ah) according to the following equation:

$$E_B(\max) = V_{RATED} \times Q_{RATED}$$

As the battery is charged or discharged, the energy available in the battery at time t is equal to:

$$E_B(t) = V(t) \times Q(t)$$

Instead of capacity $Q(t)$, usually the unit-less term called state-of-charge (SoC) is used:

$$SoC(t) = \frac{Q(t)}{Q_R}$$

So that the energy available in a battery can be calculated according to the following equation:

$$E_B(t) = V(t) \times SoC(t) \times Q_R$$

Most other optimization methods use the equation above to determine the required battery capacity for proper operation of the isolated microgrid. First, for each hour the SoC is estimated, for example with the direct measurement method:

$$SoC(h) = SoC(h_0) + \frac{\eta}{Q_R} (i(h) \times (h - h_0))$$

Then the energy stored in the battery is computed as follows:

$$E_B(h) = V(h) \times SoC(h) \times Q_R$$

If the stored energy is less than the required energy for a particular hour, i.e.

$$E_B(h) < |P_G(h) + P_S(h) + P_W(h) - P_{LOAD}(h)| \times (h - h_0)$$

then Q_R is increased until the energy demand is met.

2.3.4.2 State-of-Charge (SoC) Estimation Methods

Besides being inefficient, the biggest problem with the above approach is that it is quite difficult to accurately determine the state of charge of a battery in real-time like one could measure the fluid level in a gas tank. Whole dissertations and books have been written on this subject already. But since this subject is extremely important for simulation-based microgrid design methods, this section will present some of the more common SoC estimation approaches.

The different methods for state-of-charge estimation can be broadly classified into three categories as suggested in [98]: direct-measurement method, model-based method, and data-driven method as seen in the figure below:

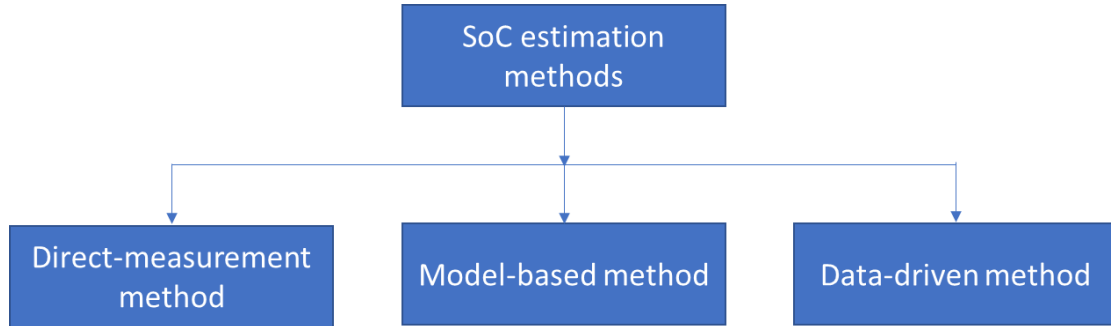


Figure 2.21. SoC estimation methods classification

The direct-measurement method is the simplest and most accurate way to estimate the capacity of a battery. It is often called the Coulomb-counting method, and it works by measuring the total amount of current that flows in and out of the battery during a complete cycle. As already briefly introduced above, the equation for the direct measurement method is:

$$SoC(t) = SoC(t_0) + \frac{\eta}{Q_R} \int_{t_0}^t i(t) dt$$

where SoC is the initial state of charge at time t_0 , Q_{RATED} is the nominal capacity, η is charging efficiency of the battery, and $i(t)$ is the current at time t .

The next SoC estimation method, called the model-based method, relies on mathematical models that describe the battery behavior and dynamics. There are quite a few models, such as kinetic models, electrochemical models, equivalent circuit models, analytical models, etc. [99] Only some of the more commonly used models will be discussed more in-depth in this section.

One of the most popular models is the kinetic battery model (KiBaM). According to this model every battery has two tanks of charge: one that is available for immediate use, and one that is bound and needs time to transfer to the available tank, as shown in the figure below:

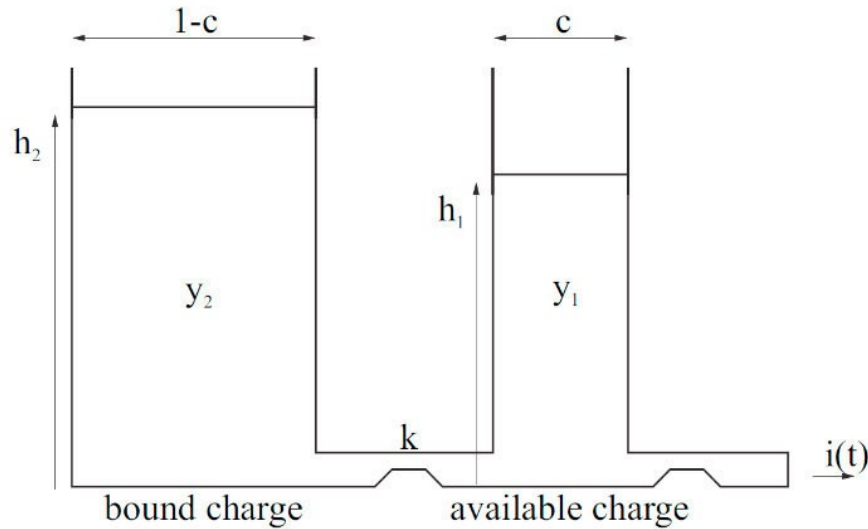


Figure 2.22. Kinetic Battery Model illustration

(Source: [100])

In this model, a fraction c of the total capacity Q is in the available charge tank (y_1), and the remaining fraction $1 - c$ is in the bound charge tank (y_2). The available charge tank supplies

current directly to the load $i(t)$; the bound-charge tank supplies charges only to the available-charge tank.

The excess charge flows from the bound charge tank to the available charge tank through a valve with a fixed conductance k . The rate at which charge flows between the tanks depends on the potential difference (height) between the two tanks.

The heights in the two tanks can be determined by the following equations [101]:

$$h_1(t) = \frac{y_1}{c}$$

$$h_2(t) = \frac{y_2}{1-c}$$

The rate of change of charges in the two tanks is governed by the system of equations:

$$\frac{dy_1}{dt} = -i(t) + k(h_2 - h_1)$$

$$\frac{dy_2}{dt} = -k(h_2 - h_1)$$

with initial conditions $y_1(0) = c \times C$, and $y_2(0) = (1 - c) \times C$.

A simplification can be performed via coordinate transformation:

$$\gamma = y_1 + y_2$$

$$\delta = h_2 - h_1$$

resulting in the following differential equations:

$$\frac{d\gamma}{dt} = -i(t)$$

$$\frac{d\delta}{dt} = \frac{i(t)}{c} - k'\delta$$

with initial conditions $\gamma(0) = C$, and $\delta(0) = 0$, and $k' = \frac{k}{c(1-c)}$

With a constant current drain I , the equations above can then be solved (with Laplace transforms) as follows:

$$\gamma(t) = (y_1 + y_2)(t) = C - It$$

$$\delta(t) = (h_2 - h_1)(t) = \frac{I}{c} \times \frac{1 - e^{-k't}}{k}$$

The KiBaM model is one of the most popular models because it captures some important features of batteries, such as the rate-capacity-effect and the recovery-effect. The rate-capacity effect means that the battery capacity decreases when the discharge current increases. The recovery effect means that the battery voltage will increase after the load is disconnected, as additional bound charges become available. The KiBaM is also popular because it can be used to model different types of batteries, such as lead-acid, lithium-ion, or nickel-metal hydride.

There are other models, for example the equivalent circuit model, which uses ideal resistors, capacitors, current and voltage sources to represent complex impedance, current, power and voltages in the battery. One can then estimate the battery capacity by solving the simplified equivalent circuit of the battery.

Another model, called the electrochemical model, measures the internal chemical and electrical parameters of the battery, such as concentration, potential, and temperature, and estimates the battery capacity by solving sets of differential equations that represent the conservation laws of mass, charge, and energy.

The analytical model estimates the battery capacity by deriving some analytical expressions and equations that relate the battery capacity to some measurable variables, such as voltage, current, or state of charge [102].

The last SoC estimation method, called the data-driven method, uses machine learning or statistical techniques to learn the relationship between the battery capacity and some features

extracted from the measured data, such as terminal voltage, current, temperature, internal resistance, etc. This method can estimate the battery capacity without requiring a specific battery model, but it needs a large amount of data for training and validation and may not work well for different operating conditions or different battery types.

To visualize the data-driven method, observe the plot below that shows the relationship between battery voltage and the SoC for an LFP battery. This data can be stored in tables and then be used to train algorithms to accurately predict the SoC based on measured battery voltages.

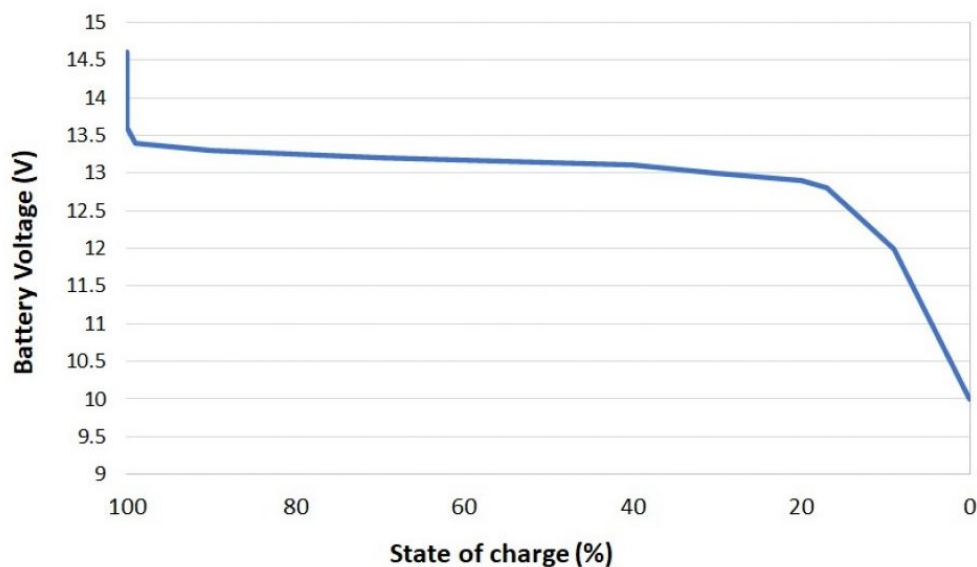


Figure 2.23. SoS vs voltage plot

(Source: [103])

There are different training and learning algorithms. For example, the deep transfer learning method can estimate the battery capacity by using partial segments of charging/discharging data, which are often easier to obtain than full cycles. A convolutional neural network (CNN) is used to extract the features and a fully connected network (FCN) is

used to estimate the capacity. The CNN and FCN are trained on part of the source data and then fine-tuned with the rest of the data [104].

Another learning method is called the electrochemical impedance spectroscopy (EIS). It is based on the measurement of the battery impedance at different frequencies, which reflects the internal states of the battery. The EIS data is then used as inputs for machine learning models, such as Gaussian process regression (GPR), support vector machines (SVM), or neural networks (NNs), to predict the battery capacity [105].

There are quite a few additional methods such as “cloud charging data method” [106], “visual cognition method” [107], “differential thermal voltammetry method” [108], etc. All methods basically measure battery parameters such as terminal voltage, current, temperature, state of charge, etc., during different charging and discharging processes. They then use various classification and aggregation approaches to estimate the remaining battery capacity.

2.3.4.3 IEEE Battery Sizing Methods and Standards

Besides SoC approaches which are very computationally intensive, there are other published methods with reduced complexity which can be used to determine the proper size of batteries. Unfortunately, these methods apply only indirectly to the microgrid design dilemma, because they are meant to be used only for designing battery-backup systems.

For example, there is the IEEE 485 standard that is applicable for sizing batteries for short duration, high-current applications, such as uninterruptible-power-supplies (UPS) for data centers, hospitals, etc., where the maximum discharge current might significantly exceed the average discharge current.

The suggested procedure is to divide the power demand into piece-wise constant load sections as shown in the diagram below:

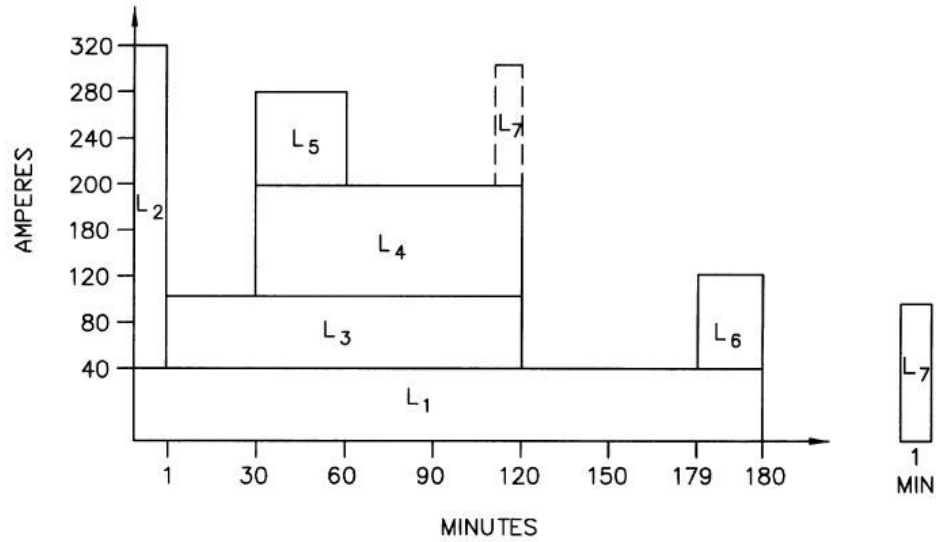


Figure 2.24. Diagram of a battery duty-cycle

(Source:[109])

For each section, the required capacity is determined with the following equation:

$$Q_s = \sum_{p=1}^s [A_p - A_{p-1}] \times k_t$$

The discharge factor k_t is calculated as follows:

$$k_t = \frac{Q_{nom} (Ah)}{A_T (A)}$$

where Q_{nom} is nominal capacity of the battery, and A_T is the available current during section T .

These parameters are usually given by battery manufacturers in tables:

Table 2-2. Battery capacity and discharge parameters

(Source: [109])

	Hours											Minutes		
Discharge time	24	12	10	8	7	6	5	4	3	2	1	30	15	1
Discharge current [A]	5.1	9.3	11	13	14	16	18	22	27	37	58	94	133	189
Capacity [Ah]	122	112	110	104	98	96	90	88	81	74	58	47	33.3	3.15

Using this table, for a battery with an 8-hour nominal capacity of 104 Ah, if a section requires 100 A for 2 hours, then:

$$k_t = \frac{104 \text{ Ah}}{37 \text{ A}} = 2.81 \text{ hr}$$

And the required capacity would then be equal to:

$$Q = A \times k_T = 100 \text{ A} \times 2.81 \text{ hr} = 281 \text{ Ah}$$

The total unadjusted capacity is the sum of all section capacities. It needs to be adjusted for temperature & age, as well as a small safety (design) margin needs to be added to the total required capacity.

Another standard is called IEEE 1013 and is applicable for longer-duration, lower current applications, when the maximum discharge current is not much greater than the average discharge current. This standard is mostly applicable to off-grid applications, where a certain number of autonomy days are desired when no input power is available. The standard lists several sample applications, for example keeping a remote communication station powered for several days without any other source of power.

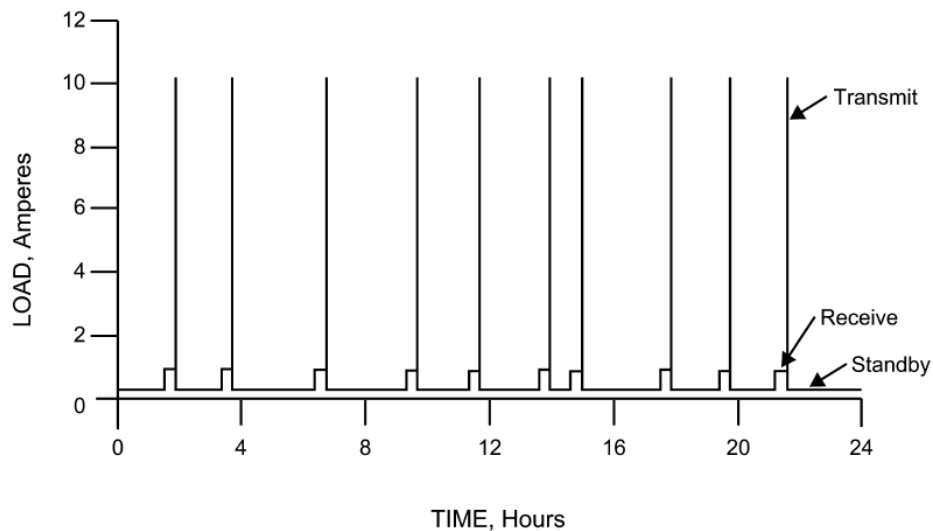


Figure 2.25. Load profile of a communication station

(Source: [110])

The design procedure is similar to IEEE 485. First, the expected daily load, including momentary and also running currents, along the duration of each load are recorded in a table. Based on this data, the unadjusted capacity is calculated by multiplying daily amp-hour requirements by the number of desired autonomy days. This capacity is then adjusted for different battery characteristics and operating conditions.

For the example plot above, the total unadjusted capacity Q_T can be calculated as follows:

$$Q_D = \sum_{i=1}^{i_{max}} A_i \times t_i = 17.8 \text{ Ah}$$

$$Q_T = Q_D \times D = 17.8 \text{ Ah} \times 15 \text{ days} = 267 \text{ Ah}$$

This capacity then needs to be adjusted for depth-of-discharge (DoD), which refers to the degree that a battery's capacity has been used during a discharge cycle. It is typically expressed as a percentage, where 0% indicates no discharge (fully charged) and 100% indicates complete discharge (fully depleted).

The maximum depth-of-discharge (MDoD) refers to the deepest level to which a battery can be discharged without causing damage or significantly reducing its lifespan. The MDoD depends on the battery chemistry and is usually given by battery manufacturers. To ensure longevity, the DoD for flooded lead acid batteries should typically not exceed 50%, with 80% for AGM and Gel batteries, and 90% for LFP batteries.

So for the example above, given an AGM battery with a MDoD of 80%, the required battery capacity would be:

$$Q_T = \frac{267 \text{ Ah}}{0.8} = 333.75 \text{ Ah}$$

Besides IEEE guidelines, other simplified guidelines are also available, for example in [111]. According to this guideline, the minimum required battery capacity can be calculated by using the following approximations for lead-acid batteries:

$$Q(t) = \frac{I \times t}{(0.02t + 0.6) \times DoD}$$

or the following approximation for lithium-ion batteries:

$$Q(t) = \frac{I \times t}{DoD}$$

Using these equations, to power a 150 W @ 12V load for 4 hours, the required flooded-lead battery capacity would be:

$$Q(t) = \frac{12.5 \times 4}{(0.02 \times 4 + 0.6) \times 0.5} = 147 \text{ Ah}$$

However, if a lithium battery with a MDoD of 80% is used, then the same load can be powered with only a 62.5-Ah battery.

2.3.4.4 Battery Sizing Equations for the DEB Method

But as already mentioned, the methods described in the section above are only designed for battery back-up applications, and are not really helpful for designing a microgrid system with variable hybrid power sources. Therefore, alternate methods and equations were developed for the daily energy balance (DEB) method to determine the correct amount of storage capacity which is necessary for the proper operation of a microgrid.

The most accurate method found was a kW-counting procedure. The basic idea is that for a microgrid to function properly, the minimum required energy storage capacity of the battery bank needs to match the difference between the generated and consumed power for each

time frame. To illustrate the kW-counting procedure, observe the example power demand plot below.

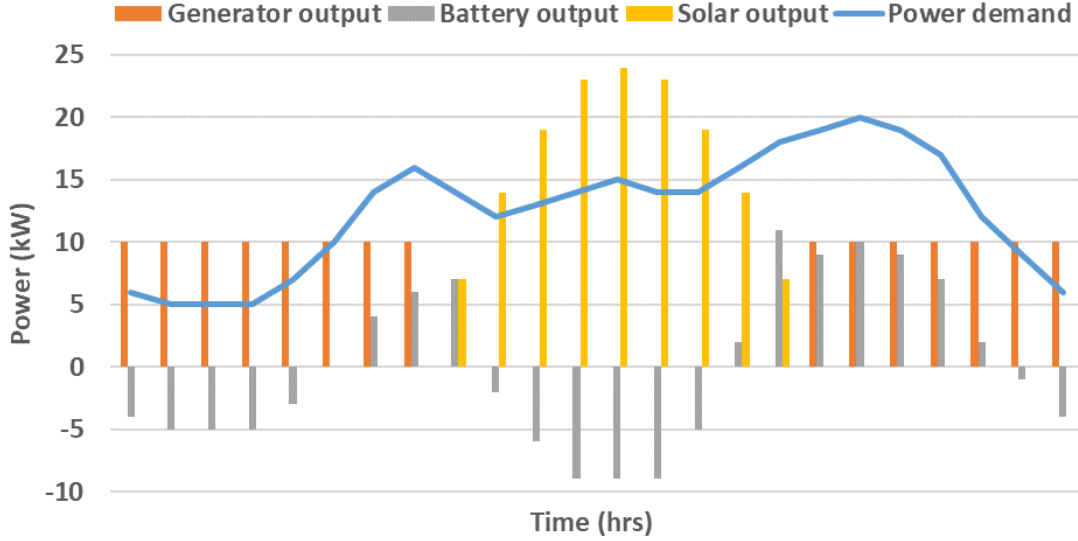


Figure 2.26. Illustration of the kW-counting procedure

For the first 5 hours, the difference between consumed and supplied energy is negative, meaning that there is a surplus of energy available to re-charge the battery. During the evening hours, the difference is positive, meaning that the battery is now delivering power to the load and is being discharged. The battery capacity needs to be sized so that it is able to absorb the positive as well as the negative demand, and can be determined as follows:

$$E_B(day) = \max \left\{ \sum_{h=1}^{24} (P_{SUPPLY}(h) - P_{LOAD}(h)), \sum_{h=1}^{24} (P_{LOAD}(h) - P_{SUPPLY}(h)) \right\}$$

In an optimally designed system, the charging and discharging energy demand is exactly the same and can be calculated as follows:

$$E_B(day) = \sum_{h=1}^{24} \frac{\| (P_{SUPPLY}(h) - P_{LOAD}(h)) \|}{2}$$

For the example above, E_B (in) and E_B (out) are both exactly 67 kWh. This number still needs to be adjusted for the MDoD of the battery to determine the total daily storage capacity.

The kW-counting procedure, similar to the SoC estimation methods discussed earlier, still requires detailed power demand and power generation data, and is also an inefficient and computationally expensive approach. However, it will be used in chapter 6 to verify the validity of the obtained solutions.

But for designing and optimizing an isolated microgrid with the DEB method, a novel battery sizing approach is proposed. Because exact power demand parameters are often unknown, this approach estimates the daily battery capacity requirements based only on the daily average and peak power demand, as well as the daily average energy generation capability of various microgrid sources.

If the generator supplies constant power that exceeds the average demand, the battery capacity for supplying load-leveling energy can be approximately computed as follows:

$$E_B(day) = \left(P_G - \frac{P_{PEAK} + P_{AV}}{2} \right) \times RunTime$$

However, if the generator is supplying only the average demand, the required battery capacity for peak-shaving energy can be approximately determined as follows:

$$E_B(day) = \left(\frac{P_{PEAK} + P_{AV}}{2} - P_G \right) \times 12$$

which simplifies to:

$$E_B(day) = \left(\frac{P_{PEAK} + P_{AV}}{2} - P_{AV} \right) \times 12 = (P_{PEAK} - P_{AV}) \times 6$$

Similarly, if the entire energy demand E_{DAY} is covered by solar energy, which is only available during the day-light hours of the day, the required battery capacity can be approximately determined as follows:

$$E_B(day) = \left(\frac{E_{DAY}}{12} - P_{AV} \right) \times 12 = \frac{E_{DAY}}{2}$$

If less than the entire demand is covered by solar energy, the total battery demand is derated by the E_S / E_{DAY} factor and can be computed as follows:

$$E_B(day) = \frac{E_{DAY}}{2} \times \frac{E_S}{E_{DAY}} = \frac{E_S}{2}$$

Wind energy is typically fairly constant over the course of the day and decreases the overall battery requirement by a derating factor of:

$$DF_W = 1 - \frac{E_W}{E_{DAY}}$$

To combine the equations above, the total battery requirement of a microgrid system can be approximately determined with the following linear equation:

$$E_B(day) = \left\{ ((P_{PEAK} - P_{AV}) \times 6) + \frac{E_S}{2} \right\} \times \left(1 - \frac{E_W}{E_{DAY}} \right)$$

The linear equation was verified in chapter 6, and proved a passable approximation. However, the actual battery requirements are non-linear. For example, using the kW-counting procedure, the following plots were obtained that show the battery capacity requirements for various combinations of wind, solar, and generator power for a system with a total energy requirement of 300 kWh.

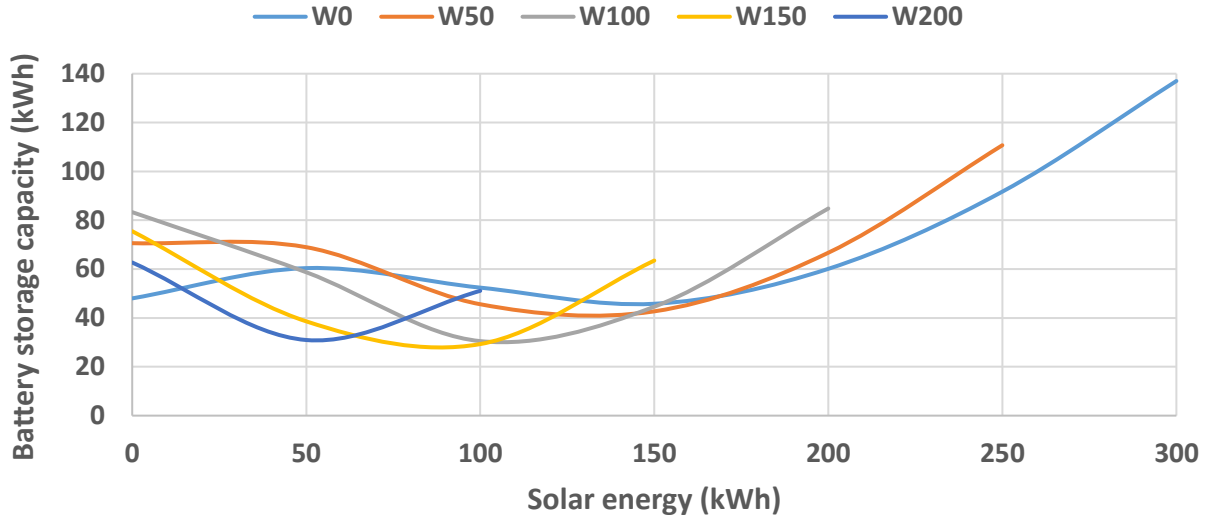


Figure 2.27. Daily battery capacity requirement plots for various power source combinations

Various curve fitting procedures were performed; the smallest root-mean-squared-error (RMSE) was achieved with a quadratic approximation with the following equation:

$$E_B(day) = ((P_{PEAK} - P_{AV}) \times 6) + \left(0.5 \times \frac{E_S^2}{E_{DAY}} - 0.2 \times E_S \right) - \left(0.2 \times \frac{E_W^2}{E_{DAY}} - 0.2 \times E_W \right)$$

Both the linear approximation and the quadratic approximation were extensively tested and compared with results from the kW-counting procedure in chapter 6, confirming the validity of the derived approximations.

2.3.5 Combined Energy Output of Microgrid Systems

To determine the levelized cost of energy (see section 3.5), it is necessary to compute the total combined energy generated by all components of a microgrid system over the lifespan of a project. The equation is as follows [112]:

$$Combined\ E = \sum_{y=1}^{ProjectLifetime} \sum_{d=1}^{365} \sum_i E(i)$$

2.4 The Reliability of Microgrid Systems

In addition to power generating and storage capabilities, the reliability of the microgrid system is often an additional technical parameter that an engineer might be tasked to optimize.

The reliability of a microgrid system can be quantified by various indices, which are used to measure the availability and quality of the power supplied to the customers or loads. Below, some of the common reliability indices for microgrid systems will be introduced, along with different types of uncertainties and ways to deal with them [113].

2.4.1 Microgrid System Reliability Indices

Loss of load expected (LOLE) is the total number of hours for which the microgrid system is unable to provide the load with the requested power. This factor accumulates the number of hours that the hybrid system cannot supply the required power to the loads during the total time period. The LOLE is computed as follows:

$$LOLE = \sum_{t=1}^T t_{out}(t)$$

Loss of load probability (LOLP) is the ratio of the number of hours for which the microgrid system was unable to provide the load with the requested power divided by the total number of hours in the time period.

$$LOLP = \frac{\sum_{i=0}^T t_{out}(i)}{T} = \frac{LOLE}{T}$$

Level of autonomy (LA) is the percentage of time that the power supply is available to the customers over a given time period.

$$LA = 1 - \frac{\sum_{i=0}^T t_{out}(i)}{T} = 1 - LOLP$$

Expected energy not supplied (EENS) is obtained by multiplying the average power demand by the total number of outage time intervals.

$$ENS = \sum_{i=0}^T P_{av}(i) \times LOLE$$

Finally, loss of power supply probability (LPSP) is the ratio of energy not supplied divided by the total energy supplied.

$$LPSP = \frac{ENS}{\sum_{i=0}^T P(i) \times \Delta t}$$

The goal of many microgrid optimization algorithms is to minimize the LPSP.

2.4.2 Power Demand Uncertainties

To minimize LPSP, it is imperative to ensure that the available power and energy is greater than or equal to the power demand of the loads for each time interval, i.e.:

$$P_G(t) + P_S(t) + P_W(t) + P_B(t) \geq P_L(t)$$

But as already discussed in section 2.1, the power demand is typically highly variable, as it depends on many factors, such as weather, economic activity, and consumer behavior.

One possible way to deal with electric power demand uncertainty is to use probabilistic forecasting methods, which estimate the probability distribution of future demand based on historical data and the likelihood of unusual events. Another approach is called “scenario analysis”, which constructs a set of plausible future demand trajectories based on different

assumptions and narratives, such as the growth of electric vehicle usage, the increase in distributed generation, the expansion and reliability of transmission and distribution networks, and the increased integration of renewable energy sources.

Probabilistic forecasting and scenario analysis can be used in a complementary way to quantify electric power demand uncertainty. Probabilistic forecasting can provide more precise and consistent estimates of demand uncertainty in the short to medium term, while scenario analysis can provide more flexible and comprehensive insights into demand uncertainty in the long term [114].

2.4.3 Power Supply Uncertainties

As discussed earlier in this chapter, the power supplied from renewable energy sources such as wind and solar is highly variable and comes with a high degree of uncertainty. Below, some of the individual uncertainties and methods to deal with them will be discussed in more detail.

Photo voltaic uncertainty is the degree of variability and unpredictability in the output of PV systems. To deal with this uncertainty, PV resource forecasting is used. It involves collecting and analyzing meteorological data as well as historical data to predict solar irradiance and PV output. One of the most important tools for PV resource forecasting are satellite images that track cloud movements and thickness. There are also ground mounted instruments such as cameras, LIDARs and ceilometers that allow to estimate cloud height and density. There are also statistical methods and algorithms that are trained with historical data, and which allow the identification of patterns in the past and making predictions for the future [115].

Another source of PV power production uncertainty is the variability related to the degradation rate of solar panels. While all solar panels experience the degradation effect, the quality of materials used in PV modules significantly affects their longevity. Additional factors like temperature, humidity, and UV radiation can also accelerate or slow down the degradation rate of PV modules. There are multiple methodologies that are used to forecast PV degradation rates such as Linear Regression (LR), Seasonal Decomposition, Autoregressive Integrated Moving Average (ARIMA), and Robust Principal Component Analysis (RPCA) [116].

There are also several software programs and tools specifically designed to predict the power output of solar panels. For example, Solcast is a company that specializes in providing solar resource assessment and forecasting data. They use a combination of weather satellites, computer vision, historical data, and machine learning algorithms to deliver quite accurate solar irradiance and PV power forecasts up to 14 days in advance [117].

Another tool is Xweather. Xweather provides forecasts for wind and solar energy, with advertised rates of up to 95% accuracy for hour-ahead forecasts and 92% for day-ahead forecasts. It accomplishes this by analyzing over 25 years of historical weather data, coupled with real-time weather monitoring, and utilizing AI and machine learning algorithms to provide accurate forecasts [118].

Similar to solar power, there is also a high degree of uncertainty in the output of wind turbines. To deal with this uncertainty, various wind resource assessment methods can be used, which estimate the uncertainty in wind energy potential over a period of time.

The wind speed distribution is a statistical description of how often different wind speeds occur at a given location. As discussed earlier, this is of utmost importance for estimating the wind energy potential. The time series method uses historical or simulated wind speed data to

calculate the frequency of occurrence of different wind speed intervals (bins). This frequency can be converted to a probability or a relative frequency by dividing it by the total number of wind measurements. The wind speed distribution can be plotted as a histogram or a curve, showing the probability or relative frequency of each wind speed bin.

The statistical analysis method then uses a mathematical function to fit the wind speed data and approximate the wind speed distribution. One of the most commonly used functions is the Weibull distribution, which has two parameters: the scale parameter (C) and the shape parameter (k). The scale parameter is a measure of the characteristic wind speed of the distribution, and the shape parameter specifies the variability and shape of the distribution. The Weibull distribution can be derived from the wind speed data using various methods, such as the method of moments, the maximum likelihood method, or the WAsP method [119], [120].

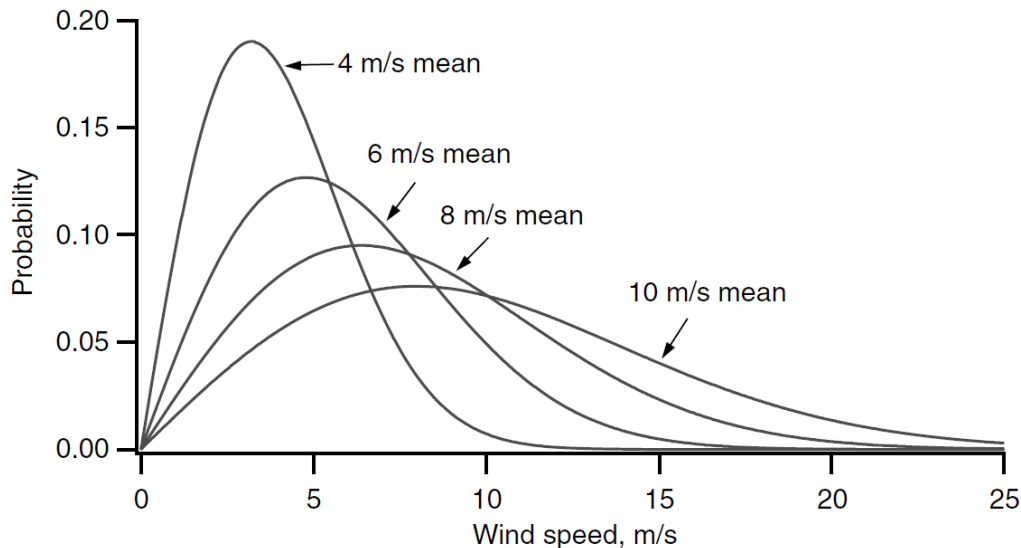


Figure 2.28. Examples of Weibull distribution functions.

(Source: [119])

Wind resource assessment methods are not always accurate, as they involve uncertainties and assumptions in the data collection and analysis. According to [121], the wind speed estimate

should be considered to be accurate to within only ± 10 to 15% of what the actual winds at a location may be, and any energy estimate generated by using the wind maps should be considered to be accurate to only $\pm 20\%$.

Just like solar power forecasting, there are also software tools for estimating the power production of wind turbines. Wind data tools such as Windographer [122], and WINDEXchange [123] are used to analyze and validate wind data, such as wind speed, direction, and turbulence. Modeling tools such as SOWFA [124], and FLORIS [125] are used to model wind turbine performance, energy output, and economic viability of wind projects.

2.5 Summary of Chapter 2

Chapter 2 introduced, described, and explained technical parameters that are relevant to the optimization of microgrid systems. In particular, the power demand of different types of customers; the power generating ability of generators, solar panels and wind turbines; and the storage capability of various batteries were explained and quantified via equations. Some of these equations are new and derived explicitly for the purpose of this research, and were extensively tested with data from real-world microgrid power systems. Also, the reliability of various microgrid system components were discussed in this chapter.

Chapter 3 - Mathematical Modeling of Economic Parameters for Microgrid Systems

When optimizing a microgrid system, often some of the most important goals are economic in nature, i.e., the designer is concerned with minimizing the cost of the system. Some of the most relevant economic parameters of a microgrid system are the Net Present Value (NPV), Net Present Cost (NPC), and the Levelized cost of energy (LCOE). These parameters will be discussed in this chapter in greater detail.

3.1 Net Present Value (NPV) and the Discount Rate

In general, the Net Present Value (NPV) is the sum of discounted benefits minus the sum of discounted costs. It considers the time value of money, which means that money received or spent in the future is worth less than money received or spent today. It is extensively used in finance and accounting for determining the value of a business, investment, project, venture, etc. [126],[127]. To compute NPV the following equation can be used [128]:

$$NPV = \sum_{y=1}^{Y_{max}} \frac{Income}{(1+r)^y} - \sum_{y=1}^{Y_{max}} \frac{Expenses}{(1+r)^y} - Initial\ cost$$

where Y_{max} is the duration of the project in years, and r is the discount rate.

The *discount rate* is the interest rate used to discount future cash flows of an investment or project to their present value. There are two main types of discount rates that are commonly used in finance: the Fed Funds Rate and the rate of return.

The Fed Funds Rate is the discount rate that the Federal Reserve charges commercial banks and other financial institutions for short-term loans. It is a monetary policy tool that

controls the supply of money and influences the economy. The Fed sets this rate independently and adjusts it according to the economic conditions.

The second type of discount rate, which is typically the rate that is used to calculate the net present value (NPV) of an investment or project, is also often called the required rate of return, the hurdle rate, or the *cost of capital*. It represents the minimum return that an investor or a company expects to earn from an investment or project, given its risk and opportunity cost. The discount rate for NPV can be derived from the weighted average cost of capital (WACC), the cost of equity, or the cost of debt, depending on the source of financing and the perspective of return.

3.2 Net Present Cost (NPC)

Again, in general, the net present cost (NPC) is a variation of net present value (NPV) and is used to evaluate the total cost of a project or investment over its lifetime. It is similar to NPV but is typically used if the discounted sum of costs exceeds the discounted sum of benefits. It is calculated as follows [129]:

$$NPC = Initial\ cost + \sum_{y=1}^{Y_{max}} \frac{Expenses}{(1+r)^y} - \sum_{y=1}^{Y_{max}} \frac{Income}{(1+r)^y}$$

For microgrid power systems, the Net Present Cost (NPC) is the total cost of installing and operating the microgrid system over its lifetime, discounted to the present value. NPC includes initial acquisition costs of each component, the replacement cost if a component's life expectancy is less than the project lifetime period, fuel costs if applicable, operation and maintenance costs, and the potential for some income if the used equipment can be sold at the end of the project's lifetime. A lower NPC indicates a more economical system.

Below, the NPC of individual microgrid system components will be discussed.

3.2.1 NPC of Internal Combustion Engine Generators

The most common types of generators for microgrid systems are diesel, natural gas, and propane generators. Diesel generators are probably the most common type of industrial generators, as they are known for their power, durability, and efficiency. They are generally reliable and easy to maintain and repair. However, they tend to be large, noisy, and produce a lot of emissions.

Natural gas generators use liquified petroleum gas for fuel. They are less expensive and quieter than diesel generators and burn fuel more cleanly. They have a comparable life expectancy; however, they tend to have higher maintenance needs than diesel generators. Natural gas is also highly explosive, so the fuel stored on site can present more of a fire hazard.

Propane generators are similar to natural gas generators but use liquified propane as fuel. Propane is more readily available than natural gas in some areas, and it can be stored in tanks for longer periods of time. However, propane generators are more expensive to run than natural gas generators, and they require more frequent fuel refills.

The initial cost of an industrial generator primarily depends on the type of generator, the size of the generator, the installation expenses, and additional features such as sound attenuation, auto-start capabilities and monitoring capabilities. According to [130], the current initial costs for industrial generators run between \$300-\$550 per kW.

The life expectancy of an industrial generator depends on several factors, such as the type, size, brand, quality, maintenance, and usage patterns of the unit. Generally, an industrial generator can last for 20,000 to 40,000 hours of use, equating to approximately 20 to 25 years of operation if used intermittently [131]. However, some generators may last longer or shorter than the average lifespan, depending on how often the generator was used, how well it was

maintained, and in what environmental conditions it was operated. Once replacement is necessary, the replacement costs of a generator are usually slightly less than the initial purchase price because the infrastructure (concrete pad, electrical connection equipment, etc.) is already in place. For the purpose of this dissertation, the same price range, \$300-\$550 per kW will be used.

The cost of maintaining an industrial generator also depends on several factors, such as the type, size, brand, quality, age, and usage pattern of the unit. According to [132], the average annual maintenance cost for a diesel generator is around \$750 for air-cooled generators up to 20 kW, \$850 for liquid-cooled generators up to 60 kW, \$1150 for large generators up to 150 kW. According to [133], the average annual maintenance cost for a natural gas or propane generator are slightly less, \$600 for air-cooled generators up to 20 kW, \$750 for liquid-cooled up to 60 kW, and \$950 for liquid cooled generators up to 150 kW.

But by far the biggest expense of running an industrial generator are the fuel costs. The fuel consumption of an industrial generator is often estimated using a fuel consumption chart that shows the approximate amount of fuel needed to power a generator based on its size and load. For example, according to [134] and [135], a 100-kilowatt (kW) diesel generator uses about 2.6 gallons per hour (gal/hr) at 25% load, 4.1 gal/hr at 50% load, 5.8 gal/hr at 75% load, and 7.4 gal/hr at 100% load.

Another way to estimate the fuel consumption of an industrial generator is to use fuel consumption calculators where the kilowatt rating and load percentage of the generator is entered and an estimated fuel consumption rate in gallons per hour or liters per hour is given. For example, according to one calculator [136], which estimates the fuel consumption of diesel as well as natural-gas powered generators, a 100-kW diesel generator running at 50% load would use about 4.28 gal/hr or 16.2 liters per hour.

For the purpose of this research, it was necessary to be able to compute the fuel consumption via an equation. The fuel consumption is typically somewhat linear and can be approximated with a linear slope-intercept equation as shown on the diagram below.

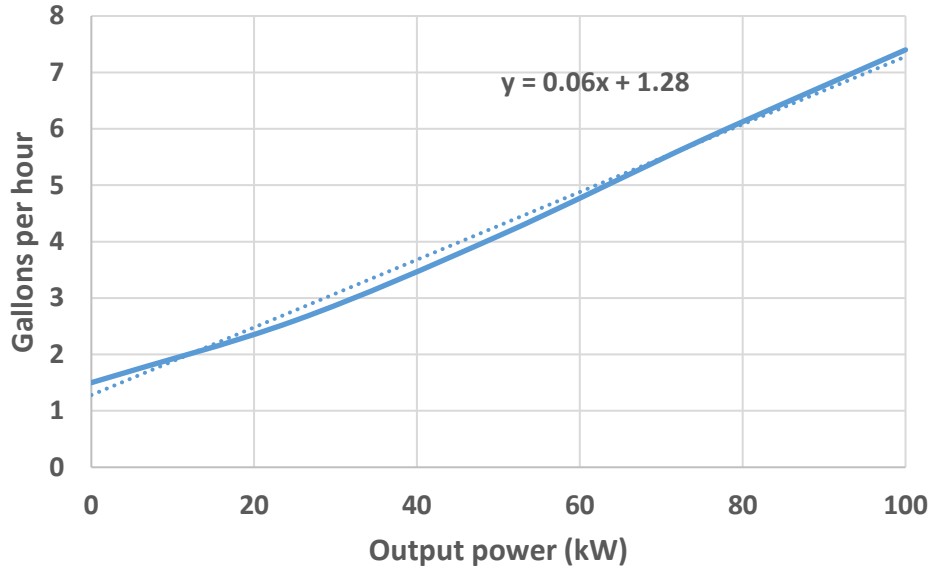


Figure 3.1. A typical fuel consumption chart of a diesel generator

The fuel consumption at any instant t can then be calculated with the following equation:

$$Qf(t) = \alpha P_R + \beta P(t)$$

where P_R is the rated power, $P(t)$ the output of the generator at time t , and α and β are coefficients on the consumption curve. For the example above, α is 0.0128, β is 0.06. Instead of gallons per hour, the fuel consumption is frequently measured in metric units - liters per hour. The corresponding coefficients would then be obtained by multiplying the numbers above with the gallon-to-liter conversion factor of 3.785, resulting in $\alpha = 0.0484$, $\beta = 0.227$.

However, several sources, e.g. [137], [138], without any justification are using $\alpha = 0.0845$, $\beta = 0.246$, while other sources recommend other numbers, e.g.: $\alpha = 0.05$, $\beta = 0.25$. However, using either of these numbers, the resulting fuel consumption of some generators, in

particular low-kW with low power utilization, appeared to be questionable, necessitating verification.

To verify, the consumption data of 14 generators with different power ratings (4 to 300 kW) and from different sources [139]-[142] were analyzed for this research, and the resulting α and β vs generator size in kW were plotted:

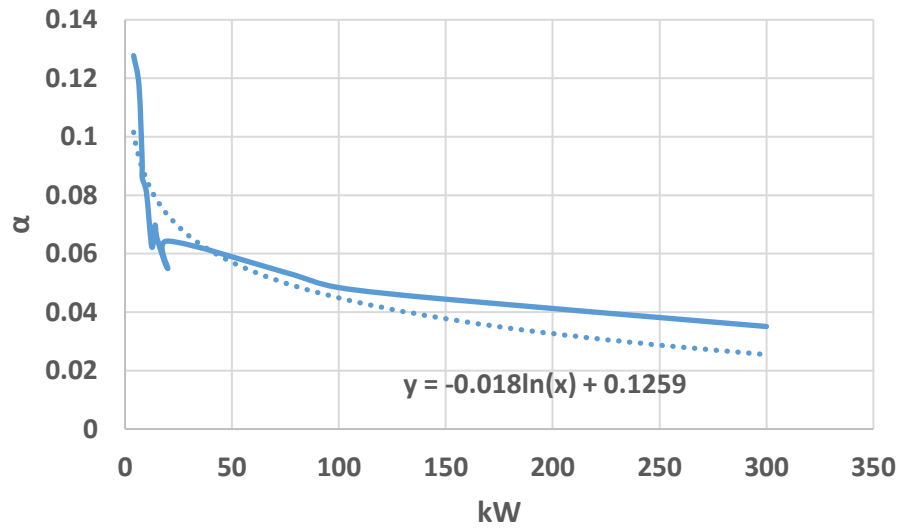


Figure 3.2. α -parameter vs kW illustration

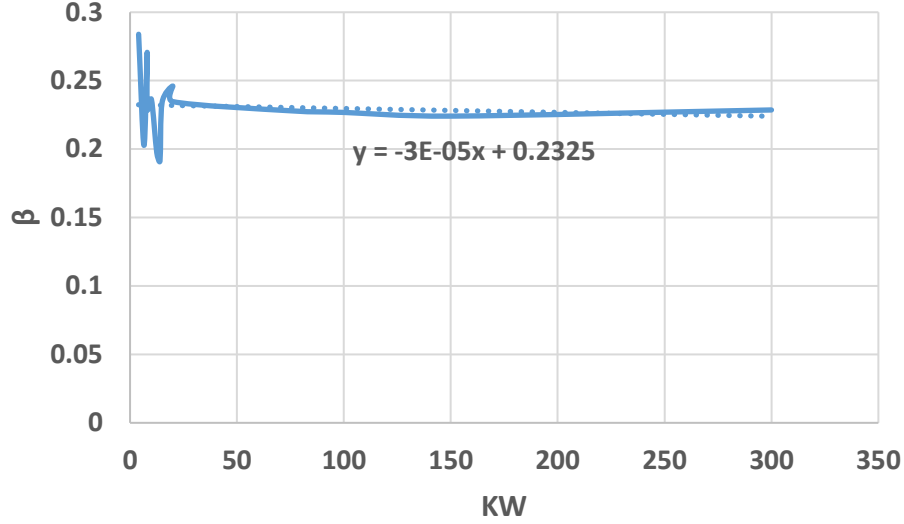


Figure 3.3. β -parameter vs kW illustration

From these plots it is evident that $\alpha \approx 0.0845$, $\beta \approx 0.246$ is a reasonable approximation only for generators with a rated power around 10 kW, while $\alpha \approx 0.05$, $\beta \approx 0.225$ is a reasonable approximation only for generators with a rated power around 100 kW. But in general, α displays logarithmic tendencies as seen on the plot, with a much larger value for low-kW generators as compared to high-kW generators. Then for β , a better approximation across the board appears to be 0.23, but again for low-kW generators the number is larger, closer to 0.3, while for high-kW generators β is smaller.

If the cost of the fuel at time t is $C_f(t)$, then the cost to run the generator i per year is:

$$FuelCost(i) = \sum_{y=1}^{ProjectLifetime} \sum_t^{Runtime} C_f(t) \times Q_f(t)$$

To summarize the cost factors of generators which were discussed above, the NPC of an engine generator can be computed as follows:

$$NPC_G = InitCosts + \sum_{y=1}^{ProjectLifetime} \frac{(ReplaceCost(y) + O\&M(y) + FuelCost(y))}{(1+r)^y}$$

$y = \text{years}$

$r = \text{discount rate} = 6\%$

$InitialCost = \$300\text{-}550 / kW$

$ReplaceCost \approx InitialCost \times ReplaceTimes$

$ReplaceTimes = ProjectLifetime / GeneratorLifetime$

$O\&M = \text{operation and maintenance costs} = \$600\text{-}900 / \text{year}$

$$FuelCost(i) = \sum_{y=1}^{ProjectLifetime} \sum_t^{Runtime} C_f(t) \times Q_f(t)$$

$C_f = \text{cost of fuel} \approx \$1 / L$

$Q_f = \text{quantity of fuel}$

$$Q_f(t) = \alpha P_{RATED} + \beta P(t)$$

$$\alpha = 0.038 - 0.14, \beta = 0.23 - 0.3$$

3.2.2 NPC of Solar Power Systems

The initial cost for solar power systems depends on the size, quality, and efficiency of the panels, as well as the labor and equipment required for installation. According to data from several sources, the average residential solar panel system cost about \$3 per watt in 2023 [143], [144].

The industry standard for the lifespan of solar panels is 25-30 years. That doesn't mean a solar panel will stop producing electricity after 25 years – rather, its power output decreases over time. According to a study from the National Renewable Energy Laboratory (NREL), the

average yearly degradation rate is approximately 0.50% across all solar panels. That means the solar output is still about 89% of its original output after 25 years [145]. So for a project lifespan of 20 years, only a limited number of panels will have to be replaced, and they are usually covered by warranty. However, other parts of the solar system, notably inverters, need to be replaced every 10 to 15 years, at an average cost of \$1,000 to \$2,000 per inverter per kW [146].

Solar panels are generally low-maintenance and durable, but they may need occasional cleaning, monitoring, and servicing to ensure optimal performance. Some components also need to be replaced over time, such as inverters as discussed above. The cost of maintenance and repairs can vary depending on the quality of the system, the warranty coverage, and the availability of service providers. A typical maintenance cost for a residential solar system is about \$150 to \$300 per year [146].

Considering these factors described above, the NPC of solar power systems can be computed as follows:

$$NPC_S = InitCost + \sum_{y=1}^{ProjectLifetime} \frac{(ReplaceInverterCost(y) + MaintCost(y))}{(1 + r)^y}$$

$$InitialCosts \approx \$3,000 / kW$$

$$ReplaceInverterCost \approx \$2,000 / kW$$

$$ReplaceTimes = ProjectLifetime / InverterLifetime$$

$$O\&M = operation\ and\ maintenance\ costs = \$150-300 / year$$

3.2.3 NPC of Wind Power Systems

The initial cost of installing a wind power turbine again depends on many factors, primarily the type, size, and location of the turbine. According [147], the initial cost of a small

wind turbine (less than 100 kW) is between \$3,000 and \$8,000 per rated kilowatt (kW) of electricity-producing capacity, while larger wind turbines (in the mega-watt range) cost between \$1,300 and \$2,200 per rated kilowatt (kW).

A wind turbine's lifespan depends on the design, manufacturing quality, maintenance schedule, and the operating environment of the turbine. According to [148], the average life span of a wind turbine is about 20 to 25 years, but they are unlikely to last much longer than this average lifespan due to the extreme loads they are subjected to. In the event that a turbine has to be replaced, the replacement cost can be budgeted as 2/3 of the initial costs because even though the tower is still available, the take-down and installation cost of the turbine are high.

The Operation & Maintenance costs of a wind turbine include administrative and monitoring costs, preventive and corrective maintenance costs for inspections, lubrication, cleaning, troubleshooting, and diagnostics, as well as site maintenance. According to NREL [149], the average O&M costs for land-based utility-scale wind projects in 2019 were \$48/kW/yr, while the average O&M costs for offshore wind projects in 2019 were \$133/kW/yr. The same report also estimated the average O&M costs for residential wind projects in 2019 at \$0.12/kWh, and the average O&M costs for commercial wind projects in 2019 at \$0.06/kWh.

Considering the factors described above, the NPC of wind power system can be computed as follows:

$$NPC_W = InitCost + \sum_{y=1}^{ProjectLifetime} \frac{(ReplaceCost(y) + MaintCost(y))}{(1 + r)^y}$$

$$InitialCosts \approx \$8,000 / kW$$

$$ReplaceCost \approx \$5,000 / kW$$

$$ReplaceTimes = ProjectLifetime / TurbineLifetime$$

$$O\&M = \text{operation and maintenance costs} = \$50 / kW / \text{year}$$

3.2.4 NPC of Battery Storage Systems

The NPC of battery systems largely depends on the type of batteries. Some of the most commonly used types of batteries are flooded, AGM, and Gel lead-acid batteries, as well as NMC and LFP batteries. Below is a short discussion on the advantages and disadvantages of the different types of batteries, as well as their characteristics and typical costs.

Lead-acid batteries are the oldest and still the most widely used rechargeable batteries in the world. They are affordable, reliable, easy to recycle, and are commonly used as start-up power sources in vehicles, as backup power sources in uninterruptible power supplies, and most recently for storing power in off-grid applications. However, they have low power and energy density, short cycle life, and high maintenance costs. They also suffer from self-discharge and sulfation problems [150].

Lithium-ion batteries in general are lightweight and efficient batteries widely used in consumer electronics and most recently in electric vehicles. They have high power and energy density, long cycle life, and fast charging and discharging rates. They also have lower maintenance costs. However, they are relatively expensive, prone to overheating and degradation, are unstable, and require complex battery management systems.

A NMC (Nickel Manganese Cobalt) battery is a subset of lithium-ion batteries. The cathode is made from a combination of nickel, manganese, and cobalt oxides. The anode is made from graphite, and the electrolyte is a lithium salt dissolved in an organic solvent. NMC batteries are widely used in electric vehicles, portable electronics, power tools, and energy storage systems due to their high energy density and good other performance characteristics such

as high cell voltage, fast charging times and long lifecycle. However, NMC batteries are quite expensive due to rare materials such as nickel, manganese, and cobalt. Mining these materials also leads to significant negative impact on the environment. Lastly, they are not as stable as LFP batteries which are discussed next [151].

LFP batteries are another subset of lithium-ion batteries that use lithium iron phosphate (LiFePO_4) as the cathode material. LFP batteries are more stable and less prone to overheating, fire, or thermal runaway (explosion) than other lithium-ion batteries. LFP batteries are also cheaper than other lithium-ion batteries, because iron as a cathode material is much more abundant and inexpensive compared to cobalt or nickel. LFP batteries also have lower operation and maintenance costs due to their longer lifespan and higher efficiency [151], [152].

Unfortunately, LFP batteries also have lower energy density and voltage than other lithium-ion batteries. This means that they can store less energy per unit of weight or volume and deliver less power per unit of charge. This can limit their applications in high-performance or long-range applications that require higher energy and power density. Below is a table that summarizes some of the key properties of different types of batteries [153]:

Table 3-1. Comparison of different battery technologies

	Flooded	AGM	NMC	LFP
Round trip efficiency (%)	80	88	65	98
Cycle Life @ 80% DoD	300	500	8,000	6,000
Off-grid life (years)	1	1.4	21.9	16.4
Energy Throughput (MWh)	1.9	3.5	41.6	47
Installation Cost (\$/10kWh)	1,200	2,200	18,000	6,900
Lifetime Cost (\$/kWh)	0.74	0.57	0.19	0.14

The initial cost of battery systems includes the cost of the batteries, plus modules, racks, inverters, wiring, and other hardware. The exact cost of whole battery storage systems was difficult to assess because different sources include or exclude different components.

But some generalizations could be made. The cost of a lead-acid, or LFP battery storage system for a home can range from \$300 to \$15,000 [154], while the cost of a utility-scale battery storage system can range from \$143/kWh to \$750/kWh [155]. The cost of a deep cycle lead acid battery per kWh can range from \$150/kWh to \$500/kWh, while the cost for a lithium-ion battery can range from \$300/kWh to \$1000/kWh.

For a complete system the following generalizations can be made [156]: it currently costs between \$250 and \$500 per kWh to install a lead-acid storage system, \$750 to \$1,000 per kWh to install an LFP storage system, \$1,000 - \$1,500 for an NMC storage system.

To determine replacement costs, estimating the life span of the batteries is of utmost importance. According to [157], lead-acid batteries have a life-span of about 1,500 charge/discharge cycles, and last between 3 and 5 years. LFP and NMC batteries can handle 7,000 or more cycles, which translates to 10-15 years of useful life [158]. When their performance decreases below an acceptable level they need to be replaced at a cost of between $\frac{1}{2}$ and $\frac{3}{4}$ of the initial costs.

To determine operation and maintenance costs, it is important to note that lead-acid batteries are higher maintenance than lithium batteries due to inspection, water top-off and electrolyte level adjustment, and periodic equalization charging. Correspondingly, it costs about \$50/year/kW to maintain lead-acid batteries, but only about half as much (\$25/year/kW) to maintain LFP or NMC batteries.

Considering the factors described above, the NPC of a battery storage system can be computed as follows:

$$NPC_B = InitCost + \sum_{y=1}^{ProjectLifetime} \frac{(ReplaceCost(y) + MaintCost(y))}{(1 + r)^y}$$

$$InitialCosts \approx \$500 / kWh \text{ (lead-acid)}, \$1,000 \text{ (LFP)}$$

$$ReplaceCost \approx \$300 / kW \text{ (lead-acid)}, \$600 / kW \text{ (LFP)}$$

$$ReplaceTimes = ProjectLifetime / BatteryLifetime$$

$$O\&M = \text{operation and maintenance costs} = \$25\text{-}\$50 / kWh / \text{year}$$

3.3 Levelized Cost of Energy (LCOE)

In general, the levelized cost of energy (LCOE) is the total cost of building and operating an energy-generating asset per unit of total electricity generated over the lifetime of the project. It can also be seen as the minimum price at which the electricity generated by the asset must be sold to break even. LCOE depends on several factors, such as the type of energy source, the location, the size, the lifespan of the project, the capital costs, the operating costs, the fuel costs (if applicable), and the discount rate. LCOE can be used to compare the cost-effectiveness of different energy-generating technologies, such as wind, solar, nuclear, etc.

As discussed earlier, the combined or total NPC for a microgrid system can be calculated as the sum of the costs of all individual components i :

$$TNPC = \sum_i NPC(i)$$

The total combined energy generated by all components of a microgrid system over the lifespan of a project can be computed as follows:

$$Combined\ E = \sum_{y=1}^{ProjectLifetime} \sum_{d=1}^{365} \sum_i E(i)$$

LCOE can then be calculated by dividing the present value of the total cost over the lifetime of the project by the sum of all electric energy generated over the lifetime of the project, as illustrated in the following figure:

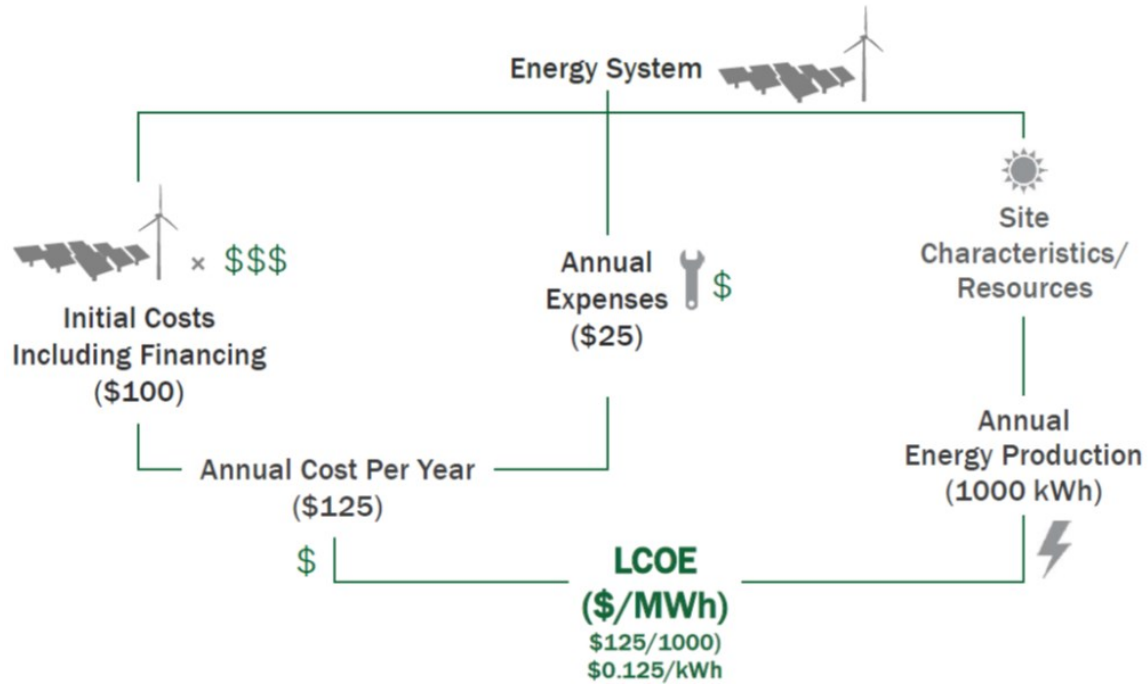


Figure 3.4. LCOE concept illustration.

(Source: [159])

To summarize the discussion above, LCOE is one of the primary factors that needs to be minimized in a microgrid system, and can be computed according to the following equation [160]:

$$LCOE \left(\frac{\$}{kWh} \right) = \frac{\sum_i NPC(i)}{\sum_i E(i)}$$

3.4 Summary of Chapter 3

Chapter 3 introduced, described, and explained economic parameters that are relevant to the optimization of microgrid systems. In particular, the Net Present Cost (NPC) of various microgrid system components were determined, and equations for calculating them were presented. Also shown was the equation for Levelized Cost of Energy (LCOE), which is of outmost importance for the design and optimization of microgrid power systems.

Chapter 4 - Survey of Optimization Techniques

As discussed earlier, the main goal of this research is to optimize a microgrid system. There are many optimization techniques for minimizing or maximizing a function, applicable depending on the type of function, the number of variables, the constraints, and the desired accuracy and speed. In this chapter, some of these techniques will be introduced and described.

In general, optimization techniques can be divided into mathematical optimization techniques and machine-learning techniques. Some of the most common techniques in each of these categories will be discussed in the following subsections, for single-objective, as well as multi-objective problems.

4.1 Mathematical Optimization Techniques

Mathematical optimization techniques can be further subdivided into iterative optimization and probabilistic optimization [161].

Below, some of the mathematical optimization methods will be discussed in more detail.

4.1.1 Iterative Methods

The iterative optimization method is trying to find the best solution to a problem by starting from an initial guess and repeatedly improving the solution until a desired level of optima is reached. Iterative methods are often used for problems that are too complex or large to solve directly, such as nonlinear equations, linear systems with many variables, or optimization problems with constraints. Some examples of iterative optimization methods are gradient descent, Newton's method and various versions of the simplex algorithm.

Gradient descent is a method that iteratively moves in the direction of the steepest descent of the function, until a local minimum is reached. It starts at an initial point x_0 , and moves a distance with the step-size α in the direction of the positive (maximization problem) or negative (minimization problem) gradient. The update equation is as follows:

$$x_{n+1} = x_n \pm \alpha f'(x_n)$$

The figure below shows the principle of operation of a basic gradient descent algorithm:

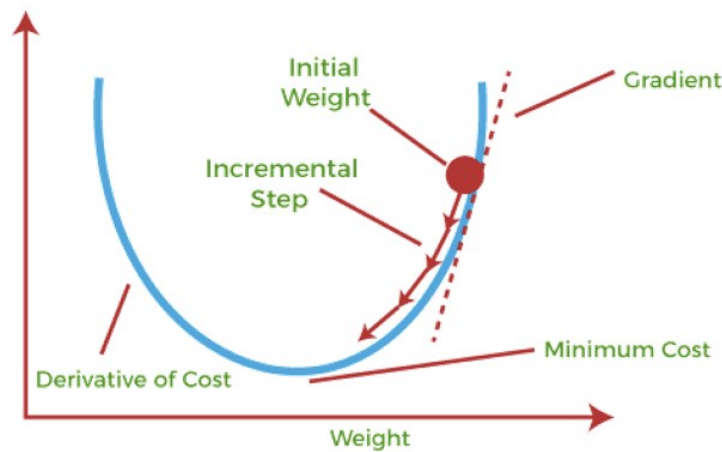


Figure 4.1. Gradient descent algorithm illustration

Source: [162]

A gradient descent is quite simple to implement, but it only works if the derivative of the objective function is obtainable. Depending on the size of the steps, it may also be slow to converge or might get stuck in a suboptimal local minimum.

Newton's method uses the first *and* the second-order derivatives (Hessian matrix) of the objective function to find the maxima or minima of a function. Like the basic gradient descent it starts with an initial point. Then the first and second derivative of the function at this point are computed. The position is then updated according to the following equation:

$$x_{n+1} = x_n - \frac{f'(x_n)}{f''(x_n)}$$

The process iterates until the change in x_n is smaller than a predefined minimum level, indicating that the solution has converged to the optimum solution.

Newton's method converges faster and more reliably than the basic gradient descent algorithm but it is also more computationally expensive. In addition, it also requires the first and the second derivative and so may not work for all functions. Finally, it might converge only to a local, as opposed to a global, minima or maxima.

The LP simplex is a constrained optimization method where the objective function and the constraints are linear. It typically involves a single objective function and several constraints that are formulated as inequalities. The inequalities form a polygonal shape, with the optimal solution lying on one of the vertices.

The principle of operation of a simplex algorithm can be best described with an example. Consider the figure below. This problem aims to maximize the function $f(x, y) = x + 2y$ where both x and y are constrained within the shaded region.

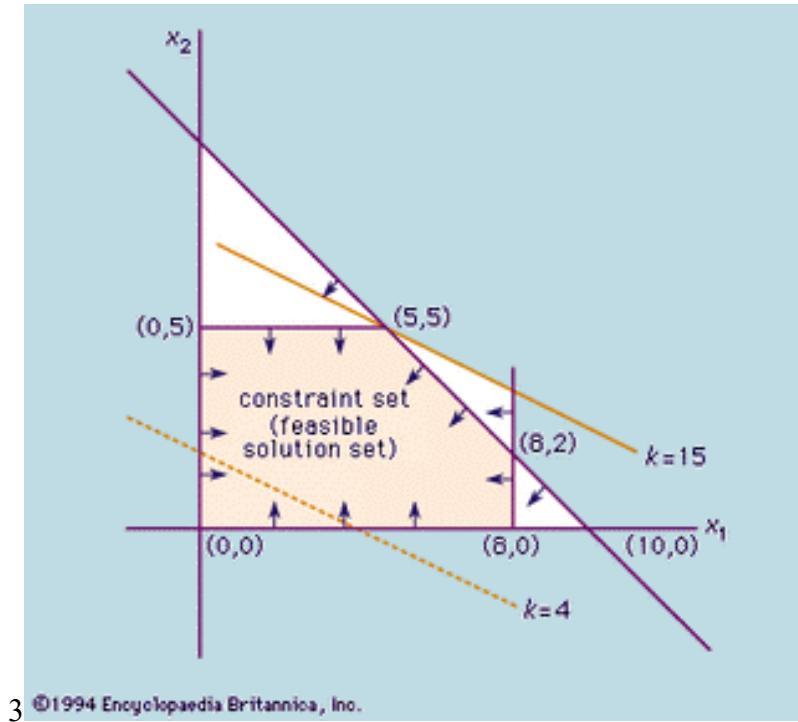


Figure 4.2. LP simplex algorithm illustration

Source: [163]

The optimization problem can be formulated as a system of equations, i.e.

$$\text{Maximize } f(x, y) = x + 2y$$

Subject to following constraints:

$$x \leq 8$$

$$y \leq 5$$

$$x + y \leq 10$$

In the first step, a set of slack variables is introduced to convert the inequalities into equalities, such that:

$$x + s_1 = 8$$

$$y + s_2 = 5$$

$$x + y + s_3 = 10$$

$$x + 2y - k = 0$$

Then the resulting equations are converted into an $Ax = B$ matrix.

$$\begin{array}{|cccccc|} \hline 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 1 & 2 & 0 & 0 & 0 & -1 \\ \hline \end{array} \cdot \begin{array}{|c|} \hline x \\ y \\ s1 \\ s2 \\ s3 \\ k \\ \hline \end{array} = \begin{array}{|c|} \hline 8 \\ 5 \\ 10 \\ 0 \\ \hline \end{array}$$

By iteratively fixing one variable and recalculating the rest of the variables, the intermediate solution first edges along the y-axis to $[0,5,8,0,5,10]'$, then along the top edge until it reaches $[5,5,3,0,0,15]'$, which is the optimal solution corresponding to the point (5,5) on the plot, with a maximum value of 15.

The simplex is very efficient and robust and one of the most useful optimization algorithms, but it does not work for non-linear problems, which limits its applicability.

The Generalized Reduced Gradient (GRG) algorithm is somewhat similar to LP simplex, except instead of traversing the boundary of feasible solutions, the gradient method moves through the interior of the feasible region following the gradient of the objective function.

Also, while simplex is only suitable for linear problems, the GRG method is also suitable for solving nonlinear optimization problems as long as the objective function and the constraint functions are differentiable. The GRG algorithm is particularly useful when the problem has smooth, continuous functions and when the constraints can be expressed as equalities, possibly by introducing slack variables for inequalities. However, just like the basic gradient descent algorithm, GRG might converge to a local optimum rather than a global one, depending on the initial conditions and the nature of the objective function.

The GRG algorithm starts with an initial feasible solution, which is a set of values for the decision variables that satisfy all constraints. The variables are divided into two groups: independent and dependent. The independent variables can be freely changed, while the dependent variables are adjusted to maintain feasibility with respect to the constraints.

The GRG algorithm then calculates the gradient of the objective function, which is the vector of its first partial derivatives with respect to the independent variables. Using the gradient information, the algorithm determines a search direction along which the objective function is expected to improve. A line search is performed to find the optimal step size that maximizes the improvement in the objective function along the search direction. The independent variables are then updated along the search direction by the optimal step size, and the dependent variables are adjusted accordingly to maintain feasibility.

At the end of each loop the GRG algorithm checks if the solution has converged, typically by looking at the magnitude of the gradient or the improvements in the objective function. If the convergence criteria are not met, the algorithm repeats the process starting with gradient calculations. Once the convergence criteria are met, the algorithm terminates, and the current solution is considered the optimal solution.

The following flowchart graphically shows the principle of operation of the GRG algorithm.

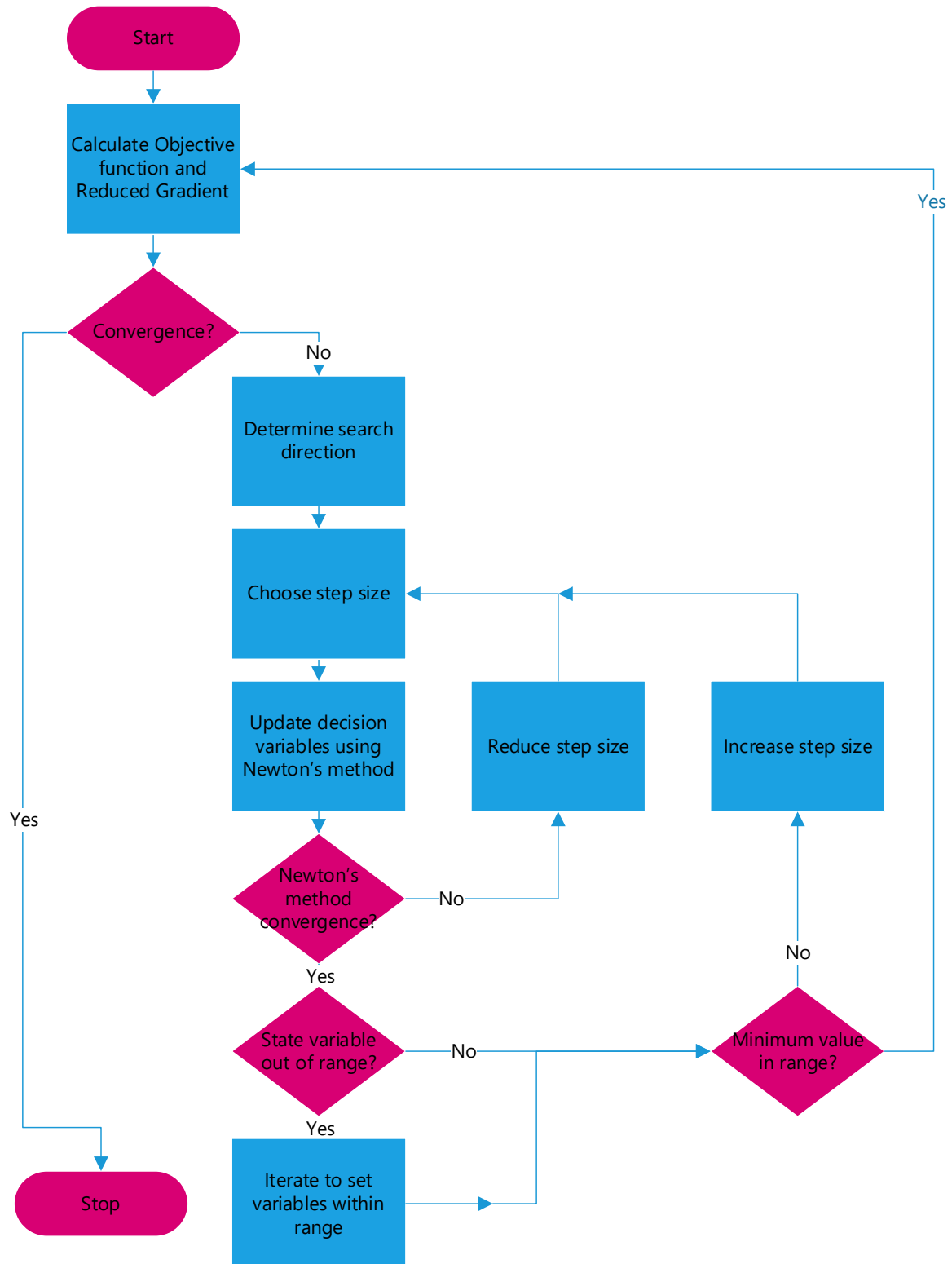


Figure 4.3. Flowchart of a Generalized Reduced Gradient (GRG) optimization algorithm

There are other popular iterative methods, such as Sequential Quadratic Programming (SQP). SQP can handle any degree of non-linearity in both the objective function and the constraints, making it suitable for a wide range of real-world applications. But just like Newton's method, this method relies on the first and second derivatives of the objective function and of the constraints, which can make it computationally expensive for problems with a large search space.

Another popular method is the Interior Point (IP) technique, which is the default method used in MATLAB. The IP method can handle a wide range of problems, including linear, nonlinear, convex, and even some non-convex problems. The IP method is known for its efficiency, especially for large-scale linear programming problems. It often outperforms other methods, but implementing the IP method can also be complex due to the need for accurate computation of barrier functions and their gradients.

4.1.2 Probabilistic Optimization Methods

Probabilistic optimization methods are another class of optimization techniques that deal with uncertainty in the problem formulation or the solution process. Some examples of probabilistic optimization methods are Stochastic programming and Bayesian optimization, which will be discussed below.

Stochastic programming is a method for solving optimization problems that involve uncertainty. Unlike deterministic optimization, where all parameters are known and fixed, Stochastic programming incorporates random variables that follow known probability distributions.

A common approach is the multiple-stage stochastic programming model: first make initial decisions before the uncertainties are considered. In the additional stages, adjust decisions based on the uncertainty parameters.

Another approach is the scenario-based method. Multiple scenarios representing different possible realizations of the uncertain parameters are generated. The optimization problem is then solved across these different scenarios to find a solution that on average performs best.

Some methods use a combination of both of these two approaches, as illustrated in the following figure [165]:

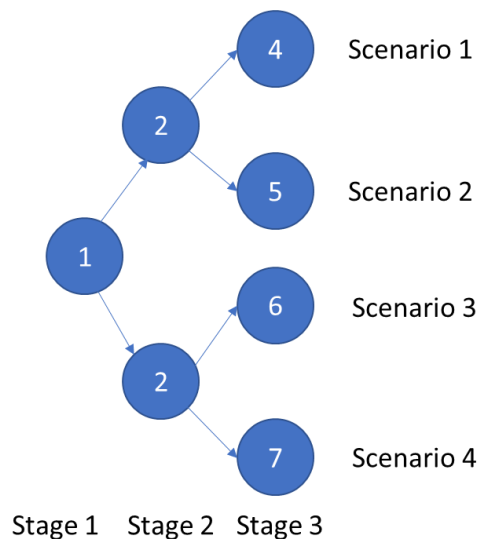


Figure 4.4. Stochastic programming tree illustration

Stochastic programming can handle a wide range of uncertainties and is applicable to various fields such as finance, energy, and supply chain management. It helps in making decisions that hedge against risks by considering the worst-case scenarios and optimizing the expected performance. But solving large-scale stochastic programs can require significant computational resources, especially for problems with a high degree of uncertainty.

Bayesian optimization is another probabilistic method. It uses Gaussian processes to model the objective function. This model provides a distribution over possible functions that fit the observed data. An acquisition function is used to determine the next point to evaluate. This function balances exploration (searching new areas) and exploitation (refining known good areas). Common acquisition functions include Expected Improvement (EI), Probability of Improvement (PI), and Upper Confidence Bound (UCB). Bayesian optimization is an iterative process. At each step, the model is updated with new data points, and the acquisition function is optimized to select the next point to evaluate.

The following illustration shows the principle of operation of Bayesian optimization:

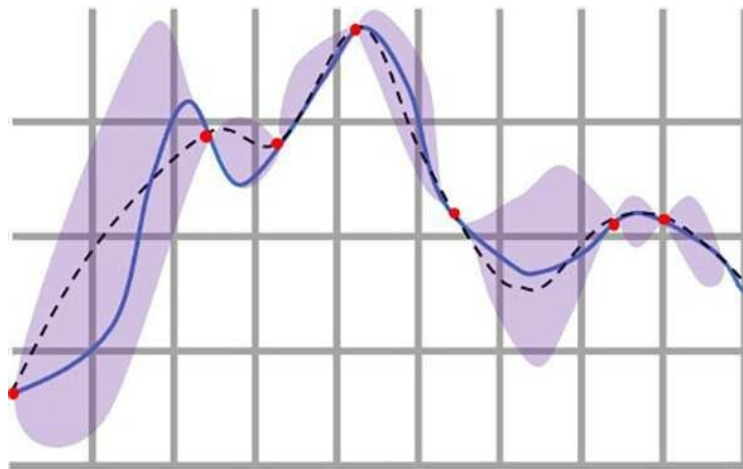


Figure 4.5. Illustration of the Bayesian optimization procedure

Source: [166]

The blue curve represents the true objective function. Red cross points are sampling points for the true objective function. The black dotted curve and purple shadow represent the mean and confidence intervals estimated with the surrogate (probability model) of the objective function.

Bayesian optimization is particularly useful for problems where the objective function is expensive to evaluate, such as hyperparameter tuning in machine learning models. It can handle noisy evaluations and is suitable for both continuous and discrete optimization problems. But while Bayesian optimization reduces the number of function evaluations, the computational cost of updating the probabilistic model and optimizing the acquisition function can be high.

There are other probabilistic optimization methods, for example the Stochastic Gradient Descent (SGD) algorithm. Stochastic Gradient Descent (SGD) is similar to other gradient-based methods, except instead of using the entire dataset to compute the gradient, SGD randomly selects a small batch of data points from the training set. The gradient of the function using the selected data points is then computed. The model parameters are then moved in the direction opposite to the gradient. This step is controlled by a learning rate, which determines the size of the steps taken. This process is then repeated for a specified number of iterations or until the model converges to a minimum or maximum.

The key advantage of SGD is that it can converge faster than traditional gradient descent algorithms, especially for large datasets, because it has fewer parameters and updates them more frequently. However, it can be more noisy and less stable, which is why additional techniques like mini-batch gradient descent and momentum are often used to improve its performance.

4.2 Machine-Learning Optimization Techniques

Machine-learning optimization algorithms, often also referred to as heuristic or metaheuristic optimization algorithms, are techniques used to find the best solutions to complex problems where traditional mathematical methods are too slow or fail to find an adequate

solution. They use controlled randomness to navigate the solution space and are often modeled by processes occurring in nature.

Below, some of the common machine-learning techniques will be introduced in greater detail.

4.2.1 Genetic Algorithms

Genetic algorithms mimic the process of natural selection and evolution to find optimal solutions for complex problems. Genetic algorithms work with a population of candidate solutions, each encoded as a string of symbols, such as bits, characters, integers, or floating-point numbers. Each candidate solution is evaluated by a “fitness” function that measures how well it solves the problem. The “fittest” solutions are then selected to produce new solutions by applying genetic operators such as crossover and mutation. This process is repeated until a termination criterion is met, such as reaching a maximum number of generations (iterations) or achieving a desired fitness level [167].

A generic pseudocode for a genetic algorithm looks as follows:

1. Initialize population with random solutions (individuals)
2. Evaluate the fitness of each individual in the population
3. Repeat until termination condition is met:
 - a. Select “parents” from the population
 - b. Perform crossover with the parents to create “offspring”
 - c. Perform mutation on the offspring
 - d. Evaluate the fitness of the offspring

- e. Select individuals for the next generation from the current population and the offspring population by various combination methods.

There are different kinds of genetic algorithms that vary in the way they represent, manipulate, and evaluate candidate solutions. Some of the common variations are binary genetic algorithms, real-valued genetic algorithms and permutation genetic algorithms [168].

A binary genetic algorithm is the simplest and possibly most widely used form of genetic algorithms, where each candidate solution is represented as a binary string of 0s and 1s. The crossover operator exchanges bits between two parent strings to create two offspring strings. The mutation operator flips one or more bits in a string randomly, as shown in the following illustration:

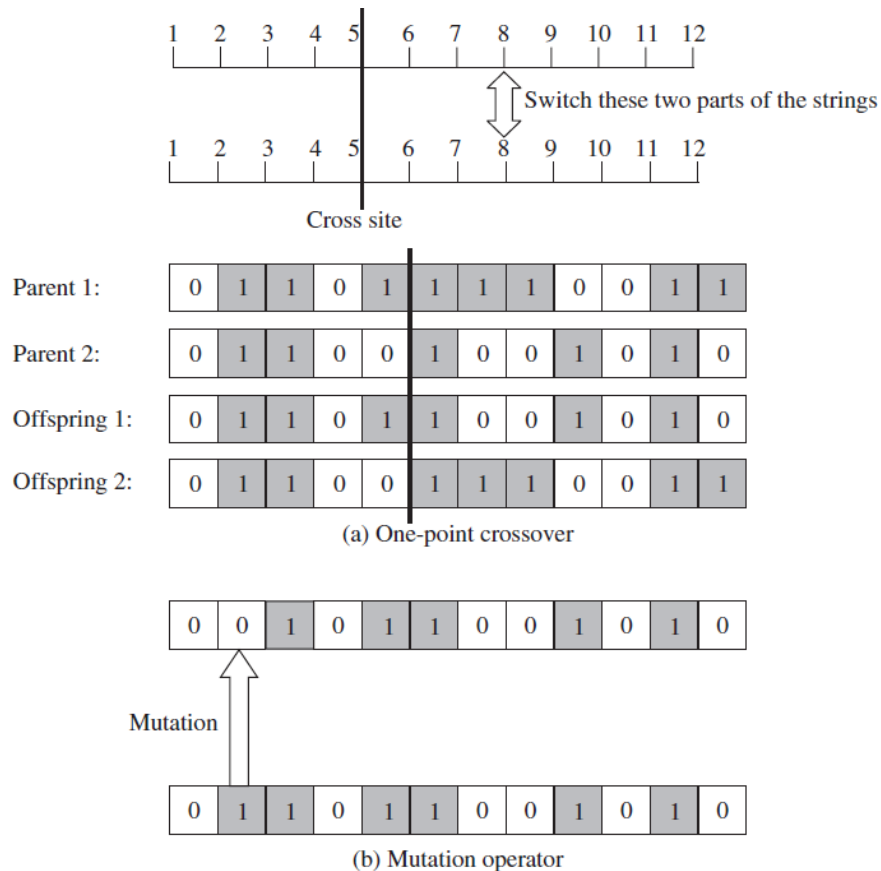


Figure 4.6. Binary GA illustration

Source: [169]

Real-valued genetic algorithms use real numbers as symbols in the candidate solutions. The crossover operator can be either arithmetic (e.g. the weighted average of two parent values) or geometric (e.g. the square root of the product of the two parent values). The mutation operator can be either uniform (adding or subtracting a random value from a parent value) or non-uniform (using a probability distribution to generate a random value). The principle of operation is shown in the following illustration:

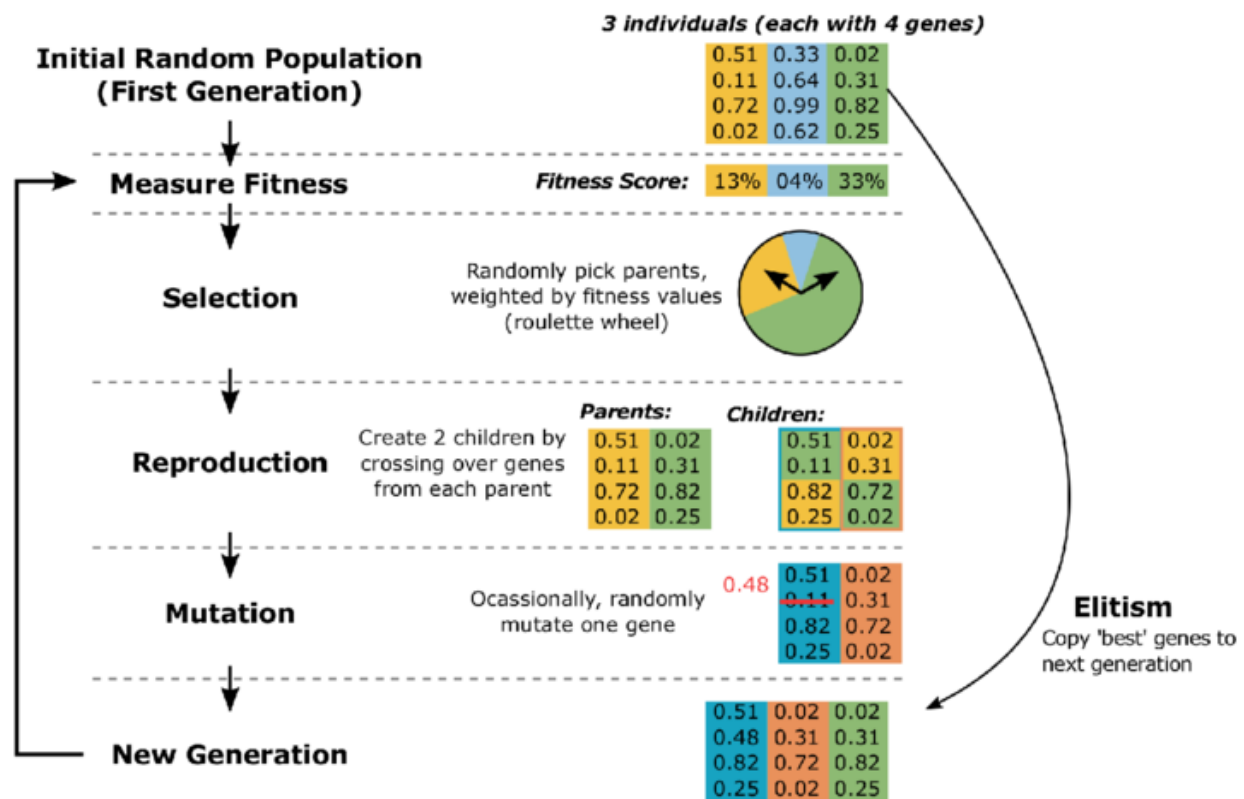


Figure 4.7. Real-valued GA illustration

Source: [170]

Permutation genetic algorithms use permutations (ordered sequences) of symbols as the candidate solutions. The symbols can be integers, characters, or any other values. The crossover operator can be either partially matched (swapping matching segments between two parent permutations) or order-based (preserving the relative order of symbols in two parent

permutations). The mutation operator can be either swap (exchanging two symbols in a permutation) or inversion (reversing a segment of symbols in a permutation).

The following illustration shows the principle of operation of a permutation GA:

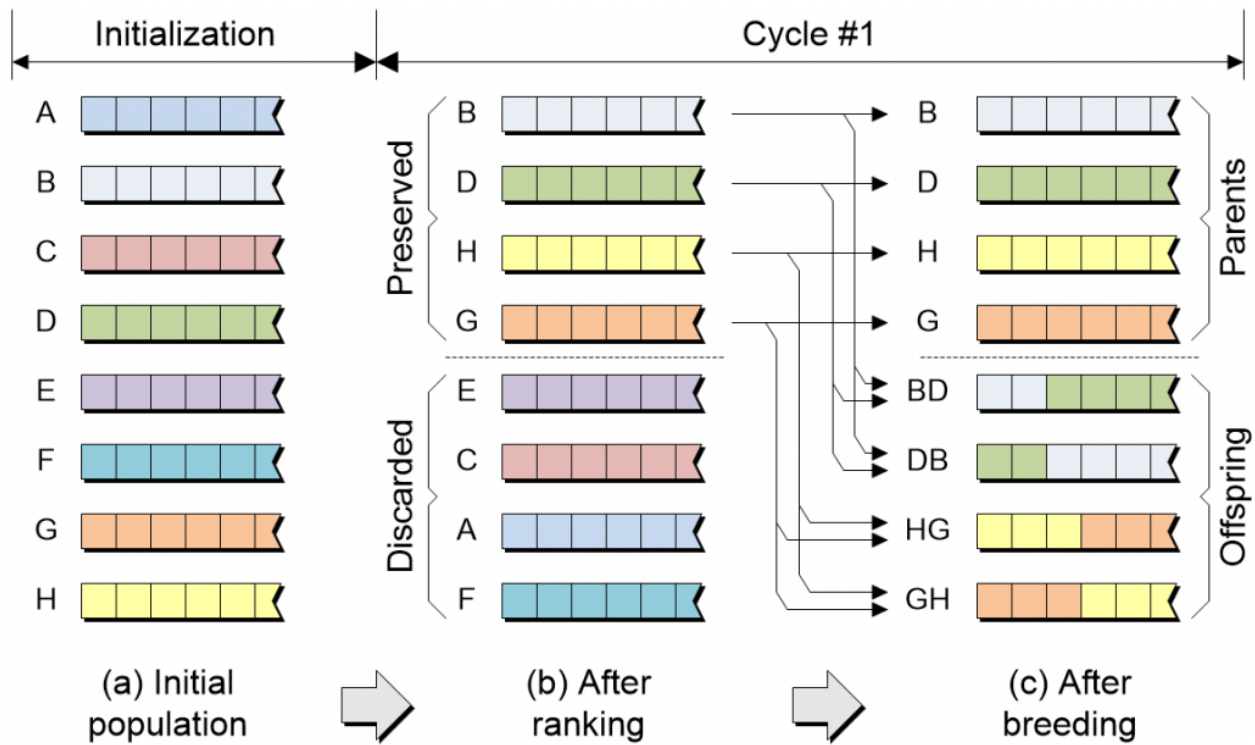


Figure 4.8. Permutation GA illustration

Source: [171]

4.2.2 Simulated Annealing

Simulated annealing (SA) is another probabilistic technique for finding the global optimum of a given function. The name of the algorithm comes from annealing in metallurgy, a technique involving heating and controlled cooling of a material to alter its physical properties. Simulated annealing can be used for difficult computational optimization problems where exact

algorithms fail. It frequently achieves only an approximate solution to the global minimum or maximum, but it is often sufficient for many practical applications [172].

The simulated annealing process starts with an initial solution and then iteratively improves the current solution by randomly perturbing it and accepting the perturbation with a certain probability. The probability of accepting a worse solution is initially high and gradually decreases as the number of iterations increases. This ensures that the algorithm doesn't get stuck at a local optima in the initial stages, and also that it then converges to a final solution in the later stages of the search process. This principle is illustrated in the following figure:

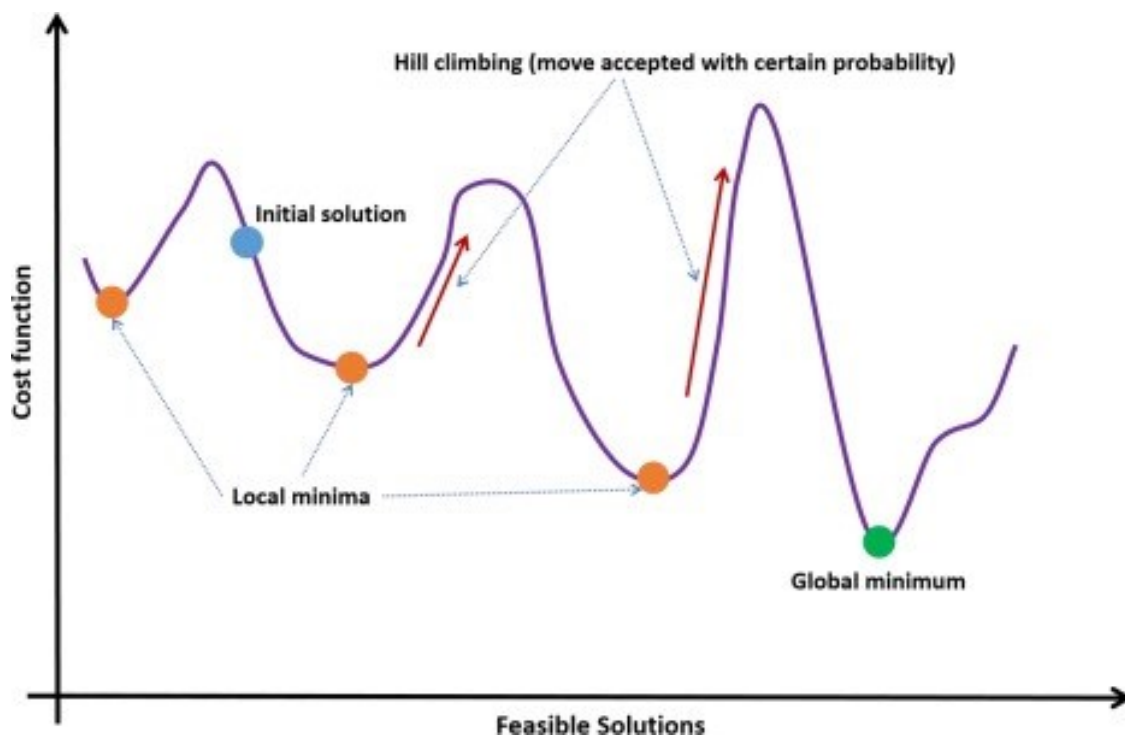


Figure 4.9. Simulated Annealing illustration

Source: [173]

A pseudocode for a basic simulated annealing algorithm looks as follows:

1. Define the objective function.
2. Set the initial “temperature” and “cooling” rate.

3. Generate the initial candidate solution.
4. Compute the “energy” (fitness) of the initial candidate solution.
5. Define a perturbation function to generate new candidate solutions.
6. Repeat until a stopping criterion is met:
 - a. Generate a new solution by perturbing the current solution.
 - b. Compute the energy of the new candidate solution.
 - c. If the new energy is lower than the current energy, accept the new solution as the current solution.
 - d. If the new energy is higher than the current energy, accept the new solution as the current solution with a probability that depends on the temperature and the difference between the energies.
 - e. Decrease the temperature gradually (according to the cooling rate).

4.2.3 Particle Swarm Optimization

Particle swarm optimization (PSO) is another computational method that optimizes a function by iteratively trying to improve a candidate solution. It is inspired by the social behavior of animals, such as birds and fish, that move in groups while foraging, and who share information about the best positions to improve the success of the flock [174].

The basic idea of PSO is to work with a population of particles, each representing a potential solution to the problem. The particles are initialized randomly in the search space and have an initial velocity. At each iteration, the particles update their positions and velocities based on their own best position, and the best position of their neighbors, and some factors designed to improve convergence. The best position of a particle is the one that has the lowest

(or highest) value of the objective function so far. The best neighbor's position is the one with the lowest (or highest) value among all the particles considered close to the current particle. The random factors improve exploration and diversity in the search process.

The principle of operation of PSO can be best illustrated with the following figure:

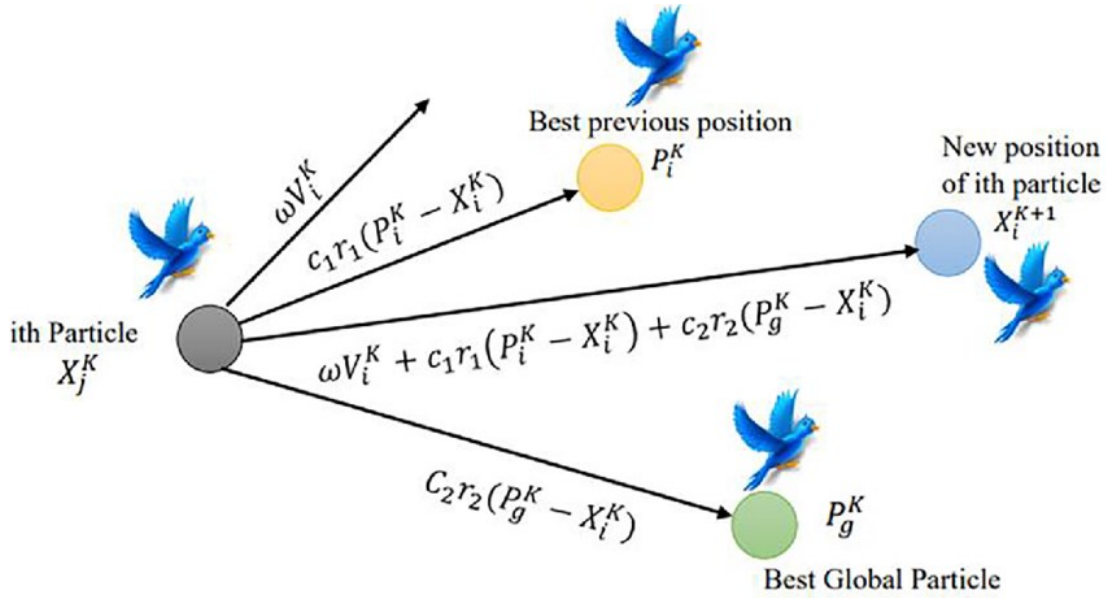


Figure 4.10. Particle Swarm optimization illustration

Source: [175]

The speed and position update equations are as follows:

$$v_i^{t+1} = wv_i^t + c_1r_1(p_i - v_i^t) + c_2r_2(g - v_i^t)$$

$$x_i^t = x_i^t + v_i^t$$

where v and x are the velocity and position of particle i at iteration t , w is an inertia weight that controls the balance between exploration and exploitation, c_1 and c_2 are acceleration constants that control how much the particle is influenced by its own best position and the global best position, r_1 and r_2 are random numbers between 0 and 1, p is the best-known position of particle i , and g is the global best position.

The Particle Swarm algorithm can also be described with the following pseudo-code:

1. Initialize a population of particles with random positions and velocities.
2. Repeat until a stopping criterion is met:
 - a. Evaluate the objective function for each particle and record its best position.
 - b. Determine the best position of all other particles and record it as the global best position.
 - c. For each particle, update its velocity and position using the formulae presented above.

4.2.4 Ant Colony Optimization

An ant colony optimization algorithm is a technique for finding optimal solutions to problems that can be represented by graphs, such as routing, scheduling, or the famous traveling-salesman problem. It is inspired by the behavior of real ants, who use pheromones to communicate and cooperate with each other while foraging [176].

The basic idea of this algorithm is to simulate a population of artificial ants that explore different paths and deposit “pheromones” as they travel. Pheromones act as a form of memory that guides the search process. The ants tend to follow paths with higher pheromone concentration, which leads them to discover good solutions over time. The pheromones also evaporate over time, which encourages exploration and prevents the algorithm from getting stuck in a local optima, as shown on the figure below:

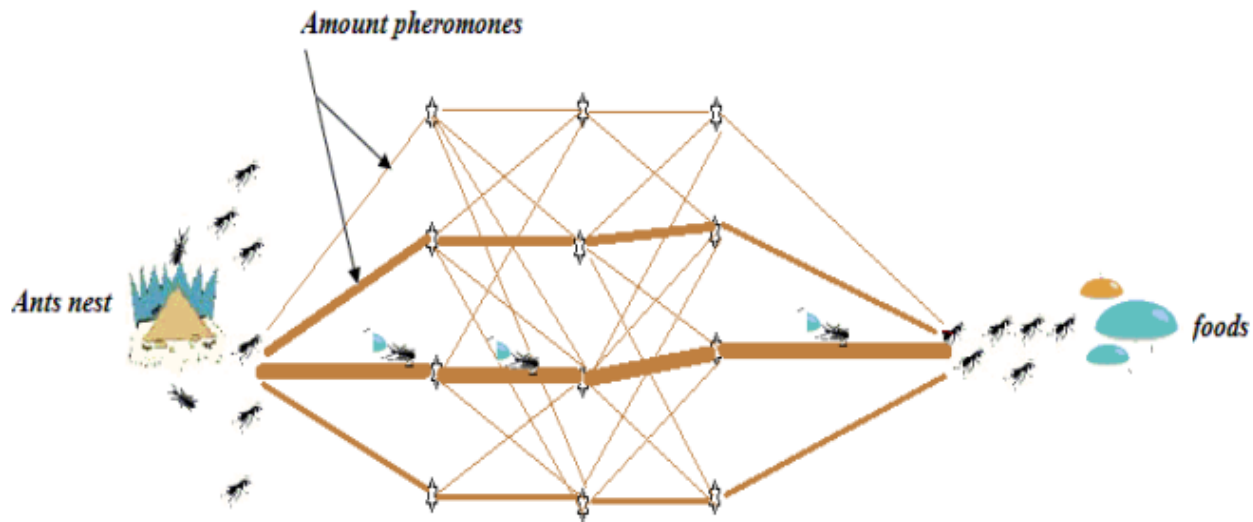


Figure 4.11. Ant Colony optimization illustration

Source: [177]

The operation of the ant-colony algorithm can be described with the following pseudo-code:

1. Initialize graph with some initial “pheromones”
2. Generate a set of ants and assign them to random nodes
3. For each ant, repeat until a solution is constructed
 - a. Choose the next node to visit that depends on the pheromones and also the distance and cost of the adjacent edges.
 - b. Update the pheromone values on the edges that the ant visited.
4. Evaluate the quality of the solutions constructed by all ants and update the pheromones accordingly.
5. Repeat steps 2-4 until a termination condition is met.

4.2.5 Other Machine-Learning Algorithms

There are quite a few other popular methods such as Artificial Immune Systems (AIS), Cuckoo Search (CS), Firefly Algorithm (FA), Bee Algorithm (BA), Harmony Search (HS), Coyote Optimization algorithm (COA), etc. To do it justice, whole books have already been written, e.g. [178]. But for the sake of brevity, a more detailed discussion of these methods will be omitted in this dissertation.

4.3 Multi-Objective Optimization Techniques

While the goal of single-objective optimization is finding the optimum configuration that results in a maximum or minimum of a *single* variable, multi-objective optimization (MOO) is a process of selecting an optimal solution in the presence of two or more variables. Typically, the optimal solution is one that achieves the best tradeoff between competing objectives.

Multi-objective optimization can be broadly divided into two approaches, as suggested by [179]:

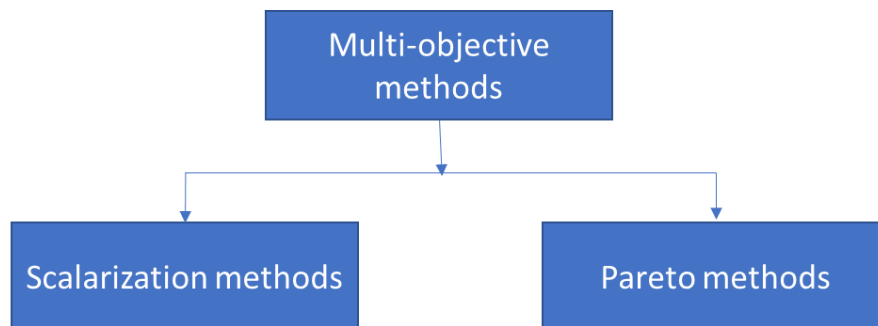


Figure 4.12. Multi-Objective Optimization (MOO) methods classification

4.3.1 Scalarization Methods

Scalarization involves converting a multi-objective optimization problem into a single-objective optimization with appropriate scaling parameters.

For example, the weighted sum method converts a multiple-objective problem into a single-objective problem by generating a function which is the weighted sum of the objectives. The weight w of each objective is chosen in proportion to the relative importance of the objective [180]. The problem formulation is as follows:

$$\begin{aligned}
\text{Minimize :} \quad & F(x) = \sum_{m=1}^M w_m f_m(x) \\
\text{Subject to:} \quad & x_i^L \leq x_i \leq x_i^U, \quad i = 1, 2, \dots, N \\
& g_j(x) \geq 0, \quad j = 1, 2, \dots, J \\
& h_k(x) = 0, \quad k = 1, 2, \dots, K
\end{aligned}$$

The weighted sum approach is simple and straightforward. However, it might be difficult to select the correct weights. In addition, this approach may not always find the best solution, especially in a non-convex search space.

The ϵ – constraint method optimizes one primary objective while transforming the other objectives into constraints by setting upper or lower limits [181]. The problem formulation is as follows:

$$\begin{aligned}
\text{Minimize:} \quad & f_\mu(x) \\
\text{Subject to:} \quad & f_m(x) \leq \epsilon_m \quad m = 1, 2, \dots, M \text{ and } m \neq \mu \\
& x_i^L \leq x_i \leq x_i^U, \quad i = 1, 2, \dots, N \\
& g_j(x) \geq 0, \quad j = 1, 2, \dots, J \\
& h_k(x) = 0, \quad k = 1, 2, \dots, K
\end{aligned}$$

The advantage of the ϵ -method is that it is applicable to either convex or non-convex problems. However, the ϵ -vector has to be chosen carefully so that it is within the minimum or maximum values of the individual objective functions.

There are also other popular scalarization methods such as norm-based scalarization, adaptive scalarization, goal programming, Sen's programming, Tchebycheff's method, lexicographic method, etc. For the sake of brevity, a more detailed discussion of these methods will be omitted in this dissertation.

4.3.2 Pareto Methods

In optimization problems with multiple competing objectives, a Pareto-front is defined as a set of solutions where each solution is not dominated by any other solution in the objective space. In other words, a solution is pareto-optimal if there is no other solution which is better in all objectives. Pareto-fronts are often represented graphically to help visualize the trade-offs between different objectives, as illustrated in the following figure:

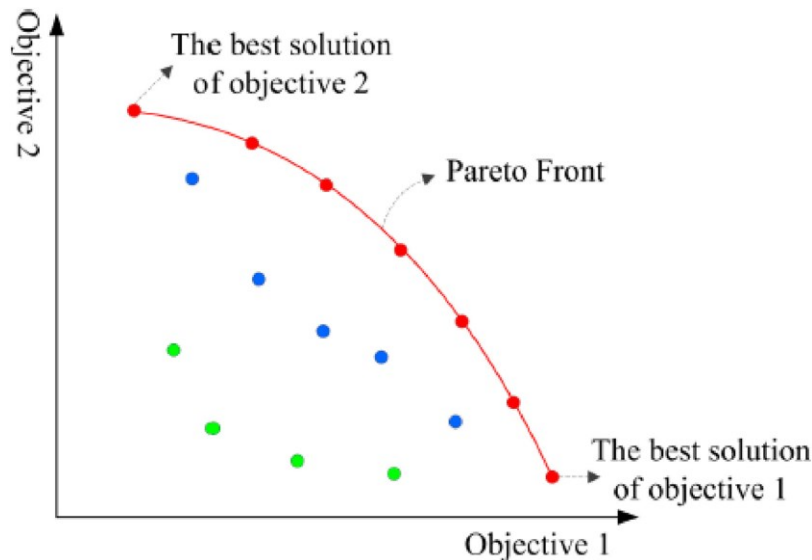


Figure 4.13. Pareto-front illustration

Source: [182]

Several approaches utilizing the concept of pareto-fronts will be discussed below. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a subset of genetic algorithms specifically designed for solving multi-objective optimization problems. The goal of NSGA-II is

to find a set of solutions that are as close as possible to the Pareto optimal front, which, as was already discussed, represents the best trade-offs among the conflicting objectives.

Below is the flowchart of NSGA-II as suggested by [183]:

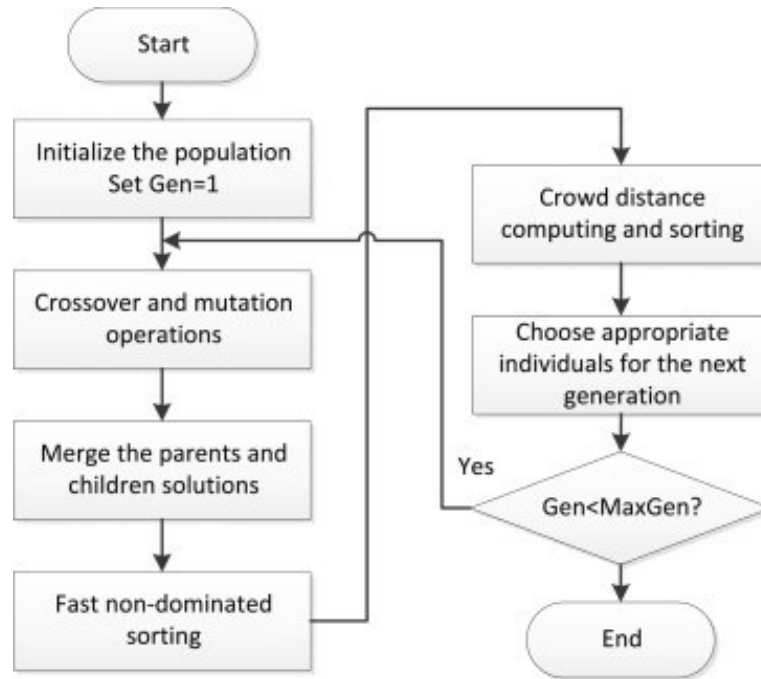


Figure 4.14. NSGA II illustration

Source: [183]

The NSGA-II algorithm sorts the population into different ‘fronts’ based on Pareto dominance. Solutions are ranked according to how many solutions they are dominated by. Within each front, solutions are then sorted based on crowding distance, which measures the density of solutions surrounding a particular point in the solution space. NSGA-II uses a binary tournament selection based on rank and crowding distance, followed by crossover and mutation to generate new solutions. NSGA-II is an elitist algorithm, meaning it preserves the best solutions (or ‘elite’ members) from the current population into the next generation.

NSGA-II's main strengths are its elitism, efficient non-dominated sorting approach, and crowding distance mechanism, which together help in maintaining a diverse set of solutions and in guiding the search towards the Pareto-optimal front. It's also relatively simple to implement and scalable to a reasonable number of objectives, which makes it a popular choice for various applications.

Similar to NSGA, the Strength Pareto Evolutionary Algorithm 2 (SPEA2) is an advanced version of genetic algorithms specifically designed for multi-objective optimization problems. SPEA2 assigns fitness values to solutions based on their dominance relationship with other solutions in the population. The algorithms then estimate the density of solutions surrounding a particular solution in the objective space. It helps maintain diversity in the population by favoring solutions in less crowded areas. SPEA2 manages an archive of non-dominated solutions from which promising candidates are selected as parents for the next generation. When the archive exceeds its size limit, it truncates the archive, i.e. removes some of the solutions while preserving the diversity of the archive. SPEA2 is also an elitist algorithm because it retains the best solutions found throughout the evolutionary process, ensuring that the quality of solutions does not degrade over time. SPEA2 has shown excellent performance in terms of the Pareto front, generation distance, and spacing. It has been successful for various applications, demonstrating its robustness and effectiveness.

Another approach, the Multi-Objective Particle Swarm Optimization (MOPSO), is an extension of the standard Particle Swarm Optimization (PSO) algorithm, adapted to handle problems with multiple objectives.

MOPSO also uses the concept of Pareto dominance to evaluate and compare solutions. Each particle in the swarm represents a potential solution to the multi-objective problem. The

particles ‘fly’ through the solution space by adjusting their velocities and positions based on their own experience and the experience of their neighbors. MOPSO maintains a repository (or archive) of non-dominated solutions found during the search process. This repository helps guide the swarm towards promising areas of the search space. MOPSO uses crowding distance to maintain diversity in the repository, ensuring a well-distributed set of solutions along the Pareto front. MOPSO incorporates techniques like the Pareto envelope and grid-making to manage the multi-objective optimization process effectively, as shown in the figure below:

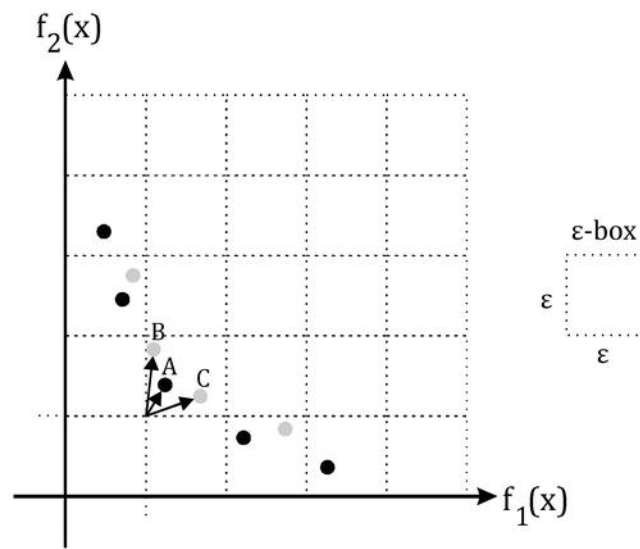


Figure 4.15. MOPSO illustration

Source: [184]

MOPSO retains the simplicity of the standard PSO algorithm, making it relatively easy to understand and implement. The algorithm can be easily adapted and extended to suit various types of multi-objective problems. MOPSO is also known for its fast convergence towards the Pareto front, which is beneficial in time-sensitive applications.

There are other methods, e.g. the pareto-envelope selection algorithm (PESA), the decomposition-based algorithm (MOEA/D), the indicator-based evolutionary algorithm (IBEA),

etc. Again, whole books have been written on this subject already, e.g. [185], so for brevity's sake a more detailed discussion of these methods will be omitted in this dissertation.

4.4 Summary of Chapter 4

Chapter 4 contained a survey of some of the more common optimization techniques, including various mathematical approaches as well as machine-learning approaches, for single-objective, as well as multi-objective problems. Some of the most commonly used techniques in each category were described, and pseudo-codes, flowcharts, and illustrations were used to explain each technique.

Chapter 5 - The Daily Energy Balance (DEB) Method

5.1 The Principle of Operation of the DEB method

As stated in chapter1, the overarching goal of this research was to develop new and better methods and techniques to design an optimum microgrid system that satisfies technical and economic objectives as outlined in previous chapters.

Virtually all currently existing optimization approaches use extensive simulations to attempt to determine configurations that match the generated and consumed power for each time frame over the course of the project lifetime before selecting a winning configuration. As mentioned earlier, this approach is computationally very inefficient and expensive, is not easily adaptable to different consumers, often requires expensive and complex software to operate, and is in general not very suitable for making practical engineering decisions.

The new method presented in this dissertation, called the “daily energy balance” (DEB) method, is radically different from all existing approaches in that it does not attempt to match hourly power quantities. Instead, this method attempts to achieve a balance between generated and consumed energy per day.

A time frame of a day was selected because in most cases the power demand is cyclical with the period of 24 hours. Similarly, solar power generated is also cyclical with a period of a day. The idea was to determine valid component configurations such that, at the end of the day the consumed energy was less than or equal to the generated energy in the system. The COE of valid configurations can then be determined, and the configuration with the smallest COE is chosen as the winning configuration.

This approach minimizes simulation needs, greatly simplifies computations and shortens computation time, and can be implemented on widely available computation platforms such as

MS Excel. The solutions can be easily verified and thereby provide a high degree of confidence in the obtained solutions, with the end effect that this method is much more engineer friendly compared to all other approaches.

With this approach there is no need for extensive simulations – the selection process is based on simple constraint checking. The constraints are computed with equations derived in chapters 2 and 3. This chapter summarizes all equations into an optimization problem formulation.

5.2 Method Parameters

5.2.1 Primary Input Data

Unlike some of the competing methods, the inputs to this algorithm are highly customizable for different applications. Some of these parameters are the customer's choice, others are obtained from easily available web resources as outlined in chapters 2 & 3, and some can be obtained from manufacturers of various equipment as outlined in chapters 2 & 3.

Compared to some other approaches such as iHOGA, the number of inputs is more limited, and are organized in logical groups, which are presented below.

Load parameters:

- Average daily energy demand (in kWh).
- Peak power demand (in kW)
- Average power demand (in kW)

Location-dependent parameters:

- Peak-sun-hours (in hrs)

- Average wind speed (in m/s)

Economic parameters:

- Project life (in years)
- Discount rate (in %)

Engine generator parameters:

- Initial costs (in \$/kW)
- Generator lifetime (in hrs)
- Replacement costs (in \$/kW)
- Operation and Maintenance costs (in \$/kW/year)
- Fuel coefficients
- Fuel price (in \$/L)
- Desired load factor (in %)

Battery parameters

- Initial costs (in \$/kWh)
- Battery lifetime (cycles)
- Replacement costs (in \$/kWh)
- Operation and maintenance costs (in \$/kWh/year)
- Maximum allowable DoD (in %)

Solar panel parameters

- Initial costs (in \$/kW)

- Panel lifetime (in yrs)
- Replacement costs (in \$/kW)
- Operation and maintenance costs (in \$/kW/year)
- System efficiency (in %)

Wind turbine parameters

- Initial costs (in \$/kW)
- Turbine lifetime (in yrs)
- Replacement costs (in \$/kW)
- Operation and maintenance costs (in \$/kW/year)
- Rated wind speed (in m/s)

Optimization parameters

- Generator minimum size index α (0-1)
- Solar system minimum size index β (0-1)
- Wind system minimum size index γ (0-1)

5.2.2 Secondary Input Data Computations

Based on the primary input parameters from the previous section, the following parameters are computed according to the equations derived in chapters 2 and 3:

1. Engine generator computations
 - a. Engine generator energy output

$$E_G(day) = P_{RATED} \times LoadFactor \times RunTime$$

$$E_G(year) = E_G(day) \times 365$$

$$E_G(\text{total}) = E_G(\text{year}) \times \text{ProjectLifetime}$$

b. Engine generator costs

$$\text{ReplaceTimes} = \frac{\text{ProjectLifetime} \times \text{RunTime} \times 365}{\text{GeneratorLifetime (hrs)}}$$

$$\text{ReplaceCost} = \text{ReplaceCost} \times \text{ReplaceTimes}$$

$$\text{FuelCost (day)} = \sum_t^{\text{RunTime}} C_f(t) \times Q_f(t)$$

$C_f = \text{cost of fuel}$

$Q_f = \text{quantity of fuel}$

$$Q_f(t) = \alpha P_{\text{RATED}} + \beta P(t)$$

$$\text{FuelCost (year)} = \text{FuelCost (day)} \times 365$$

$$\text{NPC}_G = \text{InitCosts} + \sum_{y=1}^{\text{ProjectLifetime}} \frac{(\text{ReplaceCost}(y) + \text{O\&M}(y) + \text{FuelCost}(y))}{(1+r)^y}$$

2. Solar panel computations

a. Solar panel energy output

$$E_S(\text{day}) = P_{\text{RATED}} \times \text{PeakSunHours} \times \eta(\text{efficiency})$$

$$E_S(\text{year}) = E_S(\text{day}) \times 365$$

$$E_S(\text{total}) = E_S(\text{year}) \times \text{ProjectLifetime}$$

b. Solar panel costs

$$\text{ReplaceTimes} = \frac{\text{ProjectLifetime}}{\text{SolarPanelLifetime}}$$

$$\text{ReplaceCost} = \text{ReplaceCost} \times \text{ReplaceTimes}$$

$$\text{NPC}_S = \text{InitCosts} + \sum_{y=1}^{\text{ProjectLifetime}} \frac{(\text{ReplaceCost}(y) + \text{O\&M}(y))}{(1+r)^y}$$

3. Wind turbine computations

a. Wind turbine energy output

$$E_W(day) = 2 \times P_{RATED} \times \left(\frac{V_{ave}}{V_{rated}} \right)^3 \times 24$$

$$E_W(year) = E_W(day) \times 365$$

$$E_W(total) = E_W(year) \times ProjectLifetime$$

b. Wind turbine costs

$$ReplaceTimes = \frac{ProjectLifetime}{WindTurbineLifetime}$$

$$ReplaceCost = ReplaceCost \times ReplaceTimes$$

$$NPC_W = InitCosts + \sum_{y=1}^{ProjectLifetime} \frac{(ReplaceCost(y) + O\&M(y))}{(1+r)^y}$$

4. Battery computations

a. Battery energy output

$$E_B(day) = DoD \times Q_{RATED}$$

b. Battery costs

$$ReplaceTimes = \frac{ProjectLifetime \times 365}{BatteryLifetime (cycles)}$$

$$ReplaceCost = ReplaceCost \times ReplaceTimes$$

$$NPC_B = InitCosts + \sum_{y=1}^{ProjectLifetime} \frac{(ReplaceCost(y) + O\&M(y))}{(1+r)^y}$$

5. Cost-of-energy (COE) computations

$$Combined E = \sum_{y=1}^{ProjectLifetime} \sum_{d=1}^{365} \sum_i E(i)$$

$$Combined\ NPC = \sum_i NPC(i)$$

$$COE = \frac{Combined\ NPC}{Combined\ E} \left(\frac{\$}{kWh} \right)$$

5.3 Optimization Problem Formulation

5.3.1 Objective Function

Minimize

$$COE \left(\frac{\$}{kWh} \right) = \frac{\sum NPC}{\sum Energy\ Generated} = \frac{\sum_{y=1}^{Lifetime} \sum_i NPC(i)}{\sum_{y=1}^{Lifetime} \sum_{d=1}^{365} \sum_i E(i)}$$

5.3.2 Decision Variables

The decision variable x is the rated size of each component plus the run-time of the generator, i.e. $x = [P_G, tg_{RUN}, P_S, P_W, Q_B]$

5.3.3 Constraints

1. Daily energy constraint

$$E_G(day) + E_S(day) + E_W(day) = E_{Load}(day)$$

2. Generator run-time constraint

$$0 \leq tg_{RUN} \leq 24$$

3. Generator size constraint

$$P_{MIN} \leq P_G \leq P_{MAX}$$

$$P_{MIN} = P_{AV} \times \alpha$$

$$P_{MAX} = P_{PEAK}$$

4. Solar panel size constraint

$$P_{MIN} \leq P_S \leq P_{MAX}$$

$$P_{MIN} = \frac{E_{Load}(day)}{PeakSunHours \times \eta} \times \beta$$

$$P_{MAX} = \frac{E_{Load}(day)}{PeakSunHours \times \eta}$$

5. Wind turbine size constraint

$$P_{MIN} \leq P_W \leq P_{MAX}$$

$$P_{MIN} = \frac{E_{Load}(day)}{24} \times \gamma$$

$$P_{MAX} = \frac{E_{Load}(day)}{24}$$

6. Battery size constraint

$$Q_{min} \leq Q_B \leq Q_{max}$$

$$Q_B(min) = \left\{ ((P_{PEAK} - P_{AV}) \times 6) + \frac{E_S}{2} \right\} \times \left(1 - \frac{E_W}{E_{DAY}} \right)$$

or

$$E_B(day) = ((P_{PEAK} - P_{AV}) \times 6) + \left(0.5 \times \frac{E_S^2}{E_{DAY}} - 0.2 \times E_S \right) - \left(0.2 \times \frac{E_W^2}{E_{DAY}} - 0.2 \times E_W \right)$$

$$Q_{MAX} = E_{Load}(day)$$

5.4 Summary of Chapter 5

In chapter 5, a novel method to design microgrid systems, called the Daily Energy Balance (DEB) method, was introduced. First, the principle of operation of the method was discussed. Then the input parameters were presented, along with the equations necessary for the proper operation of the method. The chapter also contained the detailed problem formulation for this design optimization method.

Chapter 6 - Results and Conclusions

In this chapter, the DEB method will be tested and verified. Different types of microgrid systems, with different power demand profiles, and different sizes, will be designed with the DEB method. The results will be verified with the kW-counting procedure to ensure viability. The results will also be compared to designs by HOMER.

The following systems, for the following locations, will be tested in this chapter:

Small-size system (12 kWh/day, industrial profile)

- Salina, KS
- Bangor, ME

Medium-size system (30 kWh/day, residential profile)

- Salina, KS
- Tucson, AZ

Large-size system (57.5 kWh/day, residential profile)

- Salina, KS
- Garrett, WY

Community-sized system (300 kWh/day, community profile)

- Salina, KS
- Stevens Village, AK

6.1 Design of a Small Microgrid System

6.1.1 Small System Description

A small system is relevant for users in survival mode, concerned with powering only essential necessities such as fridge, freezer, furnace fan, some LED lights, and powering phone chargers or other communication equipment. Since the devices do not necessarily operate simultaneously, the power demand is relatively constant, with a daily demand of 12 kWh, an average demand of 0.5 kWh and a peak demand of 0.64 kWh (*note: this is the actual consumption of a real system*).

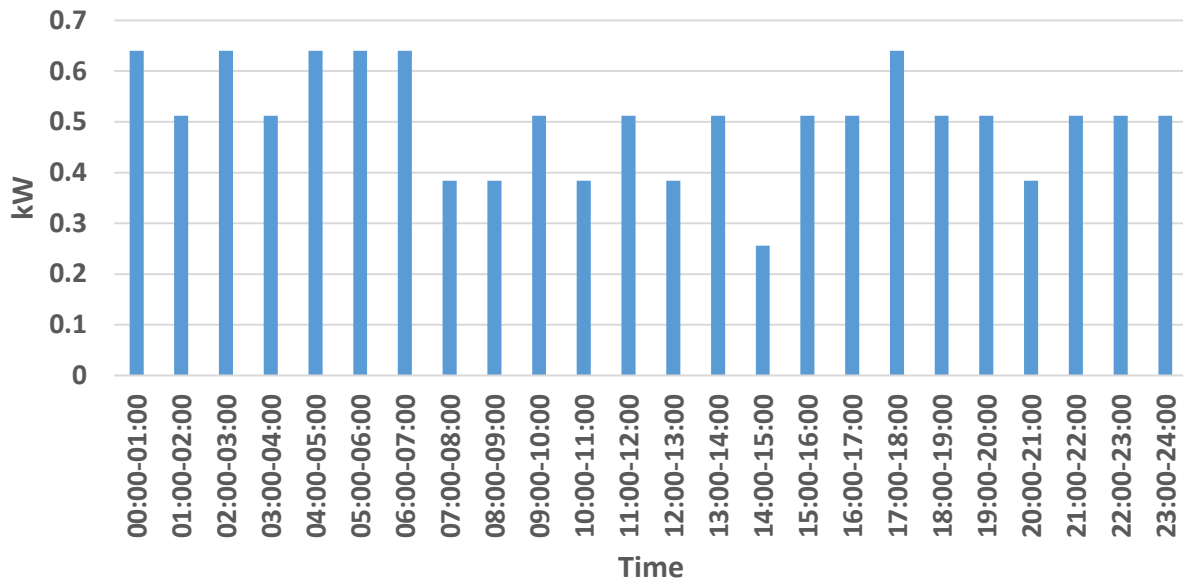


Figure 6.1. Small system load profile

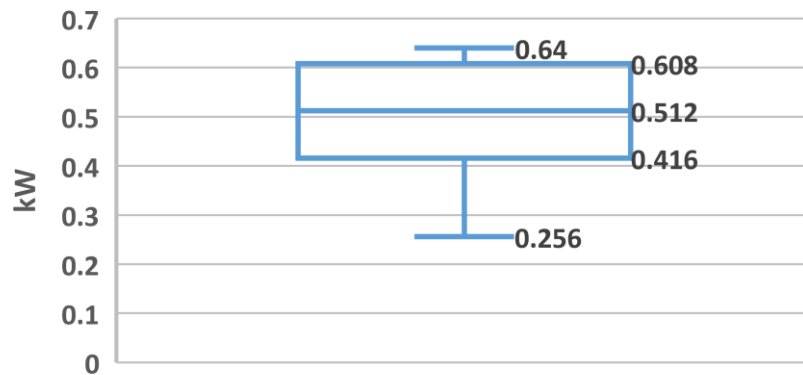


Figure 6.2. Small system demand statistics

6.1.2 Small System Design with HOMER

The first step to design a microgrid system with HOMER is to enter the geographic location (Salina, KS), from which Homer determines the NREL solar and wind data. The economic parameters are fixed, with a 6% discount rate and a 2% inflation rate. The price of fuel is adjustable, with a default price of \$1/L.

Homer does not have a way to enter exact demand parameters (which is a huge disadvantage!). Instead, the user has 4 profiles to choose from: commercial, community, industrial, or residential. The only factor that is adjustable is the daily energy consumption, which in this case was set to 12 kWh. For this system, the relatively flat industrial load profile was chosen as the closest representation of the demand.

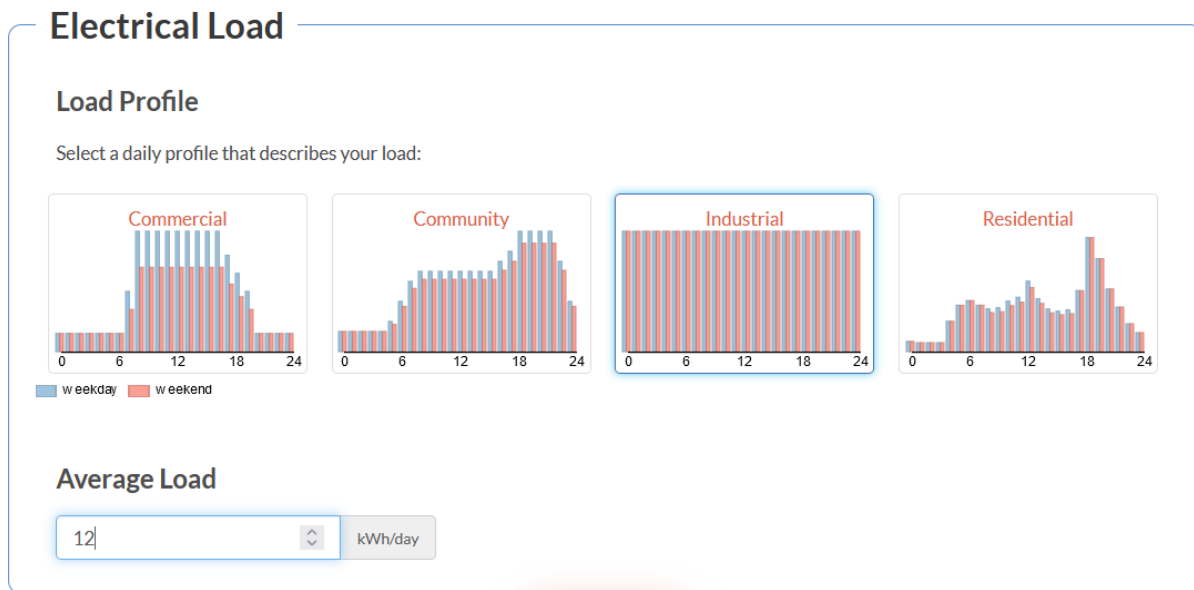


Figure 6.3. Small system load profile for HOMER

For the solar part of the system, the type of solar panels, as well as the cost per kW can be changed. The solar irradiance data is imported from NREL sources, and is set to $4.42 \text{ kW} / \text{m}^2 / \text{day}$ for Salina, KS. For the wind turbine, the adjustable parameters are the type of turbine, the cost per kW, and whether the expected load is AC or DC. The wind speed data is given as monthly and yearly averages, again from NREL sources, and is 5.21 m/s for Salina, KS. Also, a specific power curve for the wind turbine is assumed. For the battery, the adjustable parameters are the type of battery, and the cost per kW. Below is a summary of the parameters that HOMER used for the simulation.

Summary

Load

Average load: 12 kWh/day
Profile: Industrial

Photovoltaic

PV type: Generic flat plate PV
PV capital cost: 3000 \$/kW

Storage

Storage type: Generic 1kWh Li-Ion
Storage cost: 550 \$/battery

Generator

Autosize Genset
Fuel price: 1 \$/liter

Wind Turbine

Wind Turbine type: Generic 1 kW
Wind Turbine capital cost: 10000 \$/wind turbine

Figure 6.4. Small system input parameters for HOMER

After doing several minutes' worth of calculations, HOMER first displays the proposed layout of the system and the projected costs for different system configurations.

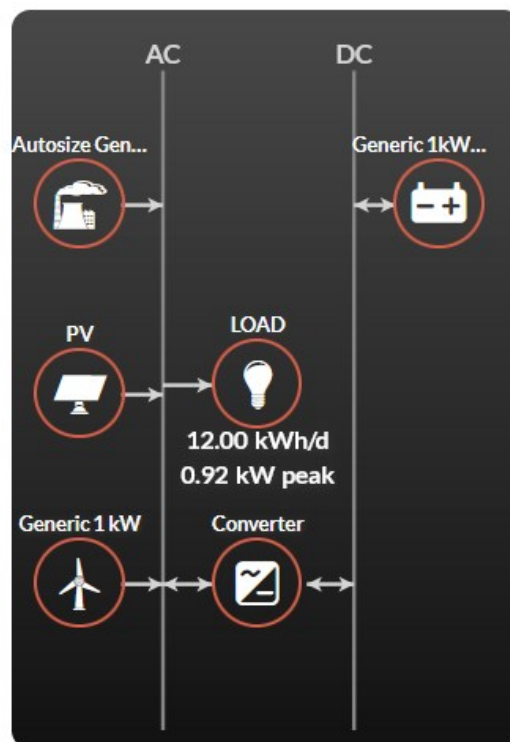


Figure 6.5. Small system layout by Homer

Table 6-1. Small system results table by Homer for Salina, KS

					Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
1	1.3	0.6	1	CC	\$5,772	\$1,408	\$0.41	\$27,957	985
1	0.3			CC	\$1,456	\$2,088	\$0.50	\$34,351	1,496
1				CC	\$550	\$2,171	\$0.50	\$34,752	1,579
1		0.1	1	LF	\$1,575	\$2,272	\$0.54	\$37,371	1,574

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
1	1	0.2			CC	\$11,038	\$2,265	\$0.68	\$46,724	1,375
1	1				CC	\$10,550	\$2,298	\$0.68	\$46,744	1,406
1	1	0.2	0.1	1	LF	\$12,063	\$2,286	\$0.70	\$48,068	1,305
1	2		0.1	1	LF	\$21,591	\$2,360	\$0.85	\$58,771	1,140

According to the table above, HOMER determined that the optimal configuration for the small system is a 1-kW generator, with a 1.3-kW rated PV system, a 1-kWh LFP battery, and a 600-W inverter/charger. The NPC of this system is \$27,957, which amounts to a COE of \$0.41 per kWh.

As already noted earlier, there is unfortunately no easy way to verify if the solutions will work as advertised. HOMER is quite restrictive when selecting load profiles and parameter sizes, which appears to skew the results. It also appears to oversimplify the results. For example, the smallest size for the battery is 1 kWh (in the initial setup), and this is then the size that the algorithm selected for all configurations. Similarly, there are no variations when using a 1-kW wind turbine. It appears that HOMER insists on a generator for all possible configurations, and the size was selected by simply doubling the average power demand. Therefore, the size of generator is probably too large, while the solar system and the battery are most likely too small, which would necessitate additional fuel to be burned by the generator to keep up with demand.

For comparison, simulations for the same system were done for Bangor, ME, which has less solar resources (irradiation 3.47 kW/m²/day) and wind potential (average wind 4.42 m/s).

Below are the results:

Table 6-2. Small system results table by HOMER for Bangor, ME

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
1		1.3	0.7	1	CC	\$5,274	\$1,449	\$0.41	\$28,102	1,050
1		0.2			CC	\$1,261	\$2,115	\$0.50	\$34,572	1,522
1					CC	\$550	\$2,171	\$0.50	\$34,752	1,579
1			0.7	3	CC	\$2,400	\$2,084	\$0.51	\$35,222	1,418

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
1	1				CC	\$10,550	\$2,360	\$0.69	\$47,719	1,458
1	1	0.1			CC	\$10,794	\$2,344	\$0.69	\$47,722	1,443
1	1	0.2	0.1	1	LF	\$11,613	\$2,384	\$0.71	\$49,172	1,386
1	2		0.1	1	LF	\$21,141	\$2,544	\$0.89	\$61,218	1,277

Surprisingly, despite the reduced renewable energy potential, HOMER calculated very similar results as compared to Salina, KS. And counter-intuitively, HOMER also suggested a smaller solar system for several configurations.

Overall, the results do not inspire confidence. It appears HOMER was not designed with small systems in mind, and does not work well for them.

6.1.3 Small System Design with the Daily Energy Balance (DEB) Method

The design with the DEB method also starts with the user entering the load parameters and other parameters. However, the input parameters are less restrictive and more customizable as compared to HOMER, but not as overwhelmingly large as in iHOGA. The input parameters for the DEB method were checked against HOMER's parameters to ensure maximum fairness when comparing the two methods.

Table 6-3. Small system input parameter table for the DEB method

<u>Load parameters</u>		<u>Economic parameters</u>	
Energy demand per day (kWh)	12.00	Project life (years)	20.00
Peak power demand (kW)	0.64	Discount rate (%)	6.00
Average power demand (kW)	0.50	Fuel price (\$/L)	1.00
<u>Location parameters</u>		<u>Fuel coefficients</u>	
Peak sun hours (hrs)	5.00	α (L/kW)	0.07
Average wind speed (m/s)	5.00	β (L/kW)	0.23
<u>Generator parameters</u>		<u>Batteries</u>	
Purchase cost (\$/kW)	550.00	Purchase cost (\$/kWh)	550.00
Generator lifetime (hrs)	20000.00	Battery lifetime (cycles @50% DoD)	4000.00
Replacement cost (\$/kW)	550.00	Replacement cost (\$/kWh)	550.00
O&M costs (\$/kW/year)	100.00	O&M costs (\$/kWh/year)	50.00
<u>Solar</u>		<u>Wind</u>	
Purchase cost (\$/kWh)	3000.00	Purchase cost (\$/kWh)	10000.00
Solar system lifetime (years)	20.00	Turbine lifetime (years)	20.00
Replacement cost (\$/kW)	1000.00	Replacement cost (\$/kW)	5000.00
O&M costs (\$/year)	50.00	O&M costs (\$/kW/year)	50.00

In general, the objective function (which in this case is the COE) can be minimized with any of the available constrained optimization algorithms. In this research, two algorithms were used, the Generalized Reduced Gradient, which was discussed in section 4.1.1, and a Genetic algorithm, which was discussed in section 4.2.1. Both were used within Microsoft Excel.

The GRG algorithm was lighting fast and usually converged within a few iterations. However, as noted already in section 4.1.1, it is highly dependent on the initial conditions, and sometimes got stuck at a local minimum. The GA algorithm was slower (but still much faster than HOMER's "proprietary algorithms), and much more exploratory than GRG, producing unique results, sometimes substantially better than the results of the GRG algorithm. A good strategy was to alternately run the calculations with both algorithms, and then pick the best results of the two algorithms.

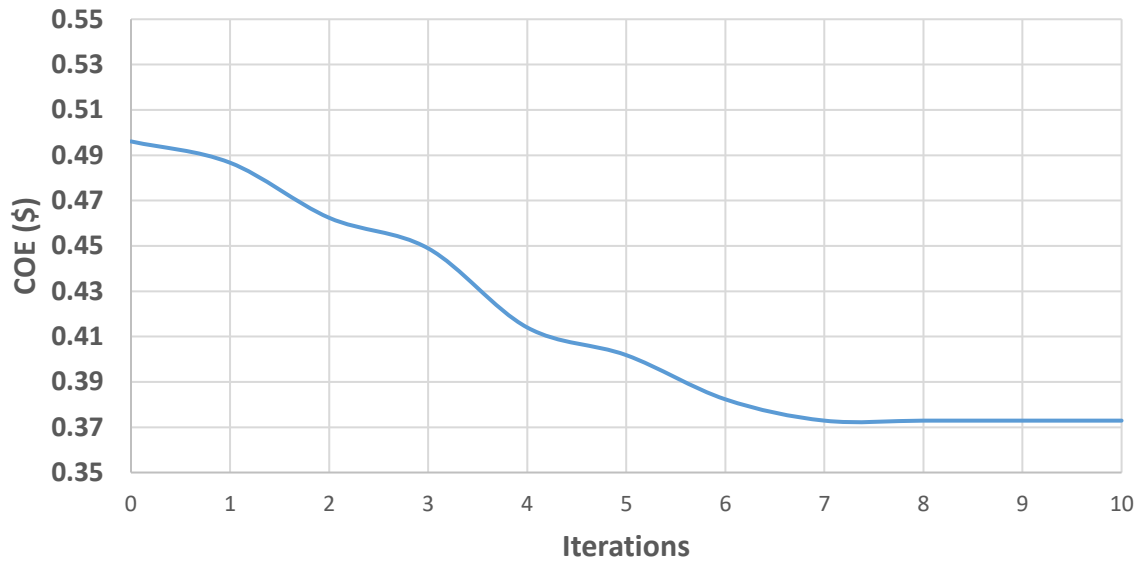


Figure 6.6. Sample convergence plot by the Generalized Reduced Gradient (GRG) algorithm

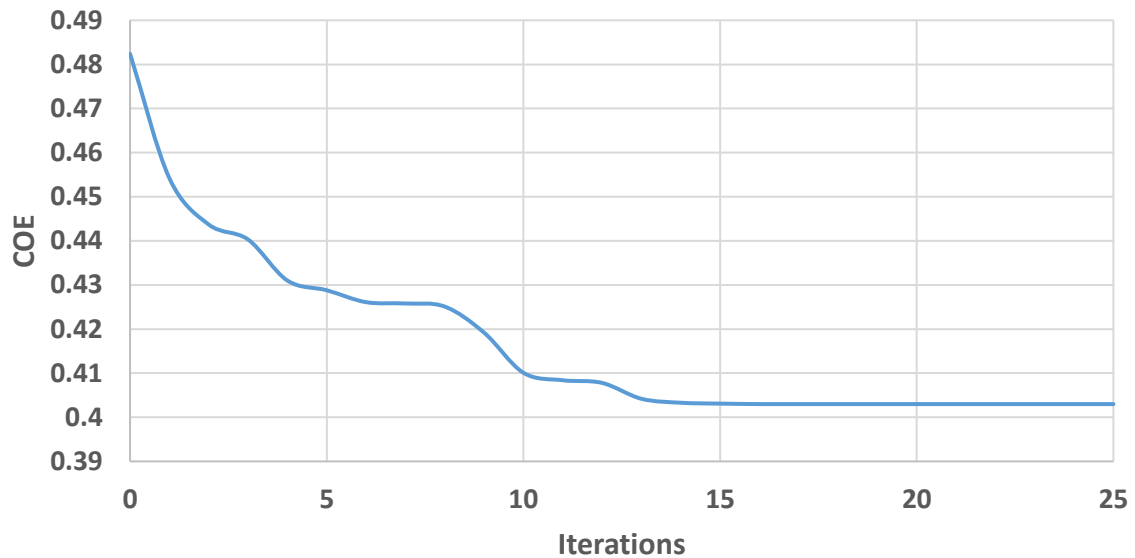


Figure 6.7. Sample convergence plot by the Genetic Algorithm (GA)

The primary objective of both algorithms was to minimize the COE, but the DEB method also provides a choice to prioritize generator, solar or wind energy via three user-selectable

operators. Depending on the operator settings different solutions were obtained as seen in the following table:

Table 6-4. Small system results table by the DEB method for Salina, KS

<u>Generator (kW)</u>	<u>Run-time (hrs)</u>	<u>Battery (kWh)</u>	<u>PV system (kW)</u>	<u>Wind turbine (kW)</u>	<u>COE (\$)</u>
		4.71	2.36	0.67	0.3616
0.64	0	4.39	2.25	0.78	0.3779
		6.86	3.01		0.3864
0.64	24	0.84			0.3944
0.8	24				0.4013
		1.68		3.06	0.4448

Compared to Homer, there are notable differences. For example, strictly generator, strictly solar, or strictly wind power combinations are possible. Also, the run-time of the generator is an optimizable parameter, which can range from 24 hours to zero hours. The solutions with zero run times means the generator serves strictly as a backup source, slightly increasing COE, but substantially increasing the reliability of the system.

The optimal configuration for the small-system with a COE of \$0.36 was obtained using a mix of only solar energy and wind power. However, when adding reliability as a second optimization criteria, the winning configuration consisted of a 0.64 kW standby generator to provide power when neither wind nor solar energy was available. This increased the COE to \$0.38, which is still better than HOMER's winning COE of \$0.41.

To verify the validity of this solution, a kW-counting procedure was run, which resulted in the following plot:

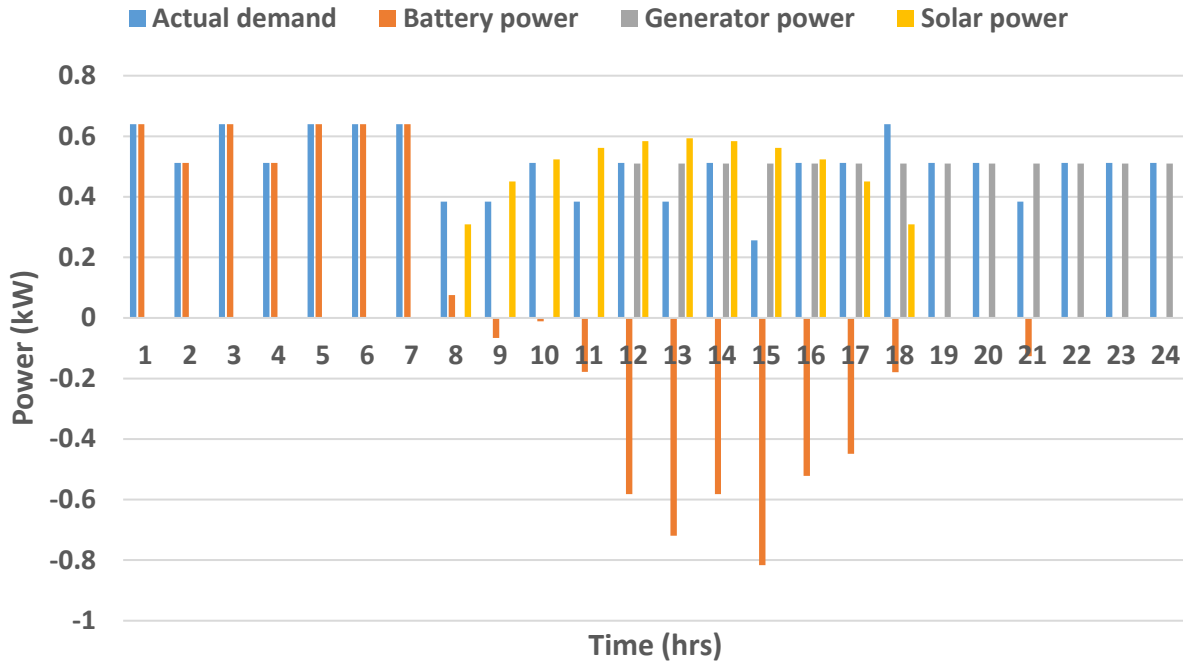


Figure 6.8. Small system design verification for the DEB method

According to the DEB method, the estimated daily battery requirements for this system are 4.39 kWh. Counting the kW resulted in a battery requirement of 4.27 kWh, a deviation of only 2.8%, in the conservative direction, indicating that this system is fully functional.

For additional comparison, the DEB method was also applied to designing the same-sized system for Bangor, ME. Below are the results of the winning configuration:

Table 6-5. Small system optimal configuration by the DEB method for Bangor, ME

<u>Generator (kW)</u>	<u>Run-time (hrs)</u>	<u>Battery (kWh)</u>	<u>PV system (kW)</u>	<u>Wind turbine (kW)</u>	<u>COE (\$)</u>
0.64	12.78	2.73	1.69	0	0.3840

This solution makes more sense than HOMER's. Compared to the solution for Salina, KS, the DEB method determined that the system cannot be supplied by renewable energy alone, and correspondingly adds more generator run-time to the mix. It also eliminated the wind turbine because at low wind speeds, wind energy becomes non-profitable.

The overall verdict is that the DEB method outperformed HOMER and is much more suitable for small-sized systems than HOMER.

6.2 Design of a Medium Microgrid System

6.2.1 Medium System Description

The medium size system represents the consumption of an average household in winter, when most off the devices are in use except the air-conditioner (AC). At night, the consumption is comparable to the consumption of the small system, but during the day the consumption is quite a bit higher due to usage of space heaters, kitchen range, clothes dryer, and other appliances along with a higher lighting load. The daily energy demand is about 2.5 times larger (30.8 kWh), the average demand is 1.3 kW and the peak demand is 2.6 kW (*again, this is the actual consumption of a real system*).

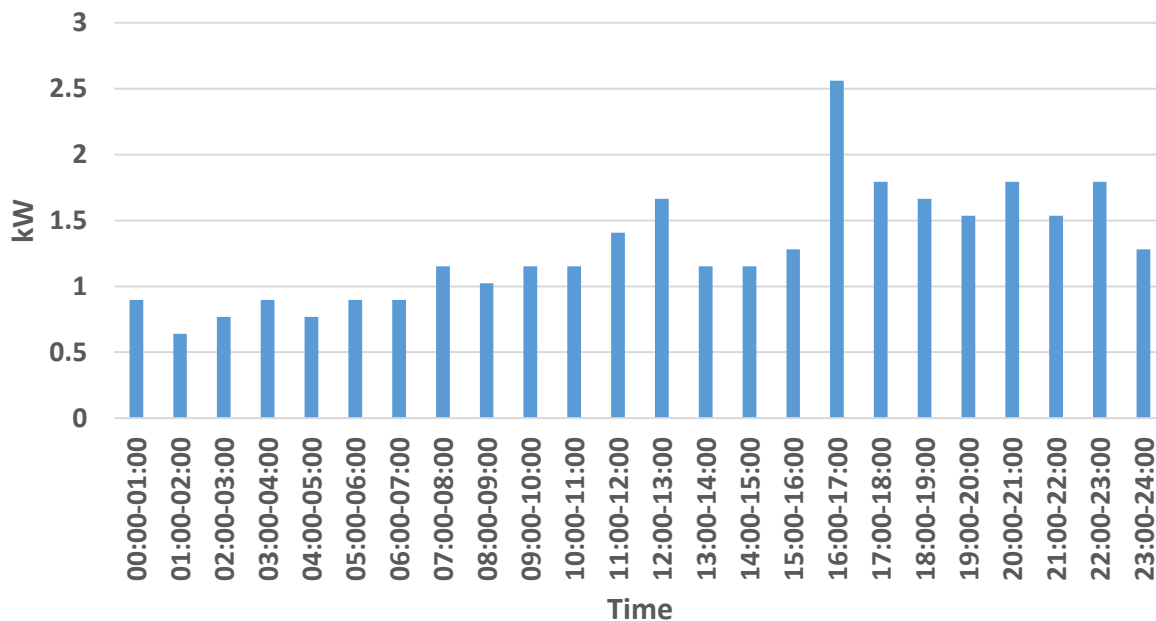


Figure 6.9. Medium system load profile

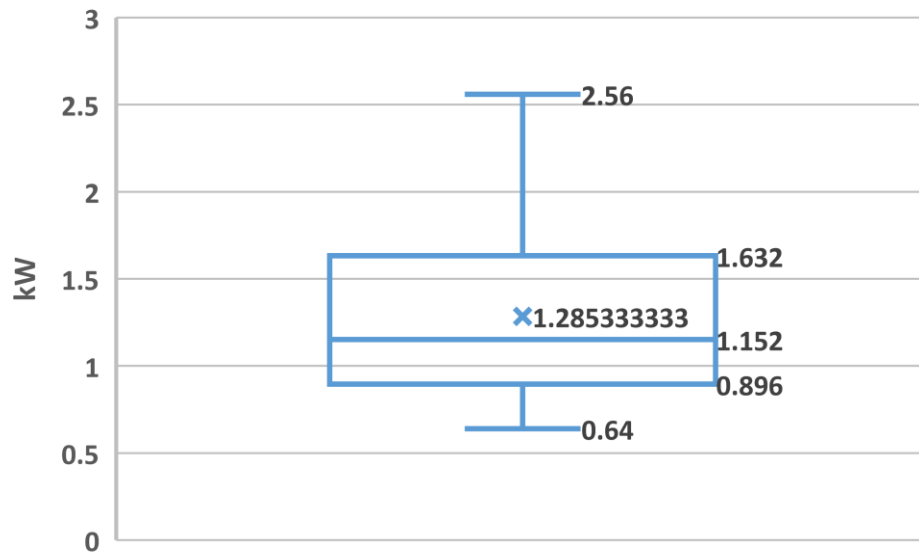


Figure 6.10. Medium system demand statistics

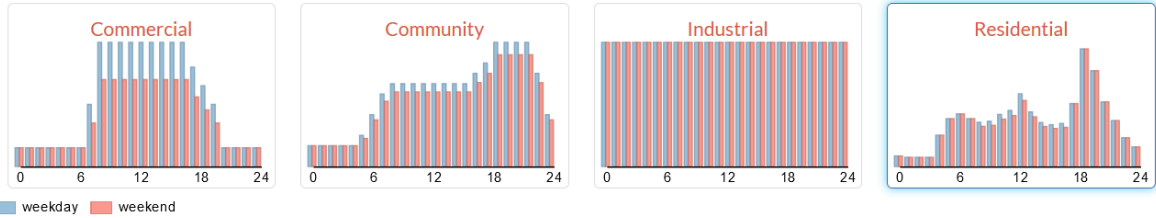
6.2.2 Medium System Design with HOMER

Most of the parameters used for the medium system were the same as for the small system. The biggest difference was the load profile, which for this system has the look of a classical residential profile, with an average daily demand of 30.8 kWh.

Electrical Load

Load Profile

Select a daily profile that describes your load:



Average Load

30.8



kWh/day

Figure 6.11. Medium system load profile for HOMER

Summary

Load

Average load: 30.8 kWh/day

Profile: Residential

Photovoltaic

PV type: Generic flat plate PV

PV capital cost: 3000 \$/kW

Storage

Storage type: Generic 1kWh Li-Ion

Storage cost: 1000 \$/battery

Generator

Autosize Genset

Fuel price: 1 \$/liter

Wind Turbine

Wind Turbine type: Generic 1 kW

Wind Turbine capital cost: 10000 \$/wind turbine

Figure 6.12. Medium system input parameters for HOMER

After several minutes' worth of calculations, HOMER proposed the following layout of the system and showed the projected costs for different system configurations for Salina, KS.

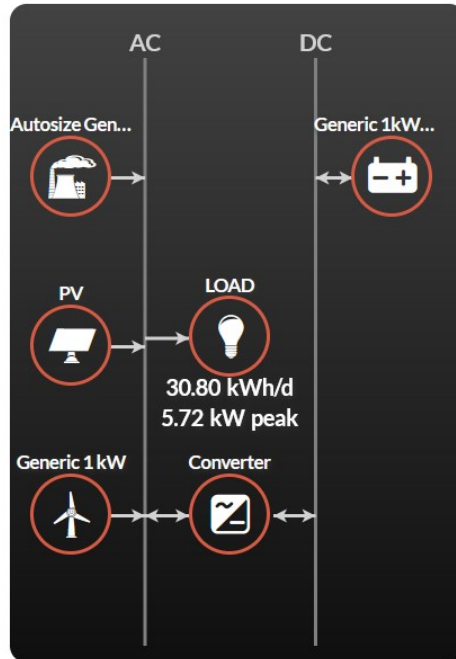


Figure 6.13. Medium system layout by HOMER

Table 6-6. Medium system results table by HOMER for Salina, KS

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
6	1	3.0	3.5	5	CC	\$28,200	\$3,341	\$0.46	\$80,830	1,875
6		3.5	3.8	5	CC	\$19,738	\$3,914	\$0.46	\$81,394	2,529
6	2		3.7	5	CC	\$29,265	\$3,975	\$0.52	\$91,879	2,099
6			4.7	6	CC	\$10,545	\$5,765	\$0.57	\$101,361	3,849

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
6					CC	\$3,150	\$10,636	\$0.96	\$170,690	7,242
6		0.0			CC	\$3,271	\$10,634	\$0.96	\$170,782	7,240
6	1				CC	\$13,150	\$10,577	\$1.02	\$179,760	6,965
6	1	0.6			CC	\$15,088	\$10,569	\$1.03	\$181,568	6,957

According to the tables above, HOMER determined that the optimal configuration for the medium system is a 6-kW generator, with 3.0 kW of installed PV power, a 5-kWh battery, a 3.5-

kW inverter/charger and a 1-kW wind turbine. The NPC of this system is \$80,200, which amounts to a COE of \$0.46 per kWh.

Overall, the COE is higher than for a small system, which is probably due to the residential profile having a smaller load factor. It also appears that for the medium system with a residential-profile, Homer over-estimated the peak demand, and over-sized the generator accordingly. Significant savings could be achieved by using a smaller generator.

As was done in section 6.2, for reference, the same-size system was designed for a different location, this time for Tuscon, AZ, which has a higher solar irradiation of 5.41 kWh/m²/day, but a reduced average wind speed of 4.7 m/s.

Table 6-7. Medium system results table by HOMER for Tucson, AZ

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
6		3.4	3.6	5	CC	\$19,399	\$3,673	\$0.44	\$77,261	2,356
6	1	3.2	3.9	5	CC	\$28,929	\$3,690	\$0.49	\$87,048	2,137
6			4.6	6	CC	\$10,536	\$5,765	\$0.57	\$101,346	3,849
6	1		4.7	6	CC	\$20,551	\$5,558	\$0.61	\$108,104	3,461

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
6					CC	\$3,150	\$10,636	\$0.96	\$170,690	7,242
6		0.0			CC	\$3,271	\$10,634	\$0.96	\$170,778	7,240
6	1				CC	\$13,150	\$10,880	\$1.04	\$184,544	7,183
6	1	0.6			CC	\$15,088	\$10,868	\$1.05	\$186,285	7,171

Interestingly, again there are only small variations between the systems in Salina, KS, and Tucson, AZ. The solar system is slightly larger, while the wind turbine was omitted. Counterintuitively, the generator run-time is increased, so the abundance of solar energy only slightly improved the cost of energy.

6.2.3 Medium System Design with the Daily Energy Balance (DEB) Method

The input parameters for the medium-system for the DEB method were similar to the parameters of the small-system and were as follows:

Table 6-8. Medium system input parameter table for the DEB method

<u>Load parameters</u>		<u>Economic parameters</u>	
Energy demand per day (kWh)	30.80	Project life (years)	20.00
Peak power demand (kW)	2.56	Discount rate (%)	6.00
Average power demand (kW)	1.30	Fuel price (\$/L)	1.00
<u>Location parameters</u>		<u>Fuel coefficients</u>	
Peak sun hours (hrs)	5.00	α (L/kW)	0.07
Average wind speed (m/s)	5.00	β (L/kW)	0.23
<u>Generator parameters</u>		<u>Batteries</u>	
Purchase cost (\$/kW)	550.00	Purchase cost (\$/kWh)	550.00
Generator lifetime (hrs)	20000.00	Battery lifetime (cycles @50% DoD)	4000.00
Replacement cost (\$/kW)	550.00	Replacement cost (\$/kWh)	550.00
O&M costs (\$/kW/year)	100.00	O&M costs (\$/kWh/year)	50.00
<u>Solar</u>		<u>Wind</u>	
Purchase cost (\$/kWh)	3000.00	Purchase cost (\$/kWh)	10000.00
Solar system lifetime (years)	20.00	Turbine lifetime (years)	20.00
Replacement cost (\$/kW)	1000.00	Replacement cost (\$/kW)	5000.00
O&M costs (\$/year)	50.00	O&M costs (\$/kW/year)	50.00

Again, the GRG and GA algorithms were used. Depending on the operator settings, different solutions were obtained as seen in the following table:

Table 6-9. Medium system results table by the DEB method for Salina, KS

<u>Generator (kW)</u>	<u>Run-time (hrs)</u>	<u>Battery (kWh)</u>	<u>PV system (kW)</u>	<u>Wind turbine (kW)</u>	<u>COE (\$)</u>
		16.79	8.21		0.4049
2.56	5.17	10.15	5.39		0.4081
2.56	0	11.41	5.3	3.14	0.4175
2.56	0	16.79	8.21		0.4339
3.2	24				0.4644
1.6	24	7.56			0.4917
		7.56		8.87	0.5616

According to the DEB method, the medium-system can be optimally supplied by an 8.21-kW solar system coupled with a 16.79-kWh battery bank, at a cost of \$0.41, which is significantly better than HOMER's result.

To verify the validity of the computed optimum solution, a kW-counting procedure was performed as seen in the figure below:

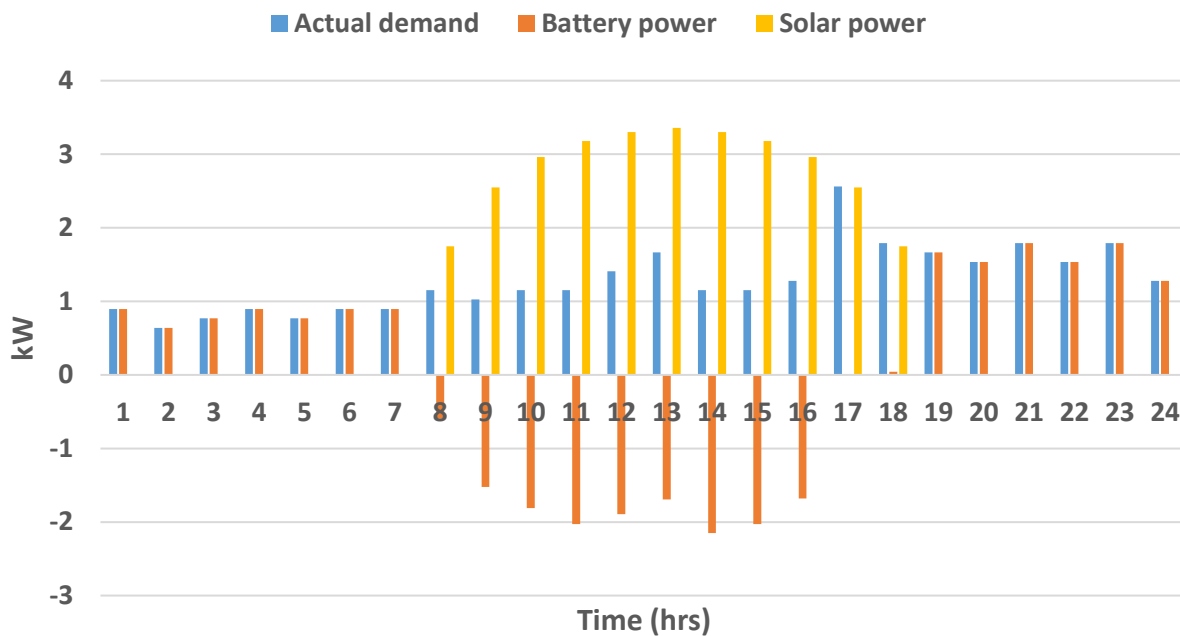


Figure 6.14. Medium system design verification for the DEB method (only solar energy)

According to the DEB method, the optimum solution with only solar power requires 16.79 kWh of battery storage. The kW-counting procedure indicates that this number is reasonable; in fact it would work with even less capacity, 15.41 kWh. This indicates that the proposed solution would work, at a COE substantially less than HOMER's solution.

To improve the reliability, adding a 2.56 kW generator only marginally adds to the expected costs over the lifetime of the project, and would be the preferable solution for most customers. Again, this solution was verified and the results are shown below:

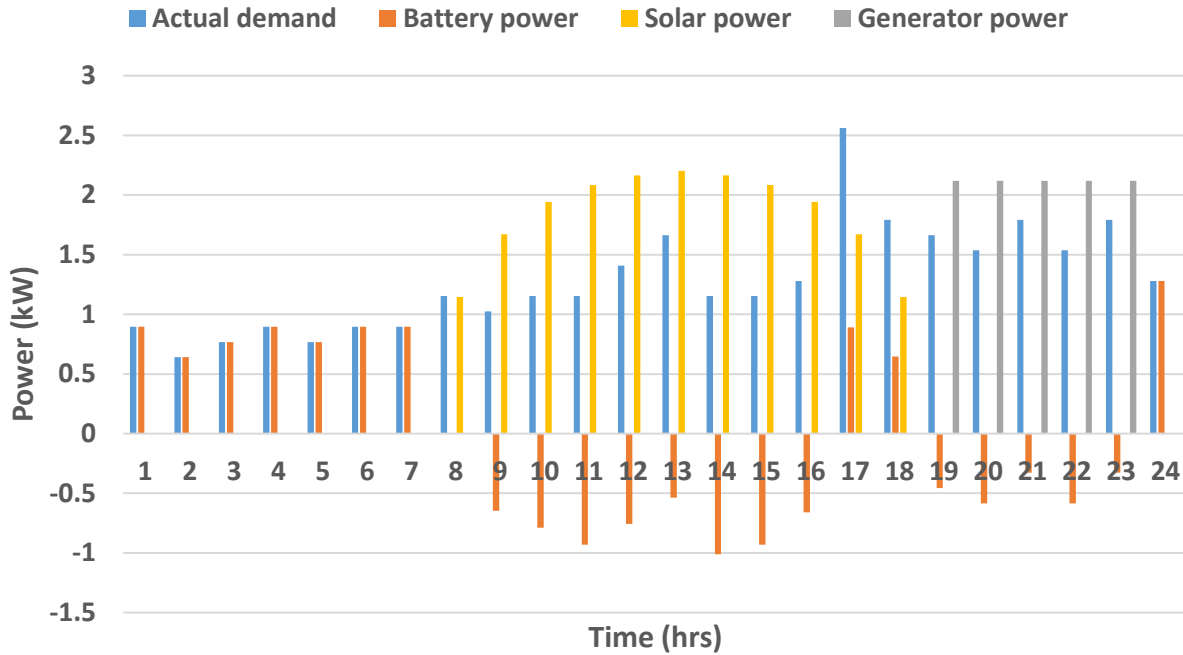


Figure 6.15. Medium system design verification for the DEB method (generator plus solar energy)

The kW-counting procedure determined the need for an 8.56-kWh battery bank. The DEB method conservatively estimated 10.15 kWh.

To further verify the DEB method for designing medium-sized systems, the optimization was performed for a different location, this time for Tucson, AZ.

Table 6-10. Medium system optimal configuration by the DEB method for Tucson, AZ

<u>Generator (kW)</u>	<u>Run-time (hrs)</u>	<u>Battery (kWh)</u>	<u>PV system (kW)</u>	<u>Wind turbine (kW)</u>	<u>COE (\$)</u>
2.56	3.54	11.85	4.83	0	0.3883

Consistent with the results for Salina, KS, and due to the abundance of solar energy in Tucson, AZ, the solution suggests less run-time for the generator, a smaller solar system, and a slightly larger battery system for an overall lower COE.

6.3 Design of a Large Microgrid System

6.3.1 Large System Description

A large system represents the actual consumption of a single household in summer at the peak of its power demand. It consumes about twice as much as the same household in winter, mostly due to the extensive usage of air-conditioning. The total daily energy demand is about 60 kWh, with a peak demand of slightly more than 5 kW, and an average demand of about 2.4 kW. It has the typical profile of a residential customer with times of low demand during the night, and times of high demand around noon, and again during the evening hours.

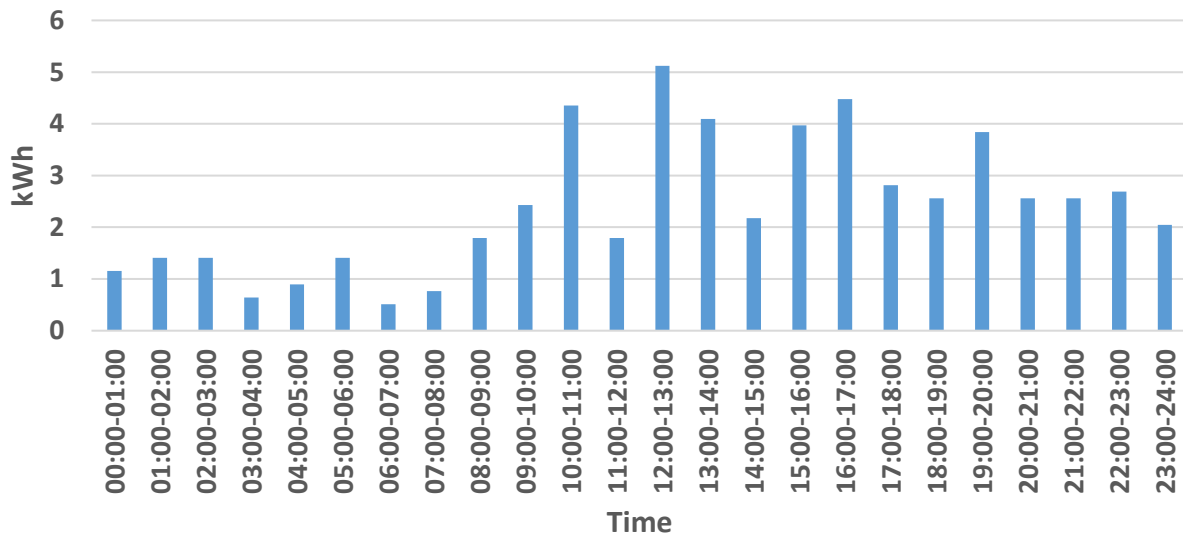


Figure 6.16. Large system load profile

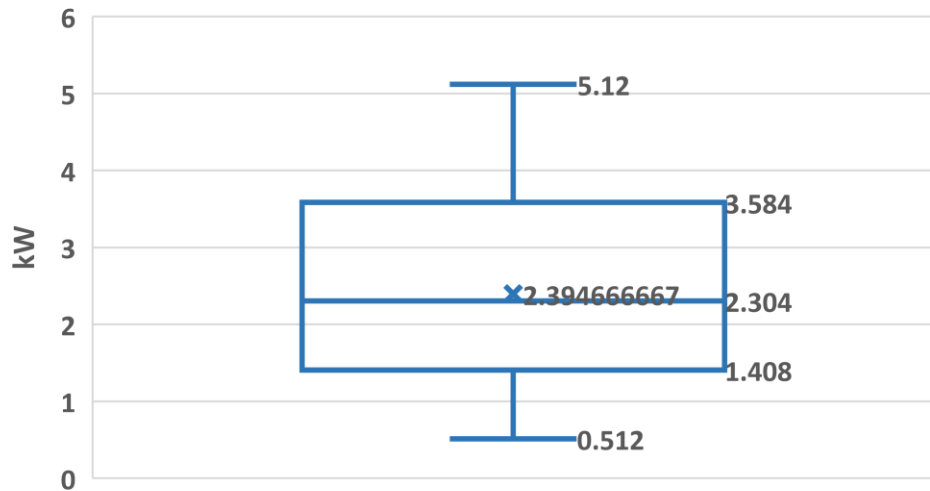


Figure 6.17. Large system demand statistics

6.3.2 Large System Design with HOMER

Most of the parameters used for the large system were the same as for the medium system. The biggest difference was the average daily load which for this system was 57.5 kWh.

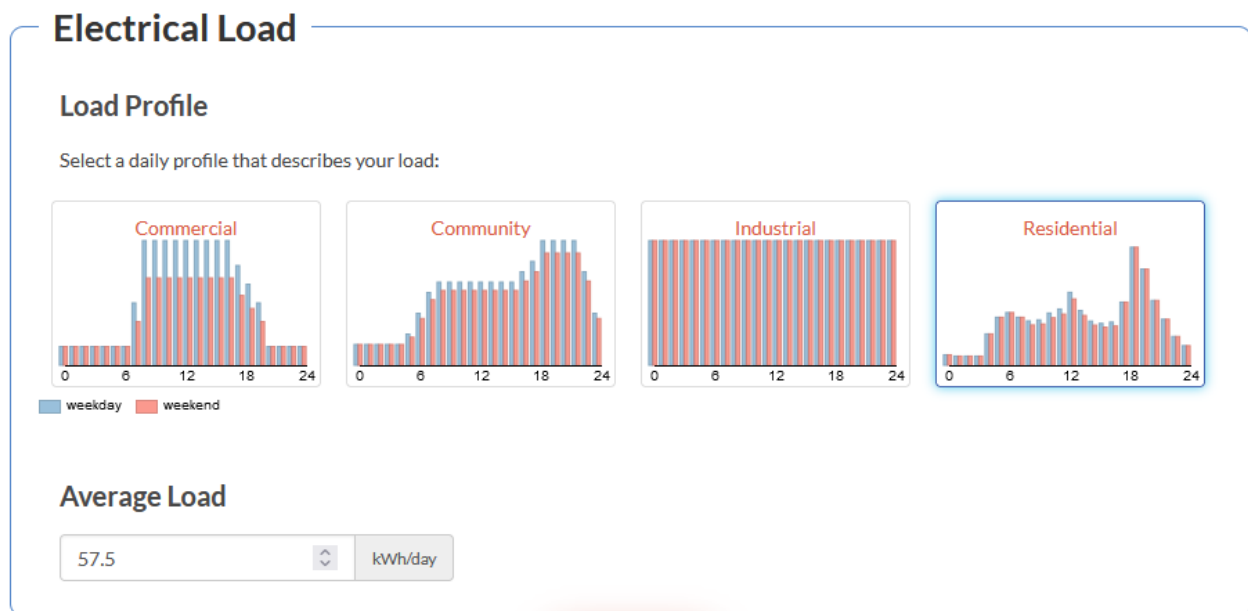


Figure 6.18. Large system load profile for HOMER

Summary	
Load	Generator
Average load: 57.5 kWh/day	Autosize Genset
Profile: Residential	Fuel price: 1 \$/liter
Photovoltaic	Wind Turbine
PV type: Generic flat plate PV	Wind Turbine type: Generic 1 kW
PV capital cost: 3000 \$/kW	Wind Turbine capital cost: 10000 \$/wind turbine
Storage	
Storage type: Generic 1kWh Li-Ion	
Storage cost: 1000 \$/battery	

Figure 6.19. Large system input parameters for HOMER

After several minutes of simulation, Homer suggested the following layout for the large system:

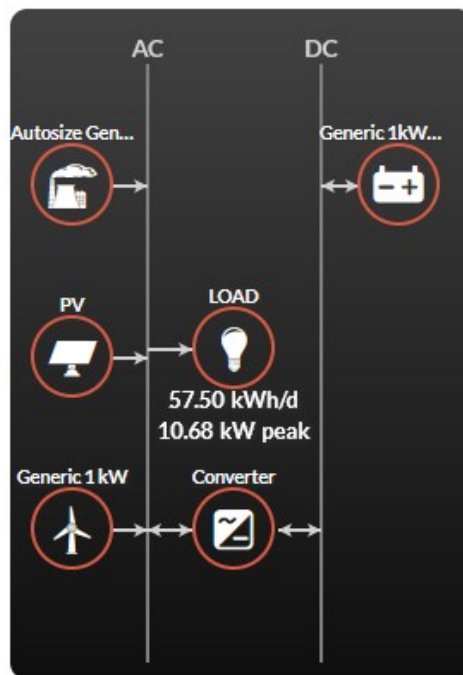


Figure 6.20. Large system layout by HOMER

The projected costs for different system configurations for Salina, KS are in the tables below:

Table 6-11. Large system results table by HOMER for Salina, KS

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
12	1	5.8	6.1	9	CC	\$44,327	\$6,796	\$0.46	\$151,378	4,112
12		6.8	6.9	9	CC	\$37,450	\$7,316	\$0.46	\$152,690	4,732
12	3		6.5	9	CC	\$46,938	\$7,942	\$0.52	\$172,046	4,469
12			8.5	11	CC	\$19,550	\$10,835	\$0.58	\$190,233	7,232

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
12					CC	\$6,000	\$20,226	\$0.98	\$324,605	13,761
12		0.1			CC	\$6,227	\$20,223	\$0.98	\$324,783	13,758
12	1				CC	\$16,000	\$20,349	\$1.02	\$336,553	13,601
12	1	0.6			CC	\$17,813	\$20,339	\$1.02	\$338,202	13,591

According to the tables, HOMER determined that the optimal configuration for the large system is a 12-kW generator, a 1-kW wind turbine, with 5.8 kW of installed PV power, 9 kWh of battery capacity, and a 6.1-kW inverter/charger. The NPC of this system is \$151,378, which amounts to a COE of \$0.46 per kWh. Not surprisingly, the suggested system is about double the medium system, with an identical COE of \$0.46 per kWh.

For additional data, the large system was also designed for a different location, this time for Garrett, WY. Garrett is located north-west of Cheyenne in the interior of Wyoming, and has a comparable solar potential (4.27 kWh/m²/day), but a larger wind potential (average wind speed 8.11 m/s). Below are the results of the simulation by HOMER:

Table 6-12. Large system results table by HOMER for Garrett, WY

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
12	2	4.8	6.3	9	CC	\$51,208	\$5,906	\$0.44	\$144,243	3,236
12		7.1	6.6	9	CC	\$38,415	\$7,254	\$0.46	\$152,682	4,692
12	3		7.6	10	CC	\$48,266	\$7,112	\$0.48	\$160,298	3,829
12			8.5	11	CC	\$19,550	\$10,835	\$0.58	\$190,233	7,232

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
12					CC	\$6,000	\$20,226	\$0.98	\$324,605	13,761
12		0.1			CC	\$6,227	\$20,223	\$0.98	\$324,786	13,758
12	1				CC	\$16,000	\$20,280	\$1.01	\$335,466	13,549
12	1	0.6			CC	\$17,813	\$20,271	\$1.02	\$337,134	13,539

These results actually make sense. Due to additional wind potential, the winning solution incorporates more wind turbines, and results in reduced run-time for the generator and a lower COE as compared to Salina, KS.

6.3.3 Large System Design with the Daily Energy Balance (DEB) Method

The input parameters for the large-sized system were similar to the medium-sized system and were as follows:

Table 6-13. Large system input parameter table for the DEB method

<u>Load parameters</u>		<u>Economic parameters</u>	
Energy demand per day (kWh)	57.50	Project life (years)	20.00
Peak power demand (kW)	5.12	Discount rate (%)	6.00
Average power demand (kW)	2.40	Fuel price (\$/L)	1.00

<u>Location parameters</u>		<u>Fuel coefficients</u>	
Peak sun hours (hrs)	5.00	α (L/kW)	0.07
Average wind speed (m/s)	5.00	β (L/kW)	0.23

<u>Generator parameters</u>		<u>Batteries</u>	
Purchase cost (\$/kW)	550.00	Purchase cost (\$/kWh)	1000.00
Generator lifetime (hrs)	20000.00	Battery lifetime (cycles @50% DoD)	4000.00
Replacement cost (\$/kW)	550.00	Replacement cost (\$/kWh)	500.00
O&M costs (\$/kW/year)	100.00	O&M costs (\$/kWh/year)	50.00

<u>Solar</u>		<u>Wind</u>	
Purchase cost (\$/kWh)	3000.00	Purchase cost (\$/kWh)	10000.00
Solar system lifetime (years)	20.00	Turbine lifetime (years)	20.00
Replacement cost (\$/kW)	1000.00	Replacement cost (\$/kW)	5000.00
O&M costs (\$/year)	50.00	O&M costs (\$/kW/year)	50.00

Depending on the operator settings, and the optimization algorithms (GA or GRG) used, the DEB method determined the following viable solutions:

Table 6-14. Large system results table by the DEB method for Salina, KS

<u>Generator (kW)</u>	<u>Run-time (hrs)</u>	<u>Battery (kWh)</u>	<u>PV system (kW)</u>	<u>Wind turbine (kW)</u>	<u>COE (\$)</u>	<u>Comments</u>
		33.75	15.33		0.4014	only solar
5.12	4.83	21.15	10.06		0.4067	GRG
5.19	5.68	19.35	8.7	0.43	0.4132	Evol
5.12	24				0.4587	only gen
5.12	14.04	16.32			0.5008	peak shaving
		16.31		16.56	0.5580	only wind

The DEB method determined that the larger system can be optimally supplied by a 34-kW solar system and a 15.3-kWh battery bank. For increased reliability, a generator can be added to the system, which only insignificantly increases the COE.

The ability of this system (with a generator) to supply power to the large system was verified with a kW-counting procedure. Below is the resulting plot:

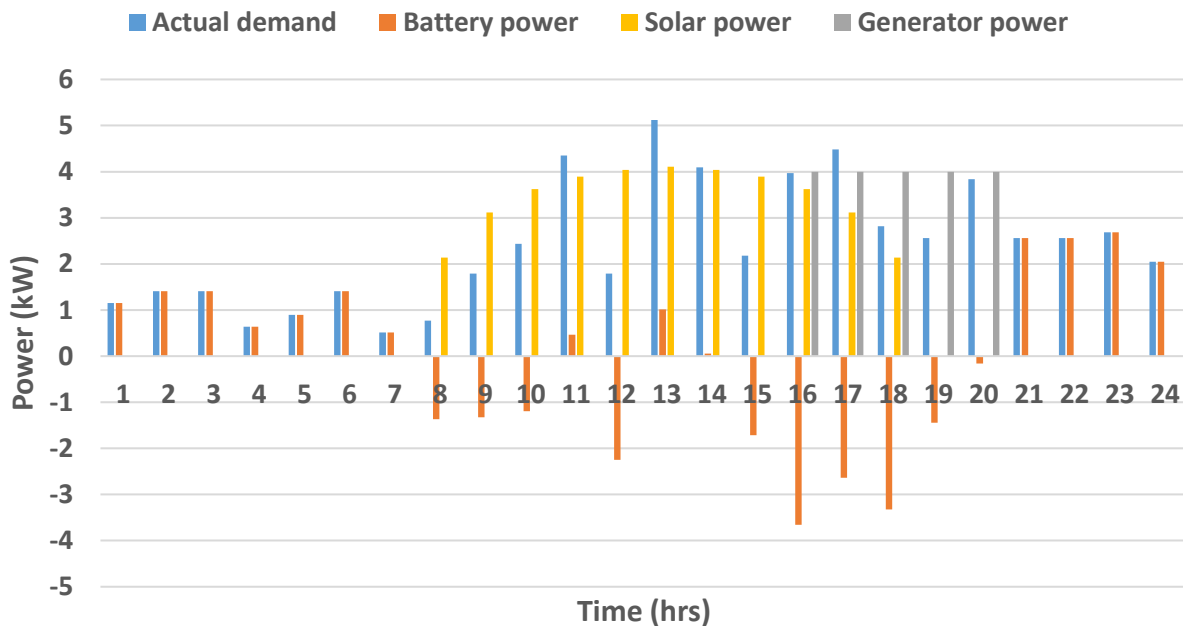


Figure 6.21. Large system design verification for the DEB method

The kW-counting procedure calculated an 18.9-kWh battery capacity requirement. The DEB method determined (conservatively) that a 21.2-kWh battery bank was necessary to cover the demand; this indicated that the proposed system would be operational.

For comparison, the community-system was also designed by the DEB method for Garrett, WY. Below are the results for the winning configuration:

Table 6-15. Large system optimal configuration by the DEB method for Garrett, WY

<u>Generator (kW)</u>	<u>Run-time (hrs)</u>	<u>Battery (kWh)</u>	<u>PV system (kW)</u>	<u>Wind turbine (kW)</u>	<u>COE (\$)</u>
5.12	0	19.08	6.14	5.75	0.4040

As expected, the DEB method determined that the optimal system for Garrett, WY, is a system with a larger wind-system component due to its abundance of wind power. A kW-counting procedure also confirmed the battery requirements, 19 kWh (conservatively) estimated vs 12.5 kWh actual energy requirements.

6.4 Design of a Community Microgrid System

6.4.1 Community System Description

The following community-sized system is modelled with power consumption data of an actual village. It consists of about 25 households with a combined daily demand of about 300 kWh, a peak demand of 20 kW, and an average demand of 12.5 kW.

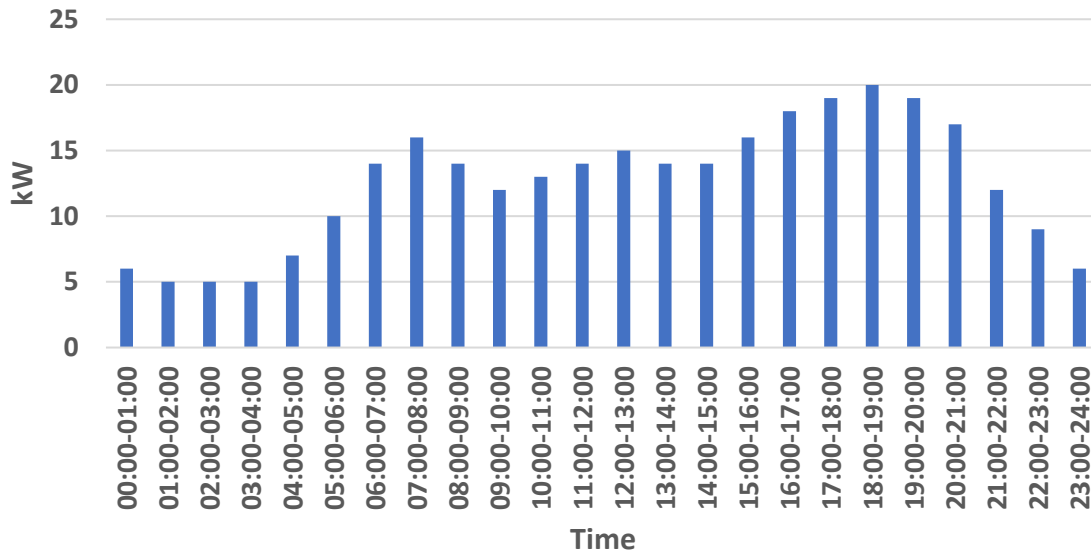


Figure 6.22. Community system load profile

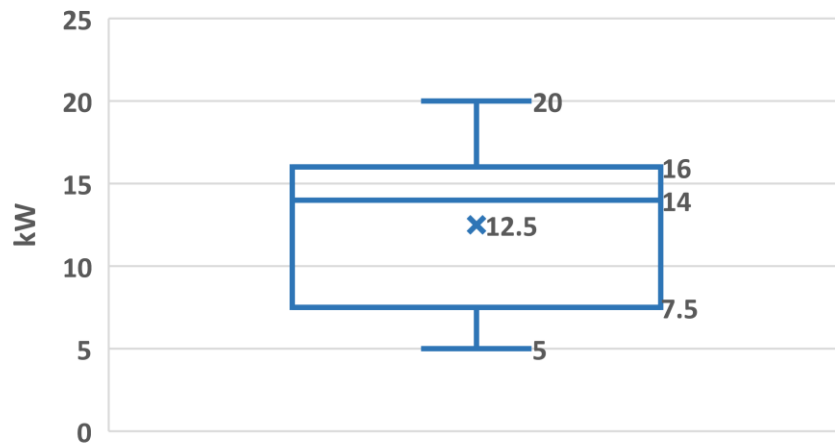


Figure 6.23. Community system demand statistics

6.4.2 Community System Design with HOMER

Most of the parameters used for the community system were the same as for the other systems. The biggest difference was the load profile, which for this system has the look of a classical community profile, with an average daily load of 300 kWh.

Electrical Load

Load Profile

Select a daily profile that describes your load:



Average Load

300 kWh/day

Figure 6.24. Community system load profile for HOMER

Below is the summary of the input parameters for Homer.

Summary

Load

Average load: 300 kWh/day
Profile: Community

Photovoltaic

PV type: Generic flat plate PV
PV capital cost: 3000 \$/kW

Storage

Storage type: Generic 1kWh Li-Ion
Storage cost: 1000 \$/battery

Generator

Autosize Genset
Fuel price: 1 \$/liter

Wind Turbine

Wind Turbine type: Generic 1 kW
Wind Turbine capital cost: 10000 \$/wind turbine

Figure 6.25. Community system input parameters for HOMER

After several minutes of calculations, HOMER suggested the following layout for the community system, and determined the following NPC and COE:

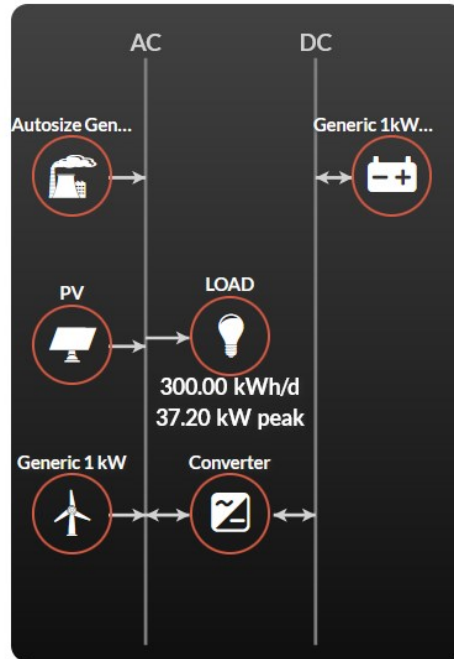


Figure 6.26. Community system layout by HOMER

Table 6-16. Community system results table by HOMER for Salina, KS

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
41	5	33.8	27.3	38	CC	\$218,246	\$32,058	\$0.42	\$723,240	20,025
41		39.6	28.7	38	CC	\$186,050	\$34,274	\$0.42	\$725,949	22,895
41	18		28.5	42	CC	\$251,042	\$36,431	\$0.48	\$824,910	19,980
41			26.5	35	CC	\$63,463	\$52,731	\$0.52	\$894,097	36,878

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
41		2.8			CC	\$28,966	\$72,884	\$0.68	\$1,177,062	50,795
41					CC	\$20,500	\$73,508	\$0.68	\$1,178,420	51,419
41	1				CC	\$30,500	\$73,375	\$0.69	\$1,186,328	50,974
41	2	1.6			CC	\$45,203	\$72,968	\$0.69	\$1,194,629	50,258

According to the tables above, HOMER determined that the optimal configuration for the community system is a 41-kW generator, a 5-kW wind turbine, with 33.8 kW of installed PV

power, 38-kWh batteries, and a 27.3-kW inverter/charger. The NPC of this system is \$723,240, which amounts to a COE of \$0.42 per kWh.

As expected, the COE of the community-sized power system is smaller than for systems with residential profiles due to a higher load factor. In addition, this system benefits from the economy of scale.

For additional data, the community microgrid system was also designed for a different location, this time for Stevens Village, AK. Stevens Village is located north of Fairbanks in the interior of Alaska, and has a quite low solar potential (only 2.54 kWh/m²/day), but still a significant wind potential (average wind speed 5.58 m/s). Below is the simulation data by HOMER:

Table 6-17. Community system results table by HOMER for Stevens Village, AK

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
41		35.9	29.5	38	CC	\$174,920	\$40,815	\$0.47	\$817,855	27,723
41	1	36.2	30.1	38	CC	\$186,238	\$40,374	\$0.48	\$822,231	27,131
41			26.5	35	CC	\$63,463	\$52,731	\$0.52	\$894,097	36,878
41	1		39.7	38	CC	\$80,417	\$52,214	\$0.52	\$902,920	36,059

						Initial Capital...	Operating Cos...	COE	NPC (\$) ▲	Fuel
41					CC	\$20,500	\$73,508	\$0.68	\$1,178,420	51,419
41		0.4			CC	\$21,676	\$73,443	\$0.68	\$1,178,584	51,354
41	1				CC	\$30,500	\$73,545	\$0.69	\$1,189,014	51,144
41	2	1.6			CC	\$45,203	\$73,376	\$0.70	\$1,201,054	50,663

As has been noted before, HOMER's results are frequently difficult to reconcile with practical considerations. In this case, it doesn't make sense that it picked in its winning configuration less wind turbine power, but a larger solar system compared to Salina, KS, despite Stevens Village having more wind and less solar potential than Salina, KS.

6.4.3 Community System Design with the Daily Energy Balance (DEB) Method

The input parameters for the community-sized system were similar to the other systems and were as follows:

Table 6-18. Community system input parameter table for the DEB method

<u>Load parameters</u>		<u>Economic parameters</u>	
Energy demand per day (kWh)	300.00	Project life (years)	20.00
Peak power demand (kW)	20.00	Discount rate (%)	6.00
Average power demand (kW)	12.50	Fuel price (\$/L)	1.00
<u>Location parameters</u>		<u>Fuel coefficients</u>	
Peak sun hours (hrs)	5.00	α (L/kW)	0.07
Average wind speed (m/s)	5.00	β (L/kW)	0.23
<u>Generator parameters</u>		<u>Batteries</u>	
Purchase cost (\$/kW)	550.00	Purchase cost (\$/kWh)	550.00
Generator lifetime (hrs)	20000.00	Battery lifetime (cycles @50% DoD)	4000.00
Replacement cost (\$/kW)	550.00	Replacement cost (\$/kWh)	550.00
O&M costs (\$/kW/year)	100.00	O&M costs (\$/kWh/year)	50.00
<u>Solar</u>		<u>Wind</u>	
Purchase cost (\$/kWh)	3000.00	Purchase cost (\$/kWh)	10000.00
Solar system lifetime (years)	20.00	Turbine lifetime (years)	20.00
Replacement cost (\$/kW)	1000.00	Replacement cost (\$/kW)	5000.00
O&M costs (\$/year)	50.00	O&M costs (\$/kW/year)	50.00

Depending on the operator settings, and the chosen algorithms, different solutions were obtained as seen in the following table:

Table 6-19. Community system results table by the DEB method for Salina, KS

<u>Generator (kW)</u>	<u>Run-time (hrs)</u>	<u>Battery (kWh)</u>	<u>PV system (kW)</u>	<u>Wind turbine (kW)</u>	<u>COE (\$)</u>
		135	80		0.3705
20	0	135	80		0.3938
20	7.5	90	48		0.3988
20	24				0.4013
20	0	73.88	45.32	37.46	0.417
20	18.75	45			0.4437
		45		86.4	0.5088

According to the DEB method, the community system can be optimally supplied by an 80-kW solar system and a 135-kWh battery bank. For a small COE increase, a stand-by generator could be added to the system.

The system is verified with a kW-counting procedure. Below is the plot:

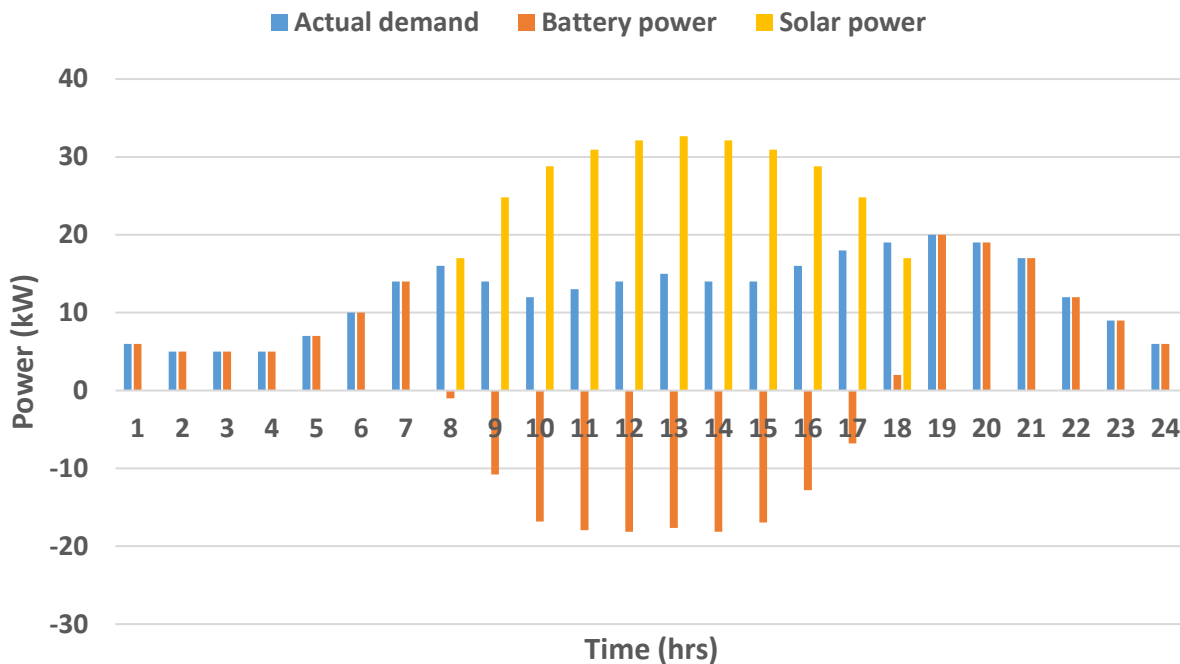


Figure 6.27. Community system design verification for the DEB method

The DEB method determined that a 135-kWh battery bank was necessary to cover the demand. The kW-counting procedure resulted in 137 kWh battery capacity, a deviation of less than 1.5 %.

For comparison, the community-system was also designed by the DEB method for Stevens Village, AK. Below are the results:

Table 6-20. Community system optimal configuration by the DEB method for Stevens Village, AK

Generator (kW)	Run-time (hrs)	Battery (kWh)	PV system (kW)	Wind turbine (kW)	COE (\$)
20	0	55.04	38.18	40.95	0.3902

As expected, the DEB method determined that the optimal system for Stevens Village, AK, is a system with a large wind-system component due to its abundance of wind power. A kW-counting procedure also confirmed the battery requirements, 55.04 kWh estimated (conservatively) vs 51.2 kWh calculated power.

6.5 Summary of Results

Extensive work was performed to develop, test, and verify the DEB method. A small system, medium system, large system and a community-sized microgrid systems were designed for various locations. The DEB method proved to be much faster, and came up with more realistic and less expensive solutions. Below is a summary of the obtained solutions by HOMER and the DEB method.

In all cases, the COE was less for DEB compared to HOMER. The primary reason is the reduced reliance of the DEB method on internal combustion engines in favor of renewable energy such as solar and wind power. This approach required additional battery capacity, but it still resulted in overall less costly and more environmentally friendly systems.

Table 6-21. Summary of Results

		Generator (kW)	Run-time (hrs/day)	Solar (kW)	Wind (kW)	Battery (kWh)	COE (\$)
Small system	Homer	1	14.16	1.3	0	1	0.41
(Salina, KS)	DEB	0.64	0	2.25	0.78	4.39	0.38
Small system	Homer	1	16.32	1.3	0	1	0.41
(Bangor, ME)	DEB	0.64	12.78	1.69	0	2.73	0.38
		Generator (kW)	Run-time (hrs/day)	Solar (kW)	Wind (kW)	Battery (kWh)	COE (\$)
Medium system	Homer	6	10.56	3	1	5	0.46
(Salina, KS)	DEB	2.56	5.17	5.39	0	10.15	0.41
Medium system	Homer	6	13.68	3.4	0	5	0.44
(Tucson, AZ)	DEB	2.56	3.54	4.83	0	11.85	0.39
		Generator (kW)	Run-time (hrs/day)	Solar (kW)	Wind (kW)	Battery (kWh)	COE (\$)
Large system	Homer	12	12.48	5.8	1	9	0.46
(Salina, KS)	DEB	5.12	4.83	10.06	0	21.2	0.41
Large system	Homer	12	9.84	4.8	2	9	0.44
(Garrett, WY)	DEB	5.12	0	6.14	5.75	19.08	0.40
		Generator (kW)	Run-time (hrs/day)	Solar (kW)	Wind (kW)	Battery (kWh)	COE (\$)
Community	Homer	41	12	33.8	5	38	0.42
(Salina, KS)	DEB	20	0	80	0	135	0.39
Community	Homer	41	17.52	35.9	0	38	0.47
(Stevens Vill., AK)	DEB	20	0	38.18	40.95	55.04	0.39

As seen in the table above, in all instances the DEB method outperformed HOMER, obtaining more reasonable solutions which were less costly and also more environmentally friendly.

6.6 Conclusions, Accomplishments and Plans for Future Work

In conclusion, the DEB proved in several ways to be a superior method of designing efficient isolated microgrid power systems:

- It is more easily adaptable to different system sizes and different locations
- It requires fewer input data
- It is computationally less intensive, and much faster
- It can be used with widely available computational software tools such as Excel
- The results are more stable
- The results are more environmentally friendly
- The results are more cost-effective

The overall goal and objective of this research was developing new optimization tools and techniques for designing and building efficient microgrid systems. In line with the goal and objective outlined above, this dissertation presents the following accomplishments and achievements:

In line with the goals and objectives outlined above, this dissertation presents the following accomplishments and achievements:

- Developed a brand-new microgrid system design method called “Daily Energy Balance” method (DEB). This method is uniquely different from all existing approaches in that it does not attempt to match power quantities for each hour. Instead, this method aims to achieve a balance between generated and consumed energy over the course of a day. As a result, this method is more efficient, much faster, more customizable, and in general more engineer friendly as compared to any

other available microgrid system design approaches, and it can operate on any available computation platform.

- Developed new and revised models and equations to accurately determine the amount of daily energy that can be generated by generators, solar panels, and wind power systems.
- Developed new models and equations to determine the daily battery capacity requirements based on the daily average power and peak power consumption, as well as the daily average energy generation capability of different microgrid sources.
- Adapted two optimization algorithms, the Generalized Reduced Gradient (GRG) and a genetic algorithm (GA), to determine the optimum combination of components that minimize cost and maximize reliability of isolated microgrid power systems.
- Employed unique multi-objective optimization operators to enable tailoring of the optimization results according to the preferences of the user.
- Extensively tested and verified the developed models and equations with real-life production data of already operational wind and solar power systems.
- Designed and optimized (with the new DEB method) small, medium, large and community-sized isolated microgrid systems using real-life power demand data.
- Compared and benchmarked the resulting configurations with configurations determined by HOMER. In all cases the new DEB method outperformed HOMER, obtaining more reasonable solutions which were less costly, more reliable, and also more environmentally friendly, hereby confirming the validity of the new method as well as its superiority to competing approaches.

Now that the microgrid system design dilemma is solved, the next step would be to obtain grants and/or other funding to actually build real-life isolated microgrid power systems, in particular in areas of the world that are still not electrified. A major area of future research would be improving the control scheme to operate these microgrid systems at maximum efficiency. The long-term ambition of this dissertation would be to provide guidance and be a leading resource for engineers who are designing microgrid systems for disadvantaged people in the world.

6.7 Summary of Chapter 6

In chapter 6, the DEB method was tested and verified. Different types of microgrid systems, with different power demand profiles, and different sizes, were designed with the DEB method. The results were verified with the kW-counting procedure to ensure viability, as well as compared to designs by HOMER. Conclusions were made, accomplishments were summarized, and plans for future work were also outlined in this chapter.

Bibliography

- [1] Mohammad Amin Babaei, Saeed Hasanzadeh, Hamid Karimi, "Cooperative energy scheduling of interconnected microgrid system considering renewable energy resources and electric vehicles," *Electric Power Systems Research*, Volume 229, 2024, 110167, ISSN 0378-7796, <https://doi.org/10.1016/j.epsr.2024.110167>.
- [2] "Hybrid Wind and Solar Electric Systems." *Energy.Gov*, <https://www.energy.gov/energysaver/hybrid-wind-and-solar-electric-systems>. Accessed 3 Aug. 2024.
- [3] Sabihuddin, Siraj & Kiprakis, Aristides & Mueller, Markus. (2015). "A Numerical and Graphical Review of Energy Storage Technologies." *Energies*. 8. 172-216. 10.3390/en8010172.
- [4] Di Piazza, Maria Carmela. (2022). "Recent Developments and Trends in Energy Management Systems for Microgrids." *Energies*. 15. 8226. 10.3390/en15218226.
- [5] Kaur A, Kaushal J, Basak P. "A review on microgrid central controller." *Renew Sustain Energy Rev* 2016;55:338–45. <http://dx.doi.org/10.1016/j.rser.2015.10.141>.
- [6] Shahzad, S.; Abbasi, M.A.; Ali, H.; Iqbal, M.; Munir, R.; Kilic, H. "Possibilities, Challenges, and Future Opportunities of Microgrids: A Review." *Sustainability* **2023**, *15*, 6366. <https://doi.org/10.3390/su15086366>
- [7] DeBlasio D. "Toward a self-healing smart grid." *Fortnightly* [\[https://www.fortnightly.com/fortnightly/2013/08/toward-self-healing-smart-grid\]](https://www.fortnightly.com/fortnightly/2013/08/toward-self-healing-smart-grid) [Accessed 20 September 2016]; 2013.
- [8] Saeed, Muhammad Hammad, et al. "A Review on Microgrids' Challenges & Perspectives." *IEEE Access*, vol. 9, 2021, pp. 166502–17. *DOI.org (Crossref)*, <https://doi.org/10.1109/ACCESS.2021.3135083>.
- [9] O. Dag and B. Mirafzal, "On stability of islanded low-inertia microgrids," 2016 Clemson University Power Systems Conference (PSC), Clemson, SC, USA, 2016, pp. 1-7, doi: 10.1109/PSC.2016.7462854.
- [10] M. S. Pilehvar, M. B. Shadmand and B. Mirafzal, "Analysis of Smart Loads in Nanogrids," in *IEEE Access*, vol. 7, pp. 548-562, 2019, doi: 10.1109/ACCESS.2018.2885557.
- [11] A. Adib, J. Lamb and B. Mirafzal, "Ancillary Services via VSIs in Microgrids With Maximum DC-Bus Voltage Utilization," in *IEEE Transactions on Industry Applications*, vol. 55, no. 1, pp. 648-658, Jan.-Feb. 2019, doi: 10.1109/TIA.2018.2865483

- [12] F. Sadeque, M. Gursoy, D. Sharma and B. Mirafzal, "Autonomous Control of Inverters in Microgrid," in *IEEE Transactions on Industry Applications*, vol. 60, no. 3, pp. 4313-4323, May-June 2024, doi: 10.1109/TIA.2024.3357043.
- [13] Khodaei, Amin, and Ali Arabnya. "The Economics of Microgrids." 1st ed., Wiley, 2023. DOI.org (Crossref), <https://doi.org/10.1002/9781394162482>.
- [14] Oliveira, Henrique, and Vítor Moutinho. "Renewable Energy, Economic Growth and Economic Development Nexus: A Bibliometric Analysis." *Energies*, vol. 14, no. 15, July 2021, p. 4578. DOI.org (Crossref), <https://doi.org/10.3390/en14154578>.
- [15] Shahzad, S.; Abbasi, M.A.; Ali, H.; Iqbal, M.; Munir, R.; Kilic, H. "Possibilities, Challenges, and Future Opportunities of Microgrids: A Review." *Sustainability* **2023**, *15*, 6366. <https://doi.org/10.3390/su15086366>
- [16] B. P. Majumder, M. N. Faqiry, S. Das and A. Pahwa, "An efficient iterative double auction for energy trading in microgrids," *2014 IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG)*, Orlando, FL, USA, 2014, pp. 1-7, doi: 10.1109/CIASG.2014.7011556.
- [17] M. N. Faqiry and S. Das, "Double Auction With Hidden User Information: Application to Energy Transaction in Microgrid," in *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 49, no. 11, pp. 2326-2339, Nov. 2019, doi: 10.1109/TSMC.2018.2800006.
- [18] M. N. Faqiry, R. Kundu, R. Mukherjee, S. Das and A. Pahwa, "Game theoretic model of energy trading strategies at equilibrium in microgrids," *2014 North American Power Symposium (NAPS)*, Pullman, WA, USA, 2014, pp. 1-4, doi: 10.1109/NAPS.2014.6965413.
- [19] Plett, Eduard, and Sanjoy Das. "A Multi-Agent Model of Energy Transactions in Microgrid under Equilibrium." *Proceedings of the 2019 3rd International Conference on Information System and Data Mining*, ACM, 2019, pp. 37-46. DOI.org (Crossref), <https://doi.org/10.1145/3325917.3325945>.
- [20] "Battery Information". [Online]. Available: <https://www.exeltech.com/Other/batteryinfo.pdf>. [Accessed 5 July 2023].
- [21] A. Colak and K. Ahmed, "A Brief Review on Capacity Sizing, Control and Energy Management in Hybrid Renewable Energy Systems," *2021 10th International Conference on Renewable Energy Research and Application (ICRERA)*, Istanbul, Turkey, 2021, pp. 453-458, doi: 10.1109/ICRERA52334.2021.9598654.
- [22] Oladigbolu, O. & Anwari, Makbul & Al-Turki, Yusuf. (2020). "Optimal Design of a Hybrid PV Solar/Micro-Hydro/Diesel/Battery Energy System for a Remote Rural Village under Tropical Climate Conditions." *Electronics*. 9. 1491. 10.3390/electronics9091491.

- [23] S. H. Alalwan and J. W. Kimball, "Optimal Sizing of a Wind/Solar/Battery Hybrid Microgrid System Using the Forever Power Method," *2015 Seventh Annual IEEE Green Technologies Conference*, New Orleans, LA, USA, 2015, pp. 29-35, doi: 10.1109/GREENTECH.2015.21.
- [24] A. Mohamed and T. Khatib, "Design of hybrid PV/diesel generator systems at minimum cost: Case study for Kuching, Malaysia," *PES T&D 2012*, Orlando, FL, USA, 2012, pp. 1-6, doi: 10.1109/TDC.2012.6281398.
- [25] Akram, U., Khalid, M. and Shafiq, S. (2018), "Optimal sizing of a wind/solar/battery hybrid grid-connected microgrid system." *IET Renewable Power Generation*, 12: 72-80.
<https://doi.org/10.1049/iet-rpg.2017.0010>
- [26] I. M. Ibrahim, A. Y. Abdelaziz, H. H. Alhelou and W. A. Omran, "Sizing of Microgrid System Including Multi-Functional Battery Storage and Considering Uncertainties," in *IEEE Access*, vol. 11, pp. 29521-29540, 2023, doi: 10.1109/ACCESS.2023.3259459.
- [27] P. N. D. Premadasa, C. M. M. R. S. Silva and D. P. Chandima, "An optimal configuration of diesel generator and battery storage system for off-grid residential applications," *2021 IEEE Electrical Power and Energy Conference (EPEC)*, Toronto, ON, Canada, 2021, pp. 1-6, doi: 10.1109/EPEC52095.2021.9621711.
- [28] Alireza Maheri, "Multi-objective design optimization of standalone hybrid wind-PV-diesel systems under uncertainties", *Renewable Energy*, Volume 66, 2014, Pages 650-661, ISSN 0960-1481, <https://doi.org/10.1016/j.renene.2014.01.009>.
- [28] M. A. B. Zafar, M. R. Islam, M. S. -U. Islam, M. Shafiullah and A. I. Ikram, "Economic Analysis and Optimal Design of Micro-grid using PSO Algorithm," *2022 12th International Conference on Electrical and Computer Engineering (ICECE)*, Dhaka, Bangladesh, 2022, pp. 421-424, doi: 10.1109/ICECE57408.2022.10088762.
- [29] L. Ge, J. Liu, T. Du, C. Zhao, R. Pian and W. Liu, "Size Optimization of Wind-PV-Diesel-Hydrogen-Ice System for Island Microgrid," *2022 IEEE Power & Energy Society General Meeting (PESGM)*, Denver, CO, USA, 2022, pp. 1-5, doi: 10.1109/PESGM48719.2022.9916871.
- [30] H. A. El-Sattar, H. M. Sultan, S. Kamel, A. S. Menesy and C. Rahmann, "Optimal Design of Hybrid Stand-alone Microgrids Using Tunicate Swarm Algorithm," *2021 IEEE International Conference on Automation/XXIV Congress of the Chilean Association of Automatic Control (ICA-ACCA)*, Valparaíso, Chile, 2021, pp. 1-6, doi: 10.1109/ICAACCA51523.2021.9465283.
- [31] M. Althani and A. Maheri, "An Ant Colony Algorithm for HRES Size and Configuration Optimisation," *2021 6th International Symposium on Environment-Friendly Energies and*

Applications (EFEA), Sofia, Bulgaria, 2021, pp. 1-6, doi: 10.1109/EFEA49713.2021.9406256.

- [32] A. M. Eltamaly and M. A. Alotaibi, "Novel Fuzzy-Swarm Optimization for Sizing of Hybrid Energy Systems Applying Smart Grid Concepts," in *IEEE Access*, vol. 9, pp. 93629-93650, 2021, doi: 10.1109/ACCESS.2021.3093169.
- [33] A. S. Omar, A. -A. A. Mohamed, T. Senjyu and A. M. Hemeida, "Multi-Objective Optimization of a Stand-alone Hybrid PV/wind/battery/diesel Micro-grid," *2019 IEEE Conference on Power Electronics and Renewable Energy (CPERE)*, Aswan, Egypt, 2019, pp. 391-396, doi: 10.1109/CPERE45374.2019.8980178.
- [34] Zong Woo Geem, "Size optimization for a hybrid photovoltaic–wind energy system," *International Journal of Electrical Power & Energy Systems*, Volume 42, Issue 1, 2012, Pages 448-451, ISSN 0142-0615, <https://doi.org/10.1016/j.ijepes.2012.04.051>.
- [35] [Online]. Available: <https://www.homerenergy.com/index.html> [Accessed 5 July 2023].
- [36] [Online]. Available: <https://www.homerenergy.com/pdf/HOMERHelpManual.pdf> [Accessed July 5, 2023].
- [37] Jean De Dieu Niyonteze, Fumin Zou, Godwin Norensa Osarumwense Asemota, Samuel Bimenyimana, Gilbert Shyirambe, "Key technology development needs and applicability analysis of renewable energy hybrid technologies in off-grid areas for the Rwanda power sector," *Heliyon*, Volume 6, Issue 1, 2020, e03300, ISSN 2405-8440, <https://doi.org/10.1016/j.heliyon.2020.e03300>.
- [38] Sawle, Yashwant, et al. "Prefeasibility Economic and Sensitivity Assessment of Hybrid Renewable Energy System." *IEEE Access*, vol. 9, 2021, pp. 28260–71. *DOI.org (Crossref)*, <https://doi.org/10.1109/ACCESS.2021.3058517>
- [39] Vargas-Salgado, Carlos & Berna, Cesar & Escrivá, A. & Díaz-Bello, Dácil. (2022). "Optimization of All-Renewable Generation Mix According to Different Demand Response Scenarios to Cover All the Electricity Demand Forecast by 2040: The Case of the Grand Canary Island." *Sustainability*. 14. 30. 10.3390/su14031738.
- [40] Kaluthanthrige, Roshani, et al. "Optimal Sizing and Performance Evaluation of a Hybrid Renewable Energy System for an Off-Grid Power System in Northern Canada." *Technology and Economics of Smart Grids and Sustainable Energy*, vol. 4, no. 1, Dec. 2019, p. 4. *DOI.org (Crossref)*, <https://doi.org/10.1007/s40866-019-0061-5>.
- [41] P. Ganguly, A. Kalam and A. Zayegh, "Design an optimum standalone hybrid renewable energy system for a small town at Portland, Victoria using iHOGA," *2017 Australasian Universities Power Engineering Conference (AUPEC)*, Melbourne, VIC, Australia, 2017, pp. 1-6, doi: 10.1109/AUPEC.2017.8282487.

- [42] J. B. Fulzele and M. B. Daigavane, "Simulation and optimization of hybrid PV-wind renewable energy system," *3rd International Conference on Electrical, Electronics, Engineering Trends, Communication, Optimization and Sciences (EEECOS 2016)*, Tadepalligudem, 2016, pp. 1-6, doi: 10.1049/cp.2016.1512.
- [43] Y. Edisson García Vera, R. Dufo-López and O. Daniel Diaz Castillo, "Optimization and Feasibility of Standalone Hybrid Diesel-PV-Battery Microgrid Considering Battery Technologies," *2020 IEEE ANDESCON*, Quito, Ecuador, 2020, pp. 1-6, doi: 10.1109/ANDESCON50619.2020.9272144.
- [44] Hoarcă, I.C.; Bizon, N.; Șorlei, I.S.; Thounthong, P. "Sizing Design for a Hybrid Renewable Power System Using HOMER and iHOGA Simulators." *Energies* **2023**, *16*, 1926. <https://doi.org/10.3390/en16041926>.
- [45] F. Alkarrami, T. Iqbal and K. Pope, "Optimal sizing of a stand-alone hybrid energy system for water pumping in Sirte, Libya," *2016 IEEE Electrical Power and Energy Conference (EPEC)*, Ottawa, ON, Canada, 2016, pp. 1-5, doi: 10.1109/EPEC.2016.7771679.
- [46] N. Saiprasad, A. Kalam and A. Zayegh, "Comparative Study of Optimal Sizing of Renewable Energy System and Triple Bottom Line (TBL) Analysis for a University in Australia," *2018 Australasian Universities Power Engineering Conference (AUPEC)*, Auckland, New Zealand, 2018, pp. 1-6, doi: 10.1109/AUPEC.2018.8757965.
- [47] M. Trape and A. Hellany, "Design optimization and simulation of Hybrid Renewable Energy Systems," *2019 International Conference on Electrical Engineering Research & Practice (ICEERP)*, Sydney, NSW, Australia, 2019, pp. 1-6, doi: 10.1109/ICEERP49088.2019.8956985.
- [48] A. P. Kumar, "Analysis of Hybrid Systems: Software tools," *2016 2nd International Conference on Advances in Electrical, Electronics, Information, Communication and Bio-Informatics (AEEICB)*, Chennai, India, 2016, pp. 327-330, doi: 10.1109/AEEICB.2016.7538302.
- [49] K. S. N. Abhishek *et al.*, "Analysis of Software Tools for Renewable Energy Systems," *2018 International Conference on Computation of Power, Energy, Information and Communication (ICCPEIC)*, Chennai, India, 2018, pp. 179-185, doi: 10.1109/ICCPEIC.2018.8525160.
- [50] [Online]. Available: <https://www.epa.gov/energy/electricity-customers>, [Accessed July 6, 2023].
- [51] [Online]. Available: <https://www.eia.gov/todayinenergy/detail.php?id=43295>, [Accessed July 6, 2023].
- [52] [Online]. Available: <https://eepower.com/technical-articles/calculating-load-profile/#>, [Online]. Available: [Accessed July 6, 2023].

- [53] [Online]. Available: <https://www.eia.gov/consumption/residential/>, [Accessed July 6, 2023].
- [54] [Online]. Available: <https://consumerenergysolutions.com/what-is-your-load-factor-and-load-profile-and-why-do-they-matter/>, [Accessed July 6, 2023].
- [55] “Reciprocating engines”, [Online]. Available: <https://www.energy.gov/sites/prod/files/2016/09/f33/CHP-Recip%20Engines.pdf> , [Accessed July 7, 2023].
- [56] “Solar Resource Maps and Data”, [Online]. Available: <https://www.nrel.gov/gis/solar-resource-maps.html>, [Accessed July 8, 2023].
- [57] “Global Solar Atlas”, [Online]. Available: <https://globalsolaratlas.info/map?c=38.832523,-97.609617,11&s=38.813713,-97.372259&m=site>, [Accessed July 8, 2023].
- [58] “Solcast Solar radiation map”, [Online]. Available: <https://solcast.com/solar-radiation-map/north-america/2023-09-26>, [Accessed September 26, 2023].
- [59] “Photovoltaic Energy Factsheet”, [Online]. Available: <https://css.umich.edu/publications/factsheets/energy/photovoltaic-energy-factsheet>, [Accessed July 28, 2024].
- [60] “Ultimate guide to utility-scale PV system losses”, [Online]. Available: <https://ratedpower.com/blog/utility-scale-pv-losses/>, [Accessed July 28, 2024].
- [61] “PVWatts calculator”, <https://pvwatts.nrel.gov/pvwatts.php>, [Accessed September 26, 2023].
- [62] “Wind Turbine Speed”, [Online]. Available: <https://www.turbinegenerator.org/wind/what-is-wind/wind-speed/>, [Accessed July 28, 2024].
- [63] “Windy App”, [Online]. Available: <https://windy.app/spots/United%20States>, [Accessed July 28, 2024].
- [64] “U.S. Average Annual Wind Speed at 30 Meters”, [Online]. Available: <https://windexchange.energy.gov/maps-data/325>, [Accessed July 28, 2024].
- [65] “Wind turbine area calculations”, [Online]. Available: <https://www.kidwind.org/performance-calculator/>, [Accessed September 26, 2023].
- [66] “Air - Density vs. Pressure and Temperature”, [Online]. Available: https://www.engineeringtoolbox.com/air-temperature-pressure-density-d_771.html, [Accessed July 28, 2024].

- [67] Stephanie Cole, "Can the Betz Limit be exceeded and does it apply to vertical axis wind turbines?", [Online]. Available: <https://theroundup.org/betz-limit/>, [Accessed July 28, 2024].
- [68] "The Betz limit", Energy Education, [Online]. Available: https://energyeducation.ca/encyclopedia/Betz_limit, [Accessed July 28, 2024].
- [69] Rachman, Aditya. (2015). "Exploring The Flow Expansion Causing The Betz Limit Using The Actuator Disk Theory." 10.13140/RG.2.1.2176.1127, [Online]. Available: <https://www.researchgate.net/publication/279533025>, [Accessed July 28, 2024].
- [70] Ouederni, Ramia, et al. "Design and Evaluation of an Island's Hybrid Renewable Energy System in Tunisia." *2022 5th International Conference on Advanced Systems and Emergent Technologies (IC_ASET)*, IEEE, 2022, pp. 418–23. DOI.org (Crossref), https://doi.org/10.1109/IC_ASET53395.2022.9765903.
- [71] A. F. Güven, N. Yörükeren, E. Tag-Eldin and M. M. Samy, "Multi-Objective Optimization of an Islanded Green Energy System Utilizing Sophisticated Hybrid Metaheuristic Approach," in *IEEE Access*, vol. 11, pp. 103044-103068, 2023, doi: 10.1109/ACCESS.2023.3296589.
- [72] A. H. Azad, V. Vahidinasab and H. Shateri, "Optimal Planning of a Stand-Alone Hybrid Energy Farm Encompassing Wind, PV, Diesel Generator and Storage Unit," *2020 10th Smart Grid Conference (SGC)*, Kashan, Iran, 2020, pp. 1-6, doi: 10.1109/SGC52076.2020.9335741.
- [73] L. Ge, J. Liu, T. Du, C. Zhao, R. Pian and W. Liu, "Size Optimization of Wind-PV-Diesel-Hydrogen-Ice System for Island Microgrid," *2022 IEEE Power & Energy Society General Meeting (PESGM)*, Denver, CO, USA, 2022, pp. 1-5, doi: 10.1109/PESGM48719.2022.9916871.
- [74] A. M. Eltamaly, M. A. Alotaibi, A. I. Alolah and M. A. Ahmed, "A Novel Demand Response Strategy for Sizing of Hybrid Energy System With Smart Grid Concepts," in *IEEE Access*, vol. 9, pp. 20277-20294, 2021, doi: 10.1109/ACCESS.2021.3052128.
- [75] Al-Shamma'a, Abdullrahman Abdullah, et al. "Techno-Economic Assessment for Energy Transition from Diesel-Based to Hybrid Energy System-Based off-Grids in Saudi Arabia." *Energy Transitions*, vol. 4, no. 1, June 2020, pp. 31–43. DOI.org (Crossref), <https://doi.org/10.1007/s41825-020-00021-2>.
- [76] Zhu, Cailing, et al. "Research on Capacity Optimization of PV-Wind-Diesel-Battery Hybrid Generation System." *2018 International Power Electronics Conference (IPEC-Niigata 2018 -ECCE Asia)*, IEEE, 2018, pp. 3052–57. DOI.org (Crossref), <https://doi.org/10.23919/IPEC.2018.8507525>.

- [77] Z. Belboul, B. Toual, A. Kouzou and A. Bensalem, "Optimal Sizing of Hybrid PV/Wind/Battery/Diesel Microgrid System Using A Multi-objective Grasshopper optimization Algorithm: A Case Study in Djelfa City Algeria," *2022 3rd International Conference on Smart Grid and Renewable Energy (SGRE)*, Doha, Qatar, 2022, pp. 1-7, doi: 10.1109/SGRE53517.2022.9774039.
- [78] Kharrich, Mohammed, et al. "Developed Approach Based on Equilibrium Optimizer for Optimal Design of Hybrid PV/Wind/Diesel/Battery Microgrid in Dakhla, Morocco." *IEEE Access*, vol. 9, 2021, pp. 13655–70. DOI.org (Crossref), <https://doi.org/10.1109/ACCESS.2021.3051573>.
- [79] R. Al-Rashed, T. Faza' and O. Ayadi, "Potential of using Off-grid PV/Wind/Diesel Battery Hybrid Energy System in Jordan," *2021 12th International Renewable Engineering Conference (IREC)*, Amman, Jordan, 2021, pp. 1-7, doi: 10.1109/IREC51415.2021.9427825.
- [80] *Buy 1 kW Wind Turbine -*. <https://unpluggedpowersystems.ca/product/wind-related/wind-turbines/1-kw-wind-turbine/>. Accessed 5 Sept. 2024.
- [81] *BergeyExcel10 8.9kW_7 — NREL/Turbine-Models Power Curve Archive 0 Documentation*. https://nrel.github.io/turbine-models/BergeyExcel10_8.9kW_7.html. Accessed 5 Sept. 2024.
- [82] Wind Turbine Calculator, [Online]. Available: https://windcycle.energy/wind_turbine_calculator/, [Accessed July 28, 2024].
- [83] "What is a battery C-rating?", [Online]. Available: <https://www.power-sonic.com/blog/what-is-a-battery-c-rating/>, [Accessed July 28, 2024].
- [84] "What is a C-rate?", [Online]. Available: <https://batteryuniversity.com/article/bu-402-what-is-c-rate>, [Accessed July 28, 2024].
- [85] "What is the C Rate for AGM & LiFePO4 Battery?", [Online]. Available: <https://sunonbattery.com/c-rate-agm-lifepo4-battery/>, [Accessed July 28, 2024].
- [86] "Battery Size Calculator", [Online]. Available: <https://www.omnicalculator.com/other/battery-size>, [Accessed July 28, 2024].
- [87] "Battery calculator for any kind of battery: lithium, Alkaline, LiPo, Li-ION, Nimh or Lead batteries", [Online]. Available: <https://power-calculation.com/battery-storage-calculator.php>, [Accessed July 28, 2024].
- [88] Zeeshan Hyder, "What is a peak sun hour? What are peak sun hour numbers for your state?", [Online]. Available: <https://www.solarreviews.com/blog/peak-sun-hours-explained>, [Accessed July 29, 2024].

- [89] “The Peak Sun Hour Table for Each State in The US”, [Online]. Available: <https://energiepanda.com/the-peak-sun-hour-table-for-each-state-in-the-us/>, [Accessed July 29, 2024].
- [90] “Solar Insolation Map”, [Online]. Available: <https://www.solarcraft.net/solutions/dc-ups-power-supplies/item/36-solar-insolation-map>, [Accessed July 29, 2024].
- [91] “Global solar atlas (Kansas details)”, [Online]. Available: https://globalsolaratlas.info/detail?c=38.515798,-98.32085,7&r=USA:USA.17_1, [Accessed July 29, 2024].
- [92] “How many sun hours do you have at your home?”, [Online]. Available: <https://smartgreensolar.com/sun-hours-calculator/>, [Accessed July 29, 2024].
- [93] K-State Salina Solar System login, <https://www.solarweb.com/PvSystems/PvSystem?pvSystemId=4a410aed-8223-42f1-83a8-26e792102480>, [Accessed July 29, 2024].
- [94] Salina, KS, Weather History, <https://www.wunderground.com/history/daily/us/ks/salina/KSLN/date/2024-6-15>, [Accessed July 29, 2024].
- [95] “Historical weather data for 67401, [Online]. Available: <https://www.visualcrossing.com/weather-history/67401/us/2024-06-01/2024-06-30>, [Accessed July 29, 2024].
- [96] “Monthly mean 10 m wind speed”, [Online]. Available: <https://www.ncei.noaa.gov/access/monitoring/wind/>, [Accessed July 29, 2024].
- [97] *Kansas State Polytechnic Bergey Excel*. <http://mybergey.aprsworld.com/A5228>. Accessed 10 Sept. 2024.
- [98] Arun Chendhuran, R., Senthil Kumar, J. (2021). „Review of Model-Based State-Of-Charge Estimation Methods for Batteries of Electric Vehicles.” In: Komanapalli, V.L.N., Sivakumaran, N., Hampannavar, S. (eds) *Advances in Automation, Signal Processing, Instrumentation, and Control. i-CASIC 2020. Lecture Notes in Electrical Engineering*, vol 700. Springer, Singapore. https://doi.org/10.1007/978-981-15-8221-9_244
- [99] R. R. Kumar, C. Bharatiraja, K. Udhayakumar, S. Devakirubakaran, K. S. Sekar and L. Mihet-Popa, "Advances in Batteries, Battery Modeling, Battery Management System, Battery Thermal Management, SOC, SOH, and Charge/Discharge Characteristics in EV Applications," in *IEEE Access*, vol. 11, pp. 105761-105809, 2023, doi: 10.1109/ACCESS.2023.3318121.

- [100] G. P. Fenner, L. F. Ramos and L. N. Canha, "Battery Analysis using Kinetic Battery Model with Voltage Response," *2020 55th International Universities Power Engineering Conference (UPEC)*, Turin, Italy, 2020, pp. 1-5, doi: 10.1109/UPEC49904.2020.9209860.
- [101] Jongerden, Marijn & Haverkort, B.R.. (2010). "Which Battery Model to Use?" Software, IET. 3. 445 - 457. 10.1049/iet-sen.2009.0001.
- [102] Zhao, H., Chen, Z., Shu, X., Shen, J., Liu, Y. (2023). "Remaining Capacity Estimation for Lithium-Ion Batteries Based on Differential Temperature Curve and Hybrid Deep Learning Approach." In: Sun, F., Yang, Q., Dahlquist, E., Xiong, R. (eds) *The Proceedings of the 5th International Conference on Energy Storage and Intelligent Vehicles (ICEIV 2022)*. ICEIV 2022. Lecture Notes in Electrical Engineering, vol 1016. Springer, Singapore.
https://doi.org/10.1007/978-981-99-1027-4_119
- [103] Romain Metaye, "A Guide To Understanding Battery Capacity", [Online]. Available: <https://climatebiz.com/battery-capacity/>, [Accessed July 29, 2024].
- [104] Yao, Jiachi & Han, Te, 2023."Data-driven lithium-ion batteries capacity estimation based on deep transfer learning using partial segment of charging/discharging data," *Energy*, Elsevier, vol. 271(C).
<https://ideas.repec.org/a/eee/energy/v271y2023ics0360544223004279.html>
- [105] Z. Ning, P. Venugopal, G. Rietveld and T. B. Soeiro, "Data-Driven Methods for Robust Battery Capacity Estimation based on Electrochemical Impedance Spectroscopy," *2023 25th European Conference on Power Electronics and Applications (EPE'23 ECCE Europe)*, Aalborg, Denmark, 2023, pp. 1-8, doi: 10.23919/EPE23ECCEurope58414.2023.10264480.
- [106] Zhou, X.; Han, X.; Wang, Y.; Lu, L.; Ouyang, M. "A Data-Driven LiFePO₄ Battery Capacity Estimation Method Based on Cloud Charging Data from Electric Vehicles." *Batteries* 2023, 9, 181. <https://doi.org/10.3390/batteries9030181>
- [107] Cheng, Yujie, Tao, Laifa, Yang, Chao, "Lithium-Ion Battery Capacity Estimation: A Method Based on Visual Cognition," *Complexity*, 2017, 6342170, 13 pages, 2017.
<https://doi.org/10.1155/2017/6342170>
- [108] Ma, B., Yu, HQ., Wang, WT. *et al.* „State of health and remaining useful life prediction for lithium-ion batteries based on differential thermal voltammetry and a long and short memory neural network." *Rare Met.* **42**, 885–901 (2023). <https://doi.org/10.1007/s12598-022-02156-1>
- [109] "IEEE Recommended Practice for Sizing Lead-Acid Batteries for Stationary Applications," in *IEEE Std 485-2010 (Revision of IEEE Std 485-1997)* , vol., no., pp.1-90, 15 April 2011, doi: 10.1109/IEEESTD.2011.5751584.

- [110] "IEEE Recommended Practice for Sizing Lead-Acid Batteries for Stand-Alone Photovoltaic (PV) Systems," in *IEEE Std 1013-2019 (Revision of IEEE Std 1013-2007)*, vol., no., pp.1-50, 20 Sept. 2019, doi: 10.1109/IEEESTD.2019.8845030.
- [111] Mehjabin Abdurrazaque, "Battery Size Calculator", [Online]. Available: <https://www.omnicalculator.com/other/battery-size>, [Accessed July 29, 2024].
- [112] A. M. Eltamaly, M. A. Alotaibi, A. I. Alolah and M. A. Ahmed, "A Novel Demand Response Strategy for Sizing of Hybrid Energy System With Smart Grid Concepts," in *IEEE Access*, vol. 9, pp. 20277-20294, 2021, doi: 10.1109/
- [113] Sun, X.A., Conejo, A.J. (2021). "Decision Making Under Uncertainty in the Power Sector." In: Robust Optimization in Electric Energy Systems. International Series in Operations Research & Management Science, vol 313. Springer, Cham. https://doi.org/10.1007/978-3-030-85128-6_1
- [114] Hosna Khajeh and Hannu Laaksonen, "Applications of Probabilistic Forecasting in Smart Grids: A Review", School of Technology and Innovations, Flexible Energy Resources, University of Vaasa, 65200 Vaasa, Finland, Appl. Sci. 2022, 12(4), 1823; <https://doi.org/10.3390/app12041823>
- [115] Matthew J. Prilliman, Clifford W. Hansen, Janine M.F. Keith, Steven Janzou, Marios Theristis, Aaron Scheiner, and Ellis Ozakyol, "Quantifying Uncertainty in PV Energy Estimates", Technical Report, NREL/TP-7A40-84993, Revised March 2024
- [116] "PV Degradation Modeling." *PV Performance Modeling Collaborative (PVPMC)*, <https://pvpmc.sandia.gov/tools/pv-degradation-methods/>. Accessed 10 Aug. 2024.
- [117] "Solar API and Weather Forecasting Tool | Solcast™." <https://solcast.com/>. Accessed 10 Aug. 2024.
- [118] "Energy Forecasting for Wind and Solar Farms - Xweather." <https://xweather.com/renewable-energy/forecasting>. Accessed 10 Aug. 2024.
- [119] Shi Huanyu , Dong Zhibao , Xiao Nan , Huang Qinni, "Wind Speed Distributions Used in Wind Energy Assessment: A Review", *Frontiers in Energy Research*, vol 9, 2021, <https://www.frontiersin.org/journals/energy-research/articles/10.3389/fenrg.2021.769920>, DOI=10.3389/fenrg.2021.769920
- [120] "Wind Speed Distributions and Fitting a Weibull Distribution", [Online]. Available: <https://windroseexcel.com/guides/wind-speed-distributions-and-fitting-a-weibull-distribution/>, [Accessed July 29, 2024].
- [121] "Wind resource assessment", [Online]. Available: https://www.windustry.org/community/wind_toolbox-4-wind-resource-assessment, [Accessed September 12, 2023].

- [122] “Windographer | Wind Data Analytics and Visualization Solution.” *UL Solutions*, <https://www.ul.com/software/windographer-wind-data-analytics-and-visualization-solution>. Accessed 10 Aug. 2024.
- [123] “WINDEXchange.” <https://windexchange.energy.gov/>. Accessed 10 Aug. 2024.
- [124] “SOWFA: Simulator fOr Wind Farm Applications.” <https://www.nrel.gov/wind/nwtc/sowfa.html>. Accessed 10 Aug. 2024.
- [125] “FLORIS: FLOW Redirection and Induction in Steady State.” <https://www.nrel.gov/wind/floris.html>. Accessed 10 Aug. 2024.
- [126] “Net Present Value (NPV): What It Means and Steps to Calculate It”, [Online]. Available: <https://www.investopedia.com/terms/n/npv.asp> [accessed July 26, 2023].
- [127] “Net present value (NPV)”, [Online]. Available: <https://corporatefinanceinstitute.com/resources/valuation/net-present-value-npv/> [accessed July 26, 2023].
- [128] “Net present value”, [Online]. Available: https://en.wikipedia.org/wiki/Net_present_value, [accessed July 26, 2023].
- [129] “Net Present Cost (NPC)”, [Online]. Available: <https://ebrary.net/32824/environment/cost>, [accessed July 26, 2023].
- [130] “How Much Do Commercial Generators Cost?”, [Online]. Available: <https://priceithere.com/commercial-generator-prices/>, [accessed July 29, 2024].
- [131] “What Is the Life Expectancy of Industrial Generators?”, [Online]. Available: <https://turnkey-industries.com/what-is-the-life-expectancy-of-industrial-generators>, [accessed September 21, 2023].
- [132] “Exploring the Cost of Investing in a Commercial Generator: What You Need to Know”, [Online]. Available: <https://turnkey-industries.com/commercial-generator-cost>, [accessed July 29, 2024].
- [133] “Generator Maintenance Repair And Service Cost”, [Online]. Available: <https://www.rcs-electricalservices.com/generator-maintenance-repair-and-service-cost.html>, [accessed September 21, 2023].
- [134] “Approximate Diesel Fuel Consumption Chart”, [Online]. Available: https://www.generatorsource.com/Diesel_Fuel_Consumption.aspx [accessed September 21, 2023].

- [135] “Diesel Fuel Consumption Chart”, [Online]. Available: <https://www.wpowerproducts.com/power-generation-resources/diesel-fuel-consumption-chart/>, [accessed September 21, 2023].
- [136] “Generator Fuel Consumption Calculator”, [Online]. Available: <https://hdpowerequipment.com/generator-fuel-consumption-calculator/>, [accessed September 21, 2023].
- [137] *Wind Energy and Power Calculations | EM SC 470: Applied Sustainability in Contemporary Culture*. <https://www.e-education.psu.edu/emsc297/node/649>. Accessed 4 Sept. 2024.
- [138] Z. Belboul, B. Toual, A. Kouzou and A. Bensalem, "Optimal Sizing of Hybrid PV/Wind/Battery/Diesel Microgrid System Using A Multi-objective Grasshopper optimization Algorithm: A Case Study in Djelfa City Algeria," *2022 3rd International Conference on Smart Grid and Renewable Energy (SGRE)*, Doha, Qatar, 2022, pp. 1-7, doi: 10.1109/SGRE53517.2022.9774039.
- [139] GMG. “Fuel Consumption For Diesel Generators ★ Green Mountain Generators.” *Green Mountain Generators*, 30 Sept. 2012, <https://greenmountaingenerators.com/2012/09/29/fuel-consumption-for-diesel-generators/>.
- [140] “Diesel Generator Fuel Consumption Chart.” *Hardy Diesel*, <https://hardydiesel.com/resources/diesel-generator-fuel-consumption-chart/>. Accessed 3 Sept. 2024.
- [141] *Yanmar Powered 6,500 Watt Diesel Generator*. <http://www.centralmainediesel.com/order/Yanmar-6875-Watt-Diesel-Generator.asp?page=Y6875>. Accessed 3 Sept. 2024.
- [142] *Diesel Generator Fuel Consumption Chart | Worldwide Power Products*. <https://www.wpowerproducts.com/power-generation-resources/diesel-fuel-consumption-chart/>. Accessed 3 Sept. 2024.
- [143] “Planning to Install a Solar Panel System? Here’s How Much It May Cost”, [Online]. Available: <https://www.cnet.com/home/energy-and-utilities/solar-panel-cost/>, [accessed July 30, 2024].
- [144] “What Do Solar Panels Cost and Are They Worth It?”, [Online]. Available: <https://www.nerdwallet.com/article/mortgages/solar-panel-cost>, [accessed July 30, 2024].
- [145] Dirk C. Jordan and Sarah R. Kurtz, “Photovoltaic Degradation Rates — An Analytical Review”, *Progress in Photovoltaics: Research and Applications*, [Online]. Available: <https://www.nrel.gov/docs/fy12osti/51664.pdf>, [accessed July 30, 2024].

- [146] By Emily Glover , Corinne Tynan, “How Long Do Solar Panels Last?”, [Online]. Available: <https://www.forbes.com/home-improvement/solar/how-long-do-solar-panels-last/>, [accessed July 30, 2024].
- [147] “How Much Does it Cost to Install a Wind Turbine?”, [Online]. Available: <https://www.windturbinemagazine.com/how-much-does-it-cost-to-install-a-wind-turbine/>, [accessed July 30, 2024].
- [148] “How Long do Wind Turbines Last? Can their Lifetime be Extended?”, [Online]. Available: <https://www.twi-global.com/technical-knowledge/faqs/how-long-do-wind-turbines-lastz>, [accessed July 30, 2024].
- [149] Tyler Stehly and Patrick Duffy, “2020 Cost of Wind Energy Review”, National Renewable Energy Laboratory, [Online]. Available: <https://www.nrel.gov/docs/fy22osti/81209.pdf>, [accessed July 30, 2024].
- [150] Matthew Bandyk, “Lead batteries make innovation push to better compete for energy storage projects”, [Online]. Available: <https://www.utilitydive.com/news/lead-batteries-make-innovation-push-to-better-compete-for-energy-storage-pr/574244/>, [accessed July 30, 2024].
- [151] “LFP Vs NMC Battery: Complete Comparison Guide”, [Online]. Available: <https://www.ecolithiumbattery.com/lfp-vs-nmc-battery/>, [accessed July 30, 2024].
- [152] “The Ultimate Guide of LiFePO4 Battery”, [Online]. Available: <https://sunonbattery.com/guides-lfp-lifepo4-battery/>, [accessed July 30, 2024].
- [153] “How to calculate the energy cost of different battery chemistries?”, [Online]. Available: <https://www.fortresspower.com/how-to-calculate-the-energy-cost-of-different-battery-chemistries/>, [accessed July 30, 2024].
- [154] “How Much Does a Solar Battery Storage System Cost?”, [Online]. Available: <https://www.homeadvisor.com/cost/energy-efficiency/install-solar-battery-storage/>, [accessed July 30, 2024].
- [155] Wesley Cole, A. Will Frazier, and Chad Augustine, “Cost Projections for Utility-Scale Battery Storage: 2021 Update”, National Renewable Energy Laboratory, [Online]. Available: <https://www.nrel.gov/docs/fy21osti/79236.pdf>, [accessed July 30, 2024].
- [156] Kendall Mongird, Vilayanur Viswanathan, Jan Alam, Charlie Vartanian, Vincent Sprenkle, “2020 Grid Energy Storage Technology Cost and Performance Assessment”, Pacific Northwest National Laboratory, Technical Report, Publication No. DOE/PA-0204, December 2020, <https://www.pnnl.gov/sites/default/files/media/file/Final%20-%20ESGC%20Cost%20Performance%20Report%2012-11-2020.pdf>

- [157] Teresa Jackson, “What is the Lifespan of a Lead-Acid Battery?”, [Online]. Available: <https://www.batteryskills.com/what-is-the-lifespan-of-a-lead-acid-battery/>, [accessed July 30, 2024].
- [158] Vladimir Karimov, “New Tests Prove: LFP Lithium Batteries Live Longer than NMC”, [Online]. Available: <https://www.onecharge.biz/blog/lfp-lithium-batteries-live-longer-than-nmc/>, [accessed July 30, 2024].
- [159] “Levelized Cost of Energy (LCOE)”, [Online]. Available: <https://www.energy.gov/sites/prod/files/2015/08/f25/LCOE.pdf>, [accessed July 30, 2024].
- [160] “Levelized cost of energy (LCOE)”, [Online]. Available: <https://corporatefinanceinstitute.com/resources/valuation/levelized-cost-of-energy-lcoe/>, [accessed July 30, 2024].
- [161] “Mathematical optimization”, [Online]. Available: https://en.wikipedia.org/wiki/Mathematical_optimization, [accessed August 12, 2023]
- [162] “Understanding Gradient Descent in Python.” <https://www.linkedin.com/pulse/understanding-gradient-descent-python-rany-elhousieny-phd%E1%B4%AC%E1%B4%AE%E1%B4%B0>. Accessed 11 Aug. 2024.
- [163] “Simplex Method | Definition, Example, Procedure, & Facts | Britannica.” [Online]. Available: <https://www.britannica.com/topic/simplex-method>, <https://www.britannica.com/topic/simplex-method#/media/1/545391/3028>. [accessed August 12, 2024]
- [164] Sakhaei, Zahra & Azin, Reza & Osfour, Shahriar. (2016). “Assessment of empirical/theoretical relative permeability correlations for gas-oil/condensate systems.”
- [165] Felfel, Houssem & Ayadi, Omar & Masmoudi, Faouzi. (2015). “A Multi-site Supply Chain Planning Using Multi-stage Stochastic Programming.” Applied Condition Monitoring. 2. 10.1007/978-3-319-14532-7_30.
- [166] Liu, Zhi-Ping & Zhou, Min-Gang & Liu, Wen-Bo & Li, Chen-Long & Gu, Jie & Hua-Lei, Yin & Chen, Teng. (2022). “Automated machine learning for secure key rate in discrete-modulated continuous-variable quantum key distribution.”
- [167] “Genetic algorithms”, [Online]. Available: https://en.wikipedia.org/wiki/Genetic_algorithm, [accessed August 12, 2023]
- [168] “Evolutionary algorithms”, [Online]. Available: https://en.wikipedia.org/wiki/Evolutionary_algorithm, [accessed August 12, 2023]
- [169] Gopal, M. 2019. “Appendix A: GENETIC ALGORITHM (GA) FOR SEARCH OPTIMIZATION.” Chap. A in Applied Machine Learning. 1st ed. New York: McGraw-

Hill Education.

<https://www.accessengineeringlibrary.com/content/book/9781260456844/back-matter/appendix1>

- [170] Woodward, Robert & Kelleher, Edmund. (2016). “Towards 'smart lasers': Self-optimization of an ultrafast pulse source using a genetic algorithm.” *Scientific Reports*. 6. 10.1038/srep37616.
- [171] Max Maxfield , “When Genetic Algorithms Meet Artificial Intelligence.” *EEJournal*, 9 July 2020, <https://www.eejournal.com/article/when-genetic-algorithms-meet-artificial-intelligence/>.
- [172] “Simulated Annealing Explained”, [Online]. Available: <https://www.baeldung.com/cs/simulated-annealing>, [accessed August 13, 2023]
- [173] Blocho, Mirosław. “Chapter 4 - Heuristics, Metaheuristics, and Hyperheuristics for Rich Vehicle Routing Problems.” *Smart Delivery Systems*, edited by Jakub Nalepa, Elsevier, 2020, pp. 101–56. *ScienceDirect*, <https://doi.org/10.1016/B978-0-12-815715-2.00009-9>.
- [174] Adrian Tam, “A Gentle Introduction to Particle Swarm Optimization”, [Online]. Available: <https://machinelearningmastery.com/a-gentle-introduction-to-particle-swarm-optimization/>, [accessed August 14, 2023].
- [175] Al-Smadi, Yazan & Eshtay, Mohammed & al-Qerem, Ahmad & Nashwan, Shadi & Ouda, Osama & Ahmed, Abd El-Aziz. (2023). “Reliable prediction of software defects using Shapley interpretable machine learning models.” *Egyptian Informatics Journal*. 24. 100386. 10.1016/j.eij.2023.05.011.
- [176] Li S, Wei Y, Liu X, Zhu H, Yu Z. “A New Fast Ant Colony Optimization Algorithm: The Saltatory Evolution Ant Colony Optimization Algorithm.” *Mathematics*. 2022; 10(6):925. <https://doi.org/10.3390/math10060925>
- [177] Poudel, Yam & Bhandari, Pratap. (2023). “Control of the BLDC Motor Using Ant Colony Optimization Algorithm for Tuning PID Parameters.” *Archives of Advanced Engineering Science*. 10.47852/bonviewAAES32021184.
- [178] Vasuki, A. “Nature-Inspired Optimization Algorithms.” CRC Press, Taylor & Francis Group, 2020.
- [179] Abhishek C.V. Salian, “A Gentle Introduction to Multi-Objective Optimization”, [Online]. Available: <https://codemonk.io/blog/a-gentle-introduction-to-multi-objective-optimization/>, [accessed July 30, 2024].
- [180] “Multiobjective optimization”, [Online]. Available: <https://openmdao.github.io/PracticalMDO/Notebooks/Optimization/multiobjective.html>, [accessed July 30, 2024].

- [181] “Multi-Objective Optimization”, [Online]. Available: <https://engineering.purdue.edu/~sudhoff/ee630/Lecture09.pdf>, [accessed July 30, 2024].
- [182] Rahman, Md. Mostafizur, and György Szabó. “Multi-Objective Urban Land Use Optimization Using Spatial Data: A Systematic Review.” *Sustainable Cities and Society*, vol. 74, Nov. 2021, p. 103214. *DOI.org (Crossref)*, <https://doi.org/10.1016/j.scs.2021.103214>.
- [183] Zhang, Peng, et al. “Multi-Objective Optimization for Materials Design with Improved NSGA-II.” *Materials Today Communications*, vol. 28, Sept. 2021, p. 102709. *DOI.org (Crossref)*, <https://doi.org/10.1016/j.mtcomm.2021.102709>.
- [184] Büyük, Ersin. “Pareto-Based Multiobjective Particle Swarm Optimization: Examples in Geophysical Modeling.” *Optimisation Algorithms and Swarm Intelligence*, IntechOpen, 2021. www.intechopen.com, <https://doi.org/10.5772/intechopen.97067>.
- [185] Sharma, Shubhkirti, and Vijay Kumar. “A Comprehensive Review on Multi-Objective Optimization Techniques: Past, Present and Future.” *Archives of Computational Methods in Engineering*, vol. 29, no. 7, Nov. 2022, pp. 5605–33. *Springer Link*, <https://doi.org/10.1007/s11831-022-09778-9>.