Microgrids with Battery Energy Storage Systems

Subjects: Engineering, Electrical & Electronic

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Worldwide, governmental organizations are restructuring energy policies, making them cleaner, encouraging transformation and energy transition by integrating renewable sources, engaging in environmental preservation, and, notably, meeting the growing demand for sustainable energy models, such as solar and wind energy. In the electricity sector, reducing carbon emissions is crucial to facilitating the integration of microgrids (MGs) with renewable sources and Battery Energy Storage Systems (BESSs).

Keywords: battery energy storage system ; battery ; renewable sources ; microgrid

1. Introduction

Nowadays, about 63.3% of the world's electrical energy is generated by burning fossil fuels [1][2][3]. Using renewable sources is one of the alternatives for reversing this scenario [4], supplying electrical loads [5], either for specific time intervals or continuously. The integration of Distributed Energy Resources (DERs) with a system's loads is referred to as a microgrid (MG) [6], aiming for a better joint operation of these sources. Most MGs operate connected to the grid (on-grid), providing bidirectional energy flow [7] with energy generators and end-users, enabling better energy management. In a grid outage, the MG can operate in an isolated (off-grid) or autonomous mode [5], but both on-grid and off-grid modes are controlled and coordinated. The advantages of MGs include increased efficiency in improving the quality and reliability of electrical energy, reduced energy costs, the ability to generate revenue by injecting energy into the grid, the potential to provide ancillary services, reduced peak energy demand, lower emissions of pollutants, and the possibility of having multiple connected generation sources [8]. However, there are challenges in designing an MG, such as the appropriate selection of DERs and optimal sizing [1][2].

However, MGs need elements to ensure network stability and supply variable loads [9]. A typical example is diesel generators that support MGs; however, this alternative contributes to the emission of polluting gases. Fortunately, the Battery Energy Storage System (BESS) offers a solution to meet this demand while providing advantages when connected to renewable energy sources. These benefits go beyond complementing the variability of these resources [10]. Significant benefits can be expected from a BESS due to its flexible operation, such as demand control, acting when the load may exceed the contracted demand [11]. Additionally, a BESS facilitates energy shifting, storing energy during periods of excess supply and used during peak demand hours when the cost is higher [12]. There are opportunities to reduce costs for small- to medium-sized end consumers, especially during peak hours when energy tariffs increase compared to off-peak hours [13][14].

2. Background of Sizing with Technical Indicators of Microgrids with Battery Energy Storage Systems

In recent decades, the optimal sizing of hybrid energy systems has emerged as a rapidly growing research field. This complex challenge involves integrating uncontrollable energy sources like solar, wind, and BESSs to meet demands economically and sustainably. In this context, various techniques have been explored, either individually or in hybrid forms. Among these, three approaches are the most prominent and promising: optimization techniques, machine learning, and statistical methods. Additionally, established software solutions in this domain are also discussed.

2.1. Optimization Techniques, Machine Learning, and Statistical Methods

2.1.1. Optimization Techniques

A solid mathematical foundation provides a rigorous framework for finding the ideal configuration of hybrid energy systems, considering a range of variables, physical and economic constraints, and specific objectives. Here are some of the most relevant optimization techniques applied in this context:

- Linear and Nonlinear Programming: Linear programming deals with optimization problems in which the objective function and constraints are linear. Nonlinear programming extends this concept to problems with nonlinear objective functions or constraints. Both approaches are widely applied in the optimal sizing of hybrid energy systems, considering costs, resource availability, and efficiency. Techniques such as Two-Constraint Linear Programming (TCLP) and Mixed-Integer Quadratic Programming (MIQP) are examples of linear programming and its variations [1][15].

- Evolutionary Algorithms: Inspired by the process of natural selection and evolution, these algorithms are used to find approximate solutions for complex optimization problems by exploring populations of candidate solutions and applying genetic operators such as selection, recombination, and mutation to enhance solutions over time. The methodologies include the Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), and the Genetic Algorithm (GA) [2][4][9][16].

- Multi-Objective Optimization: When it comes to hybrid energy systems, multiple objectives often exist, such as minimizing costs, maximizing efficiency, and reducing emissions. Multi-Objective Optimization deals with the search for solutions that balance these competing objectives, resulting in Pareto-efficient solutions representing trade-offs among the objectives. The techniques include Mixed-Integer Conic Programming (MICP) and Adaptive Mixed Differential Evolution (AMDE) [17][18].

2.1.2. Machine Learning

On the other hand, machine learning, with its ability to extract complex patterns from data and make adaptive decisions, provides a more flexible and data-driven approach to solving this problem. Here are some of the machine learning techniques relevant to hybrid energy systems:

- Neural Networks: Artificial Neural Networks (ANNs) are computational models inspired by the functioning of the human brain. They are used to learn complex patterns from data, particularly useful in predicting energy production from renewable sources such as solar and wind. Deep learning Neural Networks and Recurrent Neural Networks (RNNs) have also been applied to enhance the accuracy of predictions [18][19].

- Random Forests: Machine learning algorithms that combine multiple decision trees to create robust and accurate models. They can be used to optimize hybrid systems in real time, adapting to changes in operational conditions [20][21].

- Clustering: This is used to group similar data points into clusters or groups. In the context of hybrid energy systems, clustering is applied to identify behavior patterns of different system components. This methodologies include K-means Clustering (KC), Elman Neural Networks (ENNs), and Wavelet Neural Networks (WNNs) [19][20].

- Regression Model: Initially, regression analyses are commonly employed for prediction purposes, with their application closely overlapping with the domain of machine learning. Furthermore, regression analysis can be applied in specific cases to identify causal relationships between independent and dependent variables. Linear regression analysis can be divided into simple and multiple linear regression. Multiple linear regression is a statistical approach used to predict the outcome of a response variable by employing multiple explanatory variables. In contrast, simple linear regression isolates the influence of independent variables from the interaction among dependent variables [22][23].

2.1.3. Statistical Forecasting Procedures

In addition to optimization and machine learning techniques, statistical forecasting procedures play a fundamental role in analyzing and modeling hybrid energy systems which involves a considerable amount of time series interpretation. Some relevant statistical methods for this area are the following:

- Univariate Models: A statistical approach that deals with data collected over time, relying on only one historical series. In the context of hybrid energy systems, time series analysis is widely used to model historical behavior and make future predictions of energy production and consumption, as seen in the Auto-Regressive Integrated Moving Average (ARIMA) technique [19].

- Causal Models or Transfer Function Models: Future values of a series are not determined solely via their past values but can also be influenced by series that have some relationship with it. In the case of electricity load consumption, including the relative price as a correlated series can contribute to a more comprehensive explanation of this phenomenon [24].

- Multivariate Models: These models not only consider the autocorrelation of the main series but also incorporate values from external series that enhance the forecast and analysis of this series. These external series can provide evidence of linear or nonlinear causality or correlation, contributing to clarifying how the values of the main series develop over time. An example of such a model would be one capable of simultaneously predicting the energy consumption in various service-providing utilities in the country [24][25].

2.2. Utilization of Established Software Solutions

Continuing the analysis of optimized sizing for hybrid systems, it is important to note that many relevant articles in the literature also employ established software, incorporating the previously mentioned techniques. Examples include HOMER and MATLAB for analyses, simulations, and practical implementations. These tools are crucial in validating and applying proposed solutions in real-world scenarios.

- HOMER (Hybrid Optimization Model for Multiple Energy Resources): This is a tool designed to analyze and optimize hybrid energy systems. It enables the evaluation of various configurations of hybrid energy systems, considering renewable energy sources, energy storage, and other components. HOMER is widely employed to conduct economic and technical feasibility analyses for hybrid energy system projects [26].

- MATLAB: This is a numerical computing and programming platform that provides a flexible environment for implementing optimization and machine learning algorithms. It also allows for the integration of additional tools and the creation of custom models. MATLAB is a common choice for implementing and testing proposed solutions in hybrid energy systems [1][15][27].

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