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A Rule-Based Modular Energy Management System for AC/DC Hybrid Microgrids

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Abstract: Microgrids are considered a practical solution to revolutionize power systems due to their ability to island and sustain the penetration of renewables. Most existing studies have focused on the optimal management of microgrids with a fixed configuration. This restricts the application of developed algorithms to other configurations without major modifications. The objective of this study is to design a rule-based modular energy management system (EMS) for microgrids that can dynamically adapt to the microgrid configuration. To realize this framework, first, each component is modeled as a separate entity with its constraints and bounds for variables. A wide range of components such as battery energy storage systems (BESSs), electric vehicles (EVs), solar photovoltaic (PV), microturbines (MTs), and different priority loads are modeled as modules. Then, a rule-based system is designed to analyze the impact of the presence/absence of one module on the others and update constraints. For example, load shedding and PV curtailment can be permitted if the grid module is not included. The constraints of microgrid components present in any given configuration are communicated to the EMS, and it optimizes the operation of the available components. The configuration of microgrids could be as simple as flexible loads operating in grid-connected mode or as complex as a hybrid microgrid with AC and DC buses with a diverse range of equipment on each side. To facilitate the realization of diverse configurations, a hybrid AC/DC microgrid is considered where the utility grid and interlinking converter (ILC) are also modeled as separate modules. The proposed method is used to test performance in both grid-connected and islanded modes by simulating four typical configurations in each case. Simulation results have shown that the proposed rule-based modular method can optimize the operation of a wide range of microgrid configurations.

Keywords: distributed energy resources; energy storage; flexible configuration; microgrids; rule-based energy management



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1. Introduction

1.1. Background and Motivation

The penetration of renewable distributed energy resources (DERs) is increasing in power systems due to their sustainability and environmental friendliness [1]. However, managing a huge number of DERs is challenging for centralized entities such as utilities. Therefore, the concept of microgrids has emerged as a practical solution for the integration of DERs within local communities. On one hand, microgrids can sustain the penetration of DERs due to the presence of local loads [2]. On the other hand, they can enhance

resilience during power outages due to their ability to island [3]. In addition, microgrids are considered a viable solution for rural/remote communities without access to electricity (rural electrification). They are a cheaper and more sustainable solution compared to connecting these communities with the central grids [4].

To achieve the benefits of microgrids mentioned in the previous paragraph, efficient management of microgrids is required. Microgrids can have various configurations, ranging from simple setups with a single DER and loads connected to an AC grid to complex hybrid systems featuring both AC and DC buses, interconnected via an interlinking converter (ILC) [5]. Different components of microgrids include renewable DERs, controllable DERs, battery energy storage systems (BESSs), electric vehicles (EVs), and various types of loads with different priorities. A centralized energy management system (EMS) is generally utilized to manage the resources of the microgrids [6,7]. The EMS is responsible for communicating with the upstream grid and for the optimal utilization of the local resources. In addition, various studies have proposed decentralized [8,9] and distributed [10,11] mechanisms for the energy management of microgrids.

1.2. Literature Review

The existing microgrid energy management methods can be categorized into four major categories: mathematical modeling, heuristic and metaheuristic methods, machine learning, and expert and fuzzy systems [12]. Several studies have also combined one or more methods from each category; details are provided in the following paragraphs.

A multi-stage stochastic programming model is proposed in [13] for operating microgrids by considering short- and long-term models. The short-term model updates forecasts every six hours, while the long-term model assesses stored energy value beyond the forecast horizon. Similarly, a two-stage control strategy for a grid-connected microgrid is proposed in [14] under uncertain solar irradiance and load demand. The first stage uses scenario-based stochastic programming, while the second stage employs rule-based methods for real-time controls. A Stackelberg game approach is proposed in [15] for microgrids with prosumers and EV charging stations. This study focuses on optimizing energy sharing while allowing the microgrid to operate independently from the utility grid during the islanded mode. Chance-constrained optimization is used in [16] for scheduling local resources in microgrids while considering system ramping limits.

Several studies have employed heuristic and metaheuristic algorithms for the energy management of microgrids. For example, improved particle swarm optimization (PSO) is used in [17] to combine day-ahead multi-modal demand-side management and energy storage operation in microgrids. The operating performance of a grid-connected microgrid integrated with DERs is assessed in [18] for multi-objective problems of cost optimization and economic scheduling. It uses various physics-based metaheuristic techniques such as black hole optimization (BHO) and lightning search algorithm (LSA). A multi-objective optimization strategy for designing and operating stand-alone renewable energy systems for rural electrification is proposed in [19], aiming to balance system cost and energy/power supply. In this study, multi-objective evolutionary techniques are used to provide a manageable set of efficient configurations.

Several studies have used rule-based systems such as expert systems and fuzzy-logic-based systems for the energy management of microgrids. For example, a fuzzy inference system-based EMS for real-time control of energy flows in grid-connected microgrids is proposed in [20], and is optimized using a genetic algorithm. An optimal adaptive intelligent energy management strategy for a DC microgrid is proposed in [21] using fuzzy logic. It uses PSO and salp swarm algorithm (SSA) to update fuzzy membership functions based on energy provided by the fuel cell and main grid. A fuzzy logic control-based EMS

for isolated microgrids in rural Ecuador is proposed in [22]. The efficiency of the EMS is improved by applying PSO and cuckoo search (CS) algorithms to adjust fuzzy parameters.

Recently, reinforcement learning (RL) and deep reinforcement learning (DRL) have also been widely used for managing microgrid operations. For example, a real-time dynamic optimal energy management strategy for microgrids using a DRL algorithm (proximal policy optimization) is proposed in [23]. It can deal with the uncertainty in DERs and load by learning from historical data. Similarly, a resilience-oriented microgrid formation method is proposed in [24] to enhance distribution network resilience against extreme weather events. It uses deep RL (Q-networks) for both offline training and online applications. An optimal scheduling model for isolated microgrids is proposed in [25] that uses automated RL-based multi-period forecasting. In addition, IoT has also been used in recent studies. For example, the authors of [26] present a smart EMS incorporating IoT for efficient control, monitoring, and integration of renewable energy systems with the utility grid, addressing the unique challenges of microgrids and modern power systems.

Finally, different studies have used a combination of methods for managing the operation of microgrids. Clustering algorithms and Markov chains are used in [27] to derive consumption patterns from sociodemographic data and apply prediction interval models to generate scenarios for optimal sizing and topology of microgrids. The authors of [28] introduced a hybrid optimization strategy combining a rule-based expert system with reinforcement learning to enhance microgrid demand flexibility. The authors of [28] introduced an optimal operation approach for microgrids using a hybrid method that incorporates game theory and multi-agent systems. The approach utilizes game theory to minimize operational costs. Multi-agent guiding PSO is used to enhance the optimization process by adjusting global positions and vectors.

1.3. Research Gaps and Contributions

It can be observed from the literature review that a variety of methods are used for optimal energy management of microgrids. Since microgrids can operate in both grid-connected and islanded modes, some studies [16,17,21,23] have focused only on the grid-connected mode while others have focused on the islanded mode [22,25,27]. Some of these studies have focused on both grid-connected and islanded modes [5,18,24]. However, different problems are formulated for each mode. In addition, the configuration of microgrids could vary significantly based on the location and purpose of the microgrid. Microgrids could be as simple as a DG with the load connected to an AC grid or as complex as a hybrid AC/DC microgrid with its loads, DERs, EVs, BESSs, and AC/DC buses [29]. Most studies have used a fixed configuration of microgrids, which makes the proposed algorithms applicable to that particular configuration only. In cases of any configuration changes (addition or removal of a component), the entire algorithm needs to be rewritten or retrained. Moreover, many existing studies do not adequately address the dynamic interactions between different microgrid components, leading to suboptimal performance when system configurations change. Additionally, scalability and adaptability are often overlooked, limiting the practical application of these methods in diverse real-world scenarios. Therefore, a generalized EMS is required that contains all types of microgrid components and has the ability to island. Operators can just select the type of equipment available for that particular microgrid and obtain the optimal operation results, which is missing in the existing literature.

It is important to highlight the availability of several commercial tools designed for modeling various microgrid configurations. These include HOMER [30], which focuses on sizing and optimizing hybrid systems; RETScreen [31], which evaluates energy output, life cycle costs, and greenhouse gas emissions; and TRNSYS [32], which analyzes transient

behaviors, such as solar energy applications, building thermal performance, and electrical systems. However, these tools are neither open source nor free to use. This study aims to address this limitation by offering an open-source platform [33] that researchers can utilize and enhance for their own work.

This study introduces a rule-based modular energy management system (EMS) designed to address diverse configurations of hybrid AC/DC microgrids. The proposed framework integrates various microgrid components, including renewable DERs, controllable DERs, BESSs, EVs, and different types of loads. A hybrid AC/DC microgrid system with interconnection through an interlinking converter (ILC) is used to test the framework. The EMS dynamically adapts constraints based on the components present in the configuration and evaluates performance under grid-connected and islanded modes. The major contributions of this study are as follows:

- A rule-based modular EMS framework is proposed to support diverse microgrid configurations, dynamically incorporating specific constraints for renewable DERs, controllable DERs, BESSs, EVs, and multiple load types based on their presence.
- The framework adopts a hybrid AC/DC microgrid structure with dual buses interconnected by an ILC, ensuring compatibility with a wide range of configurations and facilitating the integration of components on either side of the microgrid.
- Detailed component models are provided, and constraints are dynamically updated for advanced configurations (e.g., AC and DC buses with BESSs, EVs, DERs, and priority loads).
- The proposed EMS optimizes operational costs and enhances service reliability, with its effectiveness demonstrated through extensive performance evaluations in grid-connected and islanded modes under various scenarios.

The remainder of this paper is organized as follows. The models of individual modules are developed in Section 2. The rule-based energy management module of the system is discussed in Section 3. The performance of the proposed method is evaluated under different cases for the grid-connected mode in Section 4 and islanded mode in Section 5. Finally, conclusions and future research directions are presented in Section 6.

2. Modular Modeling

Modular modeling refers to the modeling of individual components separately, including the constraints related to them. This also includes consideration of other factors and components whose presence could impact the operation of another component, i.e., rule-based modeling. For example, during the islanding mode, microgrids are allowed to curtail loads to maintain the power balance of the system [34]. Similarly, renewable curtailment is also allowed during the islanded mode to balance the power of the system [35]. Therefore, these modules need to have the grid status information to update their constraints based on the grid condition. In the subsequent subsections, an overview of the system under consideration and the components considered in this study are discussed.

2.1. System Configuration

In this study, a complex form of the microgrid is considered to cover diverse cases with different components. An overview of the AC/DC hybrid microgrid considered in this study is shown in Figure 1. Regarding power flow, it can be observed that the microgrid consists of an AC and a DC microgrid connected via an ILC. The AC microgrid is connected to the grid, and the DC microgrid can only exchange power with the utility grid via the ILC. Both AC and DC parts have their DERs, such as solar PV and microturbines (MTs). In addition, both sides could have stationary energy storage (BESS) and mobile energy storage (EVs). The loads on both sides are divided into critical and non-critical loads.

An EMS is responsible for managing the hybrid microgrid. Based on the selected components and the status of different equipment, the EMS determines the optimal energy management strategy for the microgrid. The EMS is also responsible for communicating with the upper stream grid and exchanging power with it [36]. An overview of the information flow (communication network) is also presented in Figure 1.

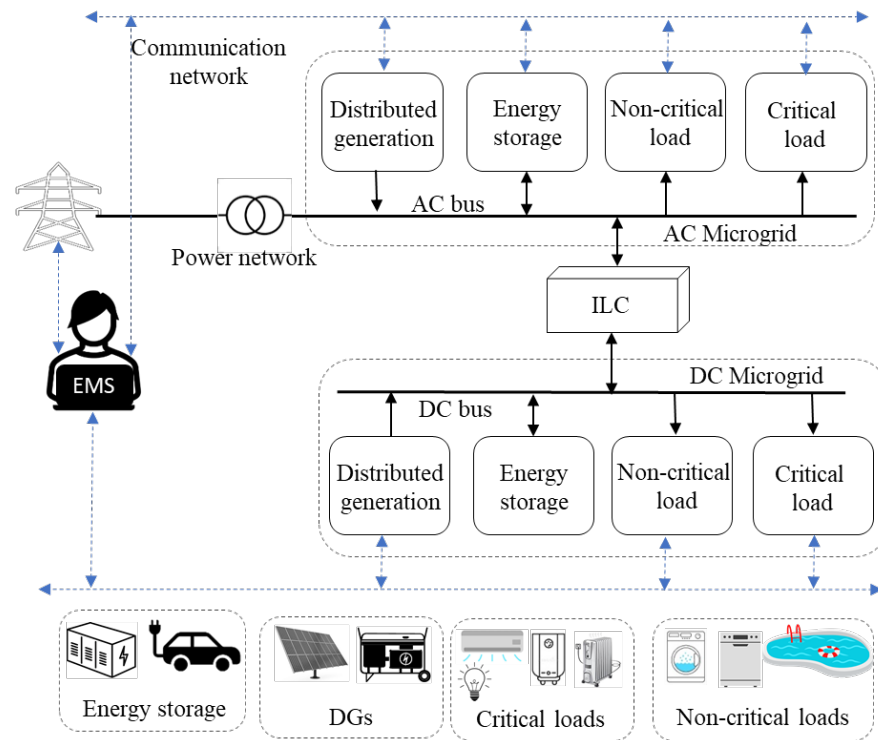


Figure 1. Overview of the hybrid AC/DC microgrid and its components.

2.2. Rule-Based Individual Module Modeling

The following subsections present the rule-based modeling of individual microgrid components, detailing their respective constraints under various operating conditions. These conditions account for the connection between AC and DC microgrids (determined by the operational status of the ILC) and the interaction with the utility grid (defined by the microgrid's operational mode). The overall optimization model, incorporating components selected by the operator, is described in the subsequent section. It is important to note that the constraints for each module are defined by their upper and lower bounds, which are set by the user, along with specific user-defined limits, such as state of charge limits for storage devices, among others.

2.2.1. Battery Energy Storage System

The first element is the BESS, and it could be on both the AC and DC sides of the microgrid. For the purposes of this study, only a battery energy storage system is considered. The constraints are generalized to accommodate various types of batteries, such as lithium-ion, Nickel-Cadmium, and others. The model is designed to accept specific input parameters from the user to represent each type of battery. An overview of the BESS model creation and the inclusion of different constraints under various conditions is shown in Figure 2. Initially, the parameters of the BESS are obtained from the graphical user interface (GUI) as input by the user or from default parameters. Then, the upper (ub_{bx}) and lower (lb_{bx}) bounds for charging and discharging are defined, as given by the following two equations.

$$\mathbf{ub}_{bx} = \begin{bmatrix} p^{bmax} \mathbf{1}_N \\ \mathbf{0}_N \end{bmatrix} \quad (1)$$

$$\mathbf{lb}_{bx} = \begin{bmatrix} \mathbf{0}_T \\ -p^{bmax} \mathbf{1}_N \end{bmatrix} \quad (2)$$

It implies that the BESS can be charged between 0 and p^{bmax} during each interval. Similarly, it can be discharged between $-p^{bmax}$ and 0. The parameter N refers to the total number of intervals in the scheduling horizon, and $\mathbf{0}_N$ refers to an $(N, 1)$ array of zeros. The term x refers to the side of the microgrid and can be replaced with AC or DC for each side.

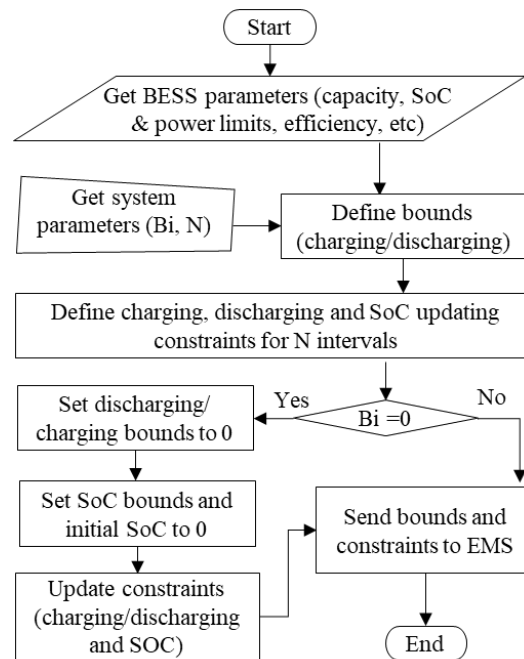


Figure 2. Modeling of BESS constraints.

Then, the constraints for the upper and lower bounds of the BESS state of charge (SoC) are introduced as inequality constraints ($Ax \leq b$) as follows:

$$\mathbf{A}_{bx} = \begin{bmatrix} -\mathbf{0}_{(N,N \times 19)} & -\frac{t \cdot 100}{B^{cap}} \mathbf{T}_{(N,N)} \cdot \frac{1}{\eta_b^c} & -\frac{t \cdot 100}{B^{cap}} \mathbf{T}_{(N,N)} \cdot \eta_b^d & -\mathbf{0}_{(N,N \times 8)} \\ \mathbf{0}_{(N,N \times 19)} & \frac{t \cdot 100}{B^{cap}} \mathbf{T}_{(N,N)} \cdot \frac{1}{\eta_b^c} & \frac{t \cdot 100}{B^{cap}} \mathbf{T}_{(N,N)} \cdot \eta_b^d & \mathbf{0}_{(N,N \times 8)} \end{bmatrix} \quad (3)$$

$$\mathbf{b}_{bx} = \begin{bmatrix} (-\text{SoC}^{bini} + \text{SoC}^{bmax}) \mathbf{1}_N \\ (\text{SoC}^{bini} - \text{SoC}^{bmin}) \mathbf{1}_N \end{bmatrix} \quad (4)$$

The first line of each matrix corresponds to the upper SoC bound (SoC^{bmax}) constraint, and the second line corresponds to the lower SoC bound (SoC^{bmin}) constraint. Zeros are padded at the beginning and the end of the matrix to keep the size of the matrix consistent. The two non-zero terms in the middle correspond to charging and discharging, respectively. It can be observed that charging (η_b^c) and discharging (η_b^d) efficiencies are considered. In these terms, B^{cap} is the capacity of the battery in kWh, t is the resolution of the time interval in hours, and $\mathbf{T}(N, N)$ is an $N \times N$ lower triangular matrix. This matrix accumulates the power charged/discharged from $t = 1$ to the current time interval, i.e., SoC. Finally, SoC^{bini} in the b matrix is the initial SoC of the BESS.

If the capacity of the BESS (B^{cap}) is set to zero or the BESS box is unchecked in the GUI ($B_i = 0$), then the upper and lower bounds are updated as follows:

$$\mathbf{lb}_{\text{bx}} = \mathbf{ub}_{\text{bx}} = \mathbf{0}_{(N,2)} \quad (5)$$

This ensures that the BESS can neither be charged nor discharged during this operation. In addition, the initial SoC (SoC^{bini}) and the lower bound of SoC (SoC^{bmin}) are also set to zero. This ensures that no energy can be used from the BESS and that the constraints are not violated.

$$\text{SoC}^{\text{bini}} = \text{SoC}^{\text{bmin}} = 0 \quad (6)$$

In the case of the presence of a non-zero-sized BESS, the original bounds and the original constraints are sent to the EMS. However, in the case of a zero-sized BESS (no BESS), the updated bounds are sent to the EMS.

2.2.2. Electric Vehicles

EVs are generally modeled similarly to BESSs, with certain additional constraints related to arrival and departure times and target SoC requirements. They can be charged (grid-to-vehicle: G2V) and discharged (vehicle-to-grid: V2G) [37]. An overview of the step-by-step process for modeling EVs is shown in Figure 3. Similar to the BESS, first, the lower ($\mathbf{lb}_{\text{ex}}$) and upper ($\mathbf{ub}_{\text{ex}}$) bounds of charging and discharging for EVs are introduced as follows:

$$\mathbf{lb}_{\text{ex}} = \begin{bmatrix} \mathbf{0}_N \\ -P^{\text{emax}} \cdot \mathbf{E}^{\text{par}} \end{bmatrix} \quad (7)$$

$$\mathbf{ub}_{\text{ex}} = \begin{bmatrix} P^{\text{emax}} \cdot \mathbf{E}^{\text{par}} \\ \mathbf{0}_N \end{bmatrix} \quad (8)$$

where

$$\mathbf{E}^{\text{par}} = \begin{cases} 0 & \text{if } n < T_a \text{ or } n \geq T_d \\ 1 & \text{otherwise} \end{cases} \quad (9)$$

EVs can charge (G2V) between 0 and the rating of the charging station, P^{emax} , and can discharge (V2G) between $-P^{\text{emax}}$ and 0. An EV parking vector ($\mathbf{E}^{\text{par}}$) is introduced to charge/discharge EVs only during their parking duration. It takes a value of 0 before the arrival time (T_a) and after the departure time (T_d), and a value of 1 otherwise. The SoC updating constraints for EVs are modeled as inequality constraints ($\mathbf{Ax} \leq \mathbf{b}$):

$$\mathbf{A}_{\text{ex}} = \begin{bmatrix} -\mathbf{0}_{(N,N \times 23)} & -\frac{t \cdot 100}{E^{\text{cap}}} \mathbf{T} \cdot \frac{1}{\eta_e^c} & -\frac{t \cdot 100}{E^{\text{cap}}} \mathbf{T} \cdot \eta_e^d & -\mathbf{0}_{(N,N \times 4)} \\ \mathbf{0}_{N \times (N \times 23)} & \frac{t \cdot 100}{E^{\text{cap}}} \mathbf{T} \cdot \frac{1}{\eta_e^c} & \frac{t \cdot 100}{E^{\text{cap}}} \mathbf{T} \cdot \eta_e^d & \mathbf{0}_{(N,N \times 4)} \\ \mathbf{0}_{(N,N \times 23)} & \frac{t \cdot 100}{E^{\text{cap}}} \mathbf{T}^{\text{tar}} \cdot \frac{1}{\eta_e^c} & \frac{t \cdot 100}{E^{\text{cap}}} \mathbf{T}^{\text{tar}} \cdot \eta_e^d & \mathbf{0}_{(N,N \times 4)} \end{bmatrix} \quad (10)$$

$$\mathbf{b}_{\text{ex}} = \begin{bmatrix} (-\text{SoC}^{\text{eini}} + \text{SoC}^{\text{emax}}) \mathbf{1}_N \\ (\text{SoC}^{\text{eini}} - \text{SoC}^{\text{emin}}) \mathbf{1}_N \\ (\text{SoC}^{\text{eini}} - \text{SoC}^{\text{etar}}) \cdot \mathbf{E}^{\text{tar}} \end{bmatrix} \quad (11)$$

where the first line corresponds to the upper SoC bound (SoC^{emax}), the second line to the lower SoC bound (SoC^{emin}), and the third line to the target SoC bound (SoC^{etar}). Similar to the BESS model, zeros are appended for consistency of the problem size. η_e^c and η_e^d are the charging and discharging efficiencies of the EV. Similarly, E^{cap} is the capacity of the EV in

kWh, t is the resolution of the time interval in hours, $\mathbf{T}(N, N)$ is an $N \times N$ lower triangular matrix, and SoC^{ini} in the $\mathbf{b}$ matrix is the initial SoC of the EV. $\mathbf{T}^{\text{tar}}$ in the last line of matrix $\mathbf{A}$ is the departure identifier matrix, which is computed as

$$\mathbf{T}^{\text{tar}} = \begin{cases} \mathbf{1}_N & \text{if } n = T_d \\ \mathbf{0}_N & \text{otherwise} \end{cases} \quad (12)$$

where T_d is the departure time of the EV, and $\mathbf{1}_N$ and $\mathbf{0}_N$ are $N \times 1$ vectors. $\mathbf{T}^{\text{tar}}$ identifies the departure time and imposes the target SoC constraints. Similarly, $\mathbf{E}^{\text{tar}}$ is defined for matrix $\mathbf{b}$ to identify the departure time, as follows:

$$\mathbf{E}^{\text{tar}} = \begin{cases} 1 & \text{if } n = T_d \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

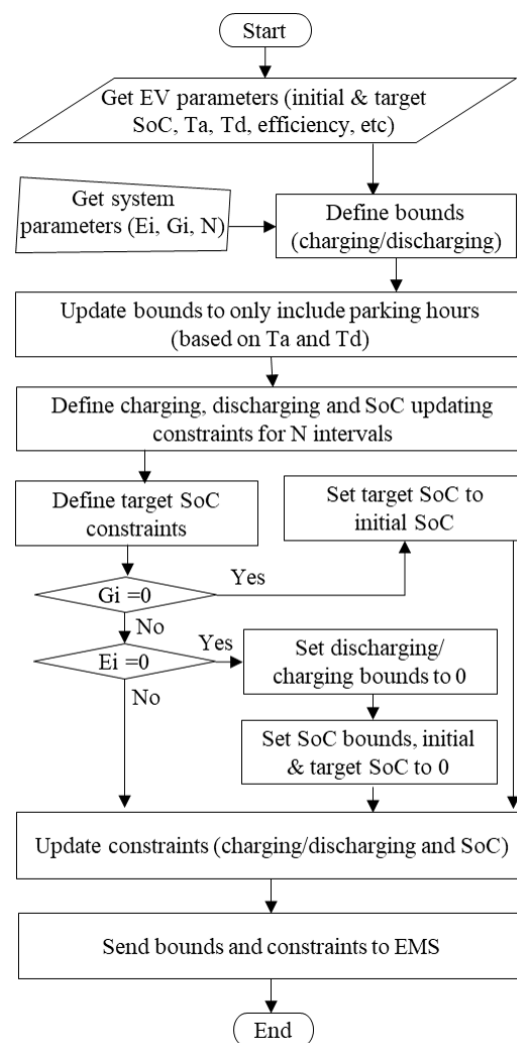


Figure 3. Modeling of EV constraints.

If the capacity of the EV (E^{cap}) is set to zero or the EV box is unchecked in the GUI ($E_i = 0$), then the upper and lower bounds are updated as follows:

$$\mathbf{lb}_{\text{ex}} = \mathbf{ub}_{\text{ex}} = \mathbf{0}_{(N,2)} \quad (14)$$

Similarly, the initial (SoC^{eini}), minimum (SoC^{emin}), and target (SoC^{etar}) SoCs are also set to zero to ensure that no constraints are violated.

$$SoC^{eini} = SoC^{emin} = SoC^{etar} = 0 \quad (15)$$

In the case of islanded mode ($G_i = 0$), the SoC target is set to the initial SoC. This ensures that all critical loads are served before charging the EVs.

$$SoC^{etar} = SoC^{eini} \quad (16)$$

Finally, if the EV is selected by the operator, the original bounds and constraints are sent to the EMS. However, in the case of zero-sized EVs (no EV), the updated bounds are sent to the EMS.

2.2.3. Microturbine

The microturbine is considered a controllable distributed generator and is available for the AC side of the microgrid. The step-by-step process for modeling the MT under different cases is shown in Figure 4. First, the parameters of the MT (defined by users or default values) are obtained. The cost function of the MT (F^{cost}) is modeled as a quadratic function.

$$F^{cost}(P^{mt}) = \alpha + \beta \cdot P^{mt} + \gamma \cdot (P^{mt})^2 \quad (17)$$

where α , β , and γ are the cost parameters, and P^{mt} is the amount of power generated by the MT. The quadratic function is then transformed into a piecewise linear function to preserve convexity. The slope of each piece a (S_a^{mt}) can be computed as

$$S_a^{mt} = \frac{F^{cost}(P^{pmax} \cdot a) - F^{cost}(P^{pmax} \cdot (a - 1))}{P^{pmax}} \quad (18)$$

where P^{pmax} is the maximum power of the MT in kW. Then, the lower and upper bounds for each piece are defined as

$$\mathbf{lb}_{mx} = \begin{bmatrix} \mathbf{0}_N \\ \cdot \\ \cdot \\ \mathbf{0}_{N \times P} \end{bmatrix} \quad (19)$$

$$\mathbf{ub}_{mx} = \begin{bmatrix} 1.51_N \\ \mathbf{P}_N^{pmax} \\ \cdot \\ \cdot \\ \mathbf{P}_{N \times P}^{pmax} \end{bmatrix} \quad (20)$$

where P is the total number of pieces and P^{pmax} is the maximum power of the MT. It implies that each piece of MT can generate power between 0 and P^{pmax} . If the capacity of the MT is set to zero or is unchecked in the GUI, the bounds are updated as

$$\mathbf{lb}_{mx} = \mathbf{ub}_{mx} = \mathbf{0}_{(N \times P + 1, N)} \quad (21)$$

This forces the MT to generate no power. The total power generated by the MT is modeled as an inequality constraint ($Ax \leq b$)

$$\mathbf{A}_{mx} = \begin{bmatrix} \mathbf{0}_{(N, N \times 8)} & -\mathbf{E}_{(N, N)} & \frac{\mathbf{E}_{(N, N \times P)}}{P^{pmax} \cdot P} & \mathbf{0}_{(N, N \times 10)} \end{bmatrix} \quad (22)$$

$$\mathbf{b}_{mx} = \begin{bmatrix} \mathbf{0}_N \end{bmatrix} \quad (23)$$

where $\mathbf{E}_{(N,N)}$ is an $N \times N$ eye matrix (matrix with 1 in diagonals only). Finally, the original constraints are sent to the EMS in case of the presence of MT, and the updated constraints are sent to the EMS if MT is not selected.

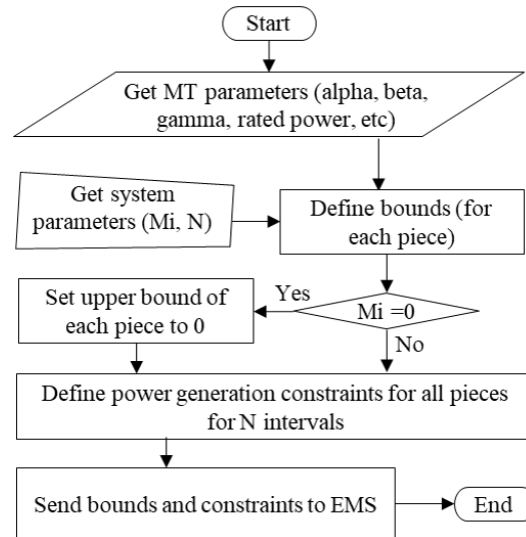


Figure 4. Modeling of microturbine constraints.

2.2.4. Solar Photovoltaic

The output power of PV is taken as a negative load, and unit profiles are used as input. The profile is scaled based on the size selected by the user. The step-by-step process for incorporating PV under different cases is shown in Figure 5. If PV is not present in the system or the rated capacity is set to zero by the user, a zero array of size $N \times 1$ is generated and sent to the EMS, as depicted below.

$$\mathbf{P}_x^{pv} = \mathbf{0}_N \quad (24)$$

However, in the case of a non-zero-sized PV, the rated capacity ($PV_x^{\max}$) is multiplied by the unit profile of the PV ($\mathbf{P}_{ux}^{pv}$), and the PV power vector ($\mathbf{P}_x^{pv}$) is sent to the EMS. The term x is used to identify the side of the microgrid, i.e., AC or DC.

$$\mathbf{P}_x^{pv} = \mathbf{P}_{ux}^{pv} \times PV_x^{\max} \quad (25)$$

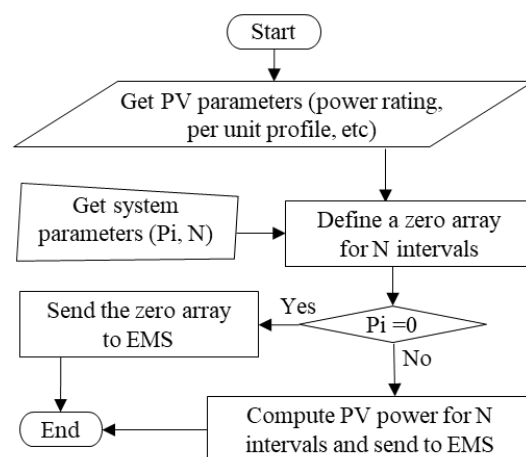


Figure 5. Modeling of PV constraints.

2.2.5. Interlinking Converter

The ILC is used to exchange power between the AC and DC parts of the microgrids. The DC part is connected to the utility grid via the ILC, i.e., not directly connected. The step-by-step process for modeling the ILC and its constraints under different cases is shown in Figure 6. First, the parameters related to the ILC are gathered from the GUI. Then, the lower ($\mathbf{l}b_i$) and upper ($\mathbf{u}b_i$) bounds of power transfer are defined as

$$\mathbf{l}b_i = \begin{bmatrix} \mathbf{0}_N \\ -\frac{p^{imax}}{\eta^i} \cdot \mathbf{1}_N \end{bmatrix} \quad (26)$$

$$\mathbf{u}b_i = \begin{bmatrix} p^{imax} \cdot \mathbf{1}_N \\ \mathbf{0}_N \end{bmatrix} \quad (27)$$

where η^i is the efficiency of the converter and p^{imax} is the rated power of the converter. It can be observed that each side can send power between 0 and p^{imax} to the other side, and the second side can receive between $-\frac{p^{imax}}{\eta^i}$ and 0. If the ILC is out of order ($I_i = 0$), then the bounds are updated as

$$\mathbf{l}b_i = \mathbf{u}b_i = \mathbf{0}_{N \times 2} \quad (28)$$

It implies that during ILC contingencies, the power exchange between the AC and DC sides is forced to zero. Finally, in the case of a healthy ILC, the original bounds are sent to the EMS, while in the case of a fault, the updated bounds are sent to the EMS.

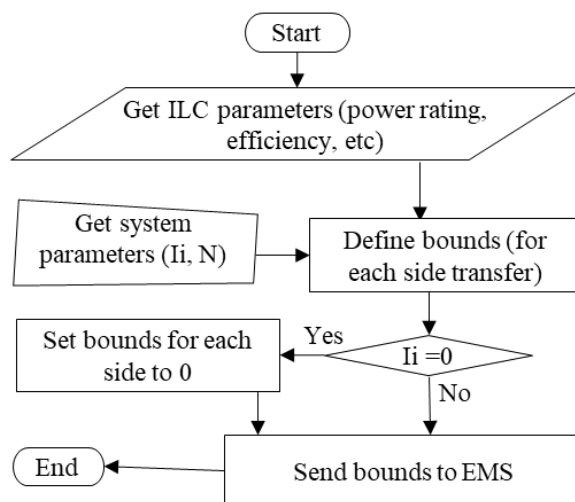


Figure 6. Modeling of interlinking converter constraints.

2.2.6. Utility Grid

The module emulates the interaction of the microgrid with the utility grid. The grid module plays an important role in managing the local resources of the microgrids under different grid conditions. The step-by-step process for modeling the grid module is shown in Figure 7. First, different parameters related to the grid and loads are defined. Then, the lower ($\mathbf{l}b_g$) and upper ($\mathbf{u}b_g$) bounds are defined as follows:

$$\mathbf{l}\mathbf{b}_g = \begin{bmatrix} \mathbf{0}_N \\ -p_{gmax} \cdot \mathbf{1}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \end{bmatrix} \quad (29)$$

$$\mathbf{u}\mathbf{b}_g = \begin{bmatrix} p_{gmax} \cdot \mathbf{1}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \end{bmatrix} \quad (30)$$

The first two rows correspond to grid buying and selling, respectively. It implies that the microgrid can buy between 0 and p_{gmax} and can also sell between $-p_{gmax}$ and 0. The third and fourth rows correspond to the load shedding of critical and non-critical loads, respectively, on the AC side, and the next two rows correspond to the shedding of critical and non-critical loads on the DC side. The last two rows correspond to the curtailment of PV power on the AC and DC sides. It implies that load shedding and PV curtailment are prohibited in normal conditions. However, in the case of grid outages, these bounds are updated as follows:

$$\mathbf{l}\mathbf{b}_g = \mathbf{0}_{N \times 8} \quad (31)$$

$$\mathbf{u}\mathbf{b}_g = \begin{bmatrix} \mathbf{0}_N \\ \mathbf{0}_N \\ \mathbf{p}^{clac} \\ \mathbf{p}^{nlac} \\ \mathbf{p}^{cldc} \\ \mathbf{p}^{nldc} \\ \mathbf{p}^{pvac} \\ \mathbf{p}^{pvdc} \end{bmatrix} \quad (32)$$

It can be observed that grid trading is not allowed during islanded mode. In addition, the upper bounds of load shedding and PV curtailment are updated to the maximum levels. Finally, in the case of ILC failure, only the limits of the DC side are updated as follows. This is because, during ILC failure, the DC part of the microgrid operates in islanded mode.

$$\mathbf{u}\mathbf{b}_g = \begin{bmatrix} p_{gmax} \cdot \mathbf{1}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \\ \mathbf{0}_N \\ \mathbf{p}^{cldc} \\ \mathbf{p}^{nldc} \\ \mathbf{0}_N \\ \mathbf{p}^{pvdc} \end{bmatrix} \quad (33)$$

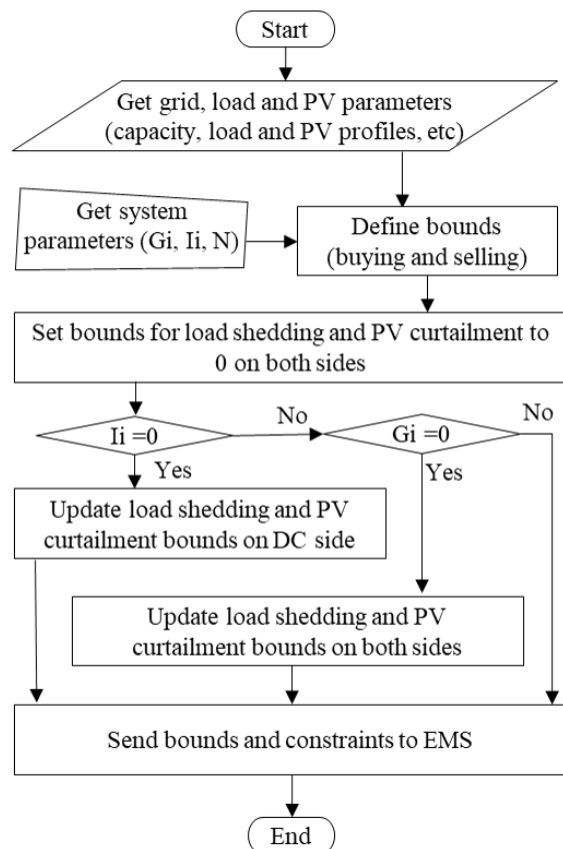


Figure 7. Modeling of utility grid constraints.

3. Modular Energy Management

In this section, an optimization model is formulated using the individual component models outlined in the previous section. A Mixed Integer Linear Programming (MILP) model is developed to represent the rule-based modular EMS. MILP is a well-established optimization framework widely used in energy management systems due to its ability to handle complex decision-making problems involving both continuous and discrete variables. Its linear structure ensures convexity, which guarantees that a global optimal solution can be found efficiently using advanced solvers. This makes MILP particularly suitable for rule-based modular EMS applications, where optimizing operational decisions under various constraints is critical. The development begins with the mathematical framework for the modular EMS, followed by a step-by-step explanation of how various components are integrated into the EMS.

3.1. Problem Formulation

The optimization problem is formulated as a linear programming problem with the following generalized form.

$$\text{minimize } f^T \mathbf{x} \quad (34)$$

subject to

$$\mathbf{A}\mathbf{x} \leq \mathbf{b} \quad (35)$$

$$\mathbf{A}_{eq}\mathbf{x} = \mathbf{b}_{eq} \quad (36)$$

$$\mathbf{lb} \leq \mathbf{x} \leq \mathbf{ub} \quad (37)$$

where f^T is the objective function and $\mathbf{x}$ is the decision variable vector. Matrix $\mathbf{A}$ and vector $\mathbf{b}$ represent the inequality constraints, while matrix $\mathbf{A}_{eq}$ and vector $\mathbf{b}_{eq}$ represent the equality constraints. Finally, vectors $\mathbf{ub}$ and $\mathbf{lb}$ represent the upper and lower bounds of the variables. Based on the different modules considered in this study, the objective function is formulated as

$$f = t \cdot \begin{bmatrix} \mathbf{PR}^{buy} \\ \mathbf{PR}^{sell} \\ \mathbf{Pen}^{clac} \\ \mathbf{Pen}^{nlac} \\ \mathbf{Pen}^{cldc} \\ \mathbf{Pen}^{nldc} \\ \mathbf{Pen}^{pvac} \\ \mathbf{Pen}^{pvd} \\ \alpha \cdot \mathbf{1}_N \\ \mathbf{S}^{mt}(1) \cdot \mathbf{1}_N \\ \vdots \\ \mathbf{S}^{mt}(P) \cdot \mathbf{1}_N \\ \mathbf{0}_{N \times 10} \end{bmatrix} \quad (38)$$

where t is the resolution of the time step in hours. The first two terms represent the grid buy ($\mathbf{PR}^{buy}$) and sell ($\mathbf{PR}^{sell}$) prices. The next two terms represent the penalty for shedding critical ($\mathbf{Pen}^{clac}$) and non-critical ($\mathbf{Pen}^{nlac}$) loads on the AC side. The 5th and 6th terms represent the penalty for shedding critical ($\mathbf{Pen}^{cldc}$) and non-critical ($\mathbf{Pen}^{nldc}$) loads on the DC side. The 7th and 8th terms represent the penalty for curtailment of PV power in the AC ($\mathbf{Pen}^{pvac}$) and DC ($\mathbf{Pen}^{pvd}$) sides, respectively. The penalty vector for shedding critical loads (AC and DC) is the same and is computed as

$$\mathbf{Pen}^{clac} = \mathbf{Pen}^{cldc} = \mathbf{Pen}^{cl} \times \mathbf{1}_N, \quad (39)$$

where $\mathbf{Pen}^{cl}$ is the penalty for shedding critical loads. Similarly, the penalty vector for shedding non-critical loads (AC and DC) is the same and is computed as

$$\mathbf{Pen}^{nlac} = \mathbf{Pen}^{nldc} = \mathbf{Pen}^{nl} \times \mathbf{1}_N, \quad (40)$$

where $\mathbf{Pen}^{nl}$ is the penalty for shedding non-critical loads. Finally, the penalty vector for curtailing PV power on both the AC and DC sides is computed as

$$\mathbf{Pen}^{pvac} = \mathbf{Pen}^{pvd} = \mathbf{Pen}^{pv} \times \mathbf{1}_N, \quad (41)$$

where $\mathbf{Pen}^{pv}$ is the penalty for curtailing PV power. The relation among different factors is set below:

$$\mathbf{Pen}^{pv} < \mathbf{Pen}^{nl} < \mathbf{Pen}^{cl}. \quad (42)$$

It can be observed that the shedding of critical loads is penalized the highest, while that of PV is penalized the lowest. This ensures that non-critical loads are shed first during emergencies.

The next few terms in the objective function correspond to MT cost, where the first term is the fixed cost, followed by the cost of generating power from each piece of the piecewise function, where P is the maximum number of pieces. Zeros are appended at the end to cater to those components that do not have an operation cost component, such as the BESS, EVs, and ILC.

The inequality constraints are formulated by combining inequality constraints from all components, such as the BESS, EV, and MT. Details about the constraints of individual components are discussed in the respective modules in the previous section.

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_{bac}; \mathbf{A}_{bdc}; \mathbf{A}_{eac}; \mathbf{A}_{edc}; \mathbf{A}_{mac} \end{bmatrix} \quad (43)$$

$$\mathbf{b} = \begin{bmatrix} \mathbf{b}_{bac}; \mathbf{b}_{bdc}; \mathbf{b}_{eac}; \mathbf{b}_{edc}; \mathbf{b}_{mac} \end{bmatrix} \quad (44)$$

The equality constraints are formulated as follows. The equality constraints correspond to the power balance on the AC and DC sides. The first line corresponds to the power balance on the AC side, while the second line corresponds to the DC side.

$$\mathbf{A}_{eq} = \begin{bmatrix} \mathbf{E}_2 & \mathbf{E}_2 & \mathbf{0}_2 & -\mathbf{E}_1 & \mathbf{0}_1 & \mathbf{E}_{p+1} & \mathbf{E}_2 & \mathbf{0}_2 & \mathbf{E}_2 & \mathbf{0}_2 & -\mathbf{E}_2/\eta^i \\ \mathbf{0}_2 & \mathbf{0}_2 & \mathbf{E}_2 & \mathbf{0}_1 & -\mathbf{E}_1 & \mathbf{0}_{p+1} & \mathbf{0}_2 & \mathbf{E}_2 & \mathbf{0}_2 & \mathbf{E}_2 & \mathbf{E}_2 \end{bmatrix} \quad (45)$$

$$\mathbf{b}_{eq} = \begin{bmatrix} \mathbf{p}^{clac} + \mathbf{p}^{nlac} - \mathbf{p}^{pvac} \\ \mathbf{p}^{cldc} + \mathbf{p}^{nldc} - \mathbf{p}^{pvd} \end{bmatrix} \quad (46)$$

In the $\mathbf{A}_{eq}$ matrix, $\mathbf{E}_2$ represents an $N \times 2$ eye matrix (1 on the diagonals), and $\mathbf{0}_2$ represents a $N \times 2$ zero matrix. The identity matrix signifies that the component is included in the power balance. For example, the first $\mathbf{E}_2$ represents the grid, which is connected to the AC side. The second $\mathbf{E}_2$ corresponds to load shedding (both critical and non-critical) on the AC side, and so forth. It can be observed that if there is an $\mathbf{E}_2$ on the AC side, there is a zero matrix on the corresponding DC side. This is because any equipment is either present on the AC side or the DC side, except for the ILC. The ILC connects the AC and DC sides; therefore, $\mathbf{E}_2$ appears on both sides (last entry). Finally, the right side of the AC power balance includes the critical loads ($\mathbf{p}^{clac}$), non-critical loads ($\mathbf{p}^{nlac}$), and PV power on that side ($\mathbf{p}^{pvac}$). The same elements on the DC side are present for the DC side of the microgrid.

Finally, the lower ($\mathbf{lb}$) and upper ($\mathbf{ub}$) bounds are computed by combining the bounds of all components, as formulated in the previous section. These components include the grid, MT, AC-side BESS, DC-side BESS, AC-side EV, DC-side EV, and ILC.

$$\mathbf{lb} = [\mathbf{lb}_g; \mathbf{lb}_m; \mathbf{lb}_{bac}; \mathbf{lb}_{bdc}; \mathbf{lb}_{eac}; \mathbf{lb}_{edc}; \mathbf{lb}_i] \quad (47)$$

$$\mathbf{ub} = [\mathbf{ub}_g; \mathbf{ub}_m; \mathbf{ub}_{bac}; \mathbf{ub}_{bdc}; \mathbf{ub}_{eac}; \mathbf{ub}_{edc}; \mathbf{ub}_i] \quad (48)$$

3.2. Operation Execution

In this section, the process of executing the proposed rule-based modular EMS is explained. The step-by-step process is detailed in Figure 8. First, users/operators select the components for each side (AC and DC) of the microgrid in the GUI. Users can set different parameters for each component in the GUI or use the pre-populated default parameters. Next, the ratio of critical to non-critical loads is determined. The total number of equipment (K) selected by the users (including ILC and the utility grid) is determined, and the scheduling horizon (N) is set. Using a for loop, the constraints and bounds related to each piece of equipment are added. Finally, the optimization is executed based on the status of the grid, ILC, and the components selected by the user. The results are displayed in the GUI, and users can change the equipment status and re-run the optimization at any time.

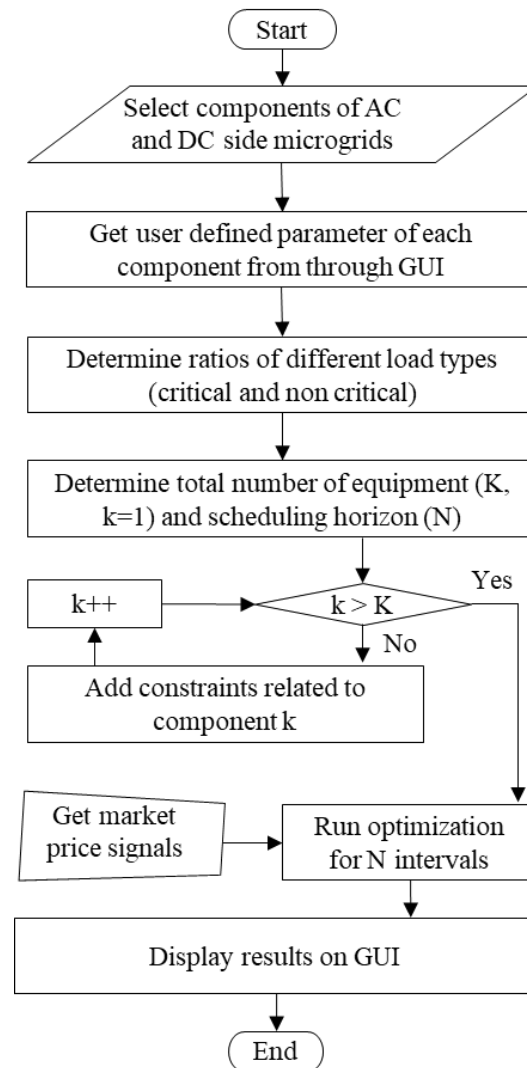


Figure 8. Step-by-step process for executing the proposed rule-based modular algorithm.

4. Performance Evaluation: Grid-Connected Cases

In this section, the performance of the developed rule-based modular EMS is evaluated for different cases in grid-connected mode. The AC side of the microgrid is connected to the utility grid in all cases. A total of four cases are simulated by adding or removing different components on both AC and DC sides. Details of each case are presented in the following subsections.

4.1. Input Data

The load on both AC and DC sides is decomposed into critical and non-critical loads. The interval-wise critical and non-critical load of the system are shown in Figure 9. It can be observed that the magnitude of the AC load is higher than the DC load. Similarly, the PV power for AC and DC sides is shown in Figure 10. The rated capacity of the AC side is taken as 30 kW and that of the DC side as 40 kW for this example. Finally, the time-of-use prices of the grid are shown in Figure 11 [5]. The default parameters used for the simulation of BESSs and EVs are tabulated in Table 1. The default parameters of other components such as MT, ILC, and PV are tabulated in Table 2. However, these parameters can be changed by the users in the GUI, and the EMS will execute the optimization algorithm based on the updated values.

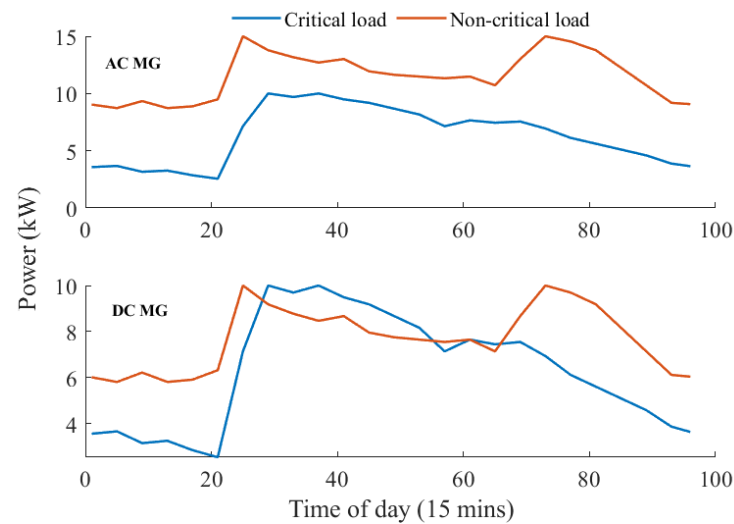


Figure 9. Interval-wise critical and non-critical loads of the AC and DC sides of the microgrid.

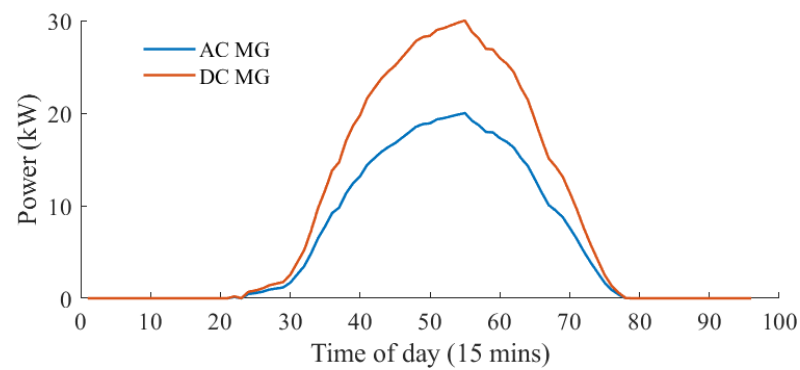


Figure 10. Interval-wise PV power of AC and DC sides of the microgrid.

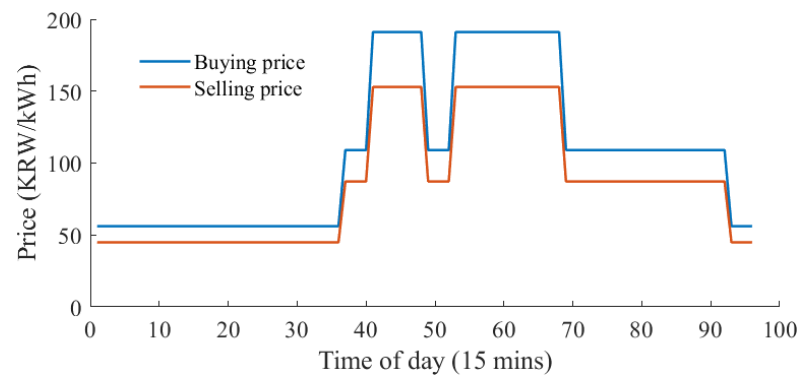


Figure 11. Interval-wise market trading prices.

Table 1. Parameters of BESSs and EVs.

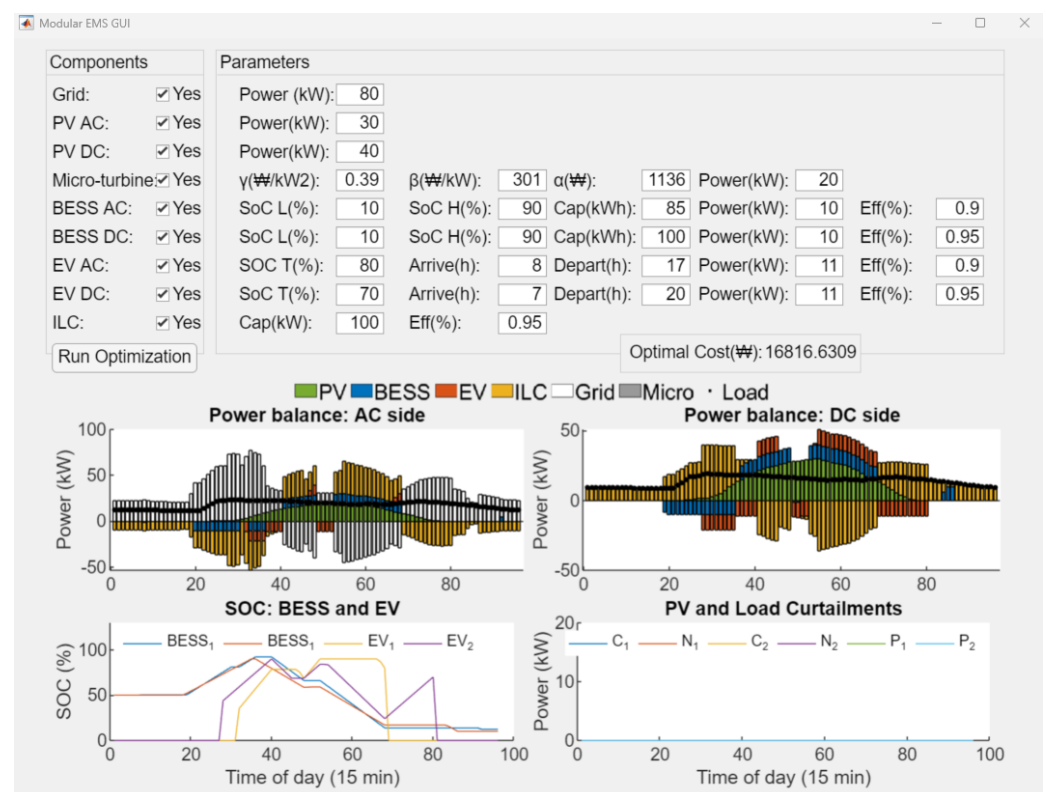
Parameter	Unit	AC-BESS	DC-BESS	AC-EV	DC-EV
Initial SoC	%	50	50	30	40
Min SoC	%	10	10	10	10
Max SoC	%	90	90	90	90
Capacity	kWh	85	100	46	68
Efficiency	%	90	95	90	95
Power rating	kWh	10	10	11	11
target SoC	%	-	-	80	70

Table 2. Parameters of MT, ILC, and PV.

Microturbine			ILC		
Parameter	Unit	Value	Parameter	Unit	Value
Alpha	KRW	1135.6	Efficiency	%	95
Beta	KRW/kW	301.03	Rated capacity	kW	100
Gamma	KRW/kW ²	0.393	Utility grid		
Rated Capacity	kW	20	Rated capacity	kW	80
AC PV			DC PV		
Rated capacity	kW	30	Rated capacity	kW	40

4.2. Interconnected

In this case, the microgrid is fully equipped, as all boxes are checked in Figure 12. The AC part is connected to the grid, and both AC and DC parts are interconnected via the ILC. Both AC and DC sides have PV, BESS, and EVs. There is also an MT on the AC side. The results are shown in the lower part of Figure 12. In these figures, positive grid values refer to buying power from the grid, and negative grid values refer to selling power to the grid. Similarly, positive BESS/EV values refer to discharging, and negative values refer to charging. Finally, positive ILC values refer to receiving power, and negative values refer to sending power.

**Figure 12.** Optimization results for grid-connected, interconnected case.

It can be observed that no load is shed and no PV is curtailed (right bottom figure) due to the connection of the microgrid with the utility grid. The AC power balance shows that energy demand is mainly fulfilled by buying power from the grid during PV absence hours. The energy bought from the grid is also sent to the DC side to fulfill the energy demand of the DC side. However, during PV hours, excess PV power from the DC side is sent to the AC side and is sold to the grid. This is because, during these intervals, the grid selling price is higher (Figure 11). BESSs on both sides are charged during lower price

intervals and are discharged to sell back the power during peak price hours. Finally, EVs on both sides are charged to the target SoC levels before the departure time (80 % for the AC-side EV and 70% for the DC-side EV).

4.3. Without BESSs

This case is similar to the previous one, except that both sides have no BESS units. It can be observed from Figure 13 that BESS units are unchecked for both sides. The same sign conventions for EV, ILC, and grid are used throughout this paper, as discussed in the previous subsection. The results for this case are shown in Figure 13.

A similar trend can be observed for balancing the loads on both AC and DC sides. Power is bought from the grid during low-price intervals to fulfill load demand and also to charge EVs. The power is sent to the DC side via the ILC to fulfill the load demand on that side. During peak price intervals, excess PV power and discharged power from EVs are sold back to the grid. This is because the objective of the microgrid is to minimize its operation cost. However, the amount of power bought and sold to the grid has decreased in this case compared to the previous case. This is due to the absence of BESS units. Therefore, the operation cost has also increased due to the absence of two BESS units which were previously used for energy arbitrage. Finally, the target SoC is achieved by both EVs before their departure time. No load shedding and PV curtailment are observed in this case, also due to the connection of the microgrid with the utility grid.

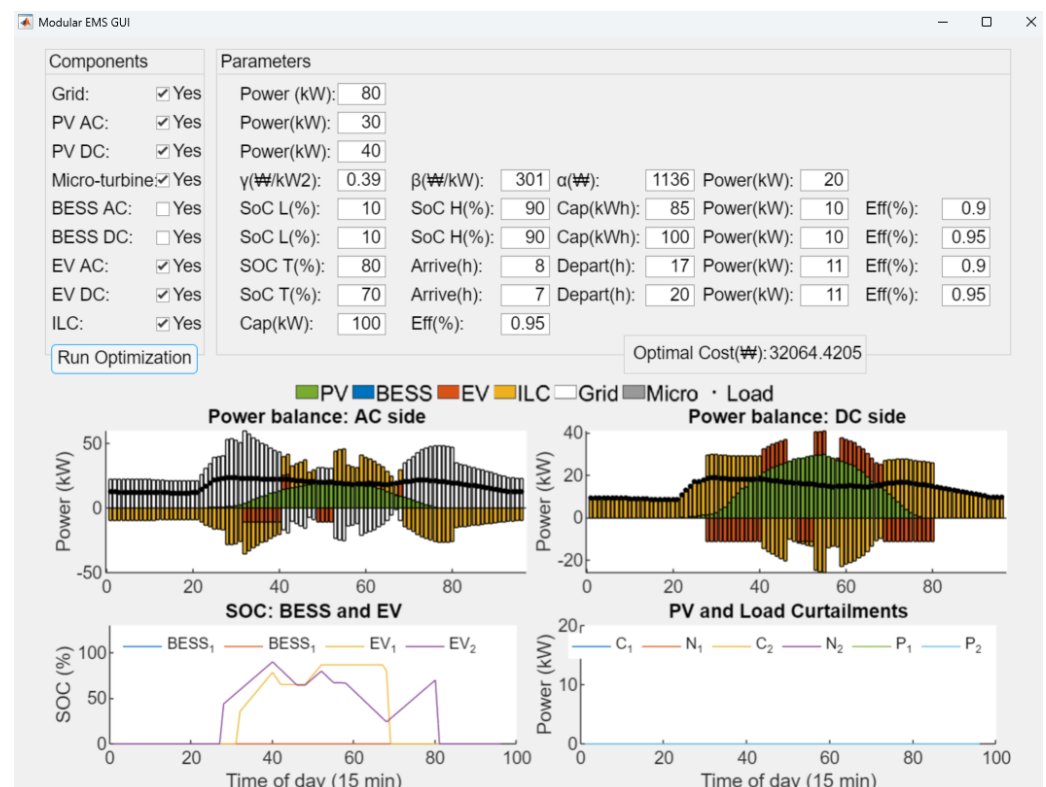


Figure 13. Optimization results for grid-connected, interconnected case without BESSs.

4.4. Without EVs and BESSs

In this case, both microgrid sides have no BESSs or EVs, meaning no energy storage elements. It can be observed from Figure 14 that BESS and EV units are unchecked for both sides. The results of this case are shown at the bottom of Figure 14.

It can be observed that only the grid and PV are used to fulfill the energy demand of both sides of the microgrid. The MT is still not used due to its higher per-unit generation cost compared to buying from the grid during off-peak intervals. The microgrid still

manages to avoid buying power from the grid during peak hours due to the presence of PV. Excess PV power from the DC side is sent to the AC side and sold to the external grid. BESS and EVs are not used, as depicted in the bottom left figure. Similarly, no load shedding or PV curtailment is carried out, as shown in the bottom right figure. The amount of power traded with the grid has further reduced in this case. However, the operation cost has slightly decreased compared to the previous case. This is because EVs generally come with a lower SOC and depart with a higher SOC, which necessitates buying or consuming more available energy. Due to the absence of EVs, as compared to the previous case, the operation cost has minutely reduced.

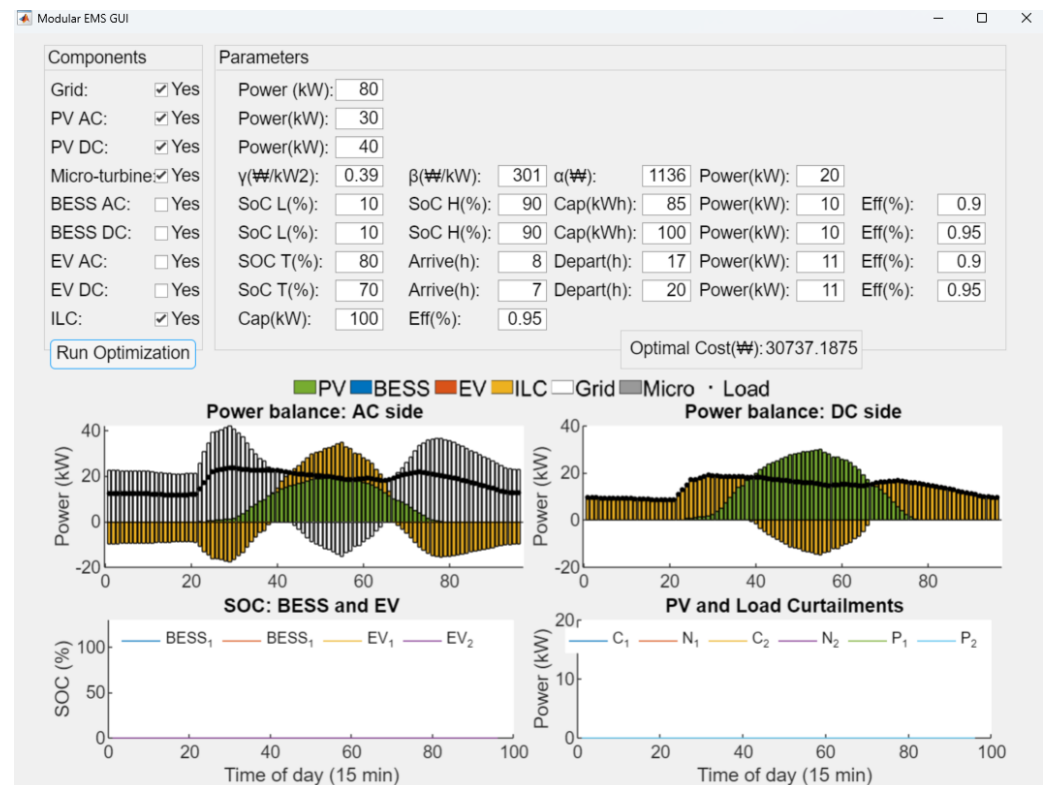


Figure 14. Optimization results for grid-connected, interconnected case without BESSs and EVs.

4.5. DC MG Isolated

In this case, both microgrids have all elements (BESSs, EVs, and PV). Additionally, the AC side has an MT and is connected to the grid. However, the ILC is not operational in this case, which causes the DC side to operate in islanded mode. This scenario is similar to the first case except that the ILC is non-functional. Therefore, power exchange between the AC and DC sides is not possible. The results are shown in Figure 15.

It can be observed that the AC side balances its power by buying from the grid and using PV. There is no power exchange with the DC side, and a small amount of power is sold back to the grid during peak price intervals by discharging the BESS and EV. The EV is charged to the target SoC (80%) before departure. On the DC side, load shedding occurs during early morning and late night hours due to the absence of PV power during these intervals. The critical loads are still supported by the energy stored in the BESS. The BESS and EVs are charged during intervals with excess PV power, and none of the critical loads are shed throughout the day. Only a limited amount of non-critical load is shed during PV absence hours. Finally, the SoC level of the EV is restored to the initial level (as discussed in constraints for islanded operation).

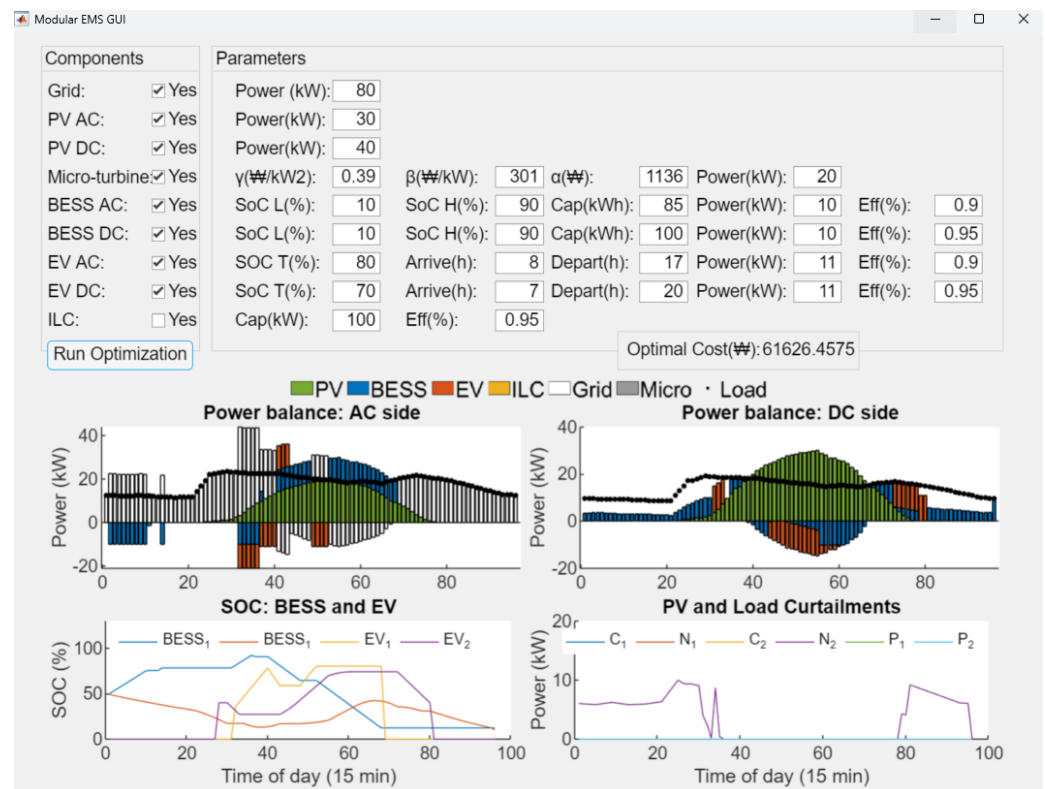


Figure 15. Optimization results for the case with the grid connected and DC side isolated.

4.6. Comparative Analysis

The results in Table 3 compare operational costs under different microgrid configurations. The interconnected case has the lowest cost (KRW 16,816.63) due to resource sharing between AC and DC sides, leveraging BESS and EVs for energy arbitrage, and avoiding load shedding. Without BESSs (+47.55%) or both BESSs and EVs (+45.29%), costs increase because the system loses storage flexibility for peak shaving and arbitrage. However, the absence of EVs slightly reduces costs compared to the "Without BESS" case, as EV charging demands are eliminated. The DC MG isolated scenario has the highest cost (+72.71%) because the non-functional ILC prevents power exchange, leading to inefficiencies and load shedding on the DC side during PV absence hours. This highlights the importance of interconnection and storage for cost-effective microgrid operation.

Table 3. Comparative analysis of different cases in grid-connected mode.

Case	Cost KRW	Increase %
Interconnected	16,816.63	0.00
Without BESSs	32,064.42	47.55
Without EVs and BESSs	30,737.19	45.29
DC MG Isolated	61,626.46	72.71

5. Performance Evaluation: Islanded Cases

In this section, the performance of the proposed rule-based modular EMS is evaluated in islanded mode. An outage on the grid side is assumed for all cases. A total of four cases are simulated by adding or removing different components on both AC and DC sides. Details of each case are presented in the following subsections.

5.1. Input Data

The load and PV profiles are identical to those discussed in the previous section. Since the microgrid operates in islanded mode, market price signals are not required in this case. The penalty for shedding critical and non-critical loads is set to 1000 KRW/kWh and 500 KRW/kWh, respectively. Similarly, the penalty for curtailment of PV is set to 100 KRW/kWh.

5.2. Interconnected

In this case, both microgrids have all the components such as BESSs, EVs, and PV. There is an MT on the AC side, and both sides are connected via the ILC. However, the AC side is not connected to the grid (the grid box is unchecked). The results of this case are shown in Figure 16.

It can be observed that the MT is used to fulfill the load demand on both AC and DC sides during the early morning hours due to the absence of a connection between the grid and PV. During noon hours, the DC side charges its BESS and EV using the excess PV power. This power is then used during the evening hours to fulfill the load demand. Due to the optimal management of the resources, no load shedding or renewable curtailment is carried out in this case. The SoC of EVs is set to the initial SoC before departure, as discussed in the problem formulation section.

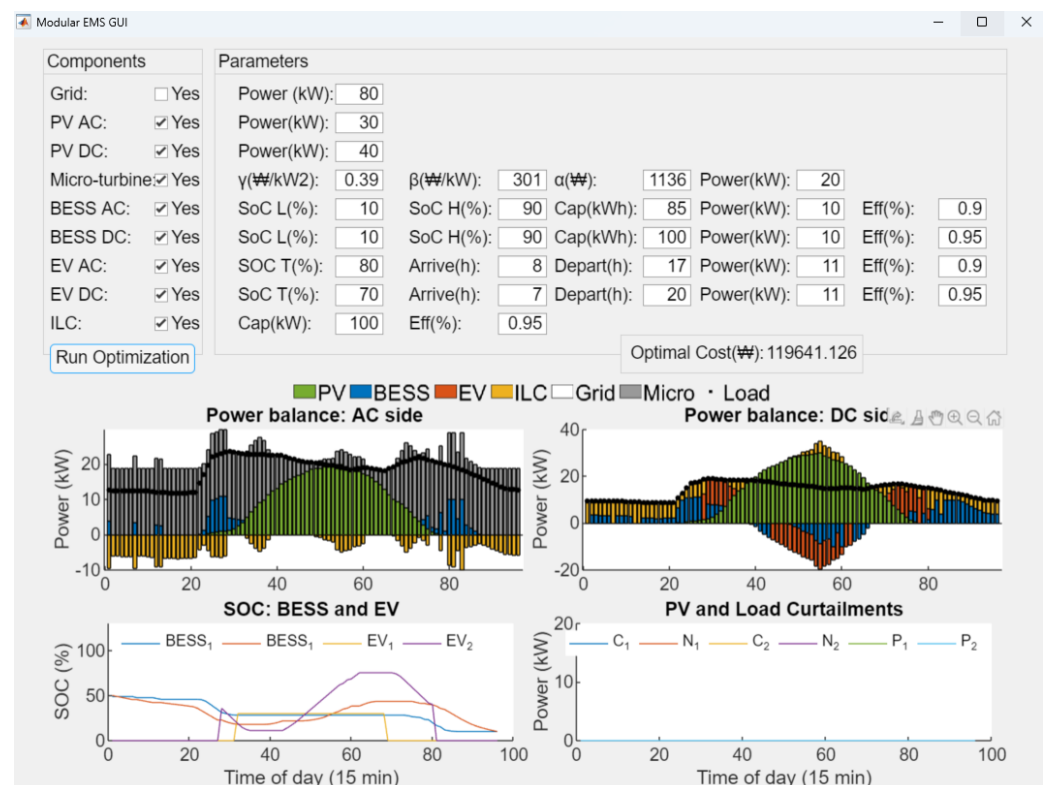


Figure 16. Optimization results for islanded, interconnected case.

5.3. Renewable-Based MG

In this case, a renewable-based microgrid scenario is simulated. It is assumed that the microgrid contains only renewable energy resources such as PV and BESSs. In comparison to the previous case, the MT is missing in this case (as evident from the GUI). The results of this case are shown in Figure 17.

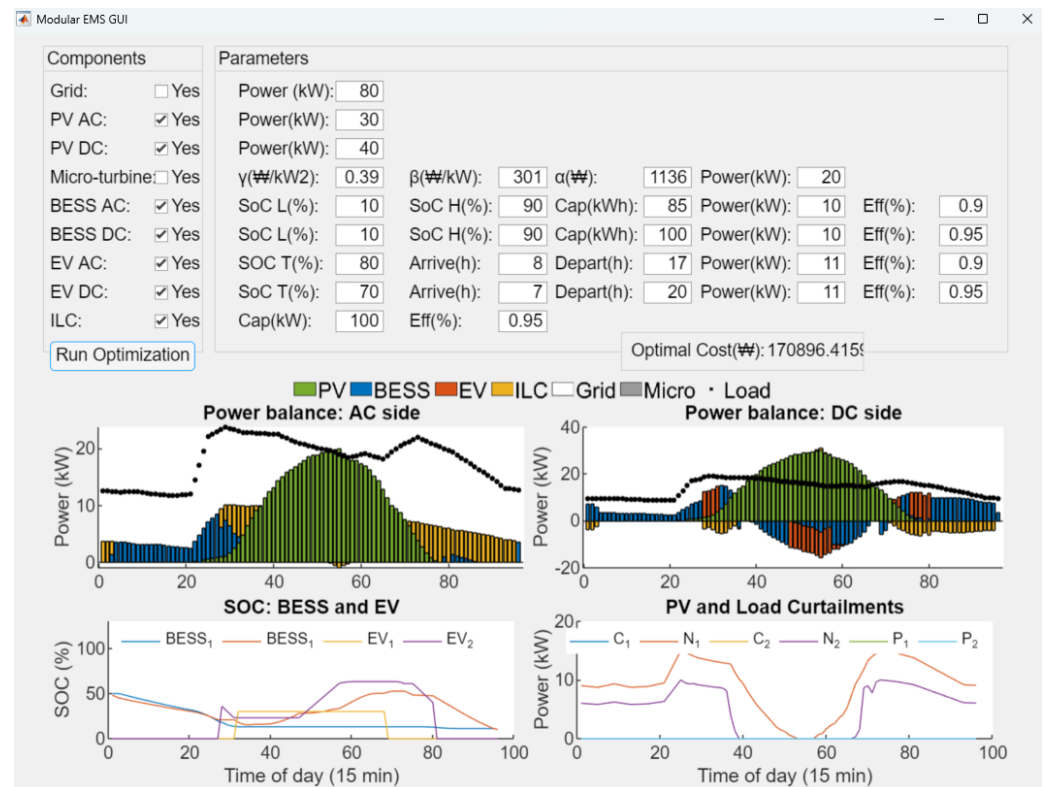


Figure 17. Optimization results for islanded case with renewables only.

It can be observed that during early morning hours, both microgrid sides try to fulfill the load demand of critical loads by using the energy of BESSs. A small amount of energy transfer from the DC to the AC side can be observed to fulfill critical load demand on the AC side. None of the critical loads are shed throughout the day, with only non-critical loads being shed during PV absence hours. During PV generation intervals, all the load demand is fulfilled, and the BESS is also charged for use during evening and night hours. The gap between the demand curve and the generation equipment in the power balance graphs corresponds to the amount of load shedding.

5.4. Conventional MG

In this case, a conventional microgrid system is considered for analysis. This is the opposite case of the previous case, i.e., without any renewable energy resources. It only contains the MT on the DC side and has EVs on both sides of the microgrid. The results of this case are shown in Figure 18.

It can be observed that the MT is generating full power (20 kW) throughout the day. The MT is used to fulfill the critical load demand of both sides. Power is transferred from the AC side to the DC side via the ILC to fulfill the critical load demand of the DC side. EVs are also used during limited intervals by the DC side to avoid the shedding of critical loads. It can be observed that only non-critical loads are shed in this case. It is worth noting that the amount of non-critical load shedding on the DC side is more than that on the AC side. This is because the MT is on the AC side, and transferring power from the AC to the DC side results in power loss. Consuming the power locally after fulfilling the critical load demand helps in maximizing the total amount of loads served.

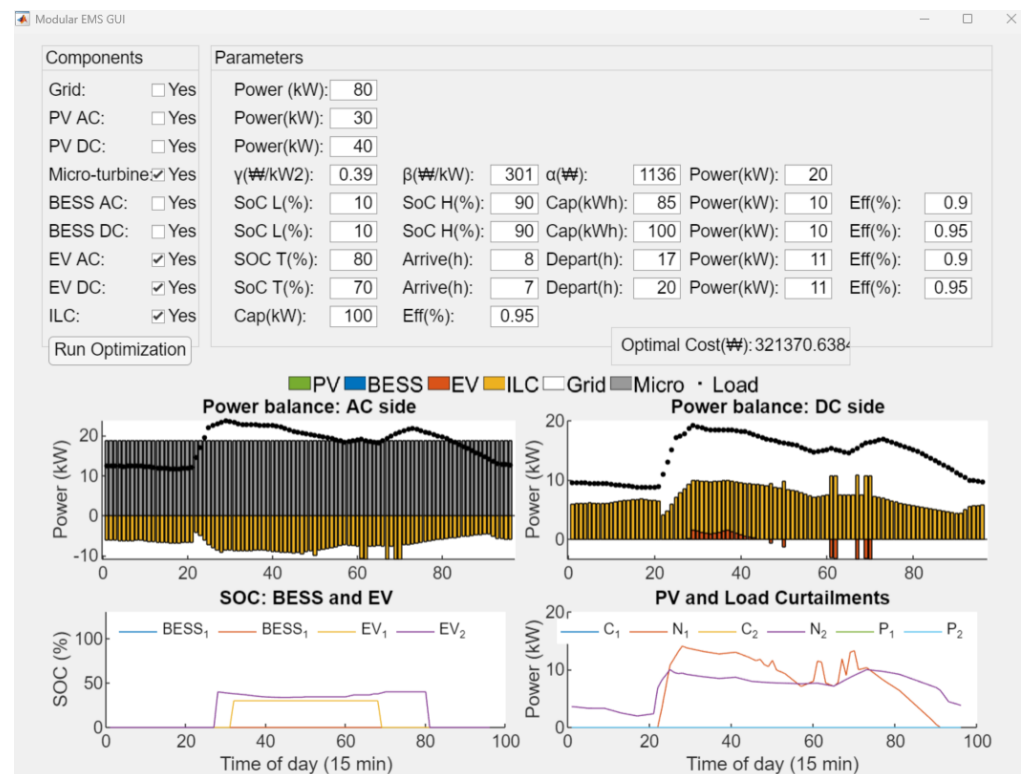


Figure 18. Optimization results for a conventional islanded case.

5.5. DC MG Isolated

In addition to the disconnection with the grid, a fault in the ILC is considered in this study. In this case, each microgrid side can only use the available resources on its side to maximize demand fulfillment. Both sides are equipped with PV, BESSs, and EVs, while there is an MT on the AC side. The results of this case are shown in Figure 19.

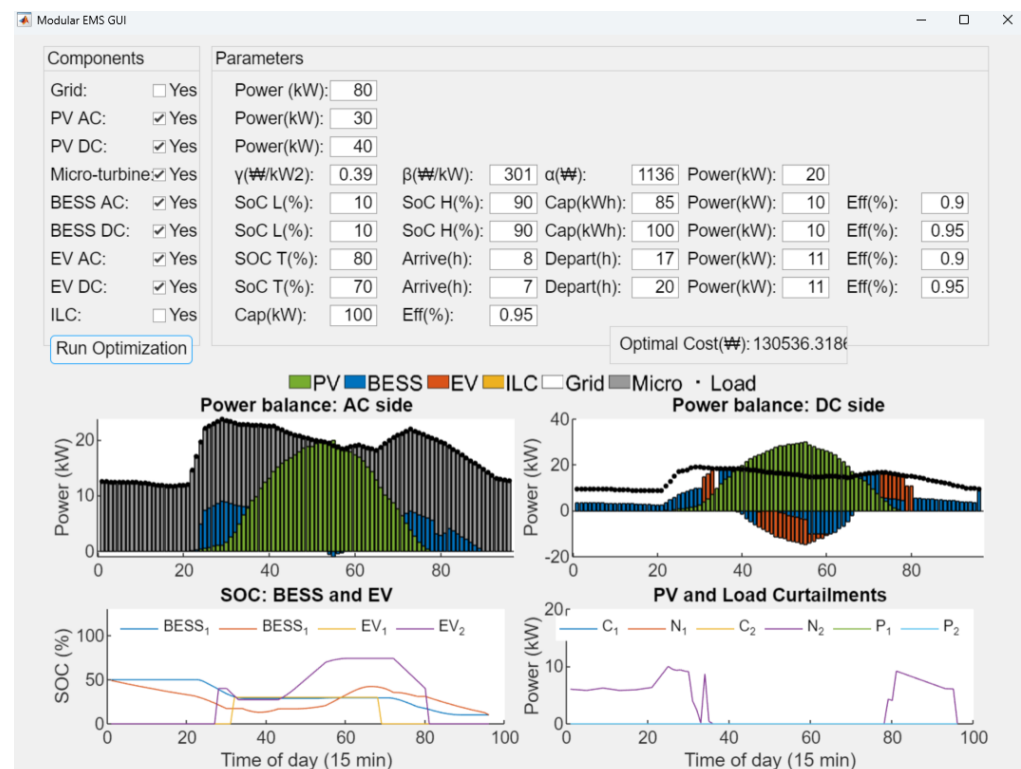


Figure 19. Optimization results for islanded and DC isolated case.

It can be observed that the MT is used to fulfill the load demand on the AC side during PV absence hours. The BESS is also partially used and is not charged since it is not required during the remaining part of the day. Instead of charging and then discharging the BESS, the MT is directly used to avoid power loss in the charging/discharging process. No load shedding is carried out on the AC side. In the case of the DC side, the BESS and EV are used to fulfill the critical load demand during initial intervals. Then, PV power is used to fulfill the total load demand, and excess PV power is charged to the BESS and EV to be used later. During evening hours, the BESS and EV are used to fulfill the load demand. It can be observed that none of the critical loads are shed during this case. A limited amount of non-critical load is shed due to the absence of a connection with the AC side.

5.6. Comparative Analysis

The results shown in Table 4 reflect how resource availability and system configuration impact costs and load shedding. The interconnected case achieves the lowest cost (KRW 119,641) and zero load shedding due to optimal resource sharing and the availability of diverse resources such as PV, BESSs, EVs, and an MT. In the DC MG isolated case, the absence of interconnection leads to a cost increase of 8.4% and limited DC load shedding (85.65 kWh), as each side relies solely on its resources. The renewable-based MG case, lacking an MT, sees a 30.0% cost increase and higher load shedding (217.63 kWh for both AC and DC) due to reliance on PV and BESS with no backup generation. The conventional MG, depending only on the MT, results in the highest cost (62.97% higher) and significant non-critical load-shedding (156.06 kWh for AC and 170.80 kWh for DC) due to inefficiencies in power transfer and limited renewable integration.

Table 4. Comparative analysis of different cases in islanded mode.

Case	Cost KRW	Increase %	AC Load Shedding kWh	DC Load Shedding kWh
Interconnected	119,641.13	0.00	0.00	0.00
Renewables only	170,896.42	29.99	217.63	217.63
Conventional	323,050.13	62.97	156.06	170.80
DC MG Isolated	130,536.32	8.35	0.00	85.65

6. Limitations and Future Research Directions

This study serves as a preliminary exploration into the rule-based modular energy management of microgrids. To ensure conciseness and maintain reader interest, a deterministic MILP model has been developed. The model includes constraints for representative devices across various categories, such as controllable DGs, renewable DGs, ESSs, loads, and hybrid AC/DC configurations. Future enhancements to the model could include the following:

1. Expanding each category to incorporate additional elements, such as wind turbines [38], diverse energy storage systems, and controllable DGs.
2. Integrating demand response mechanisms on both AC and DC sides.
3. Addressing uncertainty in renewables and loads to improve robustness.
4. Validating the algorithm by linking it with a distribution system for power flow analysis.

7. Conclusions

A rule-based modular energy management system for microgrids is proposed in this study. To facilitate the testing of diverse microgrid configurations, a hybrid AC/DC microgrid network is considered. This framework enables the optimal operation of simple AC microgrids to complex hybrid microgrids with diverse components on both sides. The

proposed rule-based modular energy management system demonstrates a high level of adaptability and effectiveness across various scenarios, including grid-connected, islanded, and DC-side isolated modes. In grid-connected mode, the EMS achieves a significant reduction in operational costs, with the interconnected configuration costing KRW 16,816.63. In contrast, costs rise by 47.6% when BESS units are removed and by 45.3% when both BESSs and EVs are excluded. The EMS leverages BESSs for energy arbitrage, charging during low-price intervals and discharging during peak-price periods. The interlinking converter (ILC) facilitates efficient energy transfer between AC and DC sides, preventing load shedding and PV curtailment. In islanded mode, the absence of grid support poses challenges, but the EMS effectively minimizes load shedding, with non-critical loads being shed during PV absence hours. For instance, in isolated DC microgrid operation, load shedding is limited to 1.2% of total demand while ensuring critical loads remain supported. Without BESSs, operational costs increase to 32,064.42 KRW, a 90.6% rise compared to the interconnected scenario. Even in the absence of both BESSs and EVs, operational costs remain lower at 30,737.19 KRW due to reduced energy storage cycling. The EMS also maintains EV target states of charge (80% for AC side EVs and 70% for DC side EVs) before departure, ensuring operational reliability.

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References

1. Rani, P.; Parkash, V.; Sharma, N.K. Technological aspects, utilization and impact on power system for distributed generation: A comprehensive survey. *Renew. Sustain. Energy Rev.* **2024**, *192*, 114257. [[CrossRef](#)]
2. Saeed, M.H.; Fangzong, W.; Kalwar, B.A.; Iqbal, S. A review on microgrids' challenges & perspectives. *IEEE Access* **2021**, *9*, 166502–166517.
3. Hussain, A.; Bui, V.H.; Kim, H.M. An effort-based reward approach for allocating load shedding amount in networked microgrids using multiagent system. *IEEE Trans. Ind. Inform.* **2019**, *16*, 2268–2279. [[CrossRef](#)]
4. Kumar, A.; He, X.; Deng, Y.; Singh, A.R.; Sah, B.; Kumar, P.; Bansal, R.; Bettayeb, M.; Rayudu, R. A sustainable rural electrification based on a socio-techno-economic-environmental-political microgrid design framework. *Energy Environ. Sci.* **2022**, *15*, 4213–4246. [[CrossRef](#)]
5. Hussain, A.; Bui, V.H.; Kim, H.M. Resilience-oriented optimal operation of networked hybrid microgrids. *IEEE Trans. Smart Grid* **2017**, *10*, 204–215. [[CrossRef](#)]
6. Vuddanti, S.; Salkuti, S.R. Review of energy management system approaches in microgrids. *Energies* **2021**, *14*, 5459. [[CrossRef](#)]
7. Espín-Sarzosa, D.; Palma-Behnke, R.; Núñez-Mata, O. Energy management systems for microgrids: Main existing trends in centralized control architectures. *Energies* **2020**, *13*, 547. [[CrossRef](#)]
8. Gao, H.; Liu, J.; Wang, L.; Wei, Z. Decentralized energy management for networked microgrids in future distribution systems. *IEEE Trans. Power Syst.* **2017**, *33*, 3599–3610. [[CrossRef](#)]
9. Darshi, R.; Shamaghdari, S.; Jalali, A.; Arasteh, H. Decentralized energy management system for smart microgrids using reinforcement learning. *IET Gener. Transm. Distrib.* **2023**, *17*, 2142–2155. [[CrossRef](#)]
10. Liu, T.; Tan, X.; Sun, B.; Wu, Y.; Tsang, D.H. Energy management of cooperative microgrids: A distributed optimization approach. *Int. J. Electr. Power Energy Syst.* **2018**, *96*, 335–346. [[CrossRef](#)]
11. Muhtadi, A.; Pandit, D.; Nguyen, N.; Mitra, J. Distributed energy resources based microgrid: Review of architecture, control, and reliability. *IEEE Trans. Ind. Appl.* **2021**, *57*, 2223–2235. [[CrossRef](#)]

12. García Vera, Y.E.; Dufo-López, R.; Bernal-Agustín, J.L. Energy management in microgrids with renewable energy sources: A literature review. *Appl. Sci.* **2019**, *9*, 3854. [\[CrossRef\]](#)
13. Aaslid, P.; Korpås, M.; Belsnes, M.M.; Fosso, O.B. Stochastic optimization of microgrid operation with renewable generation and energy storages. *IEEE Trans. Sustain. Energy* **2022**, *13*, 1481–1491. [\[CrossRef\]](#)
14. Panda, S.P.; Genest, B.; Easwaran, A.; Rigo-Mariani, R.; Lin, P. Methods for mitigating uncertainty in real-time operations of a connected microgrid. *Sustain. Energy Grids Netw.* **2024**, *38*, 101334. [\[CrossRef\]](#)
15. Erol, Ö.; Filik, Ü.B. A Stackelberg game-based dynamic pricing and robust optimization strategy for microgrid operations. *Int. J. Electr. Power Energy Syst.* **2024**, *155*, 109574. [\[CrossRef\]](#)
16. Kamrani, F.; Fattaheian-Dehkordi, S.; Abbaspour, A.; Fotuhi-Firuzabad, M.; Lehtonen, M. Flexibility-based operational management of a microgrid considering interaction with gas grid. *IET Gener. Transm. Distrib.* **2021**, *15*, 2673–2683. [\[CrossRef\]](#)
17. Hou, S.; Gebreyesus, G.D.; Fujimura, S. Day-ahead multi-modal demand side management in microgrid via two-stage improved ring-topology particle swarm optimization. *Expert Syst. Appl.* **2024**, *238*, 122135. [\[CrossRef\]](#)
18. Vaish, J.; Tiwari, A.K.; Siddiqui, K.M. Optimization of micro grid with distributed energy resources using physics based meta heuristic techniques. *IET Renew. Power Gener.* **2023**. [\[CrossRef\]](#)
19. Ponsich, A.; Domenech, B.; Ferrer-Martí, L.; Juanpera, M.; Pastor, R. A multi-objective optimization approach for the design of stand-alone electrification systems based on renewable energies. *Expert Syst. Appl.* **2022**, *199*, 116939. [\[CrossRef\]](#)
20. Kurukuru, V.S.B.; Haque, A.; Padmanaban, S.; Khan, M.A. Rule-based inferential system for microgrid energy management system. *IEEE Syst. J.* **2021**, *16*, 1582–1591. [\[CrossRef\]](#)
21. Fathy, A.; Ferahtia, S.; Rezk, H.; Yousri, D.; Abdelkareem, M.A.; Olabi, A. Optimal adaptive fuzzy management strategy for fuel cell-based DC microgrid. *Energy* **2022**, *247*, 123447. [\[CrossRef\]](#)
22. Rodriguez, M.; Arcos-Aviles, D.; Martinez, W. Fuzzy logic-based energy management for isolated microgrid using meta-heuristic optimization algorithms. *Appl. Energy* **2023**, *335*, 120771. [\[CrossRef\]](#)
23. Guo, C.; Wang, X.; Zheng, Y.; Zhang, F. Real-time optimal energy management of microgrid with uncertainties based on deep reinforcement learning. *Energy* **2022**, *238*, 121873. [\[CrossRef\]](#)
24. Huang, Y.; Li, G.; Chen, C.; Bian, Y.; Qian, T.; Bie, Z. Resilient distribution networks by microgrid formation using deep reinforcement learning. *IEEE Trans. Smart Grid* **2022**, *13*, 4918–4930. [\[CrossRef\]](#)
25. Li, Y.; Wang, R.; Yang, Z. Optimal scheduling of isolated microgrids using automated reinforcement learning-based multi-period forecasting. *IEEE Trans. Sustain. Energy* **2021**, *13*, 159–169. [\[CrossRef\]](#)
26. Gupta, P.; Ansari, M.; Ali, I. Smart Energy Management Techniques of Microgrid: A Review. In Proceedings of the 2023 International Conference on Power, Instrumentation, Energy and Control (PIECON), Aligarh, India, 10–12 February 2023; pp. 1–6.
27. Morales, R.; Marín, L.G.; Roje, T.; Caquilpan, V.; Sáez, D.; Nuñez, A. Microgrid planning based on computational intelligence methods for rural communities: A case study in the José Painecura Mapuche community, Chile. *Expert Syst. Appl.* **2024**, *235*, 121179. [\[CrossRef\]](#)
28. Lee, J.W.; Kim, M.K.; Kim, H.J. A multi-agent based optimization model for microgrid operation with hybrid method using game theory strategy. *Energies* **2021**, *14*, 603. [\[CrossRef\]](#)
29. Charadi, S.; Chaibi, Y.; Redouane, A.; Allouhi, A.; El Hasnaoui, A.; Mahmoudi, H. Efficiency and energy-loss analysis for hybrid AC/DC distribution systems and microgrids: A review. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e13203. [\[CrossRef\]](#)
30. Hüner, B. Feasibility and environmental analysis of biogas-based hybrid energy system using HOMER pro software: A case study for Hatay. *Energy Convers. Manag.* **2025**, *326*, 119480. [\[CrossRef\]](#)
31. Zaro, F.; Ayyash, N.A. Design and Management of Hybrid Renewable Energy System using RETScreen Software: A Case Study. *Int. J. Electr. Eng. Comput. Sci.* **2023**, *5*, 164–170. [\[CrossRef\]](#)
32. Pater, S. Long-term performance analysis using TRNSYS software of hybrid systems with PV-T. *Energies* **2021**, *14*, 6921. [\[CrossRef\]](#)
33. Hussain, A.; Kim, H.-M. Modular EMS. Available online: <https://github.com/Akhtar-UL/Modular-EMS> (accessed on 10 December 2024).
34. Bakar, N.N.A.; Hassan, M.Y.; Sulaima, M.F.; Na'im Mohd Nasir, M.; Khamis, A. Microgrid and load shedding scheme during islanded mode: A review. *Renew. Sustain. Energy Rev.* **2017**, *71*, 161–169. [\[CrossRef\]](#)
35. Diaz, N.L.; Luna, A.C.; Vasquez, J.C.; Guerrero, J.M. Centralized control architecture for coordination of distributed renewable generation and energy storage in islanded AC microgrids. *IEEE Trans. Power Electron.* **2016**, *32*, 5202–5213. [\[CrossRef\]](#)
36. El-Hendawi, M.; Gabbar, H.A.; El-Saady, G.; Ibrahim, E.N.A. Control and EMS of a grid-connected microgrid with economical analysis. *Energies* **2018**, *11*, 129. [\[CrossRef\]](#)

37. Kazerani, M.; Tehrani, K. Grid of hybrid AC/DC microgrids: A new paradigm for smart city of tomorrow. In Proceedings of the 2020 IEEE 15th International Conference of System of Systems Engineering (SoSE), Budapest, Hungary, 2–4 June 2020; pp. 175–180.
38. Tehrani, K.; Beikbabaie, M.; Mehrizi-Sani, A.; Jamshidi, M. A smart multiphysics approach for wind turbines design in industry 5.0. *J. Ind. Inf. Integr.* **2024**, *42*, 100704. [[CrossRef](#)]

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