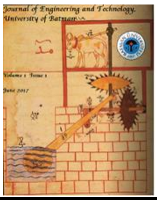

Journal of Engineering and Technology
DergiPark AKADEMİK

Journal of Engineering and Tecnology 5;1 (2024) 1-10

Placement of Optimum Supercapacitors Considering Cost and Loss Parameters in Reliability-based Sustainable Energy-Based Grid

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ARTICLE INFO

Article history:
Received June 1, 2024
Received June 15, 2024
Accepted June 24, 2024
Available online June 26, 2024

Key words:
Super Capacitors
Sustainable Energy
Reliability
Cost-benefit analysis

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ABSTRACT

This study aims to develop a method for low-cost production in power systems by analyzing key parameters such as production costs, line losses, and reliability within the contexts of production planning and load distribution processes. By taking these parameters into account, the goal is to enhance the system's sustainability and efficiency. System reliability refers to the ability of a system to perform a specified task within a given time frame. Reliability-based risk analysis is employed to assess the reliability of critical system components. Unit Commitment (UC) involves the optimal allocation of energy production units while considering production costs, line losses, and reliability factors. The amount of supercapacitors is determined by evaluating the reliability of system components, production costs, and losses. Supercapacitors are utilized in energy systems to prevent imbalances between supply and demand and are allocated to be equal to or greater than the capacity of the largest generator. Cost-benefit analysis is conducted to determine the optimal level of supercapacitors. The objective of this study is to achieve low-cost and sustainable energy production in power systems through a comprehensive analysis of production costs, line losses, and reliability parameters. The focus is on the efficient allocation of energy production units and conducting reliability-based risk analyses to achieve an optimal production balance..

1. Introduction

Meeting the connection criteria to generate and distribute sustainable and uninterrupted electricity to meet demand contributes to supply reliability. Ensuring compliance with the connection criteria of ENTSO-E (European Network of Transmission System Operators for Electricity) is essential for supply reliability. Supply reliability is also crucial for maintaining the quality of electrical energy. It is critical for ensuring that the power balance and system frequency remain within acceptable ranges, providing high-quality energy through frequency control. Common goals for the reconfiguration of distribution systems include minimizing transmission losses and/or enhancing reliability and optimal planning [1, 2]. This study presents the best combination of feeder-based units for reconfiguring storage planning in distribution systems, which is a combinatorial optimization problem that minimizes the objective function. Constraints used in this process include planning constraints for units with maximum and minimum storage capacity, line losses, and line reliability [3, 4].

The concept of reliability is generally defined as the probability that a device or system will fulfill its intended purpose under specified conditions within a certain period. This definition includes several key elements. First, reliability is a probabilistic concept, meaning it deals with the likelihood of a device or system performing its intended purpose under specific conditions at a given time [5]. Second, the concept of reliability encompasses adequate performance. For a device or system to be considered reliable, the probability of fulfilling its intended purpose must be high, indicating the importance of the device's or system's capacity to perform as expected. Third, reliability involves time. To evaluate the reliability of a device or system, the probability of it fulfilling its intended purpose over a specified period must be considered. This period is usually expressed as the lifetime of the device or a particular operational period. Finally, the concept of reliability includes operating conditions. The reliability of a device or system is assessed under specific operating conditions, which may include the characteristics of the environment in which the device is used, the frequency of use, and other factors [6]. The evaluation of these elements together determines the reliability of a device or system, playing a crucial role in its design, production, and use. Overall, reliability determines a system's ability to perform its function, aided by load changes and historical experience that help predict future performance [7]. The indices used in reliability evaluation are probabilistic and thus do not provide precise predictions. To conduct a reliability, the system's behavior in the previous period must first be known. During the analysis, various variables that can measure reliability are identified and then calculated using different methods. All these methods involve detailed examination of the future behaviors of the units [8]. The definition of reliability in electric power systems is commonly made in terms of adequacy and security [9, 10]. Adequacy refers to ensuring that all needs arising from generation, transmission, and distribution facilities are met and that demand is satisfied, taking into account planned and unplanned outages of system components. After unexpected events, the system is considered to have reached a stable point concerning transitions from one state to another without neglecting any dynamics [11]. Security refers to a system's ability to withstand failures and disruptions caused by outages of cables, transmission lines, generators, and many other components. Security analysis evaluates the system's transient response after contingency events and considers any progressive incidents arising from transient fluctuations [12].

2. Stages of Power Systems in Reliability Analysis by Function

Electric power systems are examined by dividing them into generation, transmission, and distribution regions based on functionality. These three fundamental regions contribute to the complex structure of power systems. Each region has its specific reliability indices used to evaluate the robustness and continuity of the system. The different reliability characteristics of the generation, transmission, and distribution regions necessitate a detailed approach to reliability analyses. In this context, a staged analysis should be applied to assess the reliability of the power system [13]. The first stage covers the generation process, the second stage includes both generation and transmission processes, and the third stage combines generation, transmission, and distribution processes. Each stage is designed to analyze and understand regional differences by examining specific reliability parameters in the system. This method aims to provide a comprehensive evaluation of reliability across the entire power system [14]. Staged levels in power system reliability analysis model shown as Figure 1.

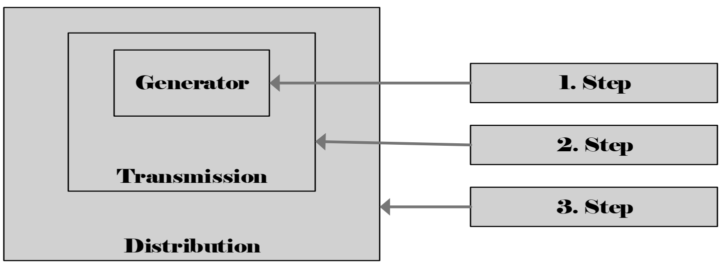

Figure 1. Staged levels in power system reliability analysis [15]

2.1. Sustainability in Power Systems

The concept of sustainability is prevalent across various disciplines, particularly in the context of energy production technologies where it is closely linked to the renewability of energy sources. The placement of optimum supercapacitors in a reliability-based sustainable energy grid must take into account not only the renewability of energy sources but also the sustainability of energy transformations. This can be effectively evaluated through Life Cycle Analysis (LCA) and exergy (usability) analyses. LCA assesses the interactions between materials, energy, emissions, solid waste, and costs involved in a production process and their impacts on the environment. In the context of a sustainable energy-based grid, sustainability is often defined as "the ability to maintain production capabilities in the future" [16]. This definition is intrinsically linked to the availability of natural resources. Another definition of sustainability is "ensuring and enhancing the integrity of life on Earth" [17]. If energy production lacks sustainability, this integrity will gradually deteriorate. In designing an optimal supercapacitor placement strategy, it is crucial to consider these sustainability principles [18]. For instance, combining LCA and exergy analyses may reveal that while biofuels can sometimes result in greater usability loss compared to gasoline, their integration into the grid with supercapacitors can mitigate such losses by balancing supply and demand. Thus, the strategic placement of supercapacitors, guided by cost-benefit and loss assessments, can significantly contribute to the sustainable and reliable operation of energy grids.

System operators (SOs) of sustainable electric power systems face technical challenges arising from the complex structures of these systems. These challenges affect the reliability and economic operation of the systems [19, 20]. In particular, the large-scale use of Renewable Energy Sources (RES) increases uncertainties during system operation, making it difficult to maintain the balance between generation and load. This situation increases the risk of load shedding, prompting system operators to plan more carefully and effectively [21]. Additionally, extra sources of uncertainty stemming from transmission systems and distribution networks add another layer to the system's reliability. The combination of these factors necessitates the development of more appropriate strategies by system operators when managing energy resources. In this context, understanding the operational challenges of sustainable energy systems and developing new strategies to address these challenges is crucial for maintaining a reliable and economical electric power system shown as Figure 2.

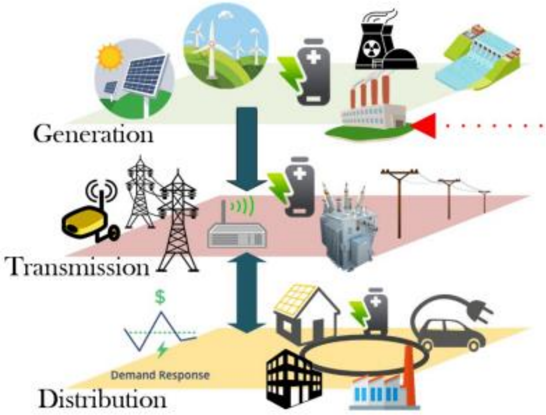

Figure 2. Sustainable Electric Energy Systems [22]

2.2. Unit Commitment in Power Systems

The Unit Commitment (UC) problem involves determining the optimal operating schedule of generation units to effectively meet load requirements on an hourly basis [23]. The aim of this optimization process is to supply energy with minimal losses and fuel consumption to maximize profit. In addition to minimizing total production cost, a generation schedule must also comply with various operational constraints. These constraints limit decisions regarding the start-up and shutdown of generation units. Typically, these constraints include individual unit status constraints, minimum up-time, minimum down-time, capacity limits, start-up and shutdown times, limited ramp rates, group constraints, power balance constraints, and spinning reserve constraints [1, 24].

Electricity demands can vary significantly between low and high demand periods, driven by different objectives. If consumption units are monitored regularly, it may be possible to shut down certain units during periods of lower demand (for example, nighttime hours when demand is typically lower) [25]. Therefore, the primary goal of this study is to plan the operating times of different generation units to meet these constraints. UC problem can be applied to both deterministic and stochastic loads [1, 26].

A deterministic approach provides exact and unique outcomes. However, the results derived from stochastic loads might not be as definitive. Deterministic load Data Envelopment Analysis (DEA) employs the Principal Component Analysis (PCA) method [27]. Data Envelopment Analysis (DEA) is a non-parametric technique that primarily identifies input and output variables. PCA reduces the number of variables utilized in the analysis. In stochastic models, constraints are transformed into deterministic constraints, allowing the formulation to be solved using established algorithms. Various objective functions for different environments are outlined below.

2.3. Traditional Fuel-Based Approach

In Equation (1), there are three costs to be minimized. The first is the fuel cost for producing power by unit i at time t, denoted as (P(i, t)), and (M(P(i, t))) represents the fuel cost of unit i at time t. The second is the start-up cost (BM), and the third is the shutdown cost (DM) [28].

$$min \sum_{t=1}^{N_t} \sum_{i=1}^{N_0} M_i(P_{i,t}) I_{i,t} + BM + DM \tag{1}$$

The profit-based approach is applied in an environment where the primary goal is to maximize the profit of an individual generation company. UC plan has an indirect impact on price and a direct impact on average cost; thus, it is a significant part of any bidding strategy. Additionally, there is flexibility within the UC schedule. The objective function (2) can be defined as maximizing the profit (F(i,t)) of the generation company (GENCO) [29]:

$$max(F_{i,t}) \tag{2}$$

Here, (F(i, t)) represents the profit obtained from unit (i) at time (t). This function accounts for revenues from electricity sales minus the costs of production, including fuel costs, start-up costs, and shutdown costs. The aim is to achieve the highest possible profit by efficiently managing the generation schedule while adhering to operational constraints and market conditions.

3. Constraints and Cost Equations in Optimization

The Security-Constrained Unit Commitment (SCUC) solution procedure is detailed in Figure 3. This diagram illustrates the flowchart of how the optimal algorithm for unit commitment is performed [30, 31]. The initial SCUC main problem (AP1) is shown in equation (2). The SCUC main problem is defined with the iteration number "APlower," unit number (N) (1-8), period (T) (24 hours), (bmi) start-up cost, (dmi) shutdown cost, and (umi) production cost [31].

$$min\ AP1, AP_{lower} \geq \sum_{t=1}^{T}\sum_{i=1}^{N} dm_i\alpha_{it} + bm_i\text{üm}_{i,t} \tag{3}$$

$$(P_{i,min})I_{i,t} \leq (P_{i,t}) \leq (P_{i,max})I_{i,t} \tag{4}$$

$$\sum\nolimits_{i=1}^{N} P_{i,t} + \sum\nolimits_{k=1}^{N_w} W_{k,t} = Talep_t \tag{5}$$

$$(P_{i,min}) \leq \sum\nolimits_{i=1}^{N} F_{i-1}P_{i,t} + \sum\nolimits_{k=1}^{N_w} G_{i-k}w_{i,t} - \sum\nolimits_{k=1}^{N_w} G_{i-k}{}_{i,t} - D_{i,t} \leq (P_{i,max}) \tag{6}$$

$$g_I(I_{i,t}) \leq 0 \tag{7}$$

$$g_r(P_{i,t}I_{i,t}) \leq 0 \tag{8}$$

$$g_r(BMI_{i,t}) \leq 0 \tag{9}$$

$$g_r(DMI_{i,t}) \leq 0 \tag{10}$$

In this equation, optimization is performed iteratively to determine which power plant will operate and to achieve the lowest cost of energy provision, represented as the (z_{lower}) value [32]. The objective is to minimize the total generation cost while meeting demand and ensuring the security and reliability of the power system. The objective function (3) includes the operating and start-up/shutdown costs of thermal generators as well as the expected wind energy curtailment. Equations (4) and (5) correspond to the system power balance constraints, while Equation (6) pertains to DC transmission constraints. The function g in Equation (7) represents constraints related to integer variables, such as minimum online/offline time limits. The g in Equation (8) signifies ramp-up and ramp-down constraints, and gc in Equations (9) and (10) indicate the constraints on the operating and start-up/shutdown costs of thermal generators.

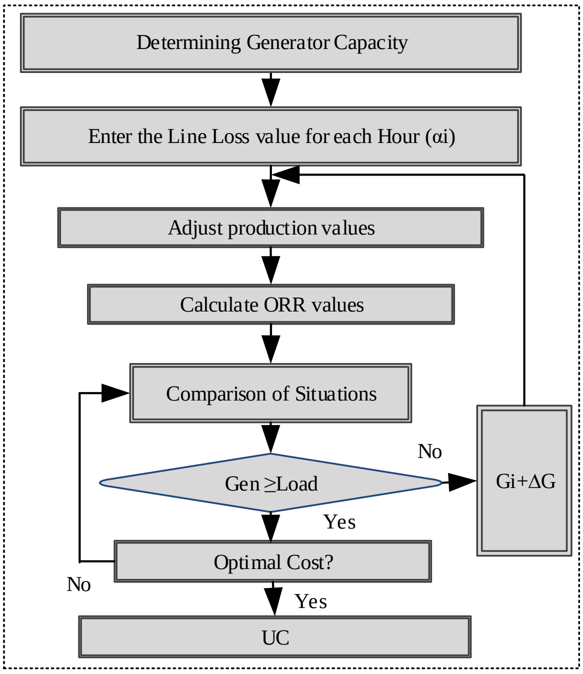

Figure 3. Foundation optimization flow chart

The following are the key components of the SCUC problem: These constraints ensure that the generation schedule adheres to the operational limits of each unit, such as minimum up and down times, ramp rate limits, and capacity limits. Power Balance Constraints ensure that the total generation meets the total demand at all times. Security Constraints include N-1 contingency criteria, ensuring that the system can withstand the failure of any single component without violating operational limits. Cost

Equations, the total cost to be minimized includes start-up costs, shutdown costs, and variable production costs.
The cost function is typically expressed as follows:

- By iterating through the SCUC problem and adjusting the unit commitments, the optimization algorithm seeks to find the most cost-effective and reliable generation schedule for the power system.
- The objective function for allocation planning is defined as follows using the Benders decomposition method to calculate the cost of replacing units in the event of outages in power systems (11):

$$AP_{lower} = 112st_{\ddot{u}b11} + 135st_{\ddot{u}b12} + 143st_{\ddot{u}b21} + 42st_{\ddot{u}b22} + \cdots + 19sd_{11} + 24sd_{12} + 31sd_{21} + 11sd_{22} + \cdots + 6595c_{\ddot{u}b11} + 7290c_{\ddot{u}b12} + 6780c_{\ddot{u}b21} + 1159c_{\ddot{u}b22} \ldots \quad (11)$$

The value "k" presented in Table 1 is a coefficient that ensures the maximum power of Gi, the strongest unit, is evenly distributed among other units. The total capacity of all units was calculated and then multiplied by the coefficient k (0.199) to determine the SKGi capacity to be maintained for each unit.

$$k = P_{max} \div \sum_{i=1}^{n=3} P_{i,max} \ and \ SK_{Gi} = k.P_{i,max} \quad (12)$$

In this analysis, a comparison between strong and weak feeders was conducted. Based on this evaluation, the use of the weak feeder will not be preferred. The SK capacity will be utilized in the most optimal and beneficial manner in conjunction with other criteria used for comparison.

Table 1. Production Capacities and Cost Functions of Generators

Unit *i* (MW)	$P_{i,min}$ *(MW)*	$P_{i,max}$ *(MW)*	P_{real} *(MW)*	SK_{Gi} *(MW)* P_{real}**0,199*	**Cost Functions**
G_1	10	22	21	4,179	$0.022P_1^2+6.5P_1+6595$
G_2	12	24	20	3,98	$0.018P_2^2+7.5P_2+7290$
G_3	14	28	18	3,582	$0.015P_3^2+5.8P_3+6780$

To assess the reliability of the test system, calculate the overall system reliability assuming each component has a reliability of 0.9 (13). An analysis was conducted for the test system depicted in Figure 4, focusing on 3 buses.

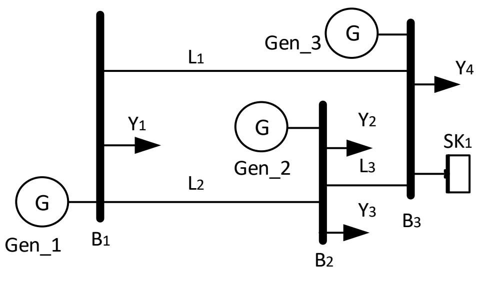

Figure 4. 3 bara, 3 Generatör, 4 Yük ve 1 Süper Kapasitör için Test Sistemi

$$Güvenirlik\ (G_s) = [\partial_s(\partial_3\partial_9)(\partial_s\partial_4) + \partial_4 - \partial_s\partial_3\partial_9\partial_4)$$

$$G_s = [0.91(0.92)(0.94) + 0.97 - 0.8719) = 0{,}8850 \quad (13)$$

If the failure rate of each component in the system is 5 f/year and the average repair time is 94.2 hours, the usability of the system is calculated as (14) and (15).

$$G_s = [\propto_s\ (3\ god\ value)(\propto_3)\ \ \propto_s\ (3\ bad\ value)(SKU_3) \quad (14)$$

$$System\ Unusability\ (SKU) = \frac{\lambda}{\lambda + \mu} = \frac{5}{5 + 95} = 0.05 \quad (15)$$

$$System\ Availability = (0.95)[0.99275] + (0.05)[0.986094] = 0.992417$$

$$System\ Unavailability = 1 - 0.99241 = 0.00759$$

In the test system, the average repair time of the supply is considered to be 0.5 f/failure per year, i.e. 2 hours. Line data are as shown in Table 2.

Table 2. Failure rate of Line

Line	**1**	**2**	**3**
Failure rate (failure/year)	3.0	4.0	5.0
Average Repair Time (hour)	4	6	8

The Decision Equation was created for the model, taking into account production cost, line losses and reliability parameters (Equation 16).

$$Decision\ Equation\ (DE)_n = \left[\left[\sum_{i=1}^{n} \frac{\propto_{i+1}}{\propto_i + \propto_{i+1}}\right]\left[\sum_{i=1}^{n} \frac{m_{i+1}}{m_i + m_{i+1}}\right]\sum_{i=1}^{n} \frac{G_i}{G_{i+1}}\right] \quad (16)$$

For the three different parameters shown in Equation (17), 23=8 cases will be analyzed as shown in Table 4. PSK is the total amount of SK and PSK1 is the amount of SK for unit 1.

$$P_{SK_n} = \sum_{i=1}^{n} \frac{KD_i}{KD_i + KD_{i+1}} P_{SK} \quad (17)$$

Following the computation of the KD values as per equation (16), the PSK value denoting Supercapacitor Power from equation (17) is determined as depicted in Table 3 for eight distinct scenarios. Taking into account the three factors of cost, loss, and reliability, a total of 2^3 = 8 comparisons among situations will be conducted.

Table 3. Determining case study options

Cases	**Case1**	**Case2**	**Case3**	**Case4**	**Case5**	**Case6**	**Case7**	**Case8**
Reliability	-	+	-	-	+	+	-	+
Cost	-	-	+	-	+	-	+	+
Lost	-	-	-	+	-	+	+	+

In the IEEE test model used: the reliability of Line1, Line2 and Line3 are 0.95, 0.99 and 0.94 respectively, Line losses are given as α1=0.0001 and α2=0.0002 and α2=0.0004 (Table 4). According to Figure 4, by subtracting the load amount from the production total, the SK amount was obtained as 50 MW.

Table 4. Data from eight different case studies

Unit	Cost (c)	Lost (α)	Reliability (R)	SK (MW)	Total Generation Cost ($/MWh)
G1	8	0.0001	0.95	50	
G2	12	0.0002	0.99	50	
G3	10	0.0004	0.94	50	
	β1	**β2**	**PSK1**	**PSK2**	
Case1	0	0	50	50	1400
Case2	0.45	0.48	55.55	44.44	1388.88
Case3	0.43	0.66	33.33	66.66	1433.33
Case4	1.05	0.97	51.06	48.93	1397.87
Case5	0.18	0.29	38.46	61.53	1423.07
Case6	0.56	0.43	56.60	43.39	1386.79
Case7	0.34	0.65	34.28	65.71	1431.42
Case8	0.18	0.29	39.47	60.52	1421.05

Utilizing the values of C, R, and α, the acceptance matrix for the 3-bar system was constructed. This matrix is of size 3x3. The bus admission matrix is illustrated in Figure 5, highlighting the locations where non-zero elements exist. The system specifications can be found in Table 5. Figure 6 depicts the convergence plot for the P values in the program, while Table 5 presents the program results. Following the program execution, the average PSK1 power was determined to be 44.84 MW, and the PSK2 power was calculated as 55.15 MW. Consequently, the total system loss amounts to (100 - 99.99(PSK1 + PSK2)) = 0.01 MW. The system loss coefficients B were derived from the power flow analysis, and the power plants were economically loaded through the MATLAB® program. The Economic Distribution Analysis flowchart is outlined in Figure 5.

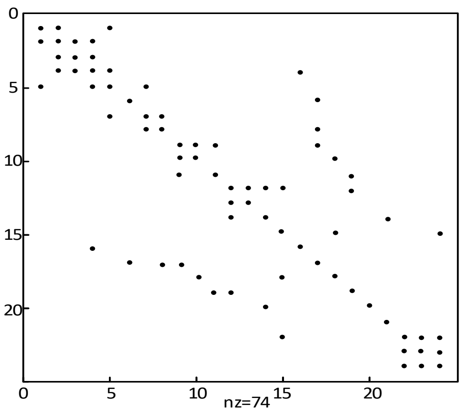

Figure 5. Non-Zero Points of the Bus Acceptance Matrix

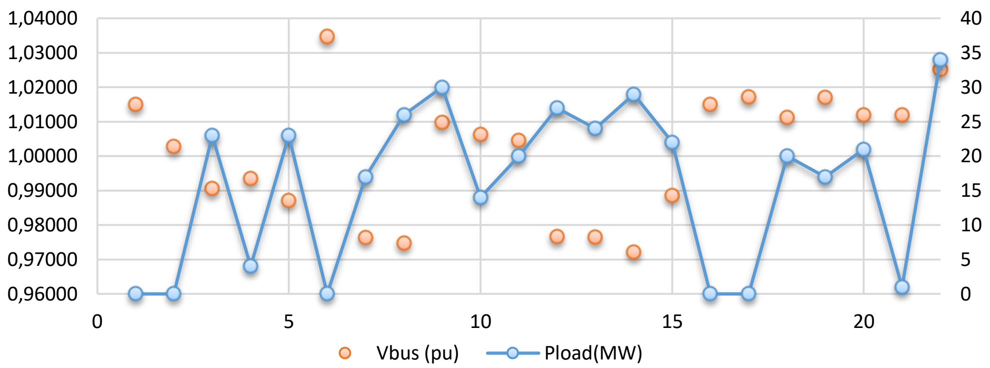

Figure 6. Program convergence chart for P and Vbus

4. Conclusion

The developed methodology entails examining production expenses, line inefficiencies, and reliability metrics to minimize production losses, optimize expenditures, and enhance system dependability. These analyses lead to improved reliability and efficiency in energy production systems. This research offers viable strategies for achieving cost-effective and sustainable energy production within power systems. Through the consideration of production costs, line inefficiencies, and reliability metrics, the methodology ensures the efficient allocation of energy production assets. It provides a comprehensive assessment of power system effectiveness and feasibility. Comparison of the results according to Table 5 reveals that the lowest cost of $8,053/MWh was attained in the sixth scenario among all cases studied. The parameters scrutinized in this scenario are production cost and reliability, indicating that the distributed production quantities are both reliable and cost-effective. Consequently, the SK allocation was achieved at a more favorable cost compared to the MATLAB result. Conversely, scenarios focusing solely on line inefficiencies or a combination of line inefficiencies and reliability appear less economical. In the case studies, a thorough examination of the scenario depicting a linear relationship between units and SK quantities reveals that the sixth scenario is the most suitable among those depicted in Figure 7. The most significant disparity in unit distribution is observed in the third case study, suggesting that only line inefficiencies were considered in the calculation.

In future studies, sophisticated modeling and simulation techniques can be employed to provide more detailed analyses of the reliability and efficiency of energy production systems. This would allow for a more realistic and comprehensive evaluation of different scenarios. Additionally, real-time data analysis and dynamic load distribution algorithms can be developed. This would contribute to a more effective allocation of energy production assets and enhance system reliability.

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