

*Research Article*

A Greedy Adaptive and Backtracking Framework for Reducing Emission Costs in Generator Scheduling

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Abstract: The growing demand for efficient and environmentally sustainable power generation calls for advanced optimization methods to address the economic and emission dispatch (EED) problem. This study introduces a novel hybrid optimization approach, GRASP-BLS, which integrates GRASP for global solution space exploration with BLS for accurate local refinement. The synergy between metaheuristic randomness and gradient-based precision is the main contribution of this work, enabling GRASP-BLS to outperform conventional methods in complex, constrained power dispatch scenarios. In a 4-h test case, GRASP-BLS reduced generation costs by 0.4% and emissions by 22.25% compared with SEA. Extended evaluations over a 24-hour period under two scenarios—Scenario 1 (stable loads) and Scenario 2 (dynamic loads with unit commitment)—show that GRASP-BLS consistently yields superior performance. It achieves 5.64%–9.84% cost savings and 1.72%–4.91% emission reductions, outperforming GSA, GWO, and PSO. Despite slightly higher computation time, GRASP-BLS satisfies all operational constraints, including power balance, generation limits, ramp rates, and unit commitment feasibility. These findings highlight the novelty and practicality of GRASP-BLS as a robust, scalable, and adaptive framework for real-world power system optimization, particularly in environments requiring a balance between economic efficiency and environmental responsibility.

Keywords: Backtracking line search; Economic emission Dispatch; GRASP; Optimization; Power system.

1. Introduction

Global warming and climate change have now become global issues, with emissions being one of the contributing factors. This encourages many countries to focus on decarbonization, a sustainable environment, energy transition, net-zero emissions, renewable energy, and the digital economy. Climate change is characterized by unpredictable patterns and extreme events and is expected to continue (Ryan and Bristow, 2023). Climate change is a global threat that has begun to put pressure on various sectors. Therefore, mitigating the impacts of climate change must be the most important thing. Therefore, this global threat requires a global commitment to address its dire implications to ensure global sustainability (Abbass et al., 2022). Various studies related to climate change have begun to emerge, especially in Indonesia. The search results found that 700 articles on the issue of mitigation and climate change were published through the Crossref and Scopus databases from January 2012 to December 2022 (Wance et al., 2024). This shows how serious Indonesia is in contributing to the problem of climate change, considering that Indonesia is one of the most vulnerable countries in the world to the impacts of climate change. Indonesia faces significant challenges in reducing its impacts and promoting sustainability (Brata and Toparakkasi, 2023). Models and tools to explore the synergy between energy transition and the digital economy have been developed (Zagloel et al., 2023). Decarbonization toward net-zero emissions has been published (Hadi et al., 2025).

Meanwhile, SDGs are a global issue and have become the target of various state leaders, including Indonesia (Farida et al., 2024), where Indonesia is very committed to the success of the SDGs as part of sustainable economic development efforts, which are also part of global commitments (Nuzula et al., 2024). Various research topics related to SDGs have continued to increase in Indonesia since 2016 (Farida et al., 2024). When financing is required to meet Indonesia's SDG targets, innovative financing and stakeholder collaboration are crucial actions that the government must take to accelerate the country's progress. A gap analysis between baseline circumstances and SDG indicator targets at the national and regional levels is necessary as an integral component of efforts to achieve the SDGs, including planning aspects (Jayanthi et al., 2024).

The seventh SDG, namely, clean and affordable energy, is one of the SDGs agendas. For this purpose, five challenges need global attention: limiting the use of fossil fuels; migration to a diverse and renewable energy matrix; decentralization of energy generation and distribution; maximizing energy efficiency and energy storage; and minimizing the cost of energy generation from chemical processes (Lup et al., 2023). The growing environmental awareness recently has driven many countries to develop strategies to minimize GHG emissions by increasing the share of new and renewable energy sources (Saroji et al., 2022). The need for a sustainable environment is crucial; this has encouraged research on the design, development, testing, and commissioning of smart grid solar-powered distributed energy resource systems as an alternative to powering loads with conventional energy sources, creating pollution-free and self-sufficient systems that can be built according to the required load capacity (Onibonoje et al., 2023). A critical review and impact analysis of energy access projects has been carried out based on empirical research from eight country case studies in Africa, Asia, and Latin America. The recommendations include bridging the gap between rural and urban areas, ensuring that energy is connected to sustainable outcomes, striking a balance between top-down and bottom-up agendas, and evaluating the effects of techno-economic factors (Minas et al., 2024). Emissions can be generated from transportation, industry, household, and electricity generation sectors. Power plant scheduling with the aim of minimizing fuel costs or what is known as economic dispatch (ED) has been widely published, from simple to more complex algorithms. The simpler the ED formulation, the easier the optimization algorithm used (Marzbani and Abdelfatah, 2024). However, in MOO, more sophisticated approaches, such as uncertainty modeling and AI-based methods, are used. Although these sophisticated algorithms are efficient in handling complex problems, they also have higher computational requirements (Marzbani and Abdelfatah, 2024).

Hybrid methods involving artificial intelligence, namely, the PSO method combined with the Bat Algorithm (hybrid PS-BA), gave 0.281% better results than PSO alone (Okelola et al., 2023). A new meta-heuristic algorithm based on a combination of the exchange market algorithm and the grasshopper optimization algorithm was published to solve the multi-area economic dispatch (MAED) problem (Sharifian and Abdi, 2023). The proposed method, namely the hybrid exchange market algorithm with grasshopper optimization, reduced fuel costs from 0.0229% to 1.1622% compared to the best results reported in the literature. An improved butterfly optimization algorithm (IBOA) to reduce load provisioning costs was published (Alhasnawi et al., 2023). In this case, the coefficients are not constant and will change as the simulation progresses, showing that the use of IBOA increased the total electricity cost, peak load, PAR, and waiting time by 3850.61 (cents), 20.1245 (kW), 6.7922 (kW), and 53 seconds, respectively.

Yang et al., 2024 focused on the improved gray wolf optimization algorithm (IGWO) and the use of the improved algorithm to optimize the unit fuel cost, considering the transmission loss and valve point effect (Yang et al., 2024). The IGWO was applied to three distinct ED case scales and contrasted with other approaches that have been documented in the literature. The findings demonstrated that the suggested IGWO efficiently lowers the unit fuel cost and has a faster convergence rate and superior global optimization capability (Yang et al., 2024). The proposed scheduling strategy, objective model, and solution algorithm can successfully accomplish multi-objective coordinated optimization scheduling for microgrid clusters (MGC)

systems, which greatly enhances the overall economic benefits of MGCs while guaranteeing a reliable power supply. Wang et al., 2024 published IGWO to address the ED problem in microgrid clusters.

Multi-area ED optimization involves prohibited operation zones (POZs) (Raharjo et al., 2021; Sharifian and Abdi, 2024). The primary goal of the MAED problem is to find the ideal quantity of generation and power exchange between nearby areas while minimizing generation and transmission costs while meeting a number of operational and physical restrictions (Sharifian and Abdi, 2024). The solution of the MAED problem using the large-to-small-area technique (LSAT) method was proposed (Raharjo et al., 2021). The results of the LSAT method outperform the GA and are very close to the results of the Lambda Iteration (LI) and Dynamic Programming (DP) methods. The basic principle of LSAT is to reduce the possible area, which is the location of a number of candidate solutions, until the optimal point is obtained (Raharjo et al., 2021). (Zein et al., 2022) proposed a ToNDA-based solution to the MAED problem. The ToNDA method is applied to ED with discounted quadratic fuel costs with 10 generators, where ToNDA shows better performance than SAMF, PSO, HM, HNN, and HGA. ToND is also applied to ED with VPE in 13 power plants, and the results outperform the QPSO, SSA, IPSO-TVAC, HCRO-DE, DSD, SHDE, HGA, and FAPSO-VDE methods. When applied to a system with large units (40 units), ToNDA is superior to QPSO and HGA, while there is a difference of 0.00028% when compared to DSD.

The solution of the ED problem using the calculus-based optimization method has also been proposed (Ikhsan et al., 2024; Wachjoe et al., 2020). The VLIM method was applied to 15 and 42 power plants (Ikhsan et al., 2024). VLIM outperformed the Lambda Iteration Method-Gravitational Search Algorithm (LIM-GSA), Artificial Bee Colony (ABC), and Genetic Algorithm (GA). Meanwhile, Wachjoe et al., 2020 proposed fast scheduling to solve the ED problem, where the proposed method simulates the economic load dispatch for a 26-Bus power system and 6-generation units. After being compared with the GA, the proposed method can save fuel cost significantly around US\$29876.46 in 24 hours, while the computation time in executing the application program is quite short, which is 0.15 seconds.

In line with the emission of power plants, which is one of the contributors of greenhouse gases, the scheduling of power plants not only aims to get the cheapest fuel costs, such as in the case of ED, but also the emissions produced need to be optimized, which is often called economic and emission dispatch (EED). Research on EED has also been widely published. The bat algorithm is applied in Nigeria's 28-bus electricity system (Tijani et al., 2024). EEDs involving renewable energy sources have been published (Aswan et al., 2019), revealing various advantages and disadvantages of various methods such as: GA, ABC, PSO, DE, HBMO, CSO, and GSA. Another artificial method, the chaotic Jaya algorithm, is also applied to solve EED problems involving renewable energy sources, such as wind and solar panels (Chaudhary et al., 2024). The impact of integrating the uncertain nature of wind and solar photovoltaic power systems on the optimal scheduling of two complex test systems is modeled using probabilistic cost functions, using a single objective/multi-objective model (Chaudhary et al., 2024). Niu et al., 2021 proposed a modified multi-objective cross-entropy algorithm (MMOCE) to solve EED problems containing renewable energy. They showed that the proposed MMOCE is superior to other multi-objective cross-entropy algorithms and published heuristic methods in all test systems.

(Habachi et al., 2019) published the cuckoo search algorithm (CSA) to solve the EED problem, where CSA can handle the nonlinearity of the ED problem and minimize the cost, total power loss in transmission and maximize the reliability of power provided to customers. Various classical, non-conventional, and hybrid methods have been proposed to solve the EED problem with and without renewable energy (in this case, PV and wind turbine) (Marouani et al., 2022), revealing that hybrid and non-conventional methods are safer and more effective in solving the EED problem.

Various optimization techniques are applied to ELD and DEED problems in power systems.

The CRO method effectively simulates molecular interactions to improve solution quality and computational efficiency in ELD problems, considering complex constraints such as ramp rate limits and prohibited operating zones (Bhattacharjee et al., 2014). Similarly, the AEFA leverages physics-based principles to achieve global optimal solutions while avoiding local minima (Shah et al., 2023). Inspired by swarm intelligence, the Sooty Tern Optimization Algorithm (STOA) enhances DEED performance by efficiently balancing fuel costs and emission reductions (Soni and Bhattacharjee, 2022). These algorithms are robust and superior to existing methods, making them valuable for solving nonlinear and constrained optimization problems in power system operations.

Furthermore, recent studies have integrated renewable energy sources (RES) and plug-in electric vehicles (PEVs) into dispatch models to address sustainability concerns (Soni and Bhattacharjee, 2024a). The EO and OEO approaches optimize power dispatch by managing uncertainties in wind and solar power generation using Weibull and beta distributions. The WSPEV DEED model innovatively incorporates RES and PEVs, smoothing charging and discharging cycles while handling the economic and environmental trade-offs in power grids (Soni and Bhattacharjee, 2024b). These techniques improve efficiency and reduce emissions by incorporating multiple fuel options and hybrid power sources, demonstrating the potential for sustainable, cost-effective energy management (Soni and Bhattacharjee, 2023). The comparative results validate these optimization strategies and highlight their effectiveness in addressing the challenges of modern power systems.

In addition to the optimization algorithm, the testing scenario is designed to realistically reflect actual power system conditions, capturing the true operational challenges in generator scheduling. The applied dispatch strategy ensures not only mathematical optimization but also practical feasibility in real-world power system operations by considering variations in load and generator operational constraints (Hong and Apolinario, 2021; Kamboj and Malik, 2023; Selvakumar et al., 2023). In a power system, when the minimum demand matches the total minimum generation capacity of all committed units, regular load conditions occur. Under these conditions, generation scheduling can be managed without requiring unit commitment, as the total demand remains at least equal to the minimum operational levels of all generators, allowing them to function efficiently within their limits. However, when the load falls below this threshold, the demand becomes lower than the combined minimum output of all available units. In such cases, keeping all units operational would lead to excessive generation, resulting in higher operational costs and inefficiencies due to unnecessary fuel consumption and increased generator wear. A unit commitment strategy must be applied to address this issue, selectively turning off certain generators while ensuring compliance with operational constraints such as ramp rates, minimum up/down times, and system reliability requirements. The on/off decision is not solely based on load balancing but also involves cost-effective power generation redistribution. In this process, cheaper units are prioritized to operate at full capacity, whereas more expensive units are deactivated to minimize overall costs. Additionally, whenever possible, unit selection is further optimized to strike a balance between cost and emissions (Selvakumar et al., 2023; Syama et al., 2024), ensuring a more sustainable and economical dispatch strategy. The dispatch process becomes more cost-efficient by implementing intelligent unit commitment, preventing excessive power generation while maintaining system stability, economic efficiency, and environmental sustainability.

Building upon this foundation, Scenarios 0–2 are used to comprehensively evaluate the performance of the proposed GRASP-BLS algorithm across a range of realistic and progressively complex power system conditions. Each scenario is designed to reflect a distinct operational challenge. Scenario 0 serves as a benchmarking case against existing methods under normal load conditions, where the combined minimum generation limits exceed the total power demand. All units remain active, and unit commitment is not required, providing a stable environment for cost and emission optimization performance assessment. Scenario 1 simulates a reduced load condition in which the demand falls below the total minimum generation capacity. This

condition requires the algorithm to make unit commitment decisions—selectively deactivating certain generators while satisfying constraints such as ramp rates and generation limits. Scenario 2 introduces additional complexities, including dynamic load variations and stricter operational constraints, to represent a more realistic and constrained dispatch environment. Together, these scenarios demonstrate the GRASP-BLS algorithm’s robustness, scalability, and adaptability in handling both standard and challenging power system operations.

The EED results can be used to calculate the cost of emission reduction as published (Intan Laily Muflikhah et al., 2024; Puspitasari et al., 2022). Using the simulated annealing (SA) method, it costs US\$258.81 to reduce 1 ton of emissions (Puspitasari et al., 2022), while the whale optimization algorithm (WOA) provides better performance than SA, which only costs 57.52% of the SA cost for the same thing (Intan Laily Muflikhah et al., 2024), assuming an exchange rate of US\$1 equal to IDR 16,221.90), on January 8, 2024.

The main motivation and novelty of this paper lie in the synergistic integration of GRASP for global exploration and BLS for local exploitation. By leveraging GRASP’s ability to diversify the search space while allowing BLS to refine solutions within a more focused region, this combination enhances both computational efficiency and solution quality. Additionally, the framework employs central finite difference methods to calculate gradients locally for each dimension, ensuring accurate derivative estimates that contribute to better solution refinement. Another key innovation is the modular system design, which enables seamless adaptation to varying numbers of generating units and demand levels, making the approach highly scalable. Furthermore, candidate solutions are probabilistically reduced during the GRASP constructive phase, accelerating the optimization process without compromising solution quality.

2. Methodology

The Methodology section encompasses a comprehensive exploration of datasets, including detailed analyses of load characteristics, such as hourly load patterns, and specific profiles of demand fluctuations. It further delves into the characteristics of the generator, highlighting aspects such as coefficient costs, coefficient emissions, and operational constraints. Additionally, this chapter provides an in-depth discussion of the algorithms used, describing their methodologies, underlying principles, and how they are applied to model, analyze, or optimize the interactions between loads and generators in the system.

2.1 Size of the datasets

This dataset is sourced from Puspitasari et al., 2022, which serves as a critical foundation for this study by providing detailed information on various generator parameters. It includes not only the cost coefficients, which reflect the economic aspects of generator operation, but also the emission coefficients, which highlight the energy production’s environmental impact. As illustrated in Table S1, these parameters enable a dual-perspective analysis that integrates economic efficiency and sustainability considerations. The dataset offers a robust framework for evaluating trade-offs between operational costs and environmental responsibilities by incorporating both cost and emission coefficients, ensuring a balanced approach to generator performance assessment in real-world scenarios. This multidimensional perspective enhances the overall understanding and supports informed decision-making in the optimization of generator operations.

Figure S1 illustrates the hourly load pattern over a 24-hour period, providing a detailed visualization of the simulated data used to test the system’s reliability in managing load fluctuations throughout the day. This simulated dataset serves as a critical component for evaluating system performance under various operational conditions. To capture different operational strategies, the load pattern is divided into two distinct scenarios. In Scenario 1, the load profile is designed for a system that does not involve unit commitment, allowing for a simplified load and generation balancing analysis without considering unit-specific constraints. This scenario provides a baseline for understanding system behavior under conditions that are less restrictive.

In Scenario 2, the load pattern is constructed to reflect a system that incorporates unit commitment. This scenario introduces more complexity by including operational constraints, such as the committed units' minimum generation levels. Specifically, the load is intentionally set below the total minimum generation capacity of all units during certain hours, creating a challenging condition to test the system's flexibility and ability to adapt to such constraints. The simulation compares the two scenarios to highlight differences in system reliability, efficiency, and feasibility under unit commitment constraints. This comprehensive approach ensures that the system's capabilities in addressing dynamic load fluctuations under varying conditions are thoroughly evaluated.

EED is a vital aspect of power system operation that addresses the dual and often conflicting objectives of minimizing power generation costs (EED) and reducing environmental impacts, particularly greenhouse gas emissions (EED). Economic dispatch focuses on cost-effectively distributing the load among available generators while adhering to system constraints such as generator capacities and operational limits. In contrast, emission dispatch prioritizes minimizing pollutants such as CO₂, NO_X, and SO₂, often requiring generator output adjustments that may lead to higher costs. Figure S2 illustrates the economic and emission dispatch inspired by Stefan Pfenninger-Lee et al., 2024.

Integrating these objectives into a single framework creates a multi-objective optimization problem, as minimizing costs and emissions simultaneously involves trade-offs; achieving lower emissions might necessitate operating less economical units or adopting additional technologies. The objective function for EED can be mathematically expressed as shown in Equation 1.

$$Z(P) = w_1 \cdot \left[\sum_{i=1}^n \frac{a_i + b_i P_i + c_i P_i^2}{\varepsilon} \right] + w_2 \cdot \left[\sum_{i=1}^n \frac{d_i + e_i P_i + f_i P_i^2}{10^6} \right] + \lambda \left| \sum_{i=1}^n P_i - P_D \right| \quad (1)$$

where:

- $Z(P)$: Objective function.
- a_i, b_i, c_i : Cost coefficients for generator i -th.
- d_i, e_i, f_i : Emission coefficients for generator i -th.
- P_i : Power output of generator i -th.
- P_D : Total power demand.
- λ : Penalty factor for any imbalance between $\sum P_i$ and P_D .
- w_1, w_2 : Weight factors for cost (w_1) and emissions (w_2).
- ε : Exchange Rate (IDR 14,385)

In addition, this study incorporates constraint functions designed to represent real-world conditions with high fidelity. These constraints ensure that the simulation and optimization processes closely mimic the operational realities of power systems. The power balance condition is a key constraint, which mandates that the total power generation must always equal the total load demand to maintain system stability. The power balance constraint can be mathematically expressed as shown in Equation 2.

$$\sum_{i=1}^n P_i = P_D + P_{\text{Loss}} \quad (2)$$

where:

- P_{Loss} : Total power loss in the system.
- a_i, b_i, c_i : Cost coefficients for generator i -th.

The generation limits constraint enforces the operational boundaries of each generator, ensuring that power output stays within specified minimum and maximum levels to prevent overloading or inefficiency. The generator limits constraint can be mathematically expressed as shown in Equation 3.

$$P_i^{(t+1)} = \begin{cases} P_{\min,i} & P_i(t) < P_{\min,i} \\ P_i^{(t)} & P_{\min,i} \leq P_i(t) \leq P_{\max,i} \\ P_{\max,i} & P_i(t) > P_{\max,i} \end{cases} \quad (3)$$

where:

$P_{\min,i}$: Minimum power output of generator i -th.

$P_{\max,i}$: Maximum power output of generator i -th.

Furthermore, the ramp rate constraint accounts for the physical limitations of generators, restricting the rate at which power output can increase or decrease over time to reflect realistic generator response capabilities. The ramp rate constraint can be mathematically expressed as shown in Equation 4.

$$P_i^{(t+1)} = P_i(t+1) \begin{cases} D_i, & P_i^{(t)} - P_i^{(t-1)} \leq D_i \\ U_i, & P_i^{(t)} - P_i^{(t-1)} \leq U_i \end{cases} \quad (4)$$

where:

$P_i^{(t+1)}$: Power output of generator i -th at time $t + 1$.

$P_i^{(t)}$: Power output of generator i -th at the current time t .

$P_i^{(t-1)}$: Power output of generator i -th at the previous time step $t - 1$.

D_i : Maximum allowable decrease in power output (down-ramp limit) for generator i -th within one time step.

U_i : Maximum allowable increase in power output (up-ramp limit) for generator i -th within one time step.

By incorporating these critical constraints, the study ensures that the proposed models and methods are both practical and applicable to real-world power system operations.

In addition, two scenarios were implemented to test the reliability of the algorithm or method used. Scenario 1 represents a condition that does not require the application of unit commitment, allowing for a simplified analysis. Scenario 2 incorporates unit commitment, where generators are turned on or off to adjust to the load demand, particularly during periods when the load is below the total minimum generation capacity of all committed units. Unlike traditional unit commitment problems, this scenario solely focuses on adjusting the on/off status of generators to align with system demand and does not account for startup or shutdown costs. The unit commitment algorithm is mathematically expressed to determine the optimal subset of active generators (A) required to meet a given load demand (P_D) while adhering to the generators' physical constraints. The formulation includes the following components:

A represent the subset of active generators, defined as shown in Equation 5:

$$A = \{i | UC_i = 1, i = 1, 2, \dots, n\} \quad (5)$$

where:

UC_i : Binary variable indicating whether generator i -th is On ($UC_i = 1$) or Off ($UC_i = 0$)

For any subset A , the total generation limits are computed as shown in Equations 6 to 7:

$$P_{\min}^A = \sum_{i \in A} p_{\min,i} \quad (6)$$

$$P_{\max}^A = \sum_{i \in A} p_{\max,i} \quad (7)$$

The subset A must satisfy the following demand constraint, as shown in Equation 8:

$$P_{max}^A \leq P_D \leq P_{max,i} \quad (8)$$

This ensures that the total generation from the active units is sufficient to meet the load demand (P_D). If no feasible subset A satisfies the demand (P_D), all units are turned ON as a default condition or fallback condition, which is called the fallback strategy. This ensures that the demand is always met, even under highly constrained conditions.

2.2 Greedy Randomized Adaptive Search Procedure with Backtracking Line Search

Recent advancements in optimization algorithms have led to significant innovations, including the development of the GRASP and enhancements in BLS techniques. Optimization algorithms have been extensively studied and refined to solve complex mathematical and computational problems. (O’neill and Wright, 2023) introduced a line-search descent algorithm tailored for strict saddle functions, leveraging backtracking line search, which adapts to unknown parameters of the strict saddle property, to achieve the best-known worst-case complexity guarantees for nonconvex optimization problems. Similarly, (Stanimirović and Miladinović, 2010) proposed an accelerated gradient descent method integrated with line search to address unconstrained optimization. Their method transforms Newton’s method by approximating the Hessian matrix and employs backtracking to achieve linear convergence for convex functions. These foundational contributions underscore the importance of efficient line search techniques in enhancing the scalability and reliability of optimization algorithms. Metaheuristic approaches, particularly GRASP, have also seen advancements in their applications across various domains. Neto et al., 2017 explored GRASP combined with differential evolution to solve non-smooth economic dispatch problems, demonstrating improved global search capability and effectiveness in avoiding local minima. Hirsch et al., 2010 enhanced continuous GRASP with speed optimizations and robustness improvements for global optimization problems with box constraints. In the domain of combinatorial optimization, Oviedo-Salas et al., 2022 applied GRASP to strip packing problems, integrating waste functions and flags to improve candidate selection. Estrada-Padilla et al., 2022 further developed GRASP/ Δ , a non-evolutionary approach for multi-objective portfolio optimization, emphasizing computational efficiency and adaptability to large search spaces.

A comprehensive review by Laguna et al., 2023 discusses two decades of GRASP research, emphasizing its hybridization with PLR, which has proven effective for solving complex optimization problems. Similarly, Chaves et al., 2024 introduced a problem-independent GRASP using the random-key optimizer paradigm, demonstrating its adaptability across diverse combinatorial optimization challenges. In the domain of backtracking line search, Kunstner et al., 2023 proposed multidimensional backtracking that optimizes per-coordinate step sizes, significantly improving convergence in smooth convex problems. They introduced the New Q-Newton’s method, which incorporates backtracking line search to achieve enhanced convergence guarantees while avoiding saddle points. Additionally, Shea and Schmidt, 2024 developed “Greedy Newton,” a variant of Newton’s method employing exact line search. This approach achieves faster global convergence rates while maintaining SL convergence. In addition to these developments, recent research has focused on adaptive strategies to enhance the efficiency and convergence properties of optimization algorithms. For instance, Cavalcanti et al., 2024 proposed an adaptive backtracking approach to more effectively adjust step sizes during optimization, leading to faster convergence rates compared to traditional backtracking methods. This method replaces the constant factor used in regular backtracking with one that considers the degree to which the chosen criterion is violated, thereby improving optimization efficiency without additional computational burden. Such advancements contribute to the development of more robust and efficient optimization techniques applicable across various domains of complex problems.

The collective advancements in GRASP and BLS highlight the versatility, adaptability, and efficiency of modern optimization techniques. GRASP has proven to be effective in solving complex combinatorial optimization challenges, including NP-hard problems such as two-dimensional

strip packing and multi-objective portfolio optimization, where hybrid and enhanced variants such as C-GRASP and GRASP/ Δ have demonstrated superior performance. Similarly, BLS innovations, such as multidimensional backtracking and adaptive strategies, have significantly improved convergence rates and efficiency, making them applicable to both small-scale mathematical functions and large-scale industrial systems. Building on these strengths, the authors propose a novel hybrid approach combining GRASP with BLS to address the EED problem. This hybridization capitalizes on the adaptive exploration capabilities of GRASP and the dynamic step size adjustments of BLS to enhance convergence efficiency, effectively optimizing both power generation costs and emissions reduction in a multi-objective setting.

The first section focuses on the GRASP, elaborating on its two key phases: the construction phase, where an initial feasible solution is generated through a GRASP, and the local search phase, which iteratively refines the solution to achieve improved quality (Resende and Ribeiro, 2014). This process is repeated for multiple iterations, with each iteration attempting to further enhance the solution by exploring different regions of the solution space. The adaptive nature of GRASP ensures that the method avoids being trapped in local optima by diversifying the search space exploration. After constructing an initial solution, the local search phase aims to improve it by exploring its neighborhood. This involves iteratively replacing the current solution with a better one found in its vicinity until no further improvements can be made, indicating a local minimum. The effectiveness of the local search depends on factors such as the neighborhood structure, search strategy, and the quality of the initial solution provided by the construction phase. GRASP balances intensification and diversification by combining these two phases, making it a robust approach for solving complex optimization problems.

A. Constructive Phase

1. The solution is initialized as shown in Equation 9:

$$P = [P_1, P_2, \dots, P_n] \quad (9)$$

2. Restricted Candidate List (τ) (Resende and Ribeiro, 2019). For each unit i , define the candidate list as shown in Equation 10:

$$\tau_i = \{P_i | P_{min,i} \leq P_i \leq P_{max,i}\} \quad (10)$$

3. Greedy selection: Choose the candidate P_{iBest} that minimize the partial objective function is chosen, as shown in Equation 11:

$$P_i^{Best} = \arg_{P_i \in \tau_i}^{min} Z([P_1, P_2, \dots, P_n]) \quad (11)$$

4. Iterate: Repeat for all units $i=1, 2, \dots, n$ until the initial solution $P_t=0$ is formed.

where:

n : The number of units.

P_i : Chosen from the search space $[P_{min,i}, P_{max,i}]$

τ_i : Restricted Candidate List for unit i

B. Local search phase

The second section delves into the BLS component, which is integrated into the GRASP framework to fine-tune the solutions obtained during the local search phase. BLS operates by iteratively adjusting the step size along the gradient direction to identify the most optimal solution within the current solution's vicinity. This process ensures efficient convergence by precisely balancing the trade-off between speed and accuracy. By leveraging BLS, the hybrid

method can navigate the highly constrained and nonlinear solution space of the economic and emission dispatch problem, ensuring a more robust optimization process. The integration of BLS into optimization algorithms significantly improves solution refinement during the local search phase. For instance, Xu et al., 2021 introduced a multi-objective learning backtracking search algorithm to address the environmental/economic dispatch problem, demonstrating improved convergence and solution quality. Similarly, Zou et al., 2018 proposed a hybrid hierarchical backtracking search optimization algorithm that effectively balances exploration and exploitation in complex optimization tasks. Additionally, Tsai et al., 2024 developed an advanced backtracking search algorithm using single- and multi-vector mutation strategies, which resulted in enhanced performance across various optimization problems. Collectively, these studies underscore the efficacy of incorporating BLS into optimization frameworks to efficiently navigate and optimize complex solution spaces.

1. Compute gradient: For each unit i , approximate the gradient using finite differences, as shown in Figure S3.

The central finite difference can be mathematically expressed as shown in Equation 12.

$$\nabla Z(P)_i = \frac{Z(P + \epsilon e_i) - Z(P - \epsilon e_i)}{2\epsilon} \quad (12)$$

2. Update the solution using Equation 13:

$$\nabla Z(P)_i = \frac{Z(P + \epsilon e_i) - Z(P - \epsilon e_i)}{2\epsilon} \quad (13)$$

3. Use Backtracking Line Search: Determine the optimal step size using Backtracking Line Search as follows.

- a. Step size acceptance condition (Armijo condition) (Asl and Overton, 2017). The step size must satisfy as expressed in Equation 14.

$$\nabla Z(P_i - \eta \cdot \nabla Z(P)) \leq Z(P_i) - \alpha \cdot \eta \cdot \|\nabla Z(P)\|^2 \quad (14)$$

- b. Step Size Reduction: If the above condition is not met, reduce as expressed in Equation 15.

$$\eta = \beta \cdot \eta \quad (15)$$

- c. Stopping criterion: The iteration is stopped when the step size becomes smaller than the tolerance (tol). Mathematically, it can be expressed as shown in Equation 16.

$$\eta \leq tol \quad (16)$$

4. Stopping criterion: Stop when the condition is met as can be mathematically expressed as shown in Equation 17.

$$\|P_i^{(t+1)} - P\| < tol \quad (17)$$

where:

- η : Step size.
- $\nabla Z(P)$: Gradient of the objective function
- α : Parameter controlling objective reduction
- $\|\nabla Z(P)\|^2$: Squared norm of the gradient
- β : Reduction Factor ($0 < \beta < 1$)
- tol : Convergence tolerance

C. Selection of the best solution

1. Solution evaluation: Calculate the objective function ZP for each candidate solution P.
2. Solution comparison: Keep the best solution as expressed in Equation 18.

$$P^{Best} = \arg \min_P Z(P) \quad (18)$$

The following is the pseudocode representation of the Greedy Randomized Adaptive Search Procedure (GRASP) combined with Backtracking Line Search (BLS) for solving optimization problems such as economic and emission dispatch (EED).

3. Results and Discussion

This study includes a series of system tests to evaluate the reliability and effectiveness of the proposed program in optimizing both operational costs and emission reductions. The tests were conducted across two different system scenarios to thoroughly examine the performance of the program under varying conditions.

In the first test system, we focused on benchmarking the proposed method against the simulated annealing algorithm, as described in Puspitasari et al., 2022. This test involved a dynamic load over a 4-hour period, allowing for a direct comparison of the program's capability to minimize costs and emissions under fluctuating load conditions. Benchmarking against an established method, such as simulated annealing, provides a robust validation of the program's optimization capabilities and ensures its competitiveness in addressing multi-objective economic and emission dispatch problems.

In the second test system, the evaluation was extended to a 24-hour period with the introduction of two distinct load scenarios to analyze the program's adaptability and robustness. In Scenario 1, the load was maintained under normal operating conditions, indicating that all generators could remain operational. The main objective in this scenario was to efficiently schedule the generators to achieve relatively low costs and emissions while ensuring that the demand was met. In Scenario 2, the load was intentionally reduced to a level below the normal condition, falling below the TMG limit. This created a challenging situation in which some generators needed to be turned off to match the reduced load, effectively introducing the concept of unit commitment. The second scenario reflects real-world operational constraints and tests the program's ability to handle more complex conditions, such as scheduling generators under limited operational flexibility. This test provides insights into the program's efficiency, reliability, and practicality in real-world applications by evaluating both normal and reduced load conditions. Overall, these system tests offer a comprehensive assessment of the proposed program's ability to balance cost optimization and emission reduction under diverse and dynamic conditions.

Table S2 provides a comprehensive overview of the parameter tuning configurations used during the program execution across all methods. These parameters were carefully selected and adjusted to ensure optimal performance for each method, considering the specific characteristics and requirements of the EED problem. The table includes key tuning variables such as iteration limits, population sizes, step sizes, and weighting factors, all of which play a crucial role in the optimization process's efficiency and effectiveness.

These parameters were systematically tested and adjusted to align with the constraints of the problem, such as power balance, ramp rate, and generation limits, as well as the presented dynamic load scenarios. This detailed account of parameter tuning underscores the methodical approach taken to ensure a fair and accurate benchmarking process across all optimization methods.

3.1 Scenario 0: Four-hour load demand

The study conducted in (Puspitasari et al., 2022) proposed the SA method for optimization and demonstrated its superiority over several comparator methods using a weighted-scenario

approach. Simulated annealing was selected as the single benchmark comparator in this study to validate the performance of the proposed GRASP-BLS method based on its proven effectiveness. To ensure a focused evaluation, this study used only the cost : emission weighting scenario of 1:0, prioritizing the reduction of economic costs while still assessing emission performance as a secondary outcome.

The results of the benchmarking (Table S3) highlight the significant advantages of the GRASP-BLS method over simulated annealing. Specifically, GRASP-BLS reduced total operational costs from US\$2,268,505 (under SA) to US\$2,259,420, reflecting a cost reduction of approximately 0.4%. Although this may seem modest, such reductions are significant in large-scale energy systems, as they result in substantial absolute savings over extended operational periods. In addition to the economic improvements, the proposed GRASP-BLS method demonstrated a considerable reduction in emissions. The total emissions decreased from 18,733 tCO₂e (under SA) to 14,565 tCO₂e, representing a significant reduction of 22.25%. This improvement underscores the ability of GRASP-BLS to not only achieve cost savings but also deliver substantial environmental benefits by lowering GHG emissions, a critical factor in sustainable energy management.

GRASP-BLS offers a more structured and flexible approach than SA, which relies on probabilistic exploration and is highly sensitive to parameter tuning, such as cooling schedules and neighborhood structures, making it less effective for complex problems like EED. SA also lacks a systematic local improvement mechanism, leading to slower convergence and suboptimal solutions. In contrast, GRASP-BLS combines GRASP for diverse initial solution generation with BLS for precise refinement, effectively balancing global exploration and local exploitation. This hybrid approach enhances robustness and adaptability, particularly in real-world scenarios with dynamic loads and multiple constraints, while also reducing parameter tuning sensitivity. Furthermore, GRASP-BLS demonstrates superior scalability, efficiently handling large and complex power systems without excessive computational requirements, whereas SA's probabilistic nature demands significantly more iterations as problem size increases. By offering better convergence, cost efficiency, and emission reduction, GRASP-BLS is a more practical and effective choice for large-scale EED optimization.

Based on the analysis presented in Table S3 and S1, all applied constraints are successfully satisfied without any violations throughout the optimization process, demonstrating the robustness and precision of the proposed GRASP-BLS method in adhering to operational and technical requirements under various scenarios. In Table S3, the power balance constraint is fully met, ensuring that total power generation precisely matches the load demand at all times, thereby eliminating the risk of electricity shortages that could lead to blackouts and avoiding overproduction, which prevents unnecessary waste and inefficiency. Consequently, the PLoss value is consistently recorded as 0 MW, indicating no system losses due to mismatched generation and demand, highlighting the algorithm's ability to maintain a perfectly balanced and stable system. Table S4 confirms that ramp rate constraints are also adhered to, with changes in power output between intervals remaining within allowable ramp-up and ramp-down limits for each generator. No sudden spikes or drops in generation levels exceeding the units' ramp rate capabilities are observed, ensuring smooth transitions and maintaining system stability. This comprehensive adherence to both power balance and ramp rate constraints underscores the effectiveness of the GRASP-BLS method in managing dynamic load scenarios while respecting the physical limitations of the generators, resulting in efficient and reliable power system operation.

3.2 Scenario 1: Dynamic loads exceeding the threshold generation levels ($P_D \geq \sum P_{\min,i}$)

In Scenario 1, the system operated under normal load conditions, where the total power demand remained within the typical operational range, allowing all generators to remain active throughout the scheduling period. Under these conditions, no unit commitment decisions—such as turning generators on or off—were necessary. The primary objective was to optimize the

generator dispatch in a manner that minimized both fuel costs and emissions while strictly satisfying the load demand at each time interval. This scenario served as a baseline for evaluating the program's ability to generate economical and environmentally efficient schedules in a stable and unconstrained environment, reflecting standard day-to-day operations in real power systems.

Table S5 presents the scheduling of power generation units optimized for the most economical operation, highlighting the GRASP-BLS method's ability to deliver cost-effective solutions. To rigorously evaluate its effectiveness and robustness, a benchmarking process was conducted against several well-established comparator methods, including GSA, GWO, and PSO. These methods were independently implemented and carefully adapted to the specific scenarios and constraints of the optimization problem, such as dynamic load scenarios, unit constraints, and multi-objective considerations. Each comparator represents a unique optimization approach: GSA, inspired by gravity and mass interactions, balances exploration and exploitation; GWO, based on wolves' social hierarchy and hunting strategies, ensures diversity while converging on optimal solutions; and PSO, inspired by swarm behavior, is known for its efficiency and simplicity in solving nonlinear problems. This diverse selection of methods provides a robust framework for comparison, ensuring a thorough assessment of the performance of GRASP-BLS.

Table S6 highlights the performance superiority of the GRASP-BLS method over other optimization techniques, including GSA, GWO, and PSO, in terms of both cost and emission reduction. The results demonstrate that GRASP-BLS achieves a 5.64% reduction in cost and a 3.92% reduction in emissions compared with GSA. When benchmarked against GWO, GRASP-BLS shows a 3.77% reduction in cost and a 2.2% reduction in emissions, while outperforming PSO with a 4.78% cost reduction and a substantial 6.36% emission reduction. From a technical perspective, these improvements can be attributed to the inherent strengths of GRASP-BLS, which combines the exploratory power of GRASP with the precise refinement capabilities of BLS. The GRASP phase enables GRASP-BLS to efficiently explore diverse regions of the solution space, ensuring a wide search for optimal solutions. In contrast, the BLS phase fine-tunes the solutions with gradient-based adjustments, allowing for precise convergence to high-quality optima. This hybrid mechanism ensures that GRASP-BLS balances exploration and exploitation more effectively than the comparator methods. GSA, while robust in balancing exploration and exploitation through gravity-inspired mechanisms, tends to converge slower in highly constrained problems like economic and emission dispatch (EED) due to its reliance on population dynamics, leading to less precise cost and emission outcomes. Similarly, GWO, which is inspired by the social hierarchy and hunting behavior of wolves, performs well in maintaining diversity but struggles with local refinement, limiting its ability to achieve the same level of cost and emission reductions as GRASP-BLS. Meanwhile, PSO, known for its simplicity and efficiency in handling non-linear optimization problems, can occasionally fall into local optima due to its particle updates lacking the BLS's gradient-based precision.

3.3 Scenario 2: Dynamic loads below generation limits enforced by unit commitment ($P_D < \sum P_{\min,i}$)

In Scenario 2, the system was subjected to a deliberately reduced load condition in which the total demand dropped below the combined minimum generation limit of all available units. This scenario introduced a more complex and constrained operational environment, as the system could no longer maintain all generators in active status without causing overpenetration. As a result, it became necessary to selectively deactivate certain generators to align the total generation with the reduced demand, thereby incorporating the concept of unit commitment into the optimization process. This scenario tested the program's ability to make strategic decisions about which units to commit or shut down while maintaining system reliability and minimizing both operational costs and environmental impact. It reflects real-world situations where demand fluctuations require a flexible and intelligent scheduling strategy to ensure system efficiency under non-ideal conditions.

Table S7 illustrates the system behavior between 00:00 and 05:00, during which the load

demand decreases below all units' total generation limit. This scenario necessitates activating the unit commitment process to ensure that the power supply matches the reduced demand while adhering to operational constraints. In this period, the GRASP-BLS method demonstrates its adaptive capability by selectively deactivating generators P3 to P8, effectively reducing the total generation capacity to align with the lower load demand. This selective deactivation ensures that only the required number of generators remains operational, minimizing unnecessary power generation and operational costs. The results clearly indicate that GRASP-BLS effectively handles the unit commitment process by optimizing the on/off status of generators, ensuring that the total power generation precisely matches the power demand. As a result, the value of PLoss is consistently recorded as 0 MW, which is similar to the results observed in Scenario 1, indicating that there is no excess power or system losses. This demonstrates the GRASP-BLS's robustness in maintaining a perfectly balanced system, even under challenging conditions where the load falls below the total minimum generation capacity.

The ability of GRASP-BLS to adaptively deactivate generators without violating constraints highlights its suitability for handling Scenario 2, where frequent generator status adjustments are required under dynamic load conditions. Unlike other methods that may struggle to effectively manage such low-demand scenarios, GRASP-BLS optimally schedules generation units, ensuring both stability and efficiency. These results confirm that GRASP-BLS is not only capable of maintaining operational reliability but is also highly adaptive to real-world challenges, making it a reliable method for managing complex and dynamic power system scenarios.

Using the same tuning as Scenario 1 (Table S5), the results in Table S8 confirm the superior performance of GRASP-BLS in Scenario 2. It achieves notable cost and emission reductions over all comparators: 8.17% and 3.79% vs GSA, 9.84% and 1.72% vs GWO, and 7.97% and 4.91% vs PSO. The added challenge of unit commitment increased the cost gap with GSA, GWO, and PSO by 2.53%, 6.07%, and 3.19%, respectively, reflecting the difficulty of deactivating generators while maintaining balance. Emission gaps narrowed—by 0.013%, 0.48%, and 1.45%—indicating that all methods adjusted under new constraints. Despite this, GRASP-BLS maintained clear superiority, showing robust adaptability to dynamic load conditions and reinforcing its reliability for real-world economic and emission dispatch.

The technical analysis of the performance shifts between GRASP-BLS and the comparator methods (GSA, GWO, and PSO) from Scenario 1 to Scenario 2 reveals critical differences in their adaptability and efficiency under dynamic operational conditions. Scenario 2 introduces the added complexity of unit commitment, requiring certain generators to be deactivated when the load demand falls below the total minimum generation capacity. In Scenario 1, GRASP-BLS demonstrates strong performance, leveraging its hybrid approach of exploratory GRASP and precise BLS refinement to achieve significant cost and emission reductions. The stable load conditions in Scenario 1 enable GRASP-BLS to maximize its structured optimization process. In Scenario 2, GRASP-BLS continues to excel by dynamically deactivating specific generators (e.g., P3 to P8) to align generation with reduced demand, effectively managing the added complexity while maintaining operational reliability and superior cost and emission optimization compared to other methods. In contrast, GSA, GWO, and PSO face notable challenges when transitioning to Scenario 2. With its gravity-inspired mechanism, GSA achieves competitive results in Scenario 1 but struggles to handle the discrete, binary decisions required for unit commitment in Scenario 2, leading to a 2.53% higher cost difference compared to GRASP-BLS. GWO, which relies on hierarchical social behavior, performs well in Scenario 1 but experiences a significant 6.07% increase in cost difference with GRASP-BLS in Scenario 2 due to its limited local refinement capabilities. PSO, known for its simplicity and efficiency, performs competitively in Scenario 1 but faces a 3.19% increase in cost difference and a 1.45% widening of the emission gap in Scenario 2, highlighting its difficulty in optimizing emissions under complex constraints. The observed performance shifts emphasize the adaptability of GRASP-BLS, which is driven by its ability to dynamically adjust generator statuses, perform precise solution refinements, and balance exploration and exploitation. These strengths enable GRASP-BLS to outperform GSA,

GWO, and PSO, particularly in managing the unit commitment problem of Scenario 2's discrete and dynamic nature.

Table 1 highlights the performance of GRASP-BLS compared to GSA, GWO, and PSO across two scenarios, focusing on cost, emissions, and computation time. In Scenario 1, GRASP-BLS achieves the lowest total cost of \$54,851,474, outperforming GSA by \$3,278,549, GWO by \$2,151,234, and PSO by \$2,756,304. Additionally, GRASP-BLS achieves the lowest emissions at 375,189 tCO₂e, reducing emissions by 15,315 tCO₂e compared with GSA, 8,460 tCO₂e compared with GWO, and 25,467 tCO₂e compared with PSO. These results demonstrate GRASP-BLS's ability to effectively optimize both cost and emissions. However, the computation time for GRASP-BLS in Scenario 1 is 21.95 s, which is longer than those for GSA (8.15 s), GWO (2.89 s), and PSO (0.02 s). While computationally more expensive, the significant reductions in cost and emissions justify this trade-off.

Table 1 Cost, emission, and execution time results for all methods

Scenario	Method	Cost (US\$)	Emission (tCO ₂ e)	Comp. Time (s)
0	GRASP-BLS	2,259,420	14,565	3.69
	SA	2,268,505	18,733	< 60
1	GRASP-BLS	54,851,474	375,189	21.94673
	GSA	58,130,023	390,504	8.15399
	GWO	57,002,708	383,649	2.89262
	PSO	57,607,778	400,656	0.02120
2	GRASP-BLS	52,039,278	346,443	19.07990
	GSA	56,669,115	360,080	7.93036
	GWO	57,720,240	352,497	2.91943
	PSO	56,547,763	364,331	0.02934

In Scenario 2, which involves unit commitment, GRASP-BLS continues to outperform the comparator methods, achieving the lowest total cost of \$52,039,278, with cost reductions of \$4,629,837 compared to GSA, \$5,680,962 compared to GWO, and \$4,508,485 compared to PSO. GRASP-BLS also maintains the lowest emissions at 346,443 tCO₂e, reducing emissions by 13,637 tCO₂e compared to GSA, 6,054 tCO₂e compared to GWO, and 17,888 tCO₂e compared to PSO. While the cost gap between GRASP-BLS and the comparator methods increases in Scenario 2 due to the complexity introduced by unit commitment, GRASP-BLS demonstrates superior adaptability and efficiency in managing this added challenge. Although GRASP-BLS requires a longer computation time (19.08 s) than GSA (7.93 s), GWO (2.91 s), and PSO (0.03 s), its ability to deliver the most cost-effective and environmentally friendly solutions across both scenarios highlights its robustness and practicality for solving complex PSO problems.

4. Conclusions and Future Works

The GRASP-BLS method demonstrates exceptional robustness, efficiency, and adaptability in optimizing economic and emission dispatch (EED) problems by integrating the GRASP for effective exploration with BLS for precise local refinement, ensuring consistently superior performance across various scenarios. Compared with other optimization techniques, such as simulated annealing (SA), gravitational search algorithm (GSA), Gray Wolf Optimization (GWO), and particle swarm optimization (PSO), GRASP-BLS achieves notable reductions in both cost and emissions. (1) In the four-hour load demand scenario, GRASP-BLS reduces total cost to US\$2,259,420, a 0.4% improvement over SA, while significantly cutting emissions by 22.25%, achieving 14,565 tCO₂e compared to SA's 18,733 tCO₂e. (2) In Scenario 1, GRASP-BLS achieves the lowest cost and emissions compared to GSA, GWO, and PSO, with cost reductions of US\$3.27 million, US\$2.15 million, and US\$2.76 million, respectively, and emission reductions of 15,315 tCO₂e, 8,460 tCO₂e, and 25,467 tCO₂e. Although it requires slightly more

computation time, the significant cost-efficiency and environmental impact improvements justify this trade-off. (3) In Scenario 2, GRASP-BLS adapts dynamically, selectively deactivating generators to maintain system balance, ensuring that no power losses ($P_{Loss}=0$) occur, leading to greater cost savings of US\$4.63 million, US\$5.68 million, and US\$4.51 million over GSA, GWO, and PSO, respectively, while achieving the lowest emissions with reductions of 13,637 tCO₂e, 6,054 tCO₂e, and 17,888 tCO₂e. Despite requiring slightly more computation time, the significant efficiency and sustainability benefits outweigh this drawback, reinforcing GRASP-BLS as a superior optimization method for EED, excelling in minimizing costs and emissions while maintaining robustness and adaptability under varying operational conditions. Its hybrid structure and ability to tackle real-world power system challenges make it a highly competitive and practical solution, outperforming traditional methods in terms of both efficiency and environmental sustainability. Although GRASP-BLS has demonstrated outstanding performance, future research should explore enhancing its computational efficiency to further reduce execution time without compromising solution quality. Additionally, the method can be extended to incorporate renewable energy sources, such as wind and solar power, to address the challenges of uncertainty and intermittency in modern power systems. Another promising direction is the integration of ML techniques, enabling adaptive parameter tuning and self-learning capabilities to improve optimization performance. Furthermore, the application of GRASP-BLS in large-scale power networks with multi-objective optimization considerations, including reliability, stability, and grid congestion management, would provide deeper insights into its real-world applicability. Finally, future studies could investigate the integration of demand response strategies and smart grid technologies to enhance the adaptability of GRASP-BLS in dynamic and decentralized power systems.

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Author Contributions

This research was a collaborative effort with contributions distributed as follows: Rifki Rahman Nur Ikhsan led the conceptualization and design of the methodology. Rifki Rahman Nur Ikhsan was also responsible for software implementation and validation. Lindiasari Martha Yustika carried out formal analysis and investigation. The management of resources and data curation was a joint effort by all authors, while Jangkung Raharjo provided supervision throughout the process.

Conflict of Interest

The authors declare that there are no conflicts of interest associated with this publication.

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