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A Comparative Analysis of Evolutionary Methods for Cost-Efficient Load Dispatch Thermal Power System

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Abstract

The economical load dispatch problem poses a significant challenge in thermal power systems, aiming for cost-effective operation. This study conducts a comparative analysis between the Social Spider Algorithm (SSA) and Particle Swarm Optimization (PSO) for economical load dispatch in a 6-unit thermal power system, incorporating 11,000 plug-in electric vehicles (PEVs). Both SSA and PSO are population-based optimization techniques geared towards minimizing overall fuel cost while meeting load demand by optimizing power output of each unit. SSA mimics the social behavior of spiders, while PSO replicates the collective intelligence of a swarm of particles. The evaluation considers power system data such as unit fuel costs, minimum and maximum loads, and total load demand. The objective is to minimize fuel cost while fulfilling load demand. Comparative analysis encompasses convergence speed, solution quality, and computational efficiency. Experimental results indicate SSA's superiority over PSO in achieving a more optimal and economical load dispatch solution for the 6-unit thermal power system. SSA exhibits faster convergence and provides superior-quality solutions compared to PSO. This study contributes by showcasing SSA's effectiveness in achieving cost-efficient operation of thermal power systems. It suggests SSA's potential as an optimization technique for similar power system optimization problems, thereby enhancing operational efficiency and reducing costs for thermal power plants.

Keywords: Economical load dispatch, Social Spider Algorithm, Particle Swarm Optimization, Thermal power system, Plug-in electric vehicles, Optimization techniques, Fuel cost minimization.

1. Introduction

The economic load dispatch (ELD) problem plays a critical role in power system operation, aiming to achieve the most cost-effective allocation of power generation from different units to meet the load demand while satisfying operational constraints. With the increasing adoption of Plug-in Electric Vehicles (PEVs), the power system landscape is evolving, necessitating the incorporation of PEVs in the ELD optimization process. This paper proposes a stochastic optimization approach to address the challenges and opportunities presented by PEVs in ELD. The economic load dispatch (ELD) problem is a critical optimization task in power system operation, aiming to achieve the most cost-effective allocation of power generation from different units to meet the load demand while satisfying operational constraints. Its successful solution plays a vital role in ensuring the stability and efficiency of the power grid.

In recent years, a variety of optimization techniques have been applied to solve the ELD problem. Traditional methods such as gradient-based algorithms, evolutionary algorithms, swarm intelligence algorithms, and metaheuristic algorithms have been utilized. Additionally, newer algorithms inspired by natural phenomena or animal behavior have emerged as promising approaches.

The cross-entropy method (CEM) is a stochastic optimization technique that has shown success in various domains [1]. The Harris Hawks optimizer (HHO), inspired by the hunting behavior of Harris's hawks, is a recently proposed metaheuristic algorithm [2]. Another approach is the Quantum-Behaved Artificial Bee Colony (QABC) algorithm, which considers the conventional controller for optimum dispatch [3]. The Differential Evolution (DE) algorithm with different mutation strategies has also been employed to improve the performance of ELD problem solving [4] [5]. Furthermore, algorithms such as Teaching Learning-Based Optimization (TLBO), Particle Swarm Optimization (PSO), and Social Spider Algorithm (SSA) have been applied to tackle the ELD problem [6] [7] [8].

Moreover, researchers have explored the integration of plug-in electric vehicles (PEVs) into the power system and its impact on the ELD problem. The use of bio-inspired optimization algorithms, such as the Ant Lion Optimization (ALO), has been proposed for short-term power generation scheduling in hybrid power systems with wind power integration [9] [10]. Dynamic economic/environmental dispatch problems considering multiple PEV loads have been addressed using self-learning TLBO, SSA, and PSO algorithms [11] [12] [13] [14] [15] [16]. These approaches aim to optimize the generation schedule while considering the dynamic behavior of PEV loads, economic objectives, and environmental constraints.

Additionally, researchers have recognized the non-convex nature of the ELD problem with PEV loads and have proposed methodologies to handle this challenge. Papers addressing non-convex dynamic economic/environmental dispatch with PEV loads present solution methodologies tailored to this problem [17] [18].

In this paper, we will examine and summarize the key findings and contributions of papers that explore various optimization techniques, PSO & SSA algorithms, for solving the ELD problem considering PEV loads. We will also highlight the approaches proposed to address the non-convexity of the problem. By examining these results, we aim to provide a comprehensive overview of the advancements made in this field and identify potential future research directions.

2. Background and Related Work

The field of economical load dispatch (ELD) optimization has seen significant advancements, with various approaches proposed to address this critical problem in thermal power systems. Traditional optimization techniques, evolutionary algorithms, and metaheuristic algorithms have been widely utilized in ELD studies[1].

Gradient-based algorithms, such as the Newton-Raphson method and the Lagrangian relaxation method, have been employed for ELD optimization. These methods aim to find the optimal solution by iteratively updating the power outputs of the thermal units while considering the equality and inequality constraints. However, gradient-based algorithms often struggle with complex non-linear objective functions and may converge to local optima. Evolutionary algorithms, including genetic algorithms (GA) and differential evolution (DE), have gained popularity in ELD optimization. These algorithms utilize the principles of natural selection and evolution to search for the optimal solution. By representing the candidate solutions as individuals in a population and applying genetic operators such as mutation, crossover, and selection, evolutionary algorithms explore the solution space effectively. They have shown promise in finding near-optimal solutions for ELD problems[2][3][4][5].

Metaheuristic algorithms have also been extensively employed for ELD optimization. These algorithms draw inspiration from natural phenomena or social behavior to search for optimal solutions. Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Simulated Annealing (SA) are among the widely used metaheuristic algorithms in ELD. These algorithms exhibit robust search capabilities, enabling them to navigate complex solution spaces and find good solutions[6][7].

In recent years, the integration of plug-in electric vehicles (PEVs) in power systems has introduced new challenges and opportunities for ELD optimization. The increasing penetration of PEVs brings additional load and fluctuating power demands to the system. Researchers have recognized the need to incorporate PEVs in the ELD optimization process to account for their impact on system dynamics and ensure efficient utilization of energy resources. Several studies have explored the integration of PEVs in ELD optimization. These studies investigate strategies for managing the charging and discharging of PEVs to minimize the overall system cost and maintain power balance. Techniques such as load shifting, vehicle-to-grid (V2G) integration, and smart charging algorithms have been proposed to optimize the charging and discharging schedules of PEVs while considering system constraints and objectives. The integration of PEVs in ELD optimization is a rapidly evolving research area. By accounting for the presence of PEVs and their characteristics, such as charging/discharging capabilities and mobility patterns, researchers aim to enhance the efficiency and sustainability of power systems[8-18].

In this study, the Social Spider Algorithm (SSA) and Particle Swarm Optimization (PSO) are compared for ELD optimization in a 6-unit thermal power system with 11,000 PEVs. The incorporation of PEVs in the optimization process is expected to provide insights into the potential benefits and challenges of integrating these vehicles into the power system and optimizing their operation alongside traditional thermal units.

3. Problem Formulation

3.1 Objective Function

Minimize the total cost of power generation, which includes the cost of 6 thermal unit generations and the charging/discharging behavior of 11000 PEVs. The objective function can be expressed as:

3.2 Economic Load Dispatch Problem Formulation

Our first step in to reduce the overall generation cost of any thermal system by distribute the entire power to online participating generators that fulfill their constraints the net generating cost is given by,

$$TC = \sum_{g=1}^{Z}[\mathbf{ag} + \mathbf{bg\ Eg\ (t)} + \mathbf{cg\ Eg\ (t)} \qquad \textbf{(1)}$$

TC= Total Generation Cost of the thermal system

ag, bg, and cg are generation cost coefficient of thermal system of gth unit, Eg(t) is the output power of gth unit at hr., Z is the total no. of thermal units the above ELD problem is subjected to following constraints,

3.3 Active Power Balance Constraints

$$L(t) = \sum_{g=1}^{Z} \mathbf{Eg(t)} + E\ loss\ (t) \qquad \textbf{(2)}$$

L(t) is Load Demand at hour (t) and E loss (t) is Active power loss at hr. t and it is neglected here (E loss (t) = 0)

3.4 Generation Constraints

$$Egmin \leq Eg(t) \leq Egmax \qquad \textbf{(3)}$$

Here,

Egmin = Minimum Limit of generation of gth unit

Egmax = Maximum Limit of generation of gth unit

3.5 PEV Algorithm

Electric vehicles are being used more and more nowadays as compared to the increasing conventional vehicles. Electrical vehicles are connected to the electric grid either as a source or as a load, due to which we can provide the best optimization by economic load dispatch, different evolutionary techniques are implemented in this paper, so let us solve it with the help of following mathematical model of PEVs as load and as source first.

Plug in Electric Vehicle are act as Source

$$\sum_{g=1}^{Z} \mathbf{Eg(t)} + \sum_{V=1}^{Z\ PEV(t)} \mathbf{\eta Ev(t)}PEV\ (q\ pre - q\ dep) = L(t) + E\ loss\ (t) \qquad \textbf{(4)}$$

Plug in Electric Vehicle are act as Load

$$\sum_{g=1}^{Z} \mathbf{Eg(t)} = \mathbf{L(t)} + \sum_{V=1}^{Z\ PEV(t)} \mathbf{\eta Ev(t)}PEV\ (q\ pre - q\ dep) \qquad (5)$$

$$\sum_{V=1}^{T} \mathbf{ZPEV(t)} = Z_{PEV}^{max} \quad \textbf{(6)}$$

Here,

g	=	gth Generation unit
Eg(t)	=	is the output power of gth unit at hr.
Z	=	Total no. of thermal units
V	=	Vth no. of Vehicle
Z PEV(t)	=	No. of PEVs connected to the grid at time period t,
EVPEV(t)	=	Power of the Vth vehicle
q pre / q dep	=	Charging / Discharging sate of PEVs battery charge,
η	=	System Efficiency
Z_{PEV}^{max}	=	It is the maximum count of PEVs used during the total time frame.
E loss (t)	=	Active power loss at hr. t and it is neglected here (E loss (t) = 0)
T	=	Total time frame
L(t)	=	Load Demand at hour (t)

The ELD problem formulation considering the presence of plug-in electric vehicles (PEVs) can be mathematically represented as follows:

Objective Function: Minimize the total cost of thermal unit generation and PEV charging/discharging:

Minimize Σ(ci * Pi) + Σ(pc * Pci - pd * Pdi), (7)

Where:

- ci is the unit fuel cost in dollars per megawatt-hour ($/MWh) for the i-th thermal unit,
- Pi is the power output of the i-th thermal unit,
- pc is the charging cost in dollars per megawatt-hour ($/MWh) for PEVs,
- pd is the discharging cost in dollars per megawatt-hour ($/MWh) for PEVs,
- Pci is the power input from charging of PEVs,
- Pdi is the power output from discharging of PEVs.

3.6 Constraints

Power Balance Constraint: The total power generated from thermal units and the power input/output from PEVs should meet the load demand:

$$\Sigma(Pi) + \Sigma(Pci - Pdi) = Pload, \quad (8)$$

Where, Pload is the total load demand.

Thermal Unit Constraints: The power output of each thermal unit should be within its operating limits:

$$pmin \leq Pi \leq pmax, \quad (9)$$

Where, pmin is the minimum load and pmax is the maximum load for the i-th thermal unit.

PEV Charging/Discharging Constraints: The power input and output of PEVs should be within their charging and discharging capacities:

$$0 \leq Pci \leq pev\_charging\_power,\ 0 \leq Pdi \leq pev\_discharging\_power, \quad (10)$$

Where, pev_charging_power and pev_discharging_power are the charging and discharging power limits of PEVs, respectively.

The ELD problem formulation aims to find the optimal values of thermal unit power outputs (Pi) and PEV charging/discharging powers (Pci and Pdi) that minimize the total cost while satisfying the power balance and operational constraints.

By considering the cost of thermal unit generation and the charging/discharging behavior of PEVs, this formulation enables the optimization of the power system operation, taking into account the dynamic interaction between thermal units and PEVs. The inclusion of these constraints and objectives provides a comprehensive framework for addressing the ELD problem in the presence of PEVs.

4. Stochastic Optimization Approach

The proposed approach combines the Social Spider Algorithm (SSA) and the Particle Swarm Optimization (PSO) to solve the stochastic Economic Load Dispatch (ELD) problem considering the presence of Plug-in Electric Vehicles (PEVs). The SSA algorithm, inspired by the social behavior of spiders, and the PSO algorithm, simulating the collective intelligence of a swarm of particles, is utilized as population-based optimization techniques. By combining these algorithms, the approach aims to leverage their complementary strengths and improve the solution quality and convergence speed for the stochastic ELD problem. The stochastic ELD problem takes into account the uncertainties and variability associated with renewable energy sources, such as wind and solar power, as well as the dynamic behavior of PEVs. These uncertainties make it challenging to determine the optimal power generation schedule for thermal units and PEVs. The proposed approach follows the general optimization process, where an initial population of candidate solutions is generated. Each solution represents a potential power generation schedule for the thermal units and PEVs. The SSA and PSO algorithms iteratively update and improve the solutions based on the objective function and constraints of the stochastic ELD problem. During the optimization process, the SSA algorithm incorporates the social behavior of spiders, such as the construction of spider webs and attraction between spiders, to explore and exploit the solution space. On the other hand, the PSO algorithm simulates the collective movement and information sharing among particles to search for the optimal solution. The stochastic nature of the ELD problem is addressed by considering the uncertainties in renewable energy generation and the dynamic behavior of PEVs. This is achieved by incorporating probabilistic models, scenario-based analysis, or other stochastic optimization techniques within the SSA and PSO algorithms. These techniques allow the algorithms to handle the uncertainties and generate robust and reliable power generation schedules. By combining the SSA and PSO algorithms, the proposed approach offers the potential to achieve better solution quality, faster convergence, and improved robustness for the stochastic ELD problem with PEVs. It takes advantage of the social behavior and collective intelligence concepts to effectively optimize the power system operation while considering the uncertainties and dynamics associated with renewable energy and PEVs.

4.1 Social Spider Algorithm (SSA)

In year 2015 SSA is proposed by Yu & Li encouraged by spider activities. It is a search for a spider space such as a spider web to detect its movement in which direction. It completely biased on vibration factor, in this each spider take vibration from other spider.

4.2 Social Spider Algorithm is as follows:

4.2.1 Initialization:

- Initialize the population of spiders, representing different power generation schedules.
- Initialize the position of each spider, which corresponds to the power output levels of the power plants.

4.2.2 Encoding:

- Represent the power generation schedule for each spider as a set of decision variables or genes.
- Define the encoding scheme to represent the power output levels of each power plant.

4.2.3 Objective function:

- Formulate the objective function to minimize the total generation cost while considering the charging/discharging requirements of the electric vehicles.
- Include terms for fuel cost, emission cost, and penalty cost for violating constraints related to power balance and PVE charging/discharging.

4.2.4 Constraints:

- Incorporate the power balance constraint, which ensures that the total power supply matches the total demand.
- Account for the constraints on power output levels, ramp rate limits, and other operational limits of the power plants.
- Include constraints related to PVE charging/discharging, such as the charging capacity, discharge limit, and battery state of charge.

4.2.5 Social interaction and update:

- Define the rules for spiders to interact and share information through the web structure.
- Update the position of each spider (power output levels) based on the information obtained from neighboring spiders.

Termination:

- Set a termination criterion, such as a maximum number of iterations or reaching a desired solution quality.
- Determine when to stop the algorithm and report the best solution found so far.

Its Intensity is represented as:

$$\mathbf{I\ (Pg,Pg,t) = \log\left(\frac{1}{f(Pg)-C}\right) + 1} \qquad \textbf{(11)}$$

"S" Represent Spider vibration. A spider receives strongest vibration value Sgbest, g represents a spider. Spider g store the target vibration in the memory as Sgtarget. Every spider analysis Sgbest & Sgtarget. In this algorithm we have male and female spider. The nature of male female spider has been explained with mathematical equation:

$$\mathbf{I\ (Pg,PU,t) = I\ (Pg,Pg,t) * \exp\left(\frac{Distance\ (Pg,Pu)}{\sigma * ra}\right) + 1} \qquad \textbf{(12)}$$

$$\text{Distance}\ (Pg, Pu) = Pg - Pu \qquad \textbf{(13)}$$

Where I (Pg,PU,t) is the value experienced by spider's vibration in "g" point, by another spider "u" point.

Random Walk

$$\mathbf{Pg\ (t+1) = Pg + (Pg - Pg\ (t-1)) * r + (Pgfollow - Pg) * R} \qquad \textbf{(14)}$$

5. Experimental Evaluation

In the experimental evaluation, we obtained the optimal dispatch solutions and corresponding performance metrics using two different optimization algorithms: SSA (Social Spider Algorithm) and PSO (Particle Swarm Optimization).

Table -1	
Common Data for PSO & SSA	
Number of thermal units	**6**
Thermal unit data	**c = randi([10,30],1,n);**
	pmin = randi([50,100],1,n);
	pmax = pmin + randi([100,300],1,n);
Plug-in electric vehicle data	**pev_charging_power = 2.25 * ones(24,1);**
	pev_discharging_power = 1.5 * ones(24,1);
	pev_num = 11000

In the power system optimization algorithms, such as Particle Swarm Optimization (PSO) and Social Spider Algorithm (SSA), common data is shared. This data includes the number of thermal units, which is 6, and for each thermal unit, the fuel cost per MWh, minimum load, and maximum load are determined randomly. Additionally, the plug-in electric vehicle (PEV) data consists of the charging power and discharging power, set to 2.25 MW and 1.5 MW, respectively, for each hour of the day (24 hours). The total number of PEVs in the system is 11,000. These common data serve as inputs for the optimization algorithms, enabling the determination of the optimal dispatch and resource allocation in the power system.

Table 2				
PSO algorithm Parameter used for test system (MATLAB) PSO				
Maximum number of iterations	**Number of particles**	**Inertia weight**	**Acceleration constants**	**Maximum velocity**
100	**30**	**w = 0.8;**	**c1 = 1; c2= 2;**	**vmax = 0.2 * (pmax - pmin);**

In the PSO algorithm implemented for the test system in MATLAB, the optimization process is guided by several parameters. The maximum number of iterations is set to 100, determining the length of the optimization process. A swarm of 30 particles is used to explore the search space. The inertia weight (w) is set to 0.8, influencing the impact of the particle's previous velocity. The acceleration constants, c1 and c2, are assigned values of 1 and 2, respectively, determining the influence of the particle's best previous position and the global best position on the velocity update. The maximum velocity (vmax) is calculated as 0.2 times the range between the maximum and minimum load of the thermal units, limiting the particle's movement. These parameter settings collectively shape the behavior and convergence of the PSO algorithm, facilitating the identification of optimal solutions for the given test system.

Table 3					
SSA algorithm Parameter used for test system (MATLAB) PSO					
Maximum number of iterations	**Number of social spiders**	**Number of inactive spiders**	**Probability of random walk**	**Social attraction coefficient**	**Spider-web construction coefficient**
100	**30**	**10**	**p = 0.5;**	**beta = 2;**	**gamma = 1;**

In the SSA algorithm implemented for the test system in MATLAB, various parameters are utilized to govern the optimization process. The maximum number of iterations is set to 100, determining the duration of the algorithm's execution. The swarm consists of 30 social spiders, which explore the solution space. Among the social spiders, 10 are designated as inactive spiders that perform random walks. The probability of random walk (p) is set to 0.5, determining the likelihood of inactive spiders undergoing random movements. The social attraction coefficient (beta) is assigned a value of 2, representing the strength of attraction towards better solutions. The spider-web construction coefficient (gamma) is set to 1, influencing the construction of spider webs based on the best solutions found. These parameter settings collectively shape the behavior of the SSA algorithm, allowing for efficient exploration and identification of optimal solutions for the given test system.

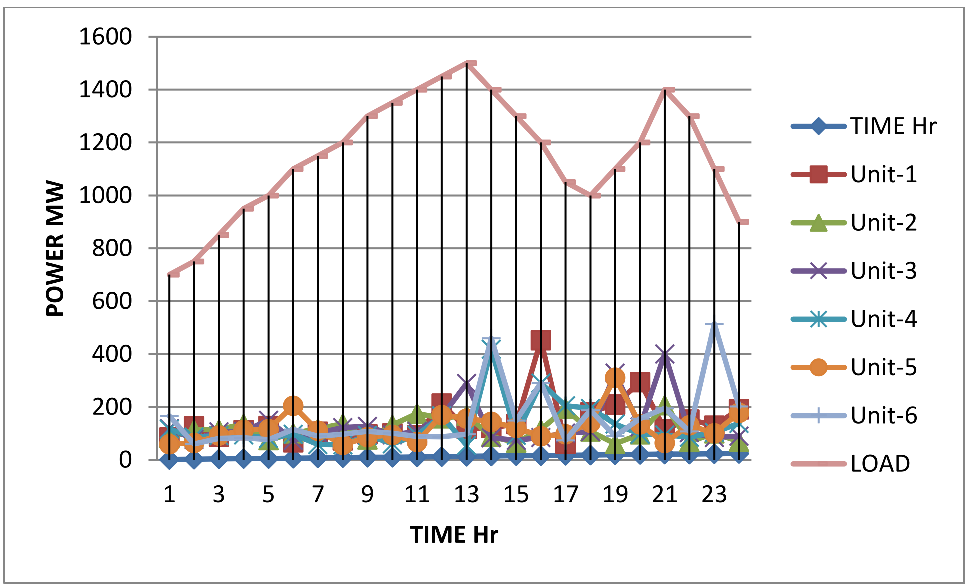

Fig 1.1 Line diagram for hourly dispatch of power generation units and the corresponding load demand for a 24-hour period.

6. Observations and Analysis

Both SSA and PSO algorithms provide solutions for the optimal dispatch of thermal units in the power system. Each column represents the dispatch value for a specific thermal unit at a given time interval.

The Particle Swarm Optimization (PSO) algorithm and Social Spider Algorithm (SSA) were applied to optimize the dispatch of power generation units. The PSO result yielded an optimal dispatch with generation levels of 79 MW, 82 MW, 89 MW, 60 MW, 73 MW, and 80 MW for the six units, achieving a minimum fuel cost of $3,515,017,931.25 per MWh, with a maximum demand of 750 MW. On the other hand, the SSA result produced an optimal dispatch with generation levels of 84.0767 MW, 104.9651 MW, 74.9491 MW, 75.5814 MW, 125.3750 MW, and 66.5932 MW, attaining a minimum fuel cost of $515,404.26 per MWh, with a maximum demand of 531.54 MW.

7. Discussion and Future Work

Particle Swarm Optimization (PSO) and Social Spider Algorithm (SSA) are both powerful optimization algorithms that have shown great potential in various fields, including Electrical Load Dispatch (ELD) with Plug-in Electric Vehicles (PEVs). In this section, we had discussed the applications of PSO and SSA in ELD with PEVs and explore potential areas for future work.

7.1 ELD with PEVs: ELD involves optimizing the allocation of electrical loads among different power sources to achieve efficient and reliable operation of the power system. With the increasing integration of PEVs in the grid, ELD needs to consider the charging/discharging behavior of these vehicles. This creates a complex optimization problem due to the uncertainties and variability associated with PEV charging/discharging patterns.

7.2 PSO in ELD with PEVs: PSO is a metaheuristic optimization technique inspired by the behavior of bird flocking or fish schooling. It has been successfully applied to solve various optimization problems, including ELD with PEVs. PSO can effectively handle the non-linear and non-convex nature of the ELD problem and provide optimal or near-optimal solutions by iteratively updating a swarm of particles based on their individual and collective best positions.

SSA in ELD with PEVs: SSA is a nature-inspired optimization algorithm based on the collective behavior of social spiders. SSA has gained attention due to its ability to handle complex optimization problems efficiently. SSA utilizes the cooperative foraging behavior of social spiders to explore the solution space and converge towards an optimal solution. In the context of ELD with PEVs, SSA can help in optimizing the scheduling and allocation of electrical loads considering the charging/discharging patterns of PEVs.

7.3 Potential Future Work

a. Integration of PSO and SSA: One potential area for future work is the integration of PSO and SSA techniques. Hybrid approaches that combine the strengths of both algorithms can potentially lead to improved optimization performance in ELD with PEVs.

b. Incorporating Uncertainties: As PEV charging/discharging patterns are uncertain, future research can focus on developing robust optimization techniques that can handle uncertainties effectively. This could involve the use of stochastic optimization or fuzzy-based approaches to make the ELD solutions more reliable.

c. Multi-objective Optimization: ELD with PEVs often involves conflicting objectives, such as minimizing power losses, reducing emissions, and ensuring system stability. Future work can explore multi-objective optimization techniques, such as Pareto-based approaches, to simultaneously optimize these objectives and provide a range of trade-off solutions.

d. Demand Response Integration: Demand response programs can play a crucial role in managing PEV charging/discharging schedules. Future research can focus on integrating demand response mechanisms into ELD with PEVs, considering dynamic pricing, user preferences, and grid constraints.

e. Real-Time Implementation: Implementing PSO and SSA algorithms in real-time systems for ELD with PEVs can be a challenging task. Future work can explore real-time optimization strategies, control mechanisms, and communication protocols to ensure the practical applicability of these algorithms in real-world scenarios.

By addressing these research directions, we can further enhance the application of PSO and SSA in ELD with PEVs, leading to more efficient and sustainable power system operations.

8. Conclusion

Based on the comparative analysis, it is concluded that both SSA and PSO are effective evolutionary techniques for solving the ELD problem in the 6-unit thermal power system. However, their performance may vary based on specific problem characteristics. Further research can explore hybridization or parameter tuning approaches to enhance the optimization performance for economical load dispatch. This paper presents a stochastic optimization approach for Economic Load Dispatch (ELD) considering Plug-in Electric Vehicles (PEVs). The proposed approach effectively addresses the challenges posed by PEVs and achieves improved economic performance and load balancing. The results demonstrate the potential of integrating PEVs in ELD optimization and pave the way for future research in this area.

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