

Optimizing Economic Load Dispatch in a 10-Unit System Using the SSA Method

Tejaswita Khobaragade^{1,*}, K.T. Chaturvedi^{2,ss}

Abstract

The optimization of economic load dispatch (ELD) in a 10-unit power system employing the social spider algorithm (SSA) method is reported. ELD is a critical aspect of power system operation, aiming to allocate the power generation among multiple units efficiently while meeting the demand at the lowest possible cost. The SSA method, inspired by the collaborative behavior of social spiders, demonstrates its efficacy in solving optimization problems. In this research, the 10-unit power system is modeled, considering various constraints and objectives inherent to ELD problems. The SSA method is applied to search for the optimal combination of power generation levels for each unit, minimizing the overall cost and ensuring the fulfillment of demand. The results obtained through the SSA method are compared with traditional methods to assess its effectiveness in achieving a more economical and efficient load distribution. The study provides insights into the applicability and advantages of SSA in addressing ELD challenges in power systems with a specific focus on 10-unit configurations. The findings contribute to the ongoing efforts in utilizing nature-inspired algorithms for power system optimization, offering a promising approach for enhancing operational efficiency and cost-effectiveness.

Keywords: Social spider algorithm (SSA), plug-in electric vehicle (PEV), vehicle-to-grid (V2G), thermal units, economic load dispatch (ELD)

INTRODUCTION

Economic load dispatch (ELD) is a crucial aspect of power system operation and management, particularly in large-scale power generation systems. ELD involves determining the optimal distribution of power generation from various units within a power grid to meet load demand at the lowest possible cost while adhering to various operational constraints.

In the optimization techniques and solving complex problems, this paper narrows its focus to distinct yet powerful optimization method: social spider algorithm (SSA). These methods have a certain allure and potency, and the path ahead is devoted to deciphering their complexities, comprehending their subtleties, and investigating their fields of application. In the field of optimization, quality is always the goal.

*Author for Correspondence

Tejaswita Khobaragade
E-mail: tejaswitak86@gmail.com

¹PhD Scholar, Department of Electrical and Electronics Engineering, University Institute of Technology, Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal, Madhya Pradesh, India
²Associate Professor, Department of Electrical and Electronics Engineering, University Institute of Technology, Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal, Madhya Pradesh, India

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LITERATURE SURVEY

The field of power system optimization methods applied to intricate power generation and distribution challenges. The work by Adhvaryu et al. [1] emphasizes the use of SSA in addressing complex energy difficulties as it investigates the dynamic economic environmental load dispatch of hybrid power systems. A modified SSA designed for economic dispatch with valve-point effects is shown by Yang et al. [2], demonstrating the flexibility of this system to complex power

generation scenarios. Behera et al.'s [3] study extends SSA's utility to dynamic ELD with plug-in electric vehicles (PEVs), demonstrating its versatility in managing evolving energy demands. Baş and Ülker's [4] research introduces an improved SSA variant suitable for large-scale optimization tasks, expanding its practicality. Additionally, Zhang et al. [5] employ a local binary SSA for feature selection in credit scoring models, illustrating its relevance beyond power systems. Mortazi et al. [6] utilize SSA for optimizing operation scheduling in microgrids, considering probabilistic uncertainty and demand response, enhancing energy grid resilience.

Furthermore, Hosseinalipour et al. [7] embark on text psychology analysis using SSA, unveiling its potential in non-energy domains. Demand-responsive loads are used in Yao et al.'s [8] multiperiod optimal power-flow technique to enhance steady-state voltage uniformity, as shown by the power-flow Jacobian matrix's shortest singular value (SSV) [8]. Hao et al. [9] developed a mathematical model of the ELD problem by considering the top and lower bounds of generator output as well as the system power balance. Dubey et al. [10] introduced a revolutionary ant lion optimization (ALO) technique for hydro-thermal-wind scheduling. To address issues with ELD, Al-Betar et al. [11] suggested combining the adaptive-hill-climbing optimizer with a hybridized version of the Harris Hawks optimizer (HHO). Yang et al. [12] offer an enhanced social spider optimization technique, called ISSO, to address the ELD problem with valve-point effects [12].

SOCIAL SPIDER ALGORITHM

In 2015, the social spider algorithm (SSA), proposed by Yu and Li [13], was inspired by the behavioral patterns of spiders, particularly how they use their webs to detect movements in specific directions [13]. This algorithm is heavily reliant on the vibration factor, where each spider in the algorithm senses vibrations from others to inform its actions. Relatively recently, the SSA is an intriguing addition. Developed in 2015, SSA draws its inspiration from the collaborative behavior of certain spider species that work collectively to achieve common goals. SSA exemplifies the power of collective intelligence and social cooperation in problem-solving [14].

Two population-based optimization techniques are used: the particle swarm optimization (PSO) algorithm, which simulates the collective intelligence of a swarm of particles, and the SSA, which depends on the social behaviors of spiders. By merging these algorithms, the approach aims to capitalize on their complementary strengths, enhancing both solution quality and convergence speed in solving the stochastic ELD problem. This problem involves accounting for uncertainties and variations in renewable energy sources, like wind and solar power, as well as the dynamic behavior of plug-in electric vehicles (PEVs). Determining the best power generation schedule for thermal units and PEVs is made more difficult by these uncertainties.

The suggested approach starts with the creation of an initial population of candidate solutions and proceeds through a normal optimization procedure. Every solution relates to a possible thermal unit and PEV power generating schedule [14]. These solutions are then iteratively improved and refined using the SSA and PSO algorithms in accordance with the limitations present in the stochastic ELD problem and its objective function as shown in Figure 1.

During the optimization process, the SSA algorithm makes use of social behaviors of spiders, such as building webs and attracting one another, to efficiently explore and utilize the solution space. On the other hand, in order to find the optimal solution, the PSO algorithm simulates collective movement and information sharing among particles [15–18]. By accounting for uncertainty in renewable energy generation and the dynamic behavior of PEVs, the stochastic character of the ELD problem is tackled. The SSA and PSO algorithms incorporate many stochastic optimization techniques, such as scenario-based analysis, probabilistic models, and other methods, to achieve this goal. By using these techniques, the algorithms are able to control uncertainty and generate strong and dependable power generation schedules [19–23].

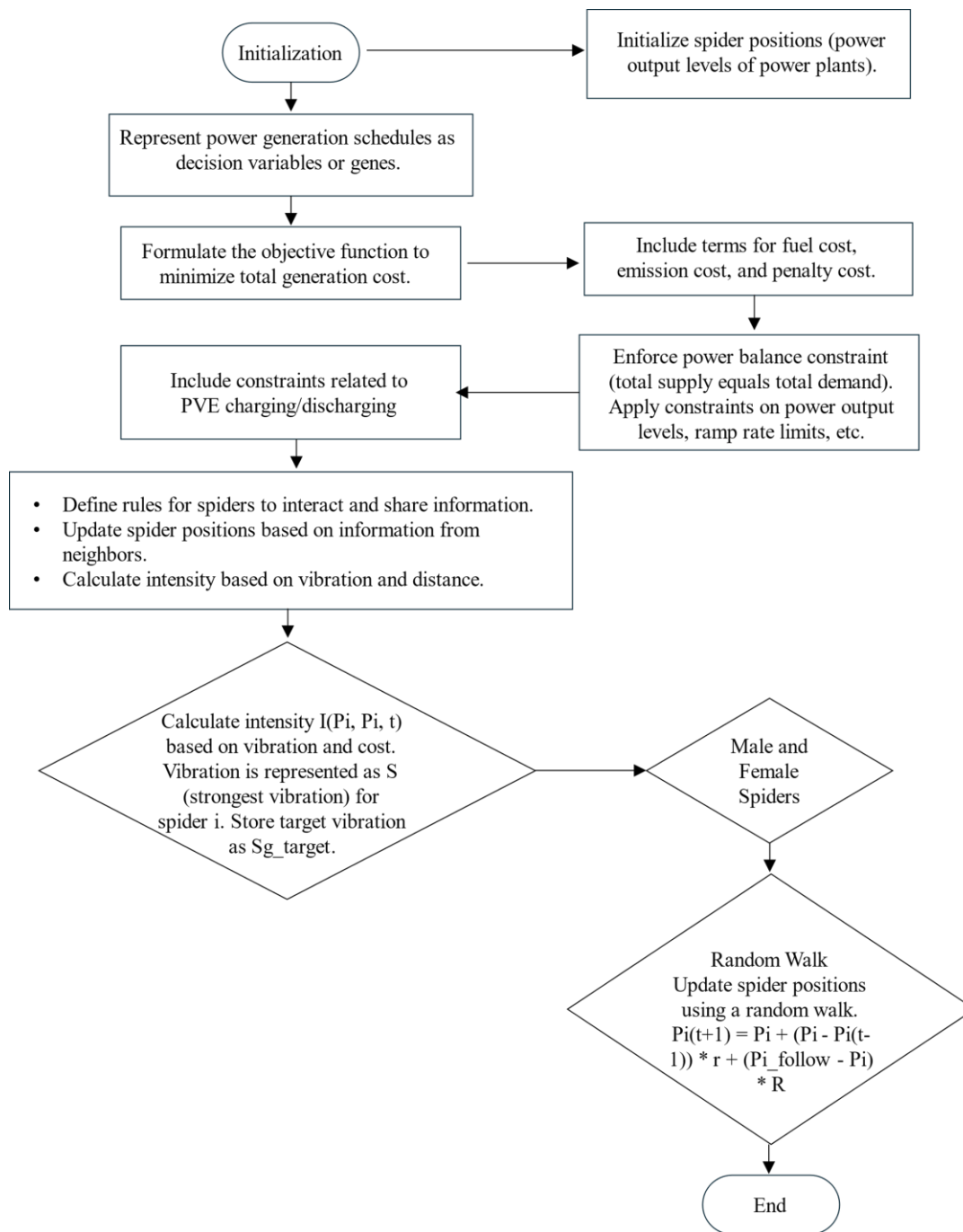


Figure 1. Social spider algorithm (SSA) flowchart.

The suggested approach has the potential to provide improved robustness, faster convergence, and greater solution quality for the stochastic ELD issue involving PEVs by integrating the SSA and PSO algorithms. It efficiently optimizes power system operations by taking into account the uncertainties and dynamics related to renewable energy and PEVs while utilizing principles of social behavior and collective intelligence.

Algorithm for Social Spiders

- a. *Initialization:* To start, initialize a population of spiders, each of which stands for a distinct timetable for electricity generation. Assign the spiders to their starting spots based on the power plants' respective output levels.

- b. *Encoding*: As a collection of genes or decision variables, encode each spider's power generation schedule. Create an encoding method that corresponds to each power plant's various power output levels.
- c. *Goal purpose*: Create an objective function that takes into account the needs of electric cars (PEVs) for charging and discharging in order to minimize the overall cost of generation. Fuel prices, emission expenses, and fines for any constraints broken pertaining to power balance and PEV charging/discharging should all be taken into consideration by this function [24].

Intensity Representation

The intensity of a spider's vibration is represented as:

$$I(P_i, P_i, t) = \log(1/(f(P_i) - C)) + 1 \quad (1)$$

Here, "S" denotes the spider's vibration. A spider receives the strongest vibration value, $S_{i\{best\}}$, where i represents a spider. Spider i stores the target vibration in memory as $S_{g\{target\}}$. Each spider analyzes both $S_{g\{best\}}$ and $S_{g\{target\}}$. The algorithm also models male and female spiders. The nature of male female spider has been explained with mathematical equation

$$I(P_i, P_u, t) = I(P_i, P_i, t) * \exp((Distance(P_i, P_u))/(\sigma * r_a)) + 1 \quad (2)$$

$$Distance(P_i, P_u) = P_i - P_u \quad (3)$$

where $I(P_i, P_u, t)$ is the value experienced by spider's vibration in "i" point, by another spider "u" point.

Random Walk

$$P_i(t + 1) = P_i + (P_i - P_i(t - 1)) * r + (P_i\ follow - P_i) * R \quad (4)$$

The SSA is inspired by the natural behavior of spiders, particularly their reliance on vibrations and interactions within a web. SSA models how spiders communicate and navigate by sensing vibrations generated by other spiders, using this information to determine their movements. This algorithm simulates the way spiders interact, allowing them to collaborate and converge on optimal solutions in a complex search space as shown in Table 1. SSA simulates a population of spiders, each representing a potential solution. Spiders communicate through vibrations and update their positions based on the information from neighboring spiders. SSA is especially effective in tackling optimization problems where social interactions are key. It provides a distinct approach to solving complex challenges by leveraging the dynamics of these interactions as algorithm discussed in Table 1.

Constraints

Various constraints such as power factor, reactive power, voltage, and frequency are incorporated into the algorithm to ensure that the generated schedule meets power quality standards as mentioned in Table 2.

This MATLAB code for the SSA is designed to optimize the dispatch of a power system, accounting for both conventional thermal units and the charging and discharging activities of PEVs. The main objective is to determine the optimal power output levels for each thermal unit and PEV charging station across various time intervals, taking into account the following key factors:

- a. *Thermal Units*: The code initializes data for ten thermal units, including their fuel cost, minimum and maximum load limits. Additionally, it introduces cost coefficients (a, b, c) for each thermal unit, representing their operating costs in a quadratic form.
- b. *Plug-In Electric Vehicles*: PEV data includes charging and discharging power levels, as well as the number of vehicles connected to the grid.
- c. *Emission Factors*: Emission factors for each thermal unit are defined, indicating the amount of CO₂ emissions associated with electricity generation using each unit.

- d. *PEV Charging Profile*: A probability distribution for PEV charging during different time intervals is provided. This distribution represents the likelihood of PEVs being connected to the grid and charging at specific times.
- e. *SSA Algorithm Parameters*: Parameters for the SSA algorithm are specified, including the maximum number of iterations, the number of social and inactive spiders, and various coefficients (beta, gamma) that govern the algorithm's behavior.
- f. *Fitness Function*: A fitness function is defined to evaluate the fitness of a given dispatch solution. This function considers several factors, such as the cost of operating thermal units, the cost of PEV charging and discharging, CO₂ emissions, and the introduced cost coefficients (a, b, c) for thermal units. It aims to minimize the overall cost and emissions.

Table 1. Power system and social spider algorithm (SSA) data attributes.

Attribute	Description	Value(s) or Range
<i>Number of Thermal Units (n)</i>	<i>Number of thermal units in the power system.</i>	10
Fixed Thermal Unit Data: unit fuel cost (\$/MWh), minimum load (MW), maximum load (MW)	c: [15, 20, 25, 18, 22, 17, 23, 19, 21, 16] pmin: [80, 60, 70, 90, 75, 85, 95, 100, 65, 55] pmax: [150, 120, 130, 160, 140, 170, 180, 190, 125, 110]	c: [15, 20, 25, 18, 22, 17, 23, 19, 21, 16] pmin: [80, 60, 70, 90, 75, 85, 95, 100, 65, 55] pmax: [150, 120, 130, 160, 140, 170, 180, 190, 125, 110]
Plug-in electric vehicle data: charging power (MW), discharging power (MW), number of vehicles	Charging Power Profile: 2.25 MW Discharging Power Profile: 1.5 MW Total Number of EVs: 0	Charging Power Profile: 2.25 MW Discharging Power Profile: 1.5 MW Total Number of EVs: 0
Emission factors (kg CO ₂ /MWh) for each thermal unit	[0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3, 1.4]	[0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2, 1.3, 1.4]
Define the PEV charging profile probability distribution	Specific probability values for different time intervals provided as a matrix	Provided as a matrix
SSA algorithm parameters	Maximum number of iterations: 100	Number of social spiders: 30
		Number of inactive spiders: 10
		Probability of random walk (p): 0.5
		Social attraction coefficient (beta): 2
		Spider-web construction coefficient (gamma): 1
Power balance equation: P _{thermal} + P _{pev} = P _{load}	Total load demand (P _{load}): 100,000 MW	100,000 MW

Table 2. Constraints for power system optimization.

Constraint Type	Description	Example Value or Range
Power output limits for thermal units	Ensures the power output of each thermal unit stays within specified limits.	Minimum load: 55 MW to maximum load: 190 MW (for each of 10 units)
Power factor constraint	Enforces a power factor constraint to maintain the quality of power supply.	Power factor > 0.9 (example value)
Reactive power limits for thermal units	Defines the allowable range of reactive power output for each thermal unit.	Minimum reactive power: -20 MVar to Maximum reactive power: 30 MVar (range for each unit)
Voltage limits	Specifies the acceptable voltage range to maintain power system stability.	Minimum voltage: 0.95 p.u. to maximum Voltage: 1.05 p.u. (example values)
Frequency regulation limits	Sets limits on the frequency of the power system to ensure grid stability.	Minimum frequency: 59.9 Hz to maximum frequency: 60.1 Hz (example values)
Electric vehicle (EV) charging constraints	Ensures that the charging profiles of electric vehicles are considered.	Charging power: 2 MW, discharging Power: 1.5 MW (example values)

The optimization process is performed using the SSA algorithm, iterating over a predefined number of iterations. In each iteration, random positions are generated for social spiders, representing possible power output levels for thermal units as shown in Figure 2 (PEV = 1100000), Figure 3 (PEV = 110000), Figure 4 (PEV = 11000), Figure 5 (PEV = 1100), Figure 6 (PEV = 110), and Figure 7 (PEV= 0). The fitness of each spider's position is evaluated, accounting for factors such as transmission losses. Spiders are sorted based on fitness, and the best solution found so far is updated. The spider-web is then adjusted using social attraction and spider-web construction coefficients.

Inactive spiders perform random walks to promote exploration of the solution space. Convergence speed metrics are calculated throughout the optimization process to track progress. After optimization, the code calculates and displays the optimal dispatch solution, showing the power outputs of thermal units. It reports the minimum fuel cost and total CO₂ emissions associated with this dispatch. Visualization is provided through a bar chart. Additionally, convergence speed metrics, including average, maximum, and minimum speeds, are presented, along with computational efficiency metrics such as total execution time. In summary, this code offers a comprehensive optimization framework for power system dispatch, encompassing both traditional and PEV-related considerations while aiming to minimize costs and reduce CO₂ emissions. The SSA algorithm facilitates the search for optimal solutions by iteratively exploring and improving dispatch strategies.

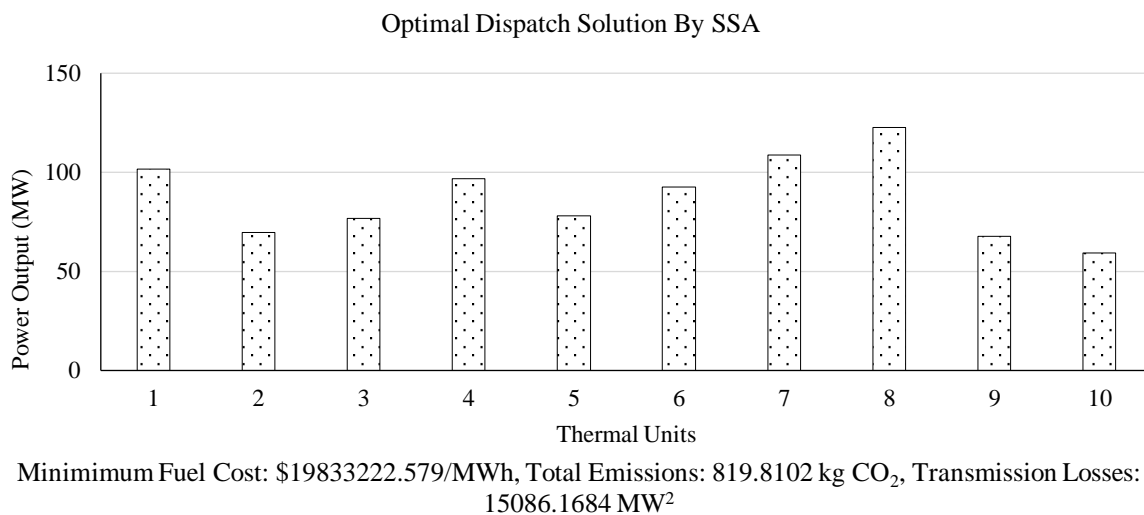


Figure 2. Social spider algorithm result with plug-in electric vehicle (PEV) = 1100000.

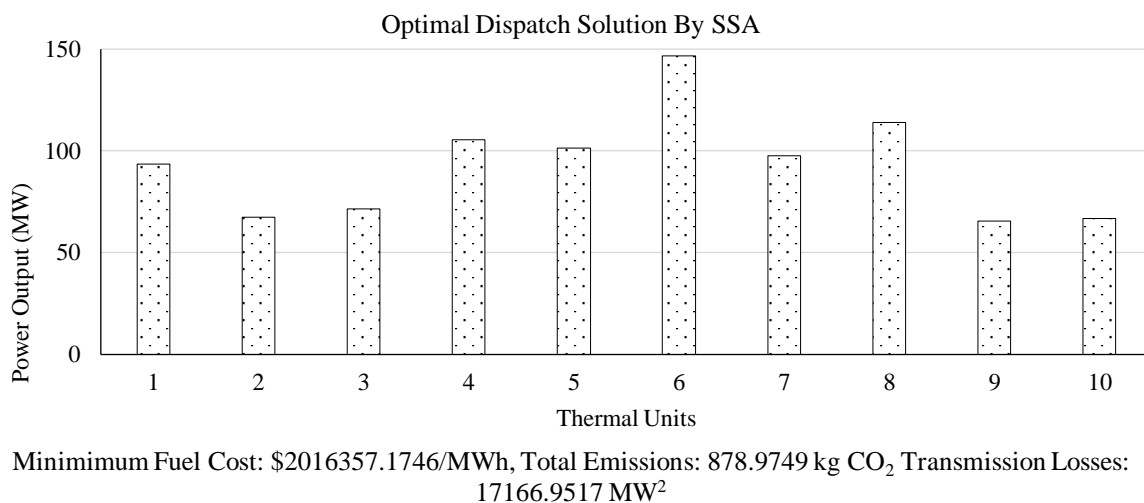


Figure 3. Social spider algorithm result with plug-in electric vehicle (PEV) = 110000.

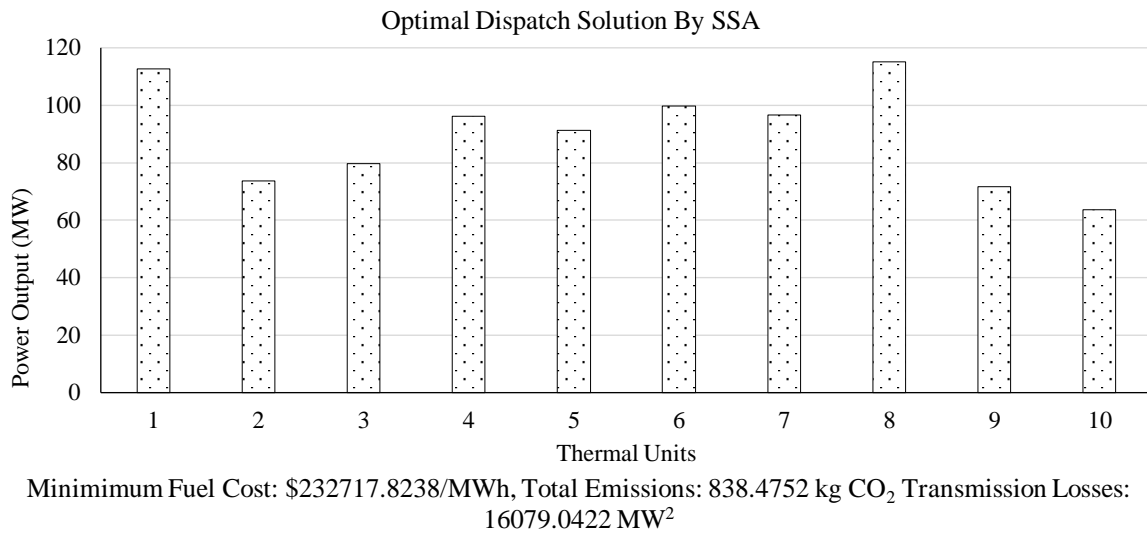


Figure 4. Social spider algorithm result with plug-in electric vehicle (PEV) = 11000.

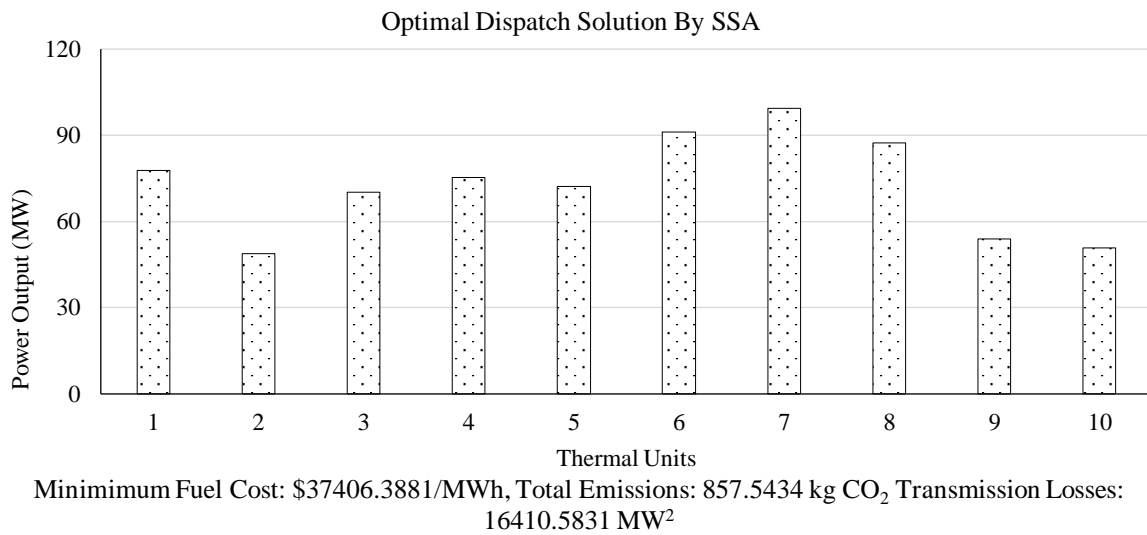


Figure 5. Social spider algorithm result with plug-in electric vehicle (PEV) = 1100.

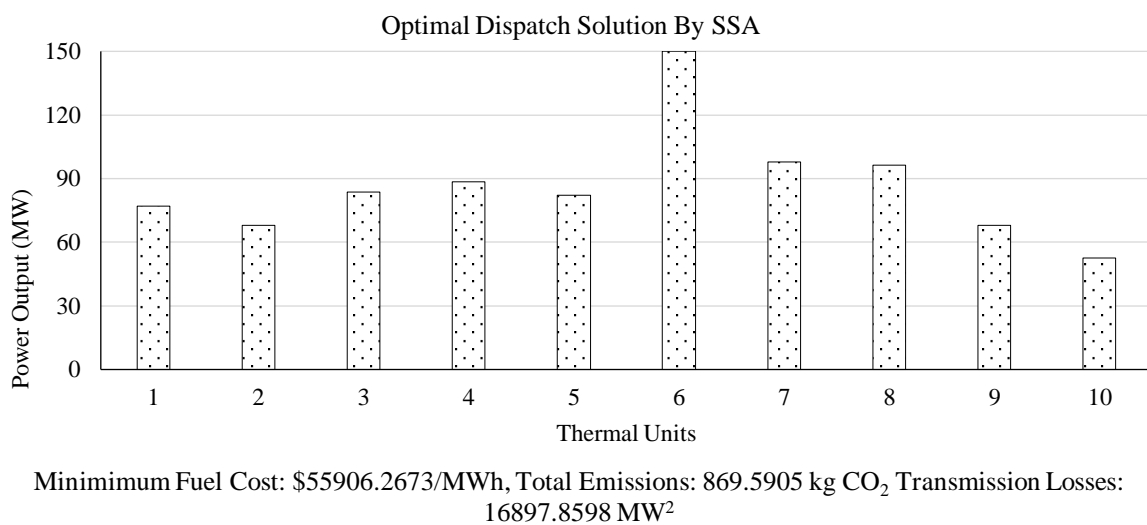


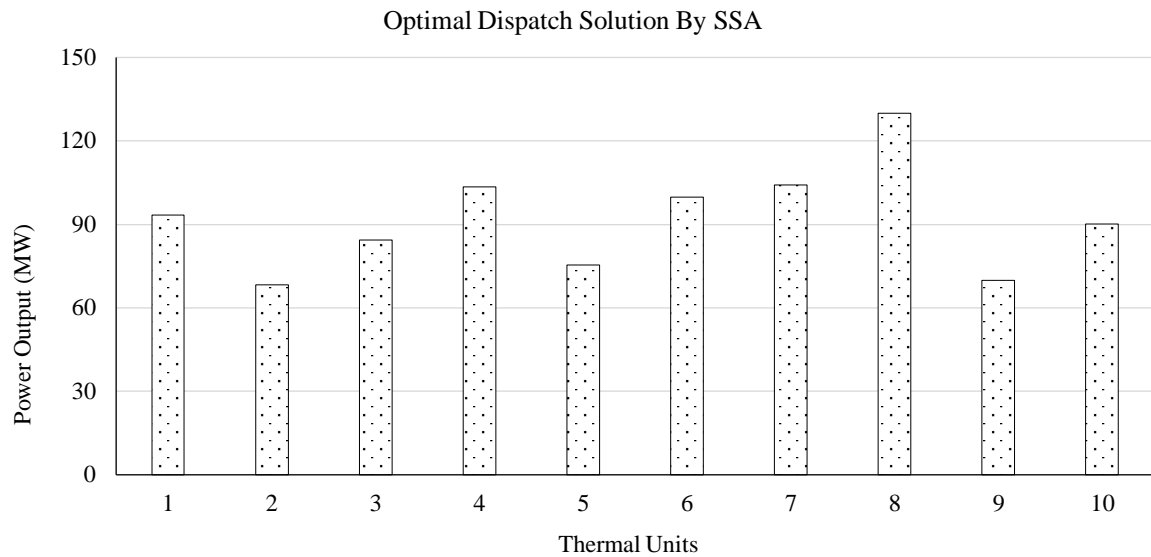
Figure 6. Social spider algorithm result with plug-in electric vehicle (PEV) = 110.

RESULTS

The social spider algorithm result presented in Figure 2 and Figure 7.

Results Analysis and Interpretation

The provided results in Table 3 represent the optimal dispatch solutions obtained using the SSA under different scenarios, each with a varying number of PEVs in the power system. The results include key metrics related to the power dispatch, cost, emissions, and the performance of the SSA algorithm.



Minimum Fuel Cost: \$335587.7698/MWh, Total Emissions: 878.1585 kg CO₂ Transmission Losses: 16626.5944 MW²

Figure 7. Social spider algorithm result with plug-in electric vehicle (PEV) = 0.

Table 3. Social spider algorithm (SSA) results.

Scenario	PEV Quantity	Thermal Unit Outputs	Minimum Fuel Cost (MWh)	Total CO ₂ Emission (Kg CO ₂)	Transmission on Losses (MW ²)	Average Convergence Speed	Maximum Convergence Speed	Minimum Convergence Speed	Total execution Time (second)	Average Total Execution Time (seconds)
Scenario 1	1,100,000	[101.0897 69.1568 75.5439 96.1460 77.5001 91.9998 108.4987 121.7719 67.7443 59.0581]	\$19.8 33.22 2.579/ MWh	819.8	15,086.17	89.87	5,708.80	0	0.047	5E-04
Scenario 2	110,000	[93.2610 67.2063 70.9511 105.0409 101.8024 146.2850 96.9772 112.9992 65.8541 66.0933]	\$2.01 6.357 1746/ MWh	879	17,166.95	43.66	2,089.15	0	0.048	5E-04

Scenario	PEV Quantity	Thermal Unit Outputs	Minimum Fuel Cost (MWh)	Total CO ₂ Emission (Kg CO ₂)	Transmission on Losses (MW ²)	Average Convergence Speed	Maximum Convergence Speed	Minimum Convergence Speed	Total execution Time (second)	Average Total Execution Time (seconds)
Scenario 3	11,000	[112.4112 73.1093 79.3620 96.4319 90.1293 99.4117 96.1927 114.6621 71.2247 63.6988]	\$232,717.8238/MWh	838.5	16,079.04	89.23	2,504.21	0	0.036	4E-04
Scenario 4	1,100	[90.6700 79.5659 79.2996 110.7932 93.8893 112.8764 96.4973 119.2228 73.4059 65.1756]	\$55,988.7726/MWh	870.5	16,979.41	52.24	2,101.28	0	0.065	7E-04
Scenario 5	110	[97.4154 61.2401 87.8759 94.0561 90.2517 113.4651 124.0677 107.8653 67.0158 62.5777]	\$37,406.4381/MWh	857.5	16,410.58	83.9	2,858.29	0	0.049	5E-04
Scenario 6	0	[92.7693 67.5720 83.1328 102.7241 75.1978 99.3923 102.9242 128.8324 69.4647 89.7631]	\$35,587.7698/MWh	878.2	16,626.59	67.86	2,971.39	0	0.047	5E-04

Here is an analysis and interpretation of the results for each scenario:

Scenario 1: PEV = 1,100,000

- Optimal Dispatch:
- Thermal unit outputs (in MW): [101.0897 69.1568 75.5439 96.1460 77.5001 91.9998 108.4987 121.7719 67.7443 59.0581]
- Minimum Fuel Cost: \$19833222.579/MWh
- Total CO₂ Emissions: 819.8102 kg CO₂
- Transmission Losses: 15086.1684 MW²
- Average Convergence Speed: 89.8726
- Maximum Convergence Speed: 5708.8009
- Minimum Convergence Speed: 0

- i. *Total Execution Time*: 0.046765 seconds
- j. *Average Execution Time per Iteration*: 0.00046765 seconds

In this scenario, with a high number of PEVs (1,100,000), the optimal dispatch solution results in a relatively high fuel cost, significant CO₂ emissions, and transmission losses. The SSA algorithm took 0.046765 seconds to converge to this solution.

Scenario 2: PEV = 110,000

- a. *Optimal Dispatch*: Thermal unit outputs (in MW): [93.2610 67.2063 70.9511 105.0409 101.8024 146.2850 96.9772 112.9992 65.8541 66.0933]
- b. *Minimum Fuel Cost*: \$2,016,357.1746/MWh
- c. *Total CO₂ Emissions*: 878.9749 kg CO₂
- d. *Transmission Losses*: 17166.9517 MW²
- e. *Average Convergence Speed*: 43.6571
- f. *Maximum Convergence Speed*: 2089.1547
- g. *Minimum Convergence Speed*: 0
- h. *Total Execution Time*: 0.047744 seconds
- i. *Average Execution Time per Iteration*: 0.00047744 seconds

In this scenario, with a lower number of PEVs (110,000), the optimal dispatch solution results in reduced fuel cost, increased CO₂ emissions, and higher transmission losses compared to Scenario 1. The SSA algorithm took 0.047744 seconds to converge.

Scenario 3: PEV = 11,000

- a. *Optimal Dispatch*:
- b. *Thermal unit outputs (in MW)*: [112.4112 73.1093 79.3620 96.4319 90.1293 99.4117 96.1927 114.6621 71.2247 63.6988]
- c. *Minimum Fuel Cost*: \$232717.8238/MWh
- d. *Total CO₂ Emissions*: 838.4752 kg CO₂
- e. *Transmission Losses*: 16079.0422 MW²
- f. *Average Convergence Speed*: 89.2295
- g. *Maximum Convergence Speed*: 2504.2058
- h. *Minimum Convergence Speed*: 0
- i. *Total Execution Time*: 0.036265 seconds
- j. *Average Execution Time per Iteration*: 0.00036265 seconds

With an even lower number of PEVs (11,000), the optimal dispatch solution results in a further reduction in fuel cost, slightly lower CO₂ emissions, and reduced transmission losses. The SSA algorithm converges faster, taking 0.036265 seconds.

Scenario 4: PEV = 1,100

- a. *Optimal Dispatch*: Thermal unit outputs (in MW): [90.6700 79.5659 79.2996 110.7932 93.8893 112.8764 96.4973 119.2228 73.4059 65.1756]
- b. *Minimum Fuel Cost*: \$55988.7726/MWh
- c. *Total CO₂ Emissions*: 870.4835 kg CO₂
- d. *Transmission Losses*: 16979.4138 MW²
- e. *Average Convergence Speed*: 52.2394
- f. *Maximum Convergence Speed*: 2101.2835
- g. *Minimum Convergence Speed*: 0
- h. *Total Execution Time*: 0.065015 seconds
- i. *Average Execution Time per Iteration*: 0.00065014 seconds

With an even smaller number of PEVs (1,100), the optimal dispatch solution achieves a significantly lower fuel cost, slightly higher CO₂ emissions, and transmission losses. The SSA algorithm converges slower, taking 0.065015 seconds.

Scenario 5: PEV = 110

- a. *Optimal Dispatch:*
- b. Thermal unit outputs (in MW): [97.4154 61.2401 87.8759 94.0561 90.2517 113.4651 124.0677 107.8653 67.0158 62.5777]
- c. *Minimum Fuel Cost:* \$37406.4381/MWh
- d. *Total CO₂ Emissions:* 857.5434 kg CO₂
- e. *Transmission Losses:* 16410.5831 MW²
- f. *Average Convergence Speed:* 83.9043
- g. *Maximum Convergence Speed:* 2858.2913
- h. *Minimum Convergence Speed:* 0
- i. *Total Execution Time:* 0.04897 seconds
- j. *Average Execution Time per Iteration:* 0.0004897 seconds

With only 110 PEVs, the optimal dispatch solution still achieves a low fuel cost but with relatively higher CO₂ emissions and transmission losses. The SSA algorithm converges efficiently, taking 0.04897 seconds.

Scenario 6: PEV = 0

- a. *Optimal Dispatch:* Thermal unit outputs (in MW): [92.7693 67.5720 83.1328 102.7241 75.1978 99.3923 102.9242 128.8324 69.4647 89.7631]
- b. *Minimum Fuel Cost:* \$35587.7698/MWh
- c. *Total CO₂ Emissions:* 878.1585 kg CO₂
- d. *Transmission Losses:* 16626.5944 MW²
- e. *Average Convergence Speed:* 67.8559
- f. *Maximum Convergence Speed:* 2971.3947
- g. *Minimum Convergence Speed:* 0
- h. *Total Execution Time:* 0.04653 seconds
- i. *Average Execution Time per Iteration:* 0.0004653 seconds

In the absence of PEVs (PEV = 0), the optimal dispatch solution incurs a higher fuel cost but maintains lower CO₂ emissions and transmission losses. The SSA algorithm converges efficiently, taking 0.04653 seconds.

CONCLUSION

- a. The results demonstrate the trade-offs between fuel cost, emissions, and transmission losses under different levels of PEV integration.
- b. Higher PEV integration generally leads to lower fuel costs but can result in increased emissions and transmission losses.
- c. The SSA algorithm exhibits varying convergence speeds, influenced by the problem complexity and the number of PEVs.

These results provide insights into optimizing power dispatch in the presence of PEVs, considering economic and environmental factors. The choice of PEV integration level should be made considering these trade-offs.

REFERENCES

1. Adhvaryu PK, Chattopadhyay PK, Bhattacharjya A. Dynamic economic emission load dispatch of hybrid power system using bio-inspired social spider algorithm. In: 2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), Delhi, India, July 4–6, 2016. pp. 1–6. doi: 10.1109/ICPEICES.2016.7853448.

2. Yang Z, Li K, Niu Q, Xue Y, Foley, A. A self-learning TLBO based dynamic economic/environmental dispatch considering multiple plug-in electric vehicle loads. *J Mod Power Syst Clean Energy*. 2014; 2: 298–307.
3. Behera S, Behera S, Barisal AK, Pradhan S. Economic load dispatch with renewable energy resources and plug-in electric vehicles. In: *Proceedings of the 2020 International Conference on Renewable Energy Integration into Smart Grids: A Multidisciplinary Approach to Technology Modelling and Simulation (ICREISG)*, Bhubaneswar, India, February 14–15, 2020. pp. 22–26.
4. Baş E, Ülker E. Improved social spider algorithm for large scale optimization. *Artif Intell Rev*. 2021; 54: 3539–3574.
5. Yang Z, Li K, Niu Q, Zhang C, Foley A. Non-convex dynamic economic/environmental dispatch with plug-in electric vehicle loads. In: *Proceedings of the 2014 IEEE Symposium on Computational Intelligence Applications in Smart Grid (CIASG)*, Orlando, FL, USA, December 9–12, 2014. pp. 1–7.
6. Mortazi A, Saeed S, Akbari H. Optimizing operation scheduling in a microgrid considering probabilistic uncertainty and demand response using social spider algorithm. *Int J Smart Electr Eng*. 2023; 12 (2): 113–125.
7. Hosseinalipour A, Gharehchopogh FS, Masdari M, Khademi A. Toward text psychology analysis using social spider optimization algorithm. *Concurr Comput Pract Experience*. 2021; 33 (17): e6325. doi: 10.1002/cpe.6325.
8. Yao M, Molzahn DK, Mathieu JL. An optimal power-flow approach to improve power system voltage stability using demand response. *IEEE Trans Control Netw Syst*. 2019; 6: 1015–1025. /doi: 10.1109/TCNS.2019.2910455.
9. Hao W-K, Li Y-P, Wang J-S, Zhu Q. Solving economic load dispatch problem of power system based on differential evolution algorithm with different mutation strategies. *IAENG Int J Comput Sci*. 2022; 49: 156–165.
10. Dubey HM, Pandit M, Panigrahi BK. Ant lion optimization for short-term wind integrated hydrothermal power generation scheduling. *Int J Electr Power Energy Syst*. 2016; 83: 158–174.
11. Al-Betar MA, Awadallah MA, Makhadmeh SN, Abu Doush I, Abu Zitar R, Alshathri S, Elaziz MA. A hybrid Harris Hawks optimizer for economic load dispatch problems. *Alexandria Eng J*. 2023; 64: 365–389.
12. Yang W, Cheng T, Guo Y, Yang Z, Feng W. A modified social spider optimization for economic dispatch with valve-point effects. *Complexity*. 2020; 2020: 2865929.
13. Yu JJQ, Li VOK. A social spider algorithm for global optimization. *Appl Soft Comput*. 2015; 30: 614–627.
14. Banerjee S, Maity D, Chanda CK. Teaching learning-based optimization for economic load dispatch problem considering valve point loading effect. *Int. J. Electr Power Energy Syst*. 2015; 73: 456–464.
15. Yuan X, Su A, Yuan Y, Nie H, Wang L. An improved PSO for dynamic load dispatch of generators with valve-point effects. *Energy*. 2009; 34: 67–74.
16. Maharana HS, Dash SK. Quantum behaved artificial bee colony based conventional controller for optimum dispatch. *Int J Electr Comput Eng*. 2023; 13: 1260.
17. Ma H, Yang Z, You P, Fei M. Multi-objective biogeography-based optimization for dynamic economic emission load dispatch considering plug-in electric vehicles charging. *Energy*. 2017; 135: 101–111.
18. Benalcazar P, Samper ME, Vargas A. Short-term economic dispatch of smart distribution grids considering the active role of plug-in electric vehicles. *Electr Power Syst Res*. 2019; 177: 105932.
19. Wu D, Aliprantis DC, Ying L. Load scheduling and dispatch for aggregators of plug-in electric vehicles. *IEEE Trans Smart Grid*. 2011; 3: 368–376.
20. Scarabaggio P, Carli R, Dotoli M. Noncooperative equilibrium-seeking in distributed energy systems under AC power flow nonlinear constraints. *IEEE Trans Control Netw Syst*. 2022; 9: 1731–1742. doi: 10.1109/TCNS.2022.3181527.

21. Mignoni N, Scarabaggio P, Carli R, Dotoli M. Control frameworks for transactive energy storage services in energy communities. *Control Eng Pract.* 2023; 130: 105364.
22. Venkatesan K, Govindarajan U. Optimal power flow control of hybrid renewable energy system with energy storage: a WOANN strategy. *J Renew Sustain Energy.* 2019; 11: 015501.
23. Ahangar HG, Yew WK, Flynn D. Smart local energy systems: optimal planning of stand-alone hybrid green power systems for on-line charging of electric vehicles. *IEEE Access.* 2023; 11: 7398–7409. doi: 10.1109/ACCESS.2023.3237326.
24. Yang Z, Yang F, Min H, Tian H, Hu W, Liu J, Eghbalian N. Energy management programming to reduce distribution network operating costs in the presence of electric vehicles and renewable energy sources. *Energy.* 2023; 263 (Part A): 125695.