SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V10I8P120

Volume 10 Issue 8, 206-214, August 2023

Original Article

An Integrated Economic and Emissions Dispatch Problem using the Sparrow Search Algorithm

V. Mahesh Kumar Reddy[1], P. Venkatesh[2], R. Dharmaprakash[3], S. Sendil Kumar[4]

[1]*Department of Electrical and Electronics Engineering, Chaitanya Bharathi Institute of Technology, Proddatur, India.*
[2]*Department of Electrical and Electronics Engineering, Mohan Babu University*
(Erstwhile Sree Vidyanikethan Engineering College), Tirupati, India.
[3]*Department of Electrical and Electronics Engineering, Panimalar Engineering College, Chennai, India.*
[4]*Department of Electrical and Electronics Engineering, S.A. Engineering College, Chennai, India.*

[2]*Corresponding Author : venkateshp.engg@gmail.com*

Received: 20 June 2023 Revised: 24 July 2023 Accepted: 16 August 2023 Published: 31 August 2023

Abstract **-** *The economic dispatch of the Micro-Grid (MG) in the current scenario considers the scheduling cycle with the lowest cost and effectively manages multiple Distributed Generations (DGs) over an extended duration, making it a more appropriate choice for a functional system. The unpredictability of wind and solar energy poses a challenge in solving the economic dispatch problem. Implementing intelligent algorithms and multi-objective optimum dispatching systems has demonstrated significant cost reduction and enhanced environmental sustainability in microgrid operations. The primary objective of the economic dispatch algorithm in the context of a Micro-Grid (MG) is to minimize expenses throughout the scheduling cycle while efficiently coordinating many distributed generators over an extended duration. This makes it highly suitable for operational systems. Due to their inherent variability, the economic resolution of the dispatch problem associated with wind and solar energy requires significant time. Utilizing smart algorithms and multi-objective functions for optimized dispatching generator capacity can potentially.*

Keywords **-** *Distributed generation, Economic-dispatch, Micro-grid, Linear integer programming, Optimization techniques.*

1. Introduction

The urgent need for decreased greenhouse gas emissions and the rising energy demand have made it essential to optimize power generation systems. The simultaneous optimization of economic cost and environmental impact in power generation is the focus of the Integrated Economic and Emissions Dispatch (IEED) problem.

Choosing the best power unit generation levels while considering the economy and emissions regulations is difficult. Metaheuristic algorithms have recently become more well-known for handling such challenging optimization problems.

The Sparrow Search Algorithm (SSA) has proven effective in resolving various optimization issues. In order to find a balanced solution that reduces operational costs and emissions, this research provides a novel application of the SSA to the IEED problem. Through this integration, the research advances affordable, environmentally friendly power generation systems, accelerating the move towards a cleaner, more energy-efficient future [1-3].

2. Literature Review

The Economic and Emissions Dispatch (EED) issue has become more complicated due to incorporating Renewable Energy Sources (RES) into power systems. Innovative dispatch strategies are needed for RES because it is intermittent and unpredictable. In order to strike a balance between cost-effectiveness and environmental sustainability, research has looked into hybrid systems that combine conventional generation with RES. Renewable generation uncertainty has been addressed using stochastic optimization and robust optimization techniques [4-7].

The initial techniques for resolving the issue were to use linear, quadratic, and dynamic programming, among other traditional methods. More sophisticated optimization algorithms appeared as computational power increased. With encouraging outcomes, EED has been solved using genetic algorithms, simulated annealing, particle swarm optimization, and ant colony optimization. These metaheuristic methods are advantageous for dealing with nonconvex, complex, and nonlinear objective functions [8-12].

Considering multiple competing goals in EED, such as financial cost, emission reduction, and system reliability, has gained popularity. Various trade-off solutions have been developed using multi-objective optimization techniques like Pareto-based optimization and evolutionary algorithms, allowing decision-makers to choose the best compromise option based on their preferences. Uncertainties in fuel prices, demand projections, and generator outages can significantly impact the effectiveness of dispatch solutions. Risk-aware dispatch methodologies that explicitly consider uncertainty into account and offer reliable or stochastic solutions have been the subject of extensive research. As a result, the operation of the power system is more dependable and stable [13-18].

The dispatch decisions of various market participants, such as generators, consumers, and independent system operators, are influenced by market mechanisms and regulatory policies. Researchers have investigated game theory and optimisation models to understand the effects of market structures on dispatch outcomes and capture the behaviours of different market players. EED issues were traditionally resolved offline while considering a set operating scenario. However, real-time or nearly real-time dispatch solutions are required due to the complexity and dynamics of modern power systems, which are becoming more complex. To enable dynamic and adaptive dispatch strategies, model predictive control, sophisticated optimization algorithms, and data-driven approaches have been investigated [19-24].

The growing emphasis on environmental sustainability has made integrating EED crucial in power systems. There are advantages and disadvantages to using metaheuristic algorithms to solve this issue, such as the SSA. The complexity of the EED, which involves maximizing power generation while simultaneously lowering economic costs and emissions, is one of the main issues.

A resilient algorithm like SSA must effectively explore the solution space to balance these competing objectives. The need to balance economic and environmental concerns creates difficulties. Finding globally optimal solutions to the EED problem is challenging due to its non-linearity and non-convexity. The SSA must successfully navigate this complicated environment to avoid settling on less-than-ideal solutions. Another level of complexity is added by including emissions factors in the optimization process.

The task of the algorithm is further complicated by accurate modelling of emissions and their impact on power generation. In addition, there are concerns about the SSA’s ability to scale to deal with massive power systems. The EED problem frequently involves many variables and constraints, and ensuring that the SSA remains efficient in such scenarios is critical [25-33].

The following objectives for economic and emissions dispatch using the sparrow search algorithm have been proposed in this paper. By reducing both financial expenses and greenhouse gas emissions, the integrated economic and emissions dispatch problem seeks to optimize the operation of power generation units. The SSA, an optimization method inspired by nature, is used to tackle this multi-objective problem. The algorithm aims to create a balanced solution that ensures cost-effective power generation while lowering carbon emissions by considering economic efficiency and environmental impact. Through this method, the fusion of financial and environmental considerations aids in managing sustainable energy in power systems, promoting a greener and more financially viable energy generation landscape.

3. Problem Formulation

3.1. Primary Objective Function

The primary objective is to optimise the utilization of generation capacity and emissions reduction in integrated economic dispatch; expression (1) identifies the primary goal of economic dispatch.

$$\min(K(P_i) = \sum_{ni=1}^{C_g} i(P_i) + \sum_{ni=1}^{C_e} i(P_i) \qquad (1)$$

In the context of the MG system, the variable ‘n’ represents the aggregate count of DG units. The variable $K(P_i)$ represents the aggregate operational expenditure, measured in $/hrs, for a collection of n DG units. $C_{g,i}$ denotes the generation cost specifically associated with the i^{th} DG unit, while $C_{e,i}$ represents the emissions cost for the same unit. Lastly, P_i signifies the power output.

The comprehensive cost of generating power from each distributed generation unit encompasses the expenditures associated with fuel procurement, maintenance activities, and operational expenses. This all-encompassing computation incorporates the diverse factors linked to the constituents mentioned above. The expression (2) illustrates the power equation in terms of input,

$$\sum_{ni=1}^{C_g} i(P_i) = \sum_{ni=1}^{C_f} i(P_i) + \sum_{ni=1}^{C_0} i(P_i) \qquad (2)$$

The variable $C_{g,i}$ (P_i) represents the expenditure associated with electricity production by the i^{th} distributed generation unit. Similarly, $C_{f,i}$ (P_i) denotes the financial outlay of fuel acquisition for the ith distributed generation unit. Lastly, $C_{o,i}$ (P_i) signifies the cost incurred for operating and maintaining the i^{th} distributed generation unit.

3.2. Fuel Cost

$$D_f(P_i) = K_{f,i} \text{ x } P_i \qquad (3)$$

Where, $P_i = P_o$ produced by the i^{th} DG unit, $K_{f,I}$ is the fuel coefficient at i^{th}, and $D_{f,i}(P_i)$ is the fuel cost of the i^{th} unit. Expression (3) indicates the fuel cost of the system.

3.3. Operation Cost

$$Y_{o,i}(P_i) = K_{o,i} \text{ x } P_i \quad (4)$$

Where, Pi is the i^{th} DG unit output power, $C_{o,i}(P_i)$ represents the operation cost ($/hrs) and $K_{o,i}$ = Operation & maintenance coefficient ($/kwh). Expression (4) indicates the operational cost of the system.

3.4. Emission Cost

$$Q_{e,i}(P_i) = K_{o,i} \text{ x } M_e \text{ x } P_i \quad (5)$$

Let $K_{e,\ i}$ represent the emissions coefficient of the ith distributed generation (DG) unit, measured in units of kilograms per kilowatt-hour (kWh). Additionally, $Q_{e,\ i}(P_i)$ denotes the cost associated with emissions for the DG mentioned above unit, expressed in units of currency per hour ($/h).

It signifies the monetary valuation of greenhouse gas emissions per kilogram, while P_i denotes the i^{th} DG unit output power. Expression (5) indicates the emission cost of the system.

3.5. Power Balance Constraint

$$VD = \sum_{ni=1} P_i + PB \quad (6)$$

Pi is the DG unit generating power, VD is the total load demand, and PB illustrates the battery's output. Expression (6) indicates the power balance constraint of the system.

3.6. DG Output Limits

$$Pi,min < P_i < P_{i,max} \quad (7)$$

$P_{i,\ min}$ and $P_{i,\ max}$ represent the DG units with min and max power limits, respectively. Expression (7) denotes DG output limits of the system.

3.7. The Operational Limitations of the Battery

$$-PBmin < PB < PB_{max} \quad (8)$$

PB_{max} represents the pinnacle of the battery's positive charging potential, and $-PB_{max}$ signifies the negative value of battery charging potential. Expression (8) denotes the operational limitations of the battery.

4. Proposed optimization Method

4.1. Concept of Sparrow Search Algorithm

The target behaviour of sparrows inspires the SSA. Gregarious sparrows may be split into producing sparrows and thieving sparrows. The feeding habits of sparrows serve as an inspiration for the SSA. According to their responsibilities in foraging, the gregarious sparrows can be split into producer and scrounger sparrows. The scroungers follow the producers as they forage while the producers actively look for food sources. In order to find more food, sparrows fight for their fellow birds' food supplies and flexibly flip. However, the population's distribution of producers and scroungers is set. The sparrows' foraging tactics are determined by their energy stores.

Additionally, sparrows' anti-predation behaviour has an impact on how they forage. The population is initialized and created in the SSA using a random technique. A matrix describes the location of every sparrow, and the individuals are given fitness ratings. The greater fitness values will go to the producers. The producers must look for food over a wider area since sparrow population migration is guided by it. Throughout iterations, the search process is essentially an extensive investigation of the search space. The scroungers are moving in an arbitrary direction away from their worst location. If not, the energy-rich scavengers migrate to the farmers from whom we have procured good food to engage in food competition. They will replace those that lose as new producers if they prevail. Additionally, some sparrows recognize danger when it arises. The anti-predatory behaviour is used to update the sparrows' location.

4.2. SSA Algorithm

A natural-inspired optimisation method called the sparrow search algorithm has been used to address challenging issues like the Economic Dispatch (ED) problem in power systems. Allocating generation outputs among power plants to meet the demand for electricity while lowering overall generation costs is the goal of the economic dispatch problem. The social behaviour of sparrows, which exhibit flocking and foraging behaviours to locate the best food sources, inspires SSA.

In order to find the best response, SSA simulates the movement of sparrows. Sparrows stand in for potential solutions and move in a manner that mimics the trade-off between exploration and exploitation in optimisation. The algorithm models sparrow movement using mathematical equations and adaptively modifies parameters to strike a balance between exploration and exploitation. Sparrows communicate by updating their positions and exchanging knowledge about better solutions, which enables the algorithm to converge over successive iterations to a nearly optimal solution.

The steps are shown in the algorithm's flow chart: initialization, fitness assessment, selection, crossover, mutation, convergence check, and output of the optimal dispatch solution. In order to achieve economically optimal power generation distribution while taking operational constraints into account in the economic dispatch problem, an iterative approach that efficiently navigates the solution space is used, as shown in Figure 1.

Step 1: Create the solution and prepare it. At this point, it is possible to compute the population size, maximum number of replicas, producer ratio (PD), and the proportion of sparrows receiving acute therapy (PV). Equation displays the sparrow population's starting location. They are created at random in expression (9).

$$X = \begin{bmatrix} x_1, x & x_1, 2 & \dots \dots & x_1, d \\ x_2, x & x_2, 2 & \dots \dots & x_2, d \\ \dots & \dots & \dots \dots & \dots \\ x_n, 1 & x_n, 2 & \dots \dots & x_n, d \end{bmatrix} \quad (9)$$

The equation's choice variables comprise n sparrows and have a d dimension. The above equation assesses each person's suitability for the next operation. The FX equation's row values are expressed as numbers. The equation below shows the fit for each sparrow, where n is the number of sparrows in expression (10).

$$F_x = \begin{bmatrix} f[x_1, x & x_1, 2 & \dots \dots & x_1, d] \\ [x_2, x & x_2, 2 & \dots \dots & x_2, d] \\ \dots & \dots & \dots \dots & \dots \\ x_n, 1 & x_n, 2 & \dots \dots & x_n, d \end{bmatrix} \quad (10)$$

Step 2: In the SSA, producers of fitness-related goods are prioritised over those who generate food. Since producers manage the entire population's movement may seek cuisine across a larger region than explorers. In line with procedure steps (1) and (4), the manufacturers update their status using the above equation (10).

$$X_{i,j}^{t+1} = \begin{Bmatrix} X_{i,j}^{t} * \exp(\frac{-i}{\alpha * iter_{\max}}) & if\ R_2 < ST \\ X_{i,j}^{t} + Q * L & if\ R_2 \geq ST \end{Bmatrix} \quad (11)$$

The constant in the above equation with the most iterations is called 〖inter〗_mix. j=1, 2..., d, X_(i, j)^t indicates the subsequent new value of j^{th} sparrow in each iteration of t, where t is the current iteration in expression (11). A random number between 0 and 1 is the safe threshold, or ST is between 0.5 and 1.0, whereas R_2, the alert value, ranges from 0 to 1. Q is a random integer based on the normal distribution. L is a picture of a 1D matrix with 1-element values. If it is R_2 ST, some sparrows saw the hunter and must immediately fly away.

When R2 is lacking, the creator uses a comprehensive search. Explorers must follow guidelines 4 and 5. After discovering a producer has found it, they leave to compete for a great feast. They can eat instantly if they succeed.; if not, Rule 5 will take effect. Expression (12) describes position updates for explorers. It is decided by 〖ex〗_pif the firm has the best position in expression (12). X_worst represents the current worst location on the earth. A is a 1d matrix in which each element's value is given a 1 or a -1 at random. If I>n/2, it means there is a probability that the I probe will starve.

$$X_{i,j}^{t+1} = \begin{Bmatrix} Q * \exp(\frac{X_{worst}^{t} - X_{i,j}^{t}}{i^2}) \ if > \frac{n}{2} \\ X_p^{t+1} + | X_{i,j}^{t} - X_p^{t+1} | * A^{+} * L \end{Bmatrix} \quad (12)$$

Step 3: After updating the location of the whole population, a group of sparrows are selected to act as scouts (exploration), who are in charge of identification and warning. They typically make up 10% to 20% of the population. Equation asserts that rule 6 defines shifting one's location as doing so (6).

$$X_{i,j}^{t+1} = \begin{Bmatrix} X_{best}^{t} + \beta * | X_{i,j}^{t} - X_{best}^{t} | & f_i > f_g \\ X_{i,j}^{t} + K * \left(\frac{\left| X_{i,j}^{t} - X_{worst}^{t} \right|}{(f_i - f_w) + \varepsilon} \right) & f_i = f_g \end{Bmatrix} \quad (13)$$

X_bestis where Equation (13) gives the global optimum solution. It is a tiny constant that prevents crimes in zero-division. Establishes the arbitrary number's step size, 0 and 1 mean, and friction normal distribution. K is a random number between 1 and 1; f_g and f_w reflect the current stylish and worst overall felicity circumstances. The current sparrow value is f_i. According to f_i=f_g, middle sparrows should approach others because they recognize the danger. If f_i>f_g, the individual is on the group's periphery. X best points to the population's centre and the secure area around it. K is the control parameter for the step size and the direction of the movement. K denotes the direction of travel and the variable that regulates step size.

Step 4: Each participant's current location is contrasted with the previous repeat. The update is complete if the new position outperforms the old one while maintaining the optimum position. Some sparrows may have a better chance of surviving after the last two stages.

Step 5: Go to step 2 if there are fewer repetitions than the limit. The algorithm then halts and chooses the optimal action in this situation. Iterative processes are used in the sparrow search algorithm to solve the economic dispatch problem. It begins by initialising a population of potential solutions and assesses each one's fitness using the principle of cost minimization. The algorithm iteratively improves the solutions through selection, crossover, and mutation. Each generator's best power generation levels are identified at convergence, where the process stops. Step-by-step processes of the SSA Flow chart are shown in Figure 1.

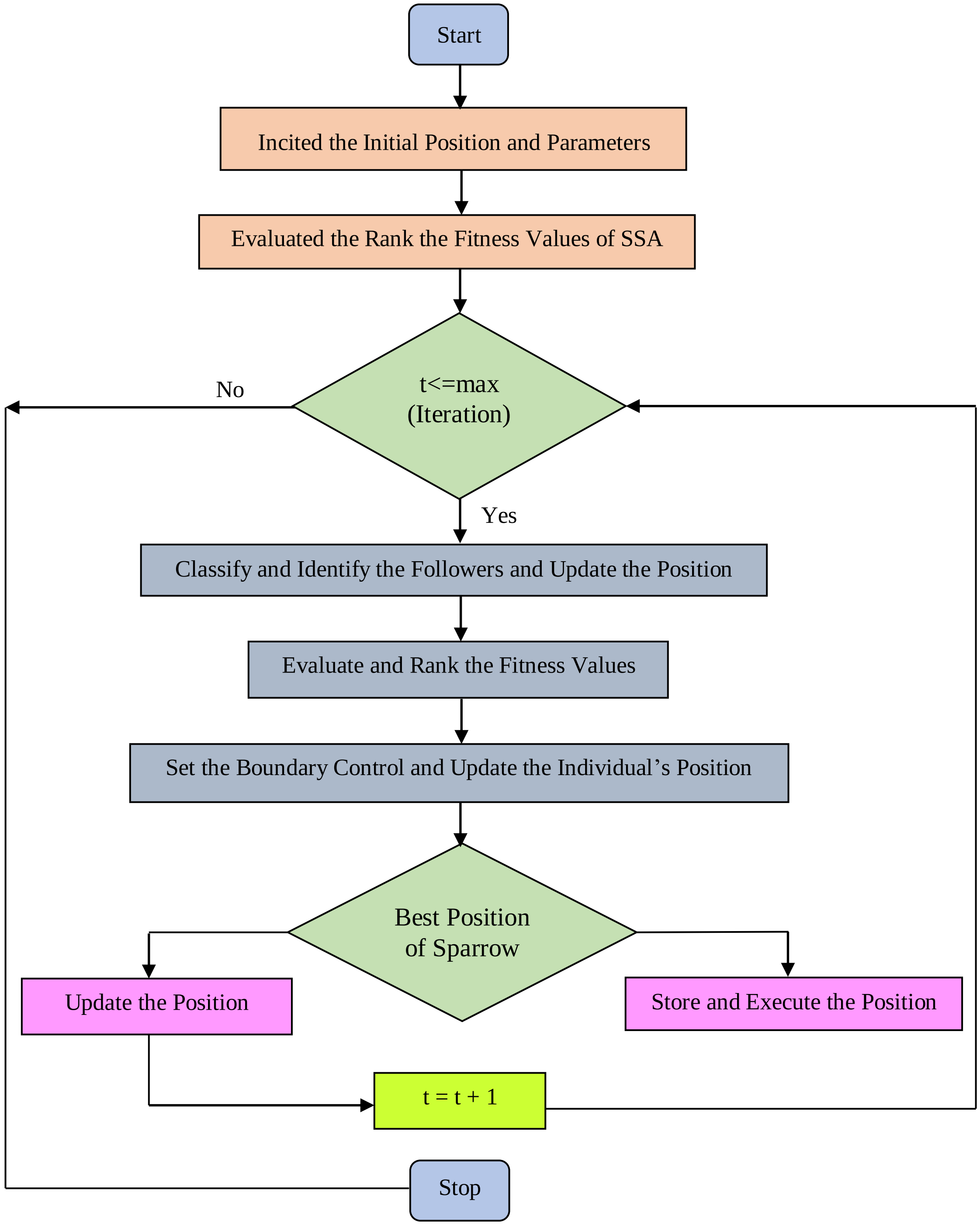

Fig. 1 Flowchart of sparrow search algorithm

5. Results and Discussion

This section displays Micro-Grid's Sparrow Search algorithms based on environmental and economic dispatch results. SSA is compared to Lagrange results to determine its efficacy. The Sparrow Search Algorithm (SSA) optimizes a complex dispatch problem considering economic and ecological factors. The economic and emission costs associated with the microgrid's load dispatch problem have been lowered thanks to the SSA methodology that was advised. The bar chart shows the optimal generating capacity corresponding to the demand, as shown in Figure 2. From Figure 3 and Figure 4, it is clear that the minimized fuel cost by optimum utilization of generator capacity using SSA is achieved when compared to Lagrange Integration Method (LIM). Table 1 and Table 2 show the numerical values of optimum generating capacity corresponding to total demand using the sparrow search algorithm-hm for three and fifteen generator units.

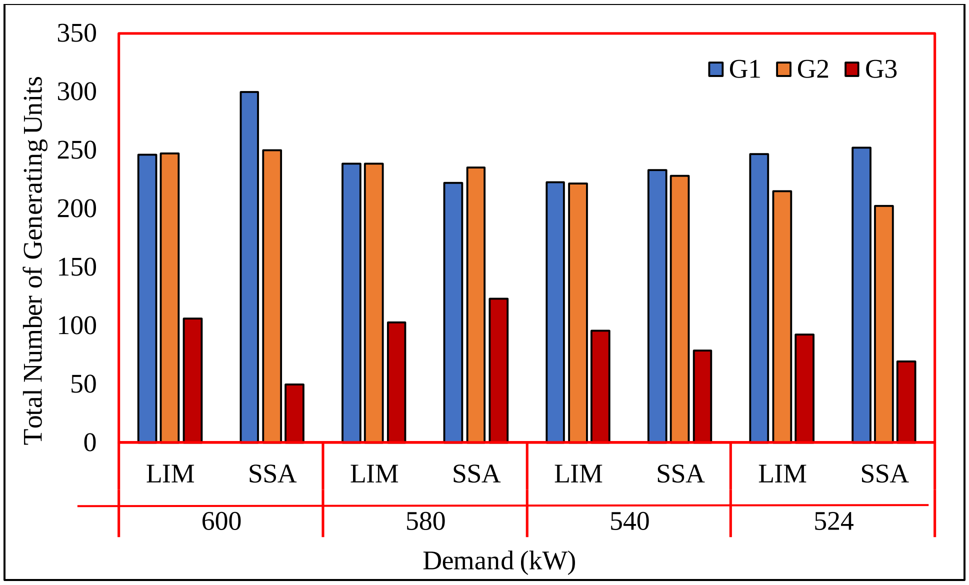

Fig. 2 Optimal generator capacity (three units) based on demand using SSs

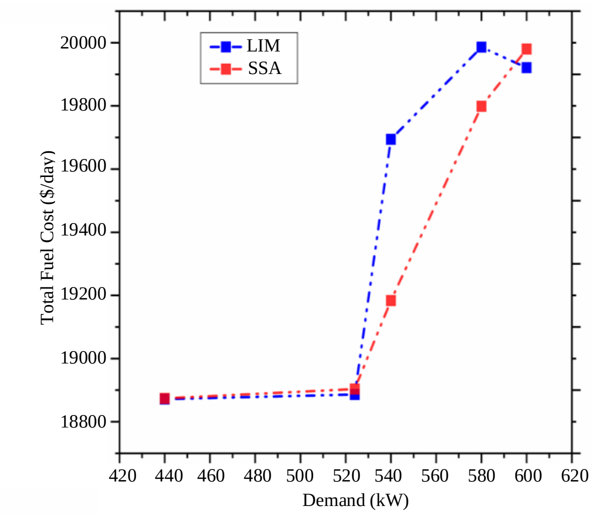

Fig. 3 Comparative analysis of SSA and LIM for demand and fuel cost for the three generating units

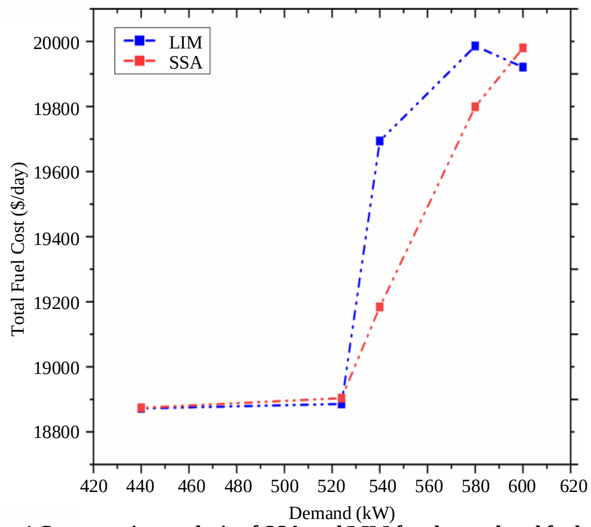

Fig. 4 Comparative analysis of SSA and LIM for demand and fuel cost for the 15 generating units

Table 1. A comparative analysis of generation and total operation cost between LIM and SSA for three generating units utilizing the minimum and maximum price penalty factors

LIM						SSA					
GA	**Demand (kW)**					**GA**	**Demand (kW)**				
	D1 600	D2 580	D3 540	D4 524	D5 440		D1 600	D2 580	D3 540	D4 524	D5 440
G1	246.35	238.51	222.81	246.53	183.57	G1	300	222.02	233.11	252.20	140.34
G2	247.37	238.82	221.72	214.88	178.98	G2	250	235.06	228.22	202.20	249.52
G3	106.26	102.66	95.46	92.57	77.44	G3	50	122.90	78.66	69.51	50.10

(GA - Total no. of generating units (kW) and D – Total Demand (kW))

Table 2. LIM and SSA generation and operating cost comparison for 15 generating units utilizing min/max price penalty factor

LIM						SSA					
Total No. of Generating Units (kW)	Demand (kW)					Total No. of Generating Units (kW)	Demand (kW)				
	D1 600	D2 580	D3 540	D4 524	D5 440		D1 600	D2 580	D3 540	D4 524	D5 440
G1	62.83	62.01	59.53	58.17	47.12	G1	20.87	57.31	52.21	57.03	31.41
G2	30	30	30	30	30	G2	65.32	40.02	41.94	30	30
G3	20.24	20	20	20	20	G3	67.27	81.74	46.41	46.13	29.98
G4	20.24	20	20	20	20	G4	20.87	21.51	34.75	29.61	62.00
G5	75.22	73.90	70.08	67.97	50.90	G5	67.94	42.61	62.51	54.83	34.21
G6	76.38	75.10	71.38	69.33	52.73	G6	61.67	32.05	92.25	50.79	25
G7	77.783	76.41	72.41	70.21	52.38	G7	30.87	28.31	34.03	47.07	28.74
G8	66.74	65.12	60.42	57.83	36.8	G8	20.87	52.48	30.80	48.36	43.02
G9	20	20	20	20	20	G9	45.03	20.93	20.80	21.45	20.75
G10	16.74	15	15	15	15	G10	33.62	33.23	25.22	20.31	30
G11	33.98	29.89	20	20	20	G11	34.05	43.07	20.80	37.17	21.29
G12	40.04	63.49	26.15	20.45	20	G12	45.80	66.76	20.80	32.18	27.74
G13	25	25	25	25	25	G13	34.05	29.91	25.80	25	25.52
G14	19.92	16.03	15	15	15	G14	30.29	15	15.80	15	15.20
G15	15	15	15	15	15	G15	15.87	15	15.80	15	15.23

6. Conclusion

The SSA algorithm optimizes a complex dispatch problem considering economic and ecological factors. The SSA methodology has acknowledged the economic and emission costs associated with the microgrid's load dispatch problem. The Price Penalty Factor (PPF) has been used to analyse the overall fuel cost of alternative solutions for particular demands. Penalty factors for maximum/minimum, minimum/maximum, and minimum/minimum scenarios have been addressed in the constrained evolutionary economic dispatch problem using the Lagrange method and sequential subspace approximation with different price penalty factors after solving the Combined Economic and Emission Dispatch (CEED) issue; the minimization/ maximization price penalty factor produces optimal results. Singular spectrum analysis outperforms the lagrange method in minimizing fuel expenditure for the CEED issue across price penalty factors. Thus, the proposed social security administration achieves better results and addresses the complex combined economic and emission dispatch problem. Linear integer programming, singular spectrum analysis generation, and operating costs will be compared for 15 generating units. This comparison has included a key optimisation aspect's min/max price penalty element.

References

[1] Sanchari Deb et al., "Recent Methodology-Based Gradient-Based Optimizer for Economic Load Dispatch Problem," *IEEE Access*, vol. 9, pp. 44322-44338, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] Abhishek Srivastava, and Dushmanta Kumar Das, "A New Aggrandized Class Topper Optimization Algorithm to Solve Economic Load Dispatch Problem in a Power System," *IEEE Transactions on Cybernetics*, vol. 52, no. 6, pp. 4187-4197, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] Xiaoting Wang et al., "A Data-Driven Uncertainty Quantification Method for Stochastic Economic Dispatch," *IEEE Transactions on Power Systems*, vol. 37, no. 1, pp. 812-815, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] E. Parimalasundar et al., "Investigation Analysis of Open Circuit and Short Circuit Fault on Cascaded H-Bridged Multilevel Inverter using Artificial Neural Network Approach," *International Journal of Electrical and Electronics Research*, vol. 10, no. 2, pp. 320-326, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] Xiaoting Wang et al., "A Data-Driven Uncertainty Quantification Method for Stochastic Economic Dispatch," *IEEE Transactions on Power Systems*, vol. 37, no. 1, pp. 812-815, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] P. Venkatesh, and N. Visali, "Machine Learning for Hybrid Line Stability Ranking Index in Polynomial Load Modeling under Contingency Conditions," *Intelligent Automation & Soft Computing*, vol. 37, no. 1, pp. 1001–1012, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Dewen Li et al., "Virtual-Action-Based Coordinated Reinforcement Learning for Distributed Economic Dispatch," *IEEE Transactions on Power Systems*, vol. 36, no. 6, pp. 5143-5152, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] K. Suresh et al., "A Performance Investigations of Modular Multilevel Inverter with Reduced Switch Count," *International Conference on Intelligent Innovations in Engineering and Technology (ICIIET)*, pp. 83-87, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Yamin Yan et al., "Distributed Consensus-Based Economic Dispatch in Power Grids using the Paillier Cryptosystem," *IEEE Transactions on Smart Grid*, vol. 12, no. 4, pp. 3493-3502, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[10] P. Venkatesh, and N. Visali, "Enhancing Power System Security using Soft Computing and Machine Learning," *Electrical Engineering & Electromechanics*, no. 4, pp. 90–94, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] B. Perumal, K. Suresh, and E. Parimalasundar, "Fault Analysis in the 5-Level Multilevel NCA DC–AC Converter," *Automation*, vol. 64, no. 3, pp. 606-612, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] K. Suresh, and E. Parimalasundar, "Fault Analysis and Clearance in FL-APC DC–AC Converter," *IEEE Canadian Journal of Electrical and Computer Engineering*, vol. 46, no. 1, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Zhenwei Zhang et al., "Multitime Scale Co-Optimized Dispatch for Integrated Electricity and Natural Gas System Considering Bidirectional Interactions and Renewable Uncertainties," *IEEE Transactions on Industry Applications*, vol. 58, no. 4, pp. 5317-5327, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] K. Suresh et al., "Design and Implementation Bidirectional DC–AC Converter for Energy Storage System," *IEEE Canadian Journal of Electrical and Computer Engineering*, vol. 46, no. 2, pp. 130-136, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Krishnan Suresh, and Ezhilvannan Parimalasundar, "Newly Designed Single-Stage Dual Leg DC-DC/AC Buck-Boost Converter for Grid Connected Solar System," *International Journal of Circuit Theory and Applications*, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Shuai Lu et al., "Economic Dispatch of Integrated Energy Systems with Robust Thermal Comfort Management," *IEEE Transactions on Sustainable Energy*, vol. 12, no. 1, pp. 222-233, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[17] Alireza Akbari-Dibavar et al., "Economic-Emission Dispatch Problem in Power Systems with Carbon Capture Power Plants," *IEEE Transactions on Industry Applications*, vol. 57, no. 4, pp. 3341-3351, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Krishnan Suresh, and Ezhilvannan Parimalasundar, "Design and Implementation of Dual-Leg Generic Converter for DC/AC Grid Integration," *International Journal of Circuit Theory and Applications*, vol. 51, no. 8, pp. 3865-3879, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Krishnan Suresh, and Ezhilvannan Parimalasundar, "Fault Analysis and Compensation in a Five Level Multilevel DC-AC Converter," *El-Cezeri*, vol. 10, no. 1, pp. 99-108, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] David Troxell, Miju Ahn, and Harsha Gangammanavar, "A Cardinality Minimization Approach to Security-Constrained Economic Dispatch," *IEEE Transactions on Power Systems*, vol. 37, no. 5, pp. 3642-3652, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] Stefanos Baros, Yu Christine Chen, and Sairaj V. Dhople, "Examining the Economic Optimality of Automatic Generation Control," *IEEE Transactions on Power Systems*, vol. 36, no. 5, pp. 4611-4620, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[22] Kasinath Jena et al., "A Single DC Source Generalized Switched Capacitors Multilevel Inverter with Minimal Component Count," *International Transactions on Electrical Energy Systems*, vol. 2023, pp. 1–12, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Kavali Janardhan et al., "Performance Investigation of Solar Photovoltaic System for Mobile Communication Tower Power Feeding Application," *International Journal of Electrical and Electronics Research*, vol. 10, no. 4, pp. 921–925, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] B. Hemanth Kumar et al., "Control of Modified Switched Reluctance Motor for EV Applications," *Trends in Electrical, Electronics, Computer Engineering Conference (TEECCON)*, pp. 123-127, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[25] B. Hemanth Kumar et al., "An Enhanced Space Vector PWM Strategies for Three Phase Asymmetric Multilevel Inverter," *International Transactions on Electrical Energy Systems*, vol. 2023, pp. 1-29, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] Abdulkerim Ali, Getachew Biru, and Belachew Bantyirga, "Design the Potential Application of Fuzzy Logic-Based AGC and AVR for Multi-Area Interconnected Power Systems: A Case Study on Ethiopia," *International Journal of Engineering Trends and Technology*, vol. 71, no. 5, pp. 84-97, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[27] E. Parimalasundar et al., "Performance Analysis of DC-DC Converter for Electric Vehicle Charging Applications," *International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 1543-1546, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[28] Thi-Mai-Phuong Dao, Ngoc-Khoat Nguyen, and Duy-Trung Nguyen, "Different Fuzzy Logic–Based Load-Frequency Controllers for Interconnected Power Systems – A Comparative Study Applied in Vietnam," *International Journal of Engineering Trends and Technology*, vol. 71, no. 7, pp. 223-232, 2023. [CrossRef] [Publisher Link]

[29] Yiqiao Xu et al., "Distributed Optimization for Integrated Frequency Regulation and Economic Dispatch in Microgrids," *IEEE Transactions on Smart Grid*, vol. 12, no. 6, pp. 4595-4606, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[30] H. S. Shreenidhi, and Narayana Swamy Ramaiah, "Sensor-Assisted Machine Learning Models Approach to Equipoise Renewable Energy using Microgrids," *SSRG International Journal of Electronics and Communication Engineering*, vol. 10, no. 7, pp. 63-73, 2023. [CrossRef] [Publisher Link]

[31] Kasinath Jena et al., "A Novel Three-Phase Switched-Capacitor Five-Level Multilevel Inverter with Reduced Components and Self-Balancing Ability," *Applied Sciences*, vol. 13, no. 3, pp. 1-19, 2023 [CrossRef] [Google Scholar] [Publisher Link]

[32] Parimalasundar Ezhilvannan et al., "Analysis of the Effectiveness of a Two-Stage Three-Phase Grid Connected Inverter for Photovoltaic Applications," *Journal of Solar Energy Research*, vol. 8, no. 2, pp. 1471-1483, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[33] Farnaz Safdarian, Amin Kargarian, and Fouad Hasan, "Multiclass Learning-Aided Temporal Decomposition and Distributed Optimization for Power Systems," *IEEE Transactions on Power Systems*, vol. 36, no. 6, pp. 4941-4952, 2021. [CrossRef] [Google Scholar] [Publisher Link]