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# An Intensified Sparrow Search Algorithm for Combined Economic Emission Dispatch including Renewables and Electric Vehicles

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**Abstract:** Security, reliability, economics and environments are the four pillars of power system operation and control. Combined economic emission dispatch (CEED) is one such problem which can able to accommodate all these aspects. Though CEED is mainly to minimize operating cost and emission costs, it has been redefined in recent times due to the emerging trends, namely, renewable energy sources (RES) and electric vehicles (EVs). In this paper, the problem of CEED is augmented in this context by considering spinning reserve (SR) due to the fluctuation in network loading conditions, and the penetration of EV load. Furthermore, the differences in power of photovoltaic (PV) and wind turbine (WT) systems are covered. These modifications transform the CEED into a non-convex, multi-objective, multi-variable optimization problem with several constraints. The proposed solution is a novel meta-heuristic intensified sparrow search algorithm (ISSA) designed to enhance search features. ISSA incorporates a neighbour search technique and saltation learning mechanism for the fundamental SSA. Simulations are performed for various scenarios on a standard 3-bus power system. At first, the solution for conventional CEED is determined using ISSA and compare it with other recent meta-heuristics. Augmented CEED is performed in the second stage, taking into account hourly variability in loading conditions on the system, RES, and EVs, along with SR requirements for stability and generation loss. With RES and EVs, the SR is estimated equal to 875.371 MWh, up from 787.182 MWh without them, indicating improvement in system. Furthermore, the penetration of RES reduces net power consumption by 1975.6 MW, leading to a reduction in fuel costs of $17,649.112 per hour. Also, it resulted in an effective solution for global warming by reducing emission costs by $537.161 every hour.

**Keywords:** Combined economic emission dispatch, Renewable energy sources, Electric vehicles, Spinning reserve, Multi-objective optimization, Sparrow search algorithm.

## 1. Introduction

Combined economic emission dispatch (CEED) problem is important in today's electric power system operation due to the need of operational enhancement aiming at joint optimization objective associated with minimization on both cost effectiveness and environment impact [1]. Its primary target is the reduction of operational costs and, along with that, pollutant emissions. Solutions are confronted with addressing the non-linear, multi-objective nature of the problem as well as pathways for integrating up-and-coming renewable energy sources characterized by variable outputs [2]. Further, the introduction of renewable energy sources (RESs) and electric vehicles (EVs), entering the CEED problem, faces challenges with REs intermittency and unpredictable EV charging demands that require advanced grid management techniques. They exhibit limitations concerning computational complexity and the reliability of convergence. That adds complexity to optimization due to which CEED problem need more sophisticated algorithms to make them stable and efficient. Metaheuristics are types of optimization algorithms developed to provide near-optimal solutions in complex, large-scale systems and they can be implemented while taking advantages like being robustness, flexibility enhancing overall grid performance sustainability [3]. In recent times, various metaheuristics have been adapted for solving the CEED problem considering REs and EVs.

In [4], multi-objective equilibrium optimizer (MOEO) is proposed for grid power (GP)/ thermal power (TP) cost and emission cost from TPs. Transmission system security margin evaluated using generalized generation distribution factors (GGDF) and considered as one of the major constraints in solving CEED. In [5], chaotic artificial ecosystem-based optimization (CAEO) is developed for solving CEED considering TP cost and cost of emissions (includes $CO_2$, $SO_2$ and $NO_x$). In [6], multi-objective combined heat and power economic emission dispatch (MO-CHPEED) problem using dynamically controlled whale optimization algorithm (DCWOA) is presented. However the works [4-6] have not handled directly RESs in solving CEED problem, instead they are optimized TP emissions only.

In [7], economic dispatch (ECD) and emission dispatch (EMD) are hybridized using price-penalty factors (PPF) and fractional programming (FP) method. A three bus TP test system integrated with photovoltaic (PV), wind turbine (WT) and load uncertainties is utilized and the multi-objective function is solved by hybridizing modified grey wolf optimizer (MGWO), sine cosine algorithm (SCA) and crow search algorithm (CSA). In [8], CSA and JAYA algorithms are hybridised for solving combined ECD and EMD problem with PVs and WTs in similar to [7]. In [9], EDP is reframed considering smart building architecture i.e., home energy management system (HEMS) for exchanging energy from one building to other using improved butterfly optimization algorithm (IBOA). Energy storage system (ESS) is mainly utilized for uncertainties with loading conditions and PV variations and consequently, GP cost is reduced. In [10], distributed gradient algorithm (DGA) is proposed for economic dispatch problem (EDP) for minimizing the total cost operation includes cost of, PV, WT, ESS, TP and conventional power sources (CPS) sources like micro-turbines (MT) and diesel generators (DG) under uncertainties. While handling uncertainties, the possibility from TP with ramp-up/down limits is not taken in to consideration as seen in conventional EDP, instead CPS and BES are experimented.

Further, CEED problem is redefined in recent times considering emerging EV trends globally. In [11], chaos moth flame optimization algorithm (CMFO) is proposed for handling fluctuations in the grid using plug-in EVs (PEVs) to the grid(V2G). In [12], teaching learning based optimization (TLBO) is proposed for PEVs embedded CEED. In [13], converged barnacles mating optimizer (CBMO) based CEED is presented. Utilization of different EV charging scenarios is proposed for handling uncertainty of WT, PV and loads and peak shaving. In [14], chaotic zebra optimization algorithm (CZOA) is employed for scheduling different conventional and RES considering EV fleets utilization for energy balance. However, [11-14] are not handled explicitly emission control from the TP units.

In [15], Time of Shift (ToS) based DR with EVs and other low-carbon P2G (power-to-gas) devices are considered in solving the CEED with mixed-integer linear programming (MILP). In [16], model predictive control (MPC) learning approach is proposed for modelling the charging behaviour of EVs and later, CEED is solved considering RE and load uncertainties. In [17], the stochastic behaviour of EVs under different time frames is modelled for handing CEED. Further, non-convex multi-objective optimization CEED is solved using an efficient black widow optimization (EBWO). In [18], dynamic combined economic emission dispatch (DCEED) is presented using multi-objective mayfly optimization algorithm (MMOA). The EV fleet is mainly used for balancing the energy under demand crest shaving and valley filling V2G and grid-to-vehicle (G2V) modes. In [19], gradual reduction of swarm size with the grey wolf optimization (GRSS-GWO) is presented for handling CEED considering the capabilities of EVS for V2G and G2V operational modes. One of the major contributions of [20] is EV modelling considering temperature, power level, and the state of charge (SoC). In addition, a comprehensive literature survey on CEED can be found in [21, 22].

From the above reviewed works, the conventional CEED problem neglects the thorough incorporation of RES and EVs, and many do not adequately consider the security limitations of transmission systems. Furthermore, the aspects of uncertainty management in RES and EVs, convergence dependability, and computational complexity have not been well investigated, emphasizing the necessity for sophisticated mathematical modelling for CEED and optimization methods.

In this paper, the modifications have made the conventional CEED problem a more non-convex, multi-objective, multi-variable optimization problem with several constraints. Empirical metaheuristics have been widely employed to address this particular form of optimization. The literature reveals that the majority of metaheuristics have certain limitations, such as their vulnerability to early convergence resulting in poor solutions, significant computing complexity in large-scale problems, and the requirement for substantial parameter tweaking. Moreover, they frequently lack assured optimality and may have difficulties in controlling the trade-off between exploration and exploitation in intricate, ever-changing settings. Therefore, based on the absence of a no-free-lunch theorem [23], it is demonstrated that there is no universal algorithm capable of addressing all types of optimization issues. In this connection, researchers are still inspiring to introduce new and efficient algorithms. Swarm bipolar algorithm (SBO) [28], swarm space hopping algorithm (SSHA) [29], Migration-crossover algorithm (MCA) [30], Addax optimization algorithm (AOA) [31], and dollmaker optimization algorithm [32] are such recently introduced metaheuristics to address various real-time optimization problems.

In this work, the authors are motivated to use an enhanced version of the sparrow search algorithm (SSA) called intensified sparrow search algorithm (ISSA) [31]. This method incorporates a neighbor search strategy and saltation learning (SL), which is inspired by the hopping forward behavior of sparrows [32]. The SL avoids premature convergence and enhances the producer's search ability, enhancing the overall algorithm's effectiveness. Further, CEED problem is reframed with SR in addition to variability in PV, WT and CS loading conditions. Simulations are performed on standard 3-thermal units and on its modified version considering load, RES, EV and SR variability. Different scenarios are analysed for highlighting the computational efficacy of ISSA.

After this introduction Section 1, this paper is structured as follows: Section 2 imparts mathematical modelling of REs and EVS, load profile. The multi-objective CEED problem formulation and its constraints are described in Section 3. Section 4 provides the mathematical overview of the proposed ISSA and its application for solving CEED problem in Section 5 by computational perspective. Finally, Chapter 6 recaptures the principal contribution of this paper as a whole.

## 2. Modelling of concepts

In this section, the mathematical modelling of PV, WT, EVs and their impact on power system loading is explained.

### 2.1. Solar power generation

The generation from solar power plant $i$ and correspondingly, total PV power penetration in the system can be determined by,

$$P_{pv,i} = \frac{P_{s,i}}{1000}\left[1 + \beta\left(T_r - T_{a,i}\right)\right] \times S_i \tag{1}$$

$$P_{PV} = \sum_{i=1}^{nS} P_{pv,i} \tag{2}$$

### 2.2. Wind power plant

The wind power plant generation at location and correspondingly, total wind power share in the system can be determined by:

$$P_{wt,i} = \begin{cases} 0 & V_{t,i} < V_{ci,i} \\ kV_{t,i}^3 & V_{ci,i} \le V_{t,i} < V_{r,i} \\ P_{r,i} & V_{r,i} \le V_{t,i} < V_{co,i} \\ 0 & V_{t,i} > V_{co,i} \end{cases} \tag{3}$$

$$P_{WT} = \sum_{k=1}^{nW} P_{w,i} \tag{4}$$

### 2.3. Public charging stations

Electric vehicles (EVs) charging stations (CSs) can be modelled as lumped load due to different levels of charging ports at a bus in the system and is given by,

$$P_{ev,i} = n_{L1,i}P_{ev}^{L1} + n_{L2,i}P_{ev}^{L2} + n_{L3,i}P_{ev}^{L3} \tag{5}$$

$$P_{EV} = \sum_{i=1}^{nCS} P_{ev,i} \tag{6}$$

### 2.4. Realization of PV/ WT/ CS impact

By integrating PV/ WT/ CS, the net-effective loading of at a location can be realised by the following relations.

*For solar PV system:*

$$P_{d,i} = P_{d(0),i} - P_{pv,i} \tag{7}$$

$$Q_{d,i} = Q_{d(0),i} \tag{8}$$

*For wind turbine system:*

$$P_{d,i} = P_{d(0),i} - P_{wt,i} \tag{9}$$

$$Q_{d,i} = Q_{d(0),i} - P_{wt,i} \times tan\left(acos\left(\emptyset_{wt,i}\right)\right) \tag{10}$$

*For EV charging station:*

$$P_{d,i} = P_{d(0),i} + P_{ev,i} \tag{11}$$

$$Q_{d,i} = Q_{d(0),i} + P_{ev,i} \times tan\left(acos\left(\emptyset_{ev,i}\right)\right) \tag{12}$$

### 2.5. Spinning reserve

A power system's spinning reserve (SR) is supplementary producing capacity that is immediately accessible and synchronised with the grid to respond to sudden load increments or generation losses.

$$P_{SR} = \begin{cases} 0.05(P_D + P_{EV}) & Stability \\ 0.1P_{RES} & RES \\ max(P_i) & Gen.loss \end{cases} \tag{13}$$

Depending on power system features and reliability, the proportion may vary. As defined in Eq. (13), SR is usually minimum 5% of demand for ensuring stability under typical working conditions. Systems with strong wind or solar power penetration may need 10% or more for handling their variability. Additionally, it should be at least the maximum generator level before generator loss.

## 3. Problem formulation

### 3.1. Objective function

The multi-objective function ($OF$) for CEED is formulated by combining the fuel cost of thermal power plants ( $C_{fl}$ ) and correspondingly, their emission costs ($C_{em}$). Mathematically,

$$C_{fl}(P_i) = \left(a_i P_i^2 + b_i P_i + c_i\right) + d_i\left\{sin\left[e_i\left(P_{i,min} - P_i\right)\right]\right\} \tag{14}$$

$$C_{em}(P_i) = \sum_{k=1}^{nT}\left\{m_i P_i^2 + n_i P_i + o_i + r_i\left[exp(s_i \times P_i)\right]\right\} \tag{15}$$

$$OF = \sum_{i=1}^{nT}\left[C_{fl}(P_i) + C_{em}(P_i)\right] \tag{16}$$

### 3.2. Operational constraints

#### 3.3.1. Power balance constraint

At any hour, the total network demand including losses should be equal to the total power generation from thermal plants and RESs. Mathematically, it is given by:

$$P_T + P_{PV} + P_{WT} = P_D + P_{EV} + P_l \tag{17}$$

$$P_l = \sum_{i=1}^{nT}\sum_{j=1}^{nT} P_i B_{ij} P_j \tag{18}$$

#### 3.3.2. Spinning reserve constraint

Th SR to be maintained in power system can be treated as extra demand on the system while solving the SR-CEED problem. Thus, Eq. (17) can be modified for SR as follows:

$$P_T + P_{PV} + P_{WT} = (P_D + P_{EV} + P_l) + P_{SR} \tag{19}$$

Further, Eq. (14) - Eq. (16) are constrained by lower and upper limits of the plant and their down and up-ramp rate limits, given by,

$$P_{i,min} \le P_i \le P_{i,max} \tag{20}$$

$$P_{i,min} = max\left[P_{i,min}, \left(P_{i(t-1)} - D_{r,i}\right)\right] \tag{21}$$

$$P_{i,max} = min\left[P_{i,max}, \left(U_{r,i} + P_{i(t-1)}\right)\right] \tag{22}$$

## 4. Solution methodology

The proposed multi-objective optimization problem is proposed to solve using intensified sparrow search algorithm (ISSA). In this section, the basic SSA [31], modifications in ISSA and their application to solve the proposed objective functions are explained briefly.

### 4.1. Sparrow search algorithm

The SSA Algorithm is inspired by sparrows' swarming intelligence, dividing them into producers and explorers based on their fitness. The algorithm allows sparrows to constantly update their positions to avoid predators and find low-risk cuisine, allowing the sparrow colony to navigate the wild.

SSA involves initializing the solution, determining population size, maximum replicates, producer ratio, and sparrow population position, and randomly producing them. The initial population is randomly generated by:

$$S = \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_n \end{bmatrix} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1d} \\ s_{21} & s_{22} & \cdots & s_{2d} \\ \vdots & \vdots & s_{ij} & \vdots \\ s_{n1} & s_{n2} & \cdots & s_{nd} \end{bmatrix} \quad (23)$$

$$F_S = \begin{bmatrix} F(S_1) \\ F(S_2) \\ \vdots \\ F(S_n) \end{bmatrix} \quad (24)$$

where $n$ is the number of sparrows and $d$ is the search dimension, respectively;$s_{ij}$ is the position of $i$th sparrow in $j$th dimension, $S_i$ is the $i$th solution variables, and $F_S$fitness of all solutions.

Producers with higher fitness values in the SSA are given preference over those producing cuisine, as they can search for a broader range and update their status each iteration.

$$s_{ij}^{k+1} = \begin{cases} s_{ij}^{k} \times exp\left(\frac{-i}{r_1 k_{max}}\right) & if r_3 < \delta \\ s_{ij}^{k} + r_2 \propto & if r_3 \geq \delta \end{cases} \quad (25)$$

where $k$ and $k_{max}$ are the current and maximum iteration numbers, $r_1$ , $r_2$ and $r_3$ are the random numbers between 0 and 1, respectively; $\delta$ is a random number between 0.5 and 1, and$\propto$ is a matrix of $(1 \times d)$ and it is set to 1 when all elements become 1.

Eq. (25) describes a system where sparrows discover a hunter when $r_3$ is high ($r_3 \geq \delta$), and when $r_3$ is low ($r_3 < \delta$), the hunter enters extensive search mode. Energy loss in entry groups reduces foraging opportunities, potentially causing immigrants to flee. Sparrows locate locators, intensify predation, and engage in competition.

$$s_{ij}^{k+1} = \begin{cases} r_2 exp\left(\frac{s_{worst}^{k} - s_{ij}^{k}}{k^2}\right) & i < \frac{n}{2} \\ s_{ij}^{k+1} + \left|s_{ij}^{k+1} - s_{ij}^{k}\right| r_4^{+} \propto & i > \frac{n}{2} \end{cases} \quad (26)$$

where $s_{worst}^{k}$ is worst position of sparrow in iteration $k$, $r_4^{+}$ is random number between -1 and 1 of dimension $d$. $r_4^{+} = r_4^{T}(r_4 r_4^{T})^{-1}$for$i < \frac{n}{2}$, it means, $i$th challenger is unfit and will going to die.

On the other hand, 10%-20% of sparrows are randomly positioned based on threat alertness, with those in the middle wandering to get close, and those on the edge flying to safe areas.

$$s_{ij}^{k+1} = \begin{cases} s_{best}^{k} + \beta . \left|s_{P}^{k} - s_{best}^{k}\right| & F_i > F_g \\ s_{ij}^{k} + r_5 \left|\frac{s_{ij}^{k} - s_{worst}^{k}}{(F_i - F_w) + \varepsilon}\right| & F_i = F_g \end{cases} \quad (27)$$

In Eq. (27), $s_{best}^{k}$represents the global optimal position, ε and β control step size, and $F_g$ and $F_w$ represent best and worst suitability values. $r_5$ represents the direction of movement and step size's control factor. Each person's current position is compared to the last repetition, updating if better than the previous one. Survival may improve after the last two steps. If repetitions are less than maximum, the algorithm stops.

By these basic surveillance features, SSA has been a competitive algorithm in recent times for solving complex optimization problem. However, it has advanced in many ways for better accuracy.

### 4.2. Intensified sparrow search algorithm

In order to improve and achieve proper balance between exploration and exploitation phases in the basic SSA, the ISSA is proposed by introducing a neighbour search strategy and saltation learning ($SL$), inspired by sparrows' jumping forward [32]. The $SL$ avoids premature convergence and enhances the producer's search ability, enhancing the overall algorithm's effectiveness.

*Neighbor search strategy*: In an Evolutionary System (SSA), the producer motivates sparrows to reach the optimal position in the evolution search process. However, this model has disadvantages, such as not exploring new search areas early and weakened exploration ability. To improve SSA performance, a more efficient producer selection strategy is needed. A novel producer selection strategy, the neighbour search strategy, is proposed for its boundary/range as defined in Eq. (28), where the producer is chosen from the sparrow individual's neighbours, based on their individual range $R$.

$$E_i^k = \left(max\left(s_{ij}^{k}.(1-R), l_b\right), min\left(s_{ij}^{k}.(1+R), u_b\right)\right) \quad (28)$$

where $i \in \{1,2,..,M\}$ and $M$ is the producer number, $s_{ij}^{k}$ is the random individual sparrow at $k$th iteration, $l_b$ and $u_b$ are the lower and upper bounds of the search variables, respectively.

As explain in [32], a sparrow individual $S_i$ is represented by a large black circle and other sparrows in the neighbourhood. The size of each $S_i$ boundary is controlled by $R$, with the boundary range dynamic. The neighbour search strategy explores the entire feasible solution space, preventing weakening exploration ability and balancing global and local search.

Table 3. Optimal solution for CEED for different cases

| Hr | Case (a) | | | | Case (b) | | | |
|---|---|---|---|---|---|---|---|---|
| | $P_{SR}$ (MW) | $P_{D(net)}$ (MW) | $C_{fuel}$ ($/hr) | $C_{emission}$ ($/hr) | $P_{SR}$ (MW) | $P_{D(net)}$ (MW) | $C_{fuel}$ ($/hr) | $C_{emission}$ ($/hr) |
| 1 | 23.983 | 509.450 | 5186.732 | 39.641 | 24.463 | 499.330 | 5102.107 | 37.559 |
| 2 | 25.625 | 564.120 | 5658.919 | 49.891 | 28.025 | 516.520 | 5254.748 | 39.877 |
| 3 | 26.722 | 590.350 | 5888.934 | 54.860 | 29.340 | 537.610 | 5429.799 | 44.704 |
| 4 | 27.875 | 636.410 | 6289.396 | 65.618 | 32.579 | 543.030 | 5480.007 | 45.144 |
| 5 | 28.461 | 623.070 | 6174.188 | 62.100 | 30.500 | 579.330 | 5794.435 | 52.301 |
| 6 | 29.511 | 639.640 | 6321.361 | 65.510 | 30.902 | 607.210 | 6036.167 | 58.457 |
| 7 | 30.750 | 702.910 | 6878.643 | 81.397 | 35.766 | 600.610 | 5979.278 | 56.844 |
| 8 | 30.788 | 752.160 | 7319.133 | 94.257 | 40.549 | 558.710 | 5612.806 | 48.668 |
| 9 | 36.025 | 857.240 | 8268.486 | 126.338 | 45.196 | 673.990 | 6624.316 | 73.529 |
| 10 | 39.574 | 946.450 | 9089.282 | 156.388 | 50.114 | 736.180 | 7178.465 | 89.055 |
| 11 | 41.164 | 921.950 | 8863.631 | 147.124 | 45.814 | 822.610 | 7953.011 | 115.589 |
| 12 | 42.763 | 967.780 | 9287.071 | 164.268 | 48.539 | 846.030 | 8167.138 | 122.250 |
| 13 | 41.010 | 959.350 | 9209.017 | 160.985 | 49.524 | 784.580 | 7611.348 | 103.129 |
| 14 | 37.725 | 850.290 | 8205.635 | 123.792 | 42.131 | 752.580 | 7323.442 | 94.192 |
| 15 | 34.474 | 812.050 | 7858.873 | 111.566 | 41.784 | 658.160 | 6482.617 | 70.248 |
| 16 | 30.964 | 706.690 | 6911.662 | 82.595 | 35.008 | 613.860 | 6092.090 | 60.461 |
| 17 | 29.163 | 657.740 | 6476.842 | 70.766 | 31.995 | 586.930 | 5856.818 | 54.644 |
| 18 | 31.660 | 699.680 | 6852.832 | 79.663 | 33.342 | 649.720 | 6408.024 | 68.294 |
| 19 | 34.235 | 740.060 | 7211.898 | 90.569 | 34.447 | 717.040 | 7003.279 | 85.512 |
| 20 | 41.223 | 886.170 | 8534.205 | 135.184 | 41.271 | 865.250 | 8342.572 | 128.381 |
| 21 | 38.433 | 828.520 | 8008.000 | 116.714 | 38.476 | 806.720 | 7811.000 | 109.779 |
| 22 | 32.425 | 703.790 | 6887.469 | 81.326 | 32.512 | 680.130 | 6678.129 | 75.210 |
| 23 | 27.653 | 606.740 | 6032.061 | 58.323 | 27.956 | 578.000 | 5780.723 | 52.444 |
| 24 | 24.975 | 550.120 | 5541.759 | 46.417 | 25.139 | 523.000 | 5304.597 | 41.860 |
| **Total** | **787.182** | **17712.73** | **172956.027** | **2265.292** | **875.371** | **15737.13** | **155306.915** | **1728.131** |
| **Minimum** | 23.983 | 509.45 | 5186.732 | 39.641 | 24.463 | 499.33 | 5102.107 | 37.559 |
| **Maximum** | 42.763 | 967.78 | 9287.071 | 164.268 | 50.114 | 865.25 | 8342.572 | 128.381 |
| **Average** | 32.80 | 738.03 | 7206.50 | 94.39 | 36.47 | 655.71 | 6471.12 | 72.01 |
| **Median** | 31.31 | 705.24 | 6899.57 | 82.00 | 34.73 | 631.79 | 6250.06 | 64.38 |
| **S.D.** | 5.744 | 138.790 | 1244.194 | 38.674 | 7.720 | 112.138 | 992.476 | 27.781 |

*Saltation learning:* This paper proposes a new foraging method called saltation learning ($SL$) inspired by sparrows' adaptability to complex environments. The algorithm's search ability is improved, but it can fall into premature convergence. The SL is adapted from the cuckoo search algorithm, but the implementation form is different. The new $SL$ is introduced in Eq. (29) for enhancing the convergence rate and avoids falling into local optimums by modifying Eq. (25).

$$s_{ij,m}^{k+1} = s_{ij,u}^{k} + \delta.\left(s_{best,v}^{k} - s_{worst,v}^{k}\right), i > \frac{n}{2} \quad (29)$$

where $m$, $v$, and $u$ stand for three distinct positive constants that are randomly selected from [1, $d$].

With these modifications, ISSA has demonstrated better convergence features than basic SSA and has become one of the most competitive algorithms in recent times for solving complex real-time optimization problems. Furthermore, the overall computational aspects of ISSA are described in [32].

## 5. Simulation results and discussion

Simulations are done on a 3-bus power system for different scenarios using a PC of 2.4 GHz, 8 GB RAM, Intel Core i5-4210U CPU in MATLAB (2023b) environment. The computational efficacy of ISSA is compared with artificial rabbits optimization (ARO) [33], butterfly optimization algorithm [34], coyote optimization algorithm (COA) [35], and basic sparrow search algorithm (SSA) [31]. The population size and number of

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maximum iterations are considered for all algorithms as 30 and 1000, respectively.

### 5.1. Scenario 1: Standard test system

In this scenario, the standard loading condition of 850 MW is considered. Simulations are performed for three cases as described in [33], i.e., Case (a) only fuel cost minimization, Case (b) only $NO_x$ cost minimization, and Case (c) only $SO_2$ minimization. The results of each case are given in Table 1.These three cases are performed with only ISSA.

From the results, Case (b) produces the most power at $P_1$ = 456.081 MW, followed by Case (c) at $P_2$ with 314.561 MW and Case (a) at $P_3$ with 129.157 MW, according to the comparison of the three cases. At 15.419 MW and \$0.096/h for $NO_x$ emissions, Case (b) also has the lowest power loss and lowest cost of emissions. But when it comes to fuel costs, Case (a) is the most economical at \$8344.777/h, while Case (c) has the lowest cost of $SO_2$ emissions at \$8.939/h. In Case (c), the CPU time is 0.242 seconds, which is marginally faster than in Case (b) and Case (a), which are 0.244 and 0.246 seconds, respectively.

In addition, ISSA is compared with ARO, BOA, COA, and SSA. The convergence characteristics Case (a) using different algorithms are given in Fig. 1, respectively. By observing these characteristics, ISSA had well experienced the better exploration and exploitation features than SSA and resulted for global optima.

In Table 2, the fuel cost of thermal units and NOx emission cost are determined combinedly. In Table 3, the fuel cost of thermal units and SO2 emission cost are determined combinedly. The total cost in Table 2 is less than Table 3 due to high cost of SO2 emission than NOx emissions. Further, in comparison to all other algorithms, ISSA in resulting global optima in both the cases.

Because of its strong convergence speed, flexibility, and effectiveness in handling intricate restrictions, the Intensified Sparrow Search Algorithm (ISSA) performs better than other algorithms while solving the Combined Economic Emission Dispatch (CEED) problem. In order to facilitate faster convergence and concentrate computing resources on areas that show promise, ISSA incorporates an intensified search method. Additionally, it promotes deeper search within high-potential zones and prevents premature convergence, improving the balance between exploration and exploitation. ISSA ensures workable solutions that satisfy both emission and economic goals by dynamically adapting to complicated restrictions. It produces high-quality, financially feasible, and ecologically friendly solutions, making it more appropriate for CEED applications due to its statistical resilience and solution quality. All things considered, ISSA is a better option for CEED issues because to its improvements in convergence efficiency, constraint adaptation, and solution resilience.

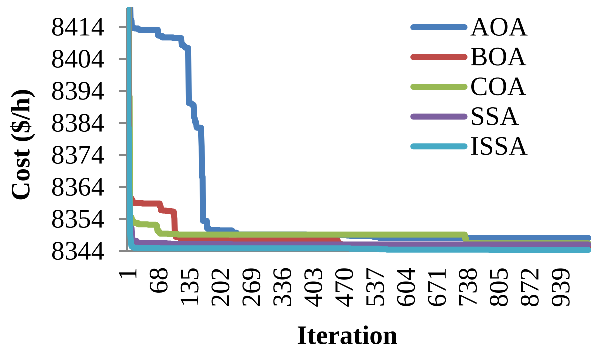


Figure. 1 Convergence of different algorithm

Table 1. Results for base case

| Item | **Objective Functions** | | |
|---|---|---|---|
| | Case (a) | Case (b) | Case (c) |
| $P_1$ *(MW)* | 442.031 | 456.081 | 443.214 |
| $P_2$ *(MW)* | 294.480 | 285.592 | 314.561 |
| $P_3$ *(MW)* | 129.157 | 123.745 | 108.434 |
| $P_{loss}$ *(MW)* | 15.668 | 15.419 | 16.209 |
| *Fuel cost (\$/h)* | **8344.777** | 8346.262 | 8348.253 |
| $NO_x$ *(\$/h)* | 0.110 | **0.096** | 0.112 |
| $SO_2$ *(\$/h)* | 9.016 | 9.004 | **8.939** |
| *CPU Time (Sec)* | 0.246 | 0.244 | 0.242 |

Table 2. Comparison of ISSA results with other algorithms for CEED (Fuel + $NO_x$)

| **Applied Method** | **Parameters** | | | |
|---|---|---|---|---|
| | $P_1$ *(MW)* | $P_2$ *(MW)* | $P_3$ *(MW)* | *Cost (\$/h)* |
| ARO [33] | 380.97 | 323.66 | 145.36 | 8325.211 |
| BOA [34] | 381.65 | 323.49 | 144.86 | 8325.205 |
| COA [35] | 381.74 | 323.46 | 144.79 | 8325.205 |
| SSA [31] | 382.17 | 320.65 | 147.17 | 8325.197 |
| ISSA | 383.36 | 320.04 | 146.60 | **8325.188** |

Table 3. Comparison of ISSA results with other algorithms for CEED (Fuel + $SO_2$)

| **Applied Method** | **Parameters** | | | |
|---|---|---|---|---|
| | $P_1$ *(MW)* | $P_2$ *(MW)* | $P_3$ *(MW)* | *Cost (\$/h)* |
| ARO [33] | 271.62 | 378.38 | 200.00 | 9215.734 |
| BOA [34] | 272.02 | 377.98 | 200.00 | 9215.708 |
| COA [35] | 276.43 | 373.57 | 200.00 | 9215.702 |
| SSA [31] | 272.48 | 377.52 | 200.00 | 9215.684 |
| ISSA | 273.26 | 376.74 | 200.00 | **9215.656** |

Table 4. Comparison of ISSA results for fuel cost

| Item | Objective Functions | | |
|---|---|---|---|
| | IPBO [33] | ABWO [34] | Proposed |
| $P_1$ (MW) | 394.532 | 435.39 | 394.531 |
| $P_2$ (MW) | 333.493 | 256.94 | 333.501 |
| $P_3$ (MW) | 121.975 | 148.70 | 121.971 |
| $C_{fl}$ (\$/h) | **8194.362** | 8255.10 | **8194.314** |
| $NO_x$ (\$/h) | 0.09956 | 0.0953 | 0.09957 |
| $SO_2$ (\$/h) | 8.8906 | - | 8.8907 |

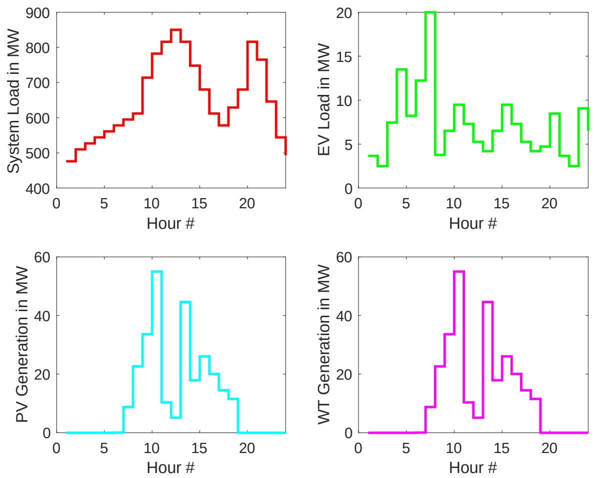


Figure. 2 Hourly variability of the sources/loads

### 5.2. Comparative study with literature

In Table 4, the performance of ISSA is compared with improved polar bear optimization (IPBO) [33] and astute black widow optimization (ABWO) [34] without considering losses. The results of ISSA are observed very competitive with IPBO, whereas superior to ABWO [34] in terms of fuel cost.

### 5.3. Scenario 2: Modified test system

In this section, CEED is simulated for dynamic loading conditions due to hourly variability in load, PV, WT, EV and SR, are given in Fig. 2. Also, as defined in Eq. (19), $P_{SR}$ is calculated for each hour considering only stability and RES variability and generator loss is ignored. By these modifications, the net-loading condition for thermal power plants is estimated using Eq. (18).

The following case studies are performed considering different uncertainties in the network.

a) Variation in system demand including load and EVs, and correspondingly SR requirement as 5% of total RES penetration.
b) Variation in system demand including load, EVs and RES (i.e., PV+WT) and SR requirement as 10% of total RES penetration.

In Case (a), fuel and emission costs are impacted by significant fluctuations in power supply and demand, according to the 24-hour combined economic emission dispatch study as given in Table 3. The power supply has a moderate standard deviation of 5.744 MW and an average of 32.80 MW, with a range of 23.983 MW to 42.763 MW. With a high degree of fluctuation (STD of 138.790 MW), net power demand varies greatly, average 738.03 MW and ranging from 509.45 MW to 967.78 MW. With a moderate fluctuation (STD of \$1244.194/hr) and an average of \$7206.50/hr, fuel prices range from \$5186.732/hr to \$9287.071/hr. With a moderate standard deviation of \$38.674/hr, emission costs average \$94.39/hr and range from \$39.641/hr to \$164.268/hr. These findings highlight the necessity of carefully weighing pollution reduction and economic efficiency when making dispatch decisions.

The 24-hour CEED data in Case (b) demonstrates notable fluctuations in fuel, emission prices, electricity supply, and demand. With a high standard deviation of 7.720 MW, an average of 36.47 MW, a median of 34.73 MW, and a range of 24.463 MW to 50.114 MW, the power supply exhibits significant swings. With a median of 631.79 MW, a standard deviation of 112.138 MW, and an average of 655.71 MW, net power demand ranges from 499.33 MW to 865.25 MW, indicating significant variations in demand over time. Fuel prices vary moderately, ranging from \$5102.107/hr to \$8342.572/hr, with an average of \$6471.12/hr, a median of \$6250.06/hr, and a standard deviation of \$992.476/hr. With an average of \$72.01/hr, a median of \$64.38/hr, and a standard deviation of \$27.781/hr, emission costs exhibit substantial variability, ranging from \$37.559/hr to \$128.381/hr. These results emphasize the necessity of cautious management in order to strike the best possible balance between environmental and economic objectives.

The SR in Case (a) is higher at 875.371 MWh than Case (a) of 787.182 MWh, indicating increased system reliability. Net power demand decreases by 1975.6 MW, due to RES penetration. Fuel cost is lower by \$17,649.112 per hour, because of RES or a better energy mix. Emission costs decrease by \$537.161 per hour, indicating effective solution for global warming. More substantial variations in spinning reserves are suggested by the second case's larger PSR average (36.47 MW vs. 32.80 MW) and higher variability (STD of 7.720 MW vs. 5.744 MW). In the second scenario, the higher range and unpredictability would suggest that reserve stability is more difficult to maintain, necessitating more adaptable control techniques. Overall, Case (b) offers a sustainable and economically viable approach to power system operation.

## 6. Conclusion

In this paper, a new intensified sparrow search algorithm (ISSA) by introducing a neighbour search strategy and saltation learning, inspired by sparrows' jumping forward is proposed. At first, conventional CEED is performed on standard 3-unit power system without RES and EVs. In second stage, CEED is performed considering hourly variability in loading conditions on the system, RES and EVs with SR requirements for stability, RES variation and generation loss. The effectiveness of ISSA is compared in each scenario for different cases. The SR with RES and EVs is higher at 875.371 MWh than SR without RES and EVs of 787.182 MWh, indicating increased system reliability. Net power demand decreases by 1975.6 MW, due to RES penetration. Fuel cost is lower by $17,649.112 per hour, because of RES or a better energy mix. Emission costs decrease by $537.161 per hour, indicating effective solution for global warming. Overall, SR with RES and EVs offers a sustainable and economically viable approach to power system operation. However, SR management is treated as the extra burden on system. This scenario projects the need of ESS for handling loss of generator, On the other hand, EVs has been treated as extra loading on system, i.e., G2V mode and ignored V2G scenario. Thus, consideration of ESS and V2G scenarios are treated as major extension of this work.

## Notations

| | |
|---|---|
| $P_{PV}$ | Total solar power share/ penetration |
| $P_{s,i}$ | Rated power capacity of solar power plant *i* |
| $nS$ | No. of SPVs in the system |
| $T_r$ & $T_{a,i}$ | Reference and ambient temperature at the SPV *i*, |
| $S_i$ | Incident solar radiation on arrays at the SPV *i*. |
| $P_{WT}$ | Total power generation from WT units in the system. |
| $V_{t,i}$ | Wind speed at a time-*t* of unit *i*, |
| $V_{ci,i}$ | Cut-in speed |
| $V_{co,i}$ | Cut-out speed |
| $V_{r,i}$ | Rated speed |
| $P_{wt,i}$ | Power generation of unit *i* |
| *k* | A constant that includes factors like turbine efficiency, air density, and rotor area, |
| $nW$ | No. of WT units in system |
| $P_{EV}$ | Total EV load penetration in system |
| $nCS$ | Number of CSs |
| $P_{ev,i}$ | Power demand of CS$i$ |
| $n_{L1,i}$, $n_{L2,i}$ & $n_{L3,i}$ | No. of level-1, 2 and 3 charging ports in *i*th CS, respectively |
| $P_{ev}^{L1}$, $P_{ev}^{L2}$ & $P_{ev}^{L3}$ | Power ratings of level-1, 2 and 3 EVs, respectively |
| $P_{d,i}$ & $Q_{d,i}$ | Real and reactive power loads at bus *i* after integrating either PV/ WT/ CS, respectively; |
| $P_{d(0),i}$ & $Q_{d(0),i}$ | Real and reactive power loads at bus-*i* before integrating either PV/ WT/ CS, respectively |
| $\emptyset_{wt,i}$ & $\emptyset_{ev,i}$ | Operating power factors WT and CS, respectively |
| $a_i$, $b_i c_i$, $d_i$ & $e_i$ | Cost coefficients of the thermal power plant –*i*, respectively;, |
| $m_i$, $n_i$, $o_i$, $r_i$ & $s_i$ | Emission cost coefficients of power plant-*i*, |
| $P_i$ | Output power from plant-*i*, |
| $nT$ | No. of thermal power plants |
| $P_l$ | Total transmission losses |
| $B_{ij}$ | *B*-coefficients, which are the loss coefficients associated with buses *i* and *j* |
| $P_T$ | Total power generation by thermal power plants, |
| $P_{i,min}$ & $P_{i,max}$ | Minimum and maximum power generation limits of thermal power plant-*i*, respectively; |
| $D_{r,i}$ & $U_{r,i}$ | Down-ramp and up-ramp limits of thermal power plant-*i*, respectively |
| $P_{i(t-1)}$ | Power generation of thermal power plant-*i*, at time (*t*-1). |

## Conflicts of Interest

The authors declare no conflict of interest.

## Author Contributions

Conceptualization, methodology, software and original draft preparation are done by Narendra Babu Kattepogu; supervision, review, and formal analysis are done by G Saravanan and A Rama Koteswara Rao.

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