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Dynamic economic dispatch using hybrid CSAJAYA algorithm considering ramp rates and diverse wind profiles

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ABSTRACT

Optimal scheduling of the conventional generating units for two different dynamic test systems are percolated in this paper. This paper compares and contrasts among three types of wind profile formulations, namely linear, quadratic, and cubic, which were used to calculate wind power from hourly wind speed to find the profile with the greatest penetration of wind power. Thereafter, the wind profiles were coupled with the test system to execute dynamic economic dispatch. The optimization tool used for the study was a unique hybrid algorithm modelled by combining the properties of the recently developed crow search algorithm (CSA) and JAYA. Involvement of ramp-rate limits and the valve point effects magnified the practicality of the work thereby assessing the proposed hybrid algorithm in solving complex non-linear functions. Results infer that maximum level of wind penetration was attained by linear wind profile and a fuel cost reduction of 2.92% was realized upon incorporation of the same. Numerical results also claims that proposed hybrid CSAJAYA approach consistently yielded better quality solutions within minimum execution time without being affected by the dimension of the problem, thereby outperforming a long list of algorithms implemented for the study.

1. Introduction

1.1. General overview

The load demand of a power producing plant cannot be met by a single generating entity. Rather, the whole need is met by a collection of similar entities. Furthermore, each unit has its own cost function (price bid) to produce the same quantity of electricity. Economic load dispatch (ELD) is basically an operational process for allocating generation among the considered generating units in order to reduce overall generation costs while meeting all the equality and inequality constraints. So precisely allocating a portion of total demand might potentially decrease fuel costs. The overall load demand is divided across several generators, affecting estimate, invoicing, unit commitment, and a variety of other activities. The overall amount of generated power must meet the complete amount of current demand. To solve this, the ELD can be divided into two types, depending on the character of the load demand. The first is Static Economic Load Dispatch (SELD), which involves allocating for a certain load demand, and the second is Dynamic Economic Load Dispatch (DELD), which involves solving the same problem for a dynamic load demand. In DELD, demand is predicted for the coming hours and allocate the load across different generators to get high quality outputs. Seemingly researches are going on to incorporate renewable energies in ELD to address the challenge of depletion of fossil fuel reservoir. Metaheuristic swarm and artificial intelligence are very essential to deal with this problem because classical methods like Lagrange multiplier cannot solve the practical constraints involved which tends to make the fitness function non-linear and non-convex.

List of abbreviations: AP, Awareness Probability; CSA, Crow Search Algorithm; CSAJAYA, Hybrid Crow Search Algorithm – Jaya Algorithm; CSASCA, Crow Search Algorithm- Sine Cosine Algorithm; DE, Differential Evolution; DER, Distributed Energy Resources; DG, Distributed Generator; ELD, Economic Load Dispatch; GWO, Grey Wolf Optimizer; JAYA, Jaya algorithm; MAE, Mean absolute error; MGWO-SCA-CSA, Modified Grey Wolf Optimizer-Sine Cosine Algorithm-Crow Search Algorithm; Pop_Size, Population size; PSO, Particle Swarm Optimization; RE, Relative error; RES, Renewable Energy Sources; RMSE, Root mean square error; SCA, Sine Cosine Algorithm; SD, Standard deviation; SOS, Symbiotic organisms search; TLBO, Teaching-learning-based optimization; UP, Utilization percentage; WOA, Whale optimization algorithm; WOASCA, Whale optimization algorithm - Sine Cosine Algorithm; VPE, Valve Point Effect.

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List of symbols

a, b, c	Cost coefficients of DG unit
A, B, C	Constraints of quadratic wind profile
d, e	Coefficients of valve point loading effect
D_t	Load demand at time *t*
FFV_{ii}	Fitness Function Value at *iith* trial
FFV_{min}	Minimum value of Fitness Function
$\overline{FFV}$	Mean value of Fitness Function
fl	Flight length of the crow
f_v^t	Weibull distribution function
i	Indices of DG units
ii	Index of trial
iter/max_iter	Current iteration/Maximum number of iterations
j	Indices of wind units
k^t, c^t	Shape parameter and scale parameter at *tth* time interval.
n	Total number of DG units
NOT	Number of trials
P_i	Power output of *ith* unit
$P_{i,max}$ $P_{i,min}$	Minimum and maximum limit of *ith* unit
$P_j^{w,t}$	Wind power of *jth* wind unit at time *t*
$P_j^{w\text{-}r}$	Rated power of *jth* wind unit
$P_{RES,t}$	RES power output at time *tth* hour
$Rand_1$, $Rand_2$, $Rand_i$, $Rand_j$, c', c''	Random numbers used in algorithms
t	Indices of time intervals
UR_i, DR_i	Up and down ramp rate of *ith* unit
v_j^i, v_j^o, v_j^r	Cut-in, cut-out and rated wind speed of *jth* unit
v_p^t	Wind speed at *tth* hour.
σ_v^t, μ_v^t	Mean and standard deviation of wind speed at time *t*

1.2. Literature review

One of the core challenges of power system operation and control (Singh and Dhillon, 2019; Roy, 2018) is problems based on cost efficient load dispatch, often known as economic load dispatch (ELD). Optimization problems in the power system by balancing the power output of collective numbers of generating units providing the power demand, ELD assists in determining the most appropriate, fault-free, and cost-effective operation (Dai et al., 2021; Toopshekan et al., 2020). The primary goal is to lower the total cost of electricity generation while keeping any constraints into accounts (Wu et al., 2021).

Economic dispatch problems are classified into two categories based on the electricity demand, or load: static economic load dispatch and dynamic economic load dispatch. In the former, the load demand is fixed for a long time span, resulting in fixed generator outputs over the duration. The goal is to determine the generated power by all generating components for each epoch of time in order to keep the total cost lower. Because the demand on the electrical system is always changing, the generators must adjust as well. In other words, if the load demand rises, the generator output must rise as well, and vice versa. Thus, in the latter kind of economic dispatch, i.e., the dynamic load dispatch, committed generating units are scheduled based on fluctuating demand at regular intervals of time with the goal of minimizing generation costs. For collective numbers of units, this study investigates the evaluation of economic dispatch on hourly changing loads, taking into account valve point effects and the participation of renewable energy sources.

Modified self-organizing hierarchical particle swarm optimization with jumping time-varying acceleration coefficients algorithm was proposed in article (Ghasemi et al., 2019) to deal with non-smooth dynamic economic dispatch (DED) problem. Elsayed et al. (Elsayed et al., 2016) developed a modified social spider algorithm, which was tested on systems of 6, 40, 80, and 140 units, respectively. Sun and Wang (Sun and Wang, 2017) used particle swarm optimization (PSO) with random direction updated velocity to evaluate a few benchmark functions before moving on to the load dispatch problem. In article (Mahmoud et al., 2020), Improved salp–swarm optimizer was introduced with accurate forecasting model for the DED problem. Authors of article (He et al., 2019), dealt with DED in a islanded microgrid considering ramp rate constraints by novel alternating direction method of multipliers. Ganjefar et al. (Ganjefar and Tofighi, 2011) proposed an improvised genetic algorithm (GA) technique with a non-stationary penalty function for solving the dynamic economic dispatch issue. To determine the method's efficacy, the dispatch problems were evaluated using 10 and 24 units of valve point effects. Maulik and Das (Maulik and Das, 2017) used lambda logic, lambda iteration, PSO, and DSM-optimization approaches to address the microgrid economic dispatch (ED) problem. After the shift from islanded mode to grid linked mode and vice versa, reliable operation of microgrids was also defined. To solve the ED problem with 5 generating units, Shrivastava and Nandrajog (Shrivastava and Nandrajog, 2017) used traditional optimization approaches including sequential quadratic programming (SQP), interior search point algorithms, and so on. Various costs such as installation cost, operation cost, maintenance cost, depreciation cost, which are dependent on the lifetime of the distributed energy resources used, are considered along with the fuel cost and emission cost and the overall cost is minimized as a whole by Dey Bhattacharyya (Dey and Bhattacharyya, 2019) using a neighborhood based differential algorithm. Economic dispatch of 10 units system, considering valve point effects, was solved using Hybrid EP-SQP in (Attaviriyanupap et al., 2002), Hybrid PSO-SQP (Victoire and Ebenezer Jeyakumar, 2005), modified differential evolution (MDE) (Yuan et al., 2008) and Improved-PSO (IPSO) (Yuan et al., 2009). In order to decrease the cost of generating and environmental emissions, Ma et al. (Ma et al., 2017) suggested a ELD model for charging plug-in electric automobiles. Three instances were investigated: a 6-unit without PEV, a 6-unit with PEV, and a 10-unit with PEV. Daniel et al. (Daniel et al., 2018) utilised an artificial neural network based on the Levenbergh marquardt back-propagation algorithm (LMBP) to handle DELD issues. The tests were carried out on 9 generating units while keeping the ramp rate limit (RRL) in account. Kumar and Dhillon (Kumar and Dhillon, 2018) present a combination of the artificial algae algorithm (AAA) and the simplex Search method (SSM) with dynamically adjusted parameters, where AAA acts as a global optimizer and SSM provides local search. The developed method was evaluated on 13 units, 40 units, and 80 units (by duplicating 40 units) with VPE, 140 generating units with POZs and VPE, and 40 generating units with VPE and transmission losses. Enhanced exploratory whale optimization algorithm was developed in article (Yang et al., 2021), where the authors solved dynamic economic dispatch considering various effects and constraints.

Yuan et al. (Yuan et al., 2009) use improved PSO (IPSO) to tackle DELD problems involving VPE. Inequality constraints are handled with a feasibility-based selection strategy, whereas power balance constraints are handled with heuristic strategies that do not require penalty factors. Tests were done on a ten-unit system with and without transmission losses, as well as a tripled ten-unit system to get 30-unit data. For ELD of 26 hydro units in the Three Gorges Reservoir, Xu et al. (Xu et al., 2014) compared GA with dynamic programming (DP). Azizipanah-Abarghooee (Azizipanah-Abarghooee, 2013) tested a hybridised bacterial foraging (BF) algorithm with simplified swarm optimization coupled with opposition-based initialization and a new mutation operator on 5-unit, 10-unit, 30-unit, and 100-unit systems while considering POZs and VPE. Daryani and Zare (Daryani and Zare, 2018) describe a modified group search algorithm for addressing problems based on an economic emission dispatch on an IEEE 30 bus

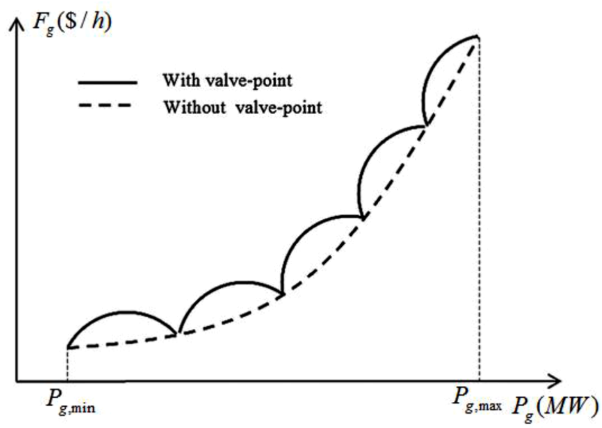

Fig. 1. Fuel cost curve of generating unit with and without VPE.

system with and without system loss and other limitations. Jadoun et al. (Jadoun et al., 2018) investigate a solution to a stochastic DELD system including wind and solar-based generation systems using an improved fireworks algorithm (IFWA). 15-generator Using POZs, ramp-rate restrictions, and transmission losses, stochastic DELD systems of solar and wind with rated capacity of 100 and 400 units, respectively, are being evaluated. Dey et al. (Dey et al., 2018) used a neighborhood-based differential algorithm to execute economic dispatch on a renewable integrated microgrid for four different load sharing scenarios. Liu and Nair (Liu and Nair, 2015) use a two-stage stochastic DELD model with a stochastic decomposition technique to manage uncertainty and system variability caused by wind generation, which has been tested on the RTS-24 and PJM-5 systems. For the best scheduling of a six-unit system with transmission losses, Chauhan et al. (Chauhan et al., 2017) used the lambda iteration approach. Authors in article (Mandal and Roy, 2021) introduced grasshopper optimization algorithm (GOA) for explaining dynamic economic load dispatch (DELD) problem with hybrid wind based power system. A comparative analysis among them proved that WOA outperformed all the other algorithms in all aspects. For the coalition forming microgrids and utilities, Lahon and Gupta (Lahon and Gupta, 2018) presented an energy management system. Conditional-value at risk was also proposed as a way to reduce the aggregator's risk from power transaction variations. The ant lion optimization algorithm (ALOA) was proposed by the authors in the article (Ali et al., 2016), to deal with the optimal allocation and sizing problem considering the renewables viz. solar and wind turbine on 33 and 69 bus radial distribution systems. The authors of article (Xiong and Shi, 2018) and (Zou et al., 2018) introduced Alternating biogeography-based optimization with brain storm optimization and a memory-based global differential evolution algorithm to address non convex dynamic economic dispatch, respectively.

1.3. Research gap, motivation and contribution

Literatures review shows that different types of formula are used in different articles to formulate the hourly output of wind power from variable wind speed throughout the day but no journal specifies the reason of using the particular formulae. Authors in this article, brought together all of those methods, and performed exhaustive analysis to sort out the method which yields maximum wind penetration to be incorporated in the dynamic systems. Thereafter, dynamic economic dispatch was evaluated on two different test systems consisting of 10 and 15 conventional generators. Practical constraints such as ramp-rate and valve point effects were considered during the study. The fuel costs for all were evaluated using proposed CSAJAYA approach and results were compared with various other algorithms along with some available in literatures. Finally statistical analysis was percolated to analyze the robustness and efficiency of the proposed CSAJAYA algorithm.

1.4. Paper orientation

The rest of the paper is structured as follows: Section 2 formulates the objective function; CSAJAYA is discussed in detail in Section 3; Various test systems are studied, and the results are shown and discussed in Section 4; The main conclusions are presented in Section 5.

2. Problem formulation

The purpose of Economic Load Dispatch is to generate power in a cost-effective manner while taking into account all equality and inequality limitations. Dynamic economic load dispatch is necessary to allocate the optimal scheduling of electrical power for the dynamic demand.

2.1. Cost function for DG units

The cost function equation is not a linear equation in the case of DG units. In reality, it's a quadratic equation (Attaviriyanupap et al., 2002; Victoire and Ebenezer Jeyakumar, 2005; Yuan et al., 2008) and the equation is given below.

$$C_{DG} = \sum_{t=1}^{24} \sum_{i=1}^{n} \left(a_i P_{i,t}^2 + b_i P_{i,t} + c_i \right) \tag{1A}$$

$$C_{DG} = \sum_{t=1}^{24} \sum_{i=1}^{n} \left(a_i P_{i,t}^2 + b_i P_{i,t} + c_i + \left| d_i \times \sin\left(e_i \left(P_{i,\min} - P_{i,t}\right)\right) \right| \right) \tag{1B}$$

P_i is the electrical power output of the i^{th} unit. The cost coefficients of *ith* unit are a_i, b_i, and c_i while d_i and e_i are the coefficients of valve point effect. As a result, the total cost is C_{DG}, with n number of DG units involved. In the case of DELD or dynamic economic load dispatch, the total cost for 24 hours is estimated, where t is the hour indicator. The economic dispatch Eq. (1B) takes into consideration the valve-point impact, which is a practical limitation. The function is multimodal due to the inclusion of sinusoidal term of the valve point effect. A pictorial description of the fuel cost curve without and with considering the valve point effect is shown in Fig. 1.

2.2. Equality and inequality constraints

The equality constraints of the problems follow Eqs. (2A) and (2B), that do not include RES and problems that do include RES, respectively. The inequality constraint that keeps the DERs within their bounds is Eq. (3).

$$\sum_{i=1}^{n} P_{i,t} = D_t \tag{2A}$$

$$\sum_{i=1}^{n} P_{i,t} + P_{RES,t} = D_t \tag{2B}$$

$$P_{i,\,min} \leq P_i \leq P_{i,\,max} \tag{3}$$

The demand of t^{th} hour represented as D_t. The production of RES in terms of power is denoted by $P_{RES,t}$.

$$-DR_i \leq P_{i,\,t} - P_{i,(t-1)} \leq UR_i \tag{4}$$

Eq. (4) states the ramp-rate inequality constraint for the fossil fueled generators. DR_i and UR_i are the down and up ramp rate of the *ith* generating unit.

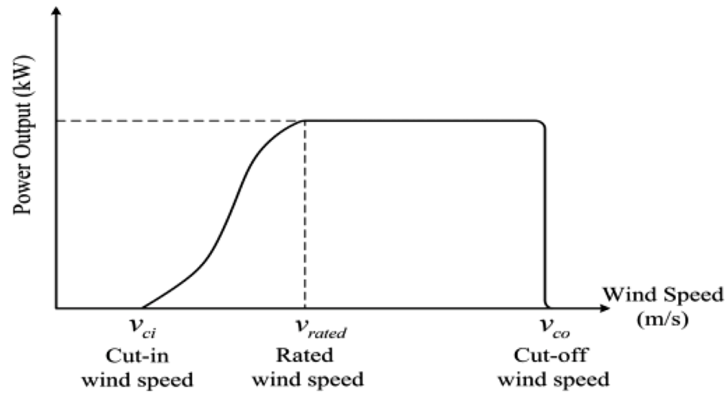

Fig. 2. Flow of wind.

$$UP = \frac{\sum_t P_{i,t}}{24 * P_{i,\max}} \tag{5}$$

The utilisation percentage is denoted by UP as mentioned in Eq. (5). UP is typically used to represent the hourly outputs of test systems with a large number of DERs displayed in tables or figures creates an imprecise and confusing situation.

2.3. Wind profile

A synchronous machine transforms mechanical input to constant frequency electrical power output and along with that, wind turbine is operated within a specific range of wind speed. The system begins producing electrical power output at a wind speed titled as the cut-in speed and gradually increases to the rated electrical power output at rated speed. The power output is kept constant according to its rating, if wind speed increases up to the cut-out speed (furling speed), after then, for safety concerns, the system is turned off. This can be viewed in Fig. 2. Because of the combined impacts of wind turbine and generator properties, within the range of cut-in speed and rated speed of wind, the relationship between electrical output and wind speed is essentially nonlinear.

We have 3 types of wind profiles as a result of our extensive literature survey. Each wind profile is examined and discussed in this paper.

2.4. Linear wind profile (Wind profile 1)

In the article (Nayak et al., 2021), authors described linear wind profile. Wind power is expressed as a conversion from wind speed to power according to Eq. (6), when the unpredictability of wind speed is characterised as a random value.

Where v_j^i and v_j^o stand for cut-in and cut-out wind speeds of *jth* wind unit, respectively, v_p^i stands for rated wind speed, and $P_j^{w\text{-}r}$ is rated wind power.

$$P_j^{w,t} = \begin{cases} P_j^{w-r} * \left(\dfrac{v_p^t - v_j^i}{v_j^r - v_j^i} \right) & v_j^i \le v_p^t < v_j^r \\ P_j^{w-r} & v_j^r \le v_p^t < v_j^o \\ 0 & otherwise \end{cases} \tag{6}$$

2.5. Quadratic wind profile (Wind profile 2)

To get the hourly wind power output from the hourly wind speed, the authors in article (Billinton and Chowdhury, 1992) utilized a method which established the relationship between hourly wind speed and wind power output. Eq. (7) is used to get the wind power output from the hourly wind speed data.

$$P_j^{w,t} = \begin{cases} P_j^{w-r} * \left(A + B * v_p^t + C * \left(v_p^t \right)^2 \right) & v_j^i \le v_p^t < v_j^r \\ P_j^{w-r} & v_j^r \le v_p^t < v_j^o \\ 0 & otherwise \end{cases} \tag{7}$$

The variables A, B and C as mentioned in Eq. (7) can be evaluated using Eqs. (8), (9) and (10) respectively as stated below.

$$A = \frac{1}{\left(v_j^i - v_j^r\right)^2} \left[v_j^i * \left(v_j^i - v_j^r \right) - 4 * v_j^i * v_j^r * \left(\frac{v_j^i + v_j^r}{2 v_j^r} \right)^3 \right] \tag{8}$$

$$B = \frac{1}{\left(v_j^i - v_j^r\right)^2} \left[4 * v_j^i * v_j^r * \left(\frac{v_j^i + v_j^r}{2 v_j^r} \right)^3 - \left(3 v_j^i + v_j^r \right) \right] \tag{9}$$

$$C = \frac{1}{\left(v_j^i - v_j^r\right)^2} \left[2 - 4 * \left(\frac{v_j^i + v_j^r}{2 v_j^r} \right)^3 \right] \tag{10}$$

where A, B and C are the functions of v_j^i and v_j^r and are evaluated using equations above (Billinton and Chowdhury, 1992). Basically these are the fixed parameters of a particular wind unit.

2.5.1. Cubic wind profile (Wind profile 3)

The authors of the paper (Lahon and Gupta, 2018) utilised a cubic wind profile to calculate the wind power output from dynamic wind speed, and the equation is given below as Eq. (11).

$$P_j^{w,t} = \begin{cases} P_j^{w-r} * \left(\dfrac{\left(v_p^t\right)^3 - \left(v_j^i\right)^3}{\left(v_j^r\right)^3 - \left(v_j^i\right)^3} \right) & v_j^i \le v_p^t < v_j^r \\ P_j^{w-r} & v_j^r \le v_p^t < v_j^o \\ 0 & otherwise \end{cases} \tag{11}$$

2.5.2. Discrete probability distribution of wind speed over time

Meteorological conditions such as wind speed, which are directly tied to geographic location, have a significant impact on wind power output. For optimal use of WTs, the peculiarities of wind conditions at the installation location should be rigorously studied at the primary stage.

The Weibull probability distribution functions are needed to estimate out the wind speed, which is based on the previous data obtained from the site under this study. A year is split into four seasons, a random day within each season represent that season. The data is then used to construct a typical day's frequency distribution of wind speed observations for each season. Each season's day is segmented into 24-hour sections, with each corresponding to a certain hourly period throughout the whole season. The mean and standard deviation for each time segment are determined from this data, and the Weibull probability density functions for each hour is constructed from them, as discussed below.

The Weibull distribution may be stated as mentioned in Eq. (12) to describe the stochastic behaviour of wind speed over a predefined time period (Nayak et al., 2021) (Kayal and Chanda, 2015) for the wind speed v^t (m/s) at the t^{th} time segment.

$$f_v^t = \frac{k^t}{c^t} \times \left(\frac{v^t}{c^t}\right)^{k^t - 1} \times \exp\left(- \left(\frac{v^t}{c^t}\right)^{k^t} \right) \quad for \;\; c^t > 1; \;\; k^t > 0 \tag{12}$$

k^t is shape parameter and c^t is scale parameter at *tth* time, which can be calculated as stated in Eqs. (13) and (14) respectively (Kayal and Chanda, 2015).

$$k^t = \left(\frac{\sigma^t}{\mu_v^t}\right)^{-1.086} \tag{13}$$

$$c^t = \left(\frac{\mu_v^t}{\Gamma(1 + 1/k^t)}\right) \tag{14}$$

σ_v^t is the mean at time t and μ_v^t is the standard deviation of wind speed at time t. Γ (gamma function) is basically defined for real $x > 0$ and it interpolates the factorial function.

3. Optimization techniques

3.1. Crow search algorithm

Crows have a tendency of following and monitoring other birds to figure out where they keep their food and take it when they aren't nearby. In addition to that, if the crow steals food from other bird, it becomes extremely cautious and continually repositions its own hiding location to avoid being robbed again. Not only that, but it also protects its food from robbers by using its own knowledge. These are the behaviors that the CSA (Askarzadeh, 2016) is formulated on.

At iteration '*iter*', the crow '*j*' is said to wish to go to its hiding location. Say crow '*i*' wants to follow crow '*j*' in the same iteration. There are two scenarios that could occur right now:

Case 1: Crow '*j*' is woefully oblivious that it is being followed by crow '*i*' and As a consequence, crow '*i*' will be able to locate the food of crow '*j*'.

Case 2: Crow '*j*' recognizes that it is being followed by crow '*i*' and deceives it by leading it to a other random location inside the search zone.

Eq. (15) is a mathematical representation of these two scenarios (Askarzadeh, 2016):

$$X^{i,iter+1} = \begin{cases} X^{i,iter} + rand_i \times fl^i \times \left(m^{j,iter} - X^{i,iter}\right), \; if \;\; rand_j \geq AP^j \\ a\ random\ position, \quad otherwise \end{cases} \tag{15}$$

The *ith* crow's flight duration is 'fl^i,' and the random numbers $rand_i$ and $rand_j$ have a uniform distribution between 0 and 1. If 'Case 1′ happens, the memory of crow '*i*' will be updated according to the formula mentioned in Eq. (16).

$$m^{i,iter+1} = \begin{cases} X^{i,iter+1}, \; if \; f\left(X^{i,iter+1}\right) \; < \; f\left(m^{i,iter}\right) \\ m^{i,iter}, \quad otherwise \end{cases} \tag{16}$$

The fitness function's value is denoted by *f(.)*.

The vicinity of the search space is determined by the value of '*fl*'. AP stands for the awareness probability of crow '*j*'. The value of AP is between 0 and 1 as it is a probability factor. The crow search algorithm is still being explored and exploited by AP.

3.2. JAYA algorithm

JAYA signifies 'success', 'achievement' or 'victory' according to Sanskrit. In this algorithm, there is just one governing equation. With each iteration, when the termination criteria are met, the algorithm tends to move away from the worst solution (failure) and toward the best solution (success). JAYA's governing equation is shown in Eq. (17). (Rao, 2016).

$$X_{k,i,iter}^{updated} = X_{k,i,iter} + c' * \left(X_{k,best,iter} - \left|X_{k,i,iter}\right|\right) - c'' * \left(X_{k,worst,iter} - \left|X_{k,i,iter}\right|\right) \tag{17}$$

where k represents the dimension and I represents particle of the population. c' and c" always lies between 0 and 1, both inclusive.

3.3. Hybrid CSAJAYA algorithm

Jaya is a greedy search algorithm. It tends to move away from the worst value of the fitness function and towards the best value with each iteration. In Hybrid CSAJAYA, this feature of the JAYA algorithm is integrated with the food-seeking approach of crows search algorithm and is represented by Eq. (18). The combination of crow's food seeking technique and JAYA's chasing towards the best value of the fitness introduce a new algorithm, hybrid CSA-JAYA. For each of the particle in the memory matrix, fitness function is figured out, which is updated with the iteration, and the best and the worst values are identified to be used in further calculation.

$$X^{i,iter+1} = \begin{cases} X^{i,iter} + rand_1 \times fl^i \times \left(m^{j,iter} - X^{i,iter}\right), \; if \;\; rand_j \geq AP \\ for\, k = 1 : n \\ \qquad X^{i,iter,k} + rand_1 \times m_{best}^k \times \left|X^{i,iter,k}\right| - rand_2 \times m_{worst}^k \times \left|X^{i,iter,k}\right|, \; otherwise \\ end \end{cases} \tag{18}$$

m is the memory matrix, updated by Eq. (16).

3.4. Reason for using CSAJAYA algorithm

3.4.1. Advantages of CSA

Key features of CSA method are explained below:

3.4.1.1. Minimum number of pivotal equations. DE, GA, WOA, GWO, and SOS all have several stages and equations to go through the whole optimization process, but CSA simply has one. This makes it simple to code and run, and also takes less time to achieve the stopping criterion, resulting in a more observable and high-quality solution. PSO, SCA, and JAYA algorithms have fewer essential equations than the CSA, but they have their own disadvantages. All three techniques have an issue with premature convergence. PSO has a proclivity for being trapped in local minima. SCA is less reliable, yielding a different fitness function value

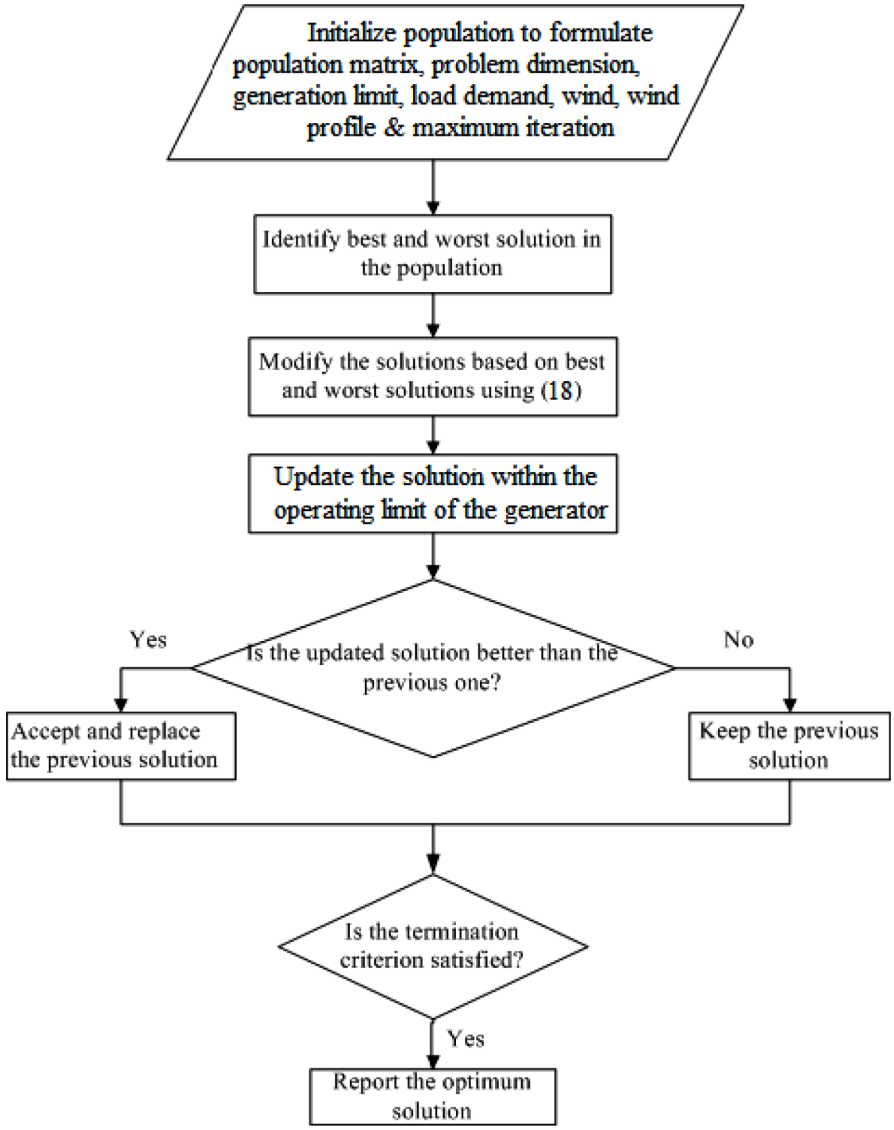

Fig. 3. Flow chart of hybrid CSA-JAYA for dynamic economic load dispatch.

each time, whereas JAYA has no specialized control over the search space.

3.4.1.2. Less number of random numbers and tuning parameters. To get a better outcome, various settings in GA, DE, and PSO must be adjusted and checked. There are several stages in DE, WOA, GWO, SOS, and TLBO, and each step utilizes certain random integers to be multiplied with a string of choice variables. Due to the tuning parameters the operation becomes time consuming, decrease consistency as well as robustness of the algorithms, to figure out the best value of fitness function. Only tuning parameters for CSA are flight duration (*fl*) and awareness probability (AP). AP can be constructed to lower its value from 1 to 0 over iterations to achieve a smooth transition between intensification and diversity. Only the value of '*fl*' influences whether the search for optimum values is done globally or locally.

3.4.1.3. Ability to solve large-scale issues in a shorter length of time. A microgrid is made up of numerous distributed energy resources whose primary goal is to meet the demand over a certain time period. These DERs now have their There are some limitations of distributed energy resources that must be followed while sort them out in order to get the best fitness function result. Assume a microgrid with n DERs is investigated during a 24-hour period. n times 24 components establish a population particle, which can be represented as:

$$P_i = \left[P^1_{i,DER1}, P^2_{i,DER1}, \ldots P^{24}_{i,DER1}, P^1_{i,DER2}, P^2_{i,DER2}, \ldots P^{24}_{i,DER2}, \ldots P^1_{i,DERD}, P^2_{i,DERD}, \ldots P^{24}_{i,DERD}\right]$$

If n is 10 (according to microgrid test system) and the population is 100, the population matrix becomes 10*24*100 elements that must be properly sized together in each iteration to get the most appropriate value of fitness function. Each of these DERs comes with its own set of constraints, including operating limits, charging and discharging limits,

Table 1
Test system description.

System	Test System 1	Test System 2
No. of generators	10 unit	15 unit
VPE	Yes	No
Cost-coefficients	Table A1	Table A1
Load Demands	Fig. 4	Fig. 4
Hourly Wind speed	NA	Table 5, Fig. 10
Hourly RES output	Fig. 5	Fig. 10
Ramp Rate	Yes	Yes
Dynamic	Yes	Yes

Table 2
Wind System parameters (Kayal and Chanda, 2015) (Zhang et al., 2016).

Hours	μ (m/sec)	σ (m/sec)	Wind speed for 15 units (m/sec)
1	10.7	3.0643	10.7
2	10.5667	2.7647	10.6875
3	10.3667	2.9501	10.675
4	9.9333	3.1005	10.67
5	9.6	3.0512	10.66
6	9.6667	3.0892	10.65
7	9.6333	3.2347	10.64
8	10.0333	2.9143	10.62
9	10.1667	2.4826	10.6
10	10.5333	2.3459	10.55
11	11	2.5515	10.565
12	11.2333	2.5891	10.525
13	6.2667	0.6807	10.515
14	6.3333	0.7506	10.5
15	5.6	0.3606	10.525
16	5.8333	0.6506	10.53
17	5.3667	1.2014	10.54
18	4.0667	1.7559	10.55
19	2.8667	1.3013	10.565
20	2.7333	1.0017	10.58
21	2.8	0.8888	10.62
22	2.8	0.7937	10.65
23	2.8333	0.6351	10.7
24	2.9	0.6083	10.8

Table 3
Wind parameters (Aranizadeh et al., 2019).

Parameter	Value	Unit
Air Density	1.225	kg/m3
Rotor Dia	15	m
Rated Power	50	kW
Cut-in	3	m/s
cut-out	25	m/s
rated Wind Speed	12	m/s

on and off time, and state of charge, which must all be met at the conclusion of each loop. So, if any of the algorithms includes several equations and stages (according to preceding paragraph), passing through all of those stages and then meeting their own given constraints is a highly time-taking procedure in the case of any particle of the population. CSA avoids this substantial and important disadvantage.

3.4.1.4. Memory-based algorithm. CSA is a memory-based optimization approach, similar to PSO. It implies that after each of the iteration, current iteration's answer to the previous iteration's solution compared by the CSA and memorizes the best of the two. Furthermore, the algorithm refreshes its particles with the best place it has ever discovered for itself and the population. Like these, the best spots are utilized to continue with subsequent iteration. CSA's critical nature allows it to achieve a higher and conspicuous quality solution when compared to several of the algorithms listed above.

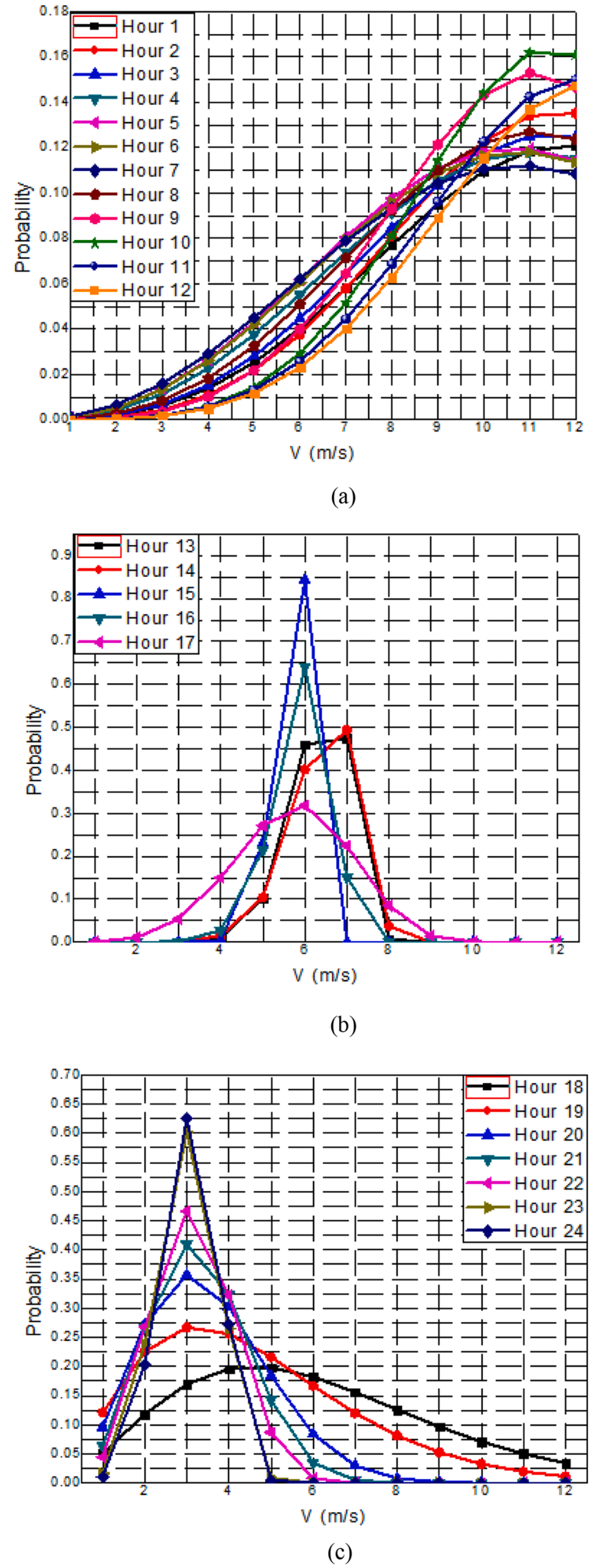

Fig. 4. Discrete probability distribution of wind speed during time period (a) 1:12 HRS (b) 13:17 HRS (c) 18:24 HRS.

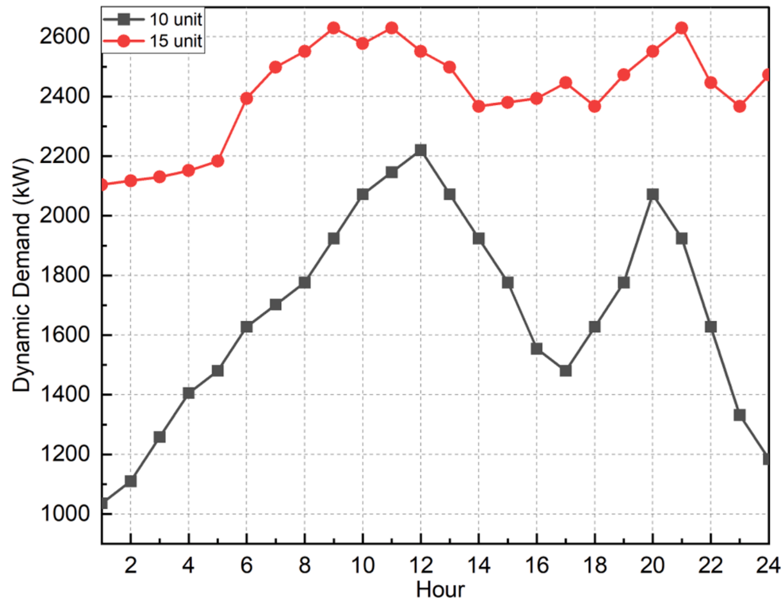

Fig. 5. Dynamic load demand of the test systems (Yong and Tao, 2007).

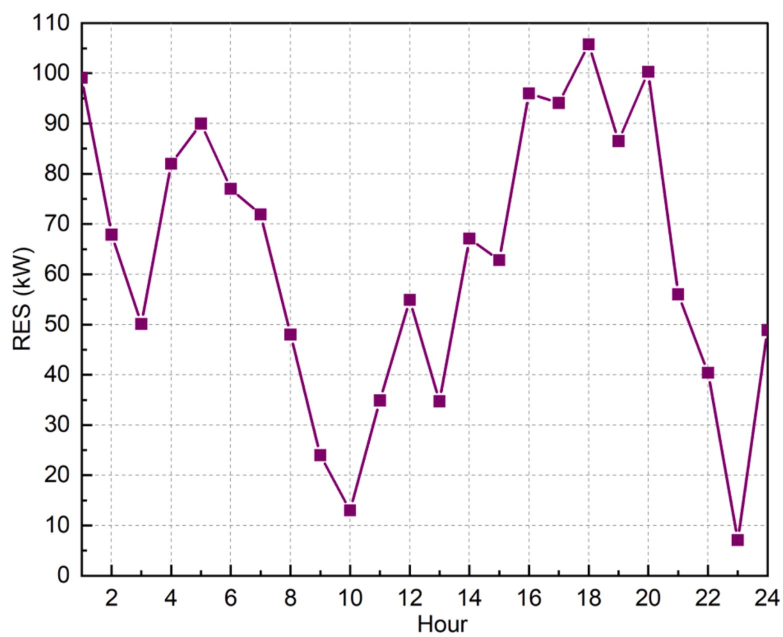

Fig. 6. Dynamic RES output (Yong and Tao, 2007).

Table 4
Comparative analysis of generation cost.

Algorithms	Without RES	With RES
SQP (Attaviriyanupap et al., 2002)	1051163	-
EP (Attaviriyanupap et al., 2002)	1048638	-
EP–SQP (Attaviriyanupap et al., 2002)	1031746	-
GA (Yong and Tao, 2007)	1037153	997528
TLBO [S]	1024306.3409	990629.2863
SCA [S]	1023553.2160	990535.9552
JAYA [S]	1023447.2549	990394.4389
CSA [S]	1022583.2790	990261.0109
CSAJAYA [P]	1022164.2384	989853.3152

S=STUDIED; P=PROPOSED.

3.4.2. Advantages of JAYA

3.4.2.1. Intelligent algorithm based on population. Jaya is basic, effective and one of the simplest optimization techniques that uses a population-based intelligence algorithm to move towards the optimal solutions. Hence the best solution should be prioritized, while the worst solution should be avoided.

3.4.2.2. Dictates the general control parameters. It specifies just the control parameters i.e. the number of generators, population size, such as particular parameters to control for various algorithms. Thus, the Jaya algorithm can be easily applied to the optimization problems in the real-world like multiple objective problems, economic emission dispatch optimization, economic dispatch optimization in micro grids, and so on, by simply choosing the common control parameters present in the

Table 5
Hourly outputs of 10 unit system without RES.

Hour	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
1	151.43	220.10	136.68	60.63	73.14	142.06	129.57	47.37	20.00	55.00
2	150.00	236.80	216.15	60.00	73.00	122.45	129.59	47.00	20.00	55.00
3	150.00	316.80	284.15	60.00	73.00	122.45	129.59	47.00	20.00	55.00
4	226.62	396.80	275.53	60.00	73.00	122.45	129.59	47.00	20.00	55.00
5	303.25	316.80	303.04	60.00	122.87	122.45	129.59	47.00	20.00	55.00
6	303.25	396.80	300.34	80.83	172.73	122.45	129.59	47.00	20.00	55.00
7	379.87	396.80	227.85	130.83	222.60	122.45	99.59	47.00	20.00	55.00
8	379.87	316.80	293.54	180.83	222.60	122.45	129.59	55.31	20.00	55.00
9	456.50	396.80	294.36	191.25	172.73	122.45	129.59	85.31	20.00	55.00
10	456.50	396.80	302.89	241.25	222.60	160.00	129.59	85.31	22.06	55.00
11	456.50	460.00	321.24	241.25	222.60	122.45	129.59	85.31	52.06	55.00
12	463.62	460.00	296.78	239.45	220.19	159.64	130.00	115.31	80.00	55.00
13	456.50	396.80	297.40	231.04	222.60	145.70	129.59	85.31	52.06	55.00
14	379.99	396.88	309.12	181.04	222.84	122.59	129.60	76.98	49.95	55.00
15	303.25	396.80	340.00	170.42	172.98	140.55	130.00	47.00	20.00	55.00
16	229.55	394.41	309.54	120.42	122.98	124.09	101.24	76.76	20.00	55.00
17	226.62	396.80	301.56	70.42	73.00	160.00	129.59	47.00	20.00	55.00
18	303.25	396.80	310.58	120.42	122.90	122.45	129.59	47.00	20.00	55.00
19	379.87	396.80	318.52	133.86	172.90	122.45	129.59	47.00	20.00	55.00
20	456.49	454.71	340.00	183.86	222.90	160.00	130.00	47.09	21.94	55.00
21	457.63	374.71	320.99	140.14	172.90	143.80	129.79	77.09	51.94	55.00
22	380.53	294.71	296.92	103.19	122.91	148.66	129.66	47.09	49.32	55.00
23	303.19	215.00	306.31	60.00	73.00	122.92	129.56	47.00	20.00	55.00
24	226.62	135.00	315.33	60.00	73.00	122.45	129.59	47.00	20.00	55.00

Table 6
Hourly outputs of 10 unit system considering RES.

Hour	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10
1	150.00	222.27	73.00	60.00	73.00	107.03	129.59	47.00	20.00	55.00
2	150.00	236.80	148.25	60.00	73.00	122.45	129.59	47.00	20.00	55.00
3	150.00	316.80	184.18	60.00	122.87	122.45	129.59	47.00	20.00	55.00
4	226.62	396.80	193.53	60.00	73.00	122.45	129.59	47.00	20.00	55.00
5	226.62	396.80	215.17	60.00	73.00	158.49	129.59	55.31	20.00	55.00
6	303.25	396.80	295.17	70.42	73.00	122.45	129.59	85.31	20.00	55.00
7	379.87	316.80	297.40	120.42	73.00	152.70	129.59	85.31	20.00	55.00
8	379.87	396.80	280.58	130.83	122.87	122.45	129.59	90.00	20.00	55.00
9	456.50	316.80	297.40	180.83	172.73	151.14	129.59	120.00	20.00	55.00
10	456.50	396.80	303.27	230.78	222.60	122.45	129.59	120.00	22.00	55.00
11	456.57	396.80	337.72	180.78	222.62	160.00	129.59	120.00	52.00	55.00
12	469.73	449.38	338.90	159.86	217.00	158.45	130.00	106.93	79.84	55.00
13	468.27	415.25	331.00	110.01	241.74	160.00	129.02	77.00	50.00	55.00
14	456.49	396.80	340.00	60.01	222.59	129.00	130.00	47.00	20.00	55.00
15	378.26	389.53	300.69	60.00	172.71	160.00	130.00	47.00	20.00	55.00
16	303.25	309.53	288.30	60.00	122.87	122.45	129.59	47.00	20.00	55.00
17	286.14	241.93	284.71	96.96	79.57	141.80	122.31	55.32	22.15	55.00
18	303.25	309.53	303.77	70.42	122.87	122.45	129.59	85.31	20.00	55.00
19	379.87	309.53	294.58	120.42	172.73	122.45	129.59	85.31	20.00	55.00
20	456.51	374.91	340.00	159.97	222.56	127.81	129.59	85.34	20.00	55.00
21	469.81	294.91	301.73	109.97	220.75	158.95	130.00	77.00	49.87	55.00
22	456.08	215.00	309.47	60.01	172.75	122.63	129.65	47.00	20.00	55.00
23	379.75	135.00	253.21	60.00	122.87	122.46	129.60	47.00	20.00	55.00
24	303.25	135.00	189.80	60.00	73.00	122.45	129.59	47.00	20.00	55.00

algorithm rather than more sophisticated control settings in applications to tune

3.4.2.3. Simple, can be used directly. It has only one basic equation. In these instances, the fundamental of Jaya technique was used directly to achieve better results than other algorithms.

3.4.3. Advantages of hybrid CSAJAYA

As discussed in details above, the various advantages of CSA and JAYA are obtained as a qualitative improvement in the proposed hybrid approach which is scaled and realized in succeeding section of the manuscript. Apart from this, the proposed CSAJAYA approach was implemented to solve both unimodal and multimodal benchmark functions by authors in (Karmakar and Bhattacharyya, 2020) to validate its robustness of solving multidimensional optimization problems. Fig. 3 shows the flowchart of hybrid CSAJAYA algorithm for solving dynamic economic dispatch problems.

3.5. Implementation of CSAJAYA

Step 1: Input the number of DERs as well as the DER parameters.
Step 2: Input the number of population size
Step 3: Input the number of maximum iterations
Step 4: Provide the load and renewable output
Step 5: Make a population matrix according to the Eq. (19)

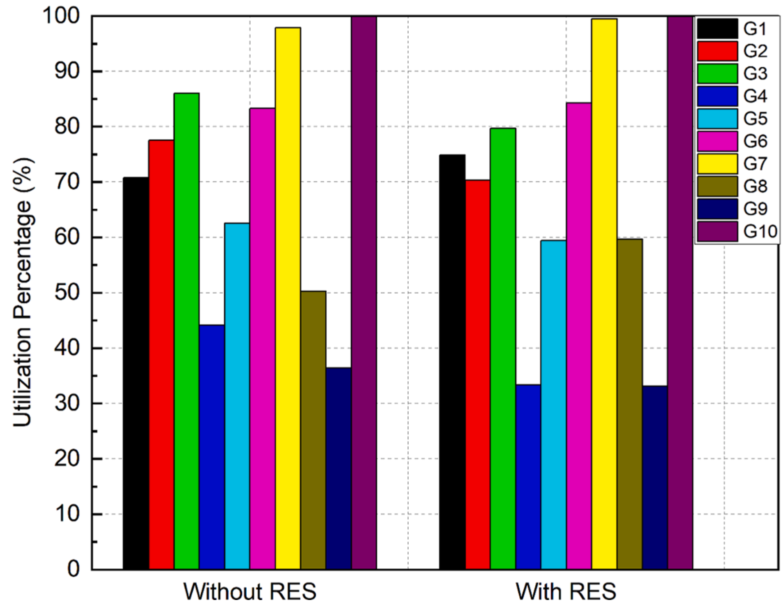

Fig. 7. Utilization percentage of 10 unit system without and with RES.

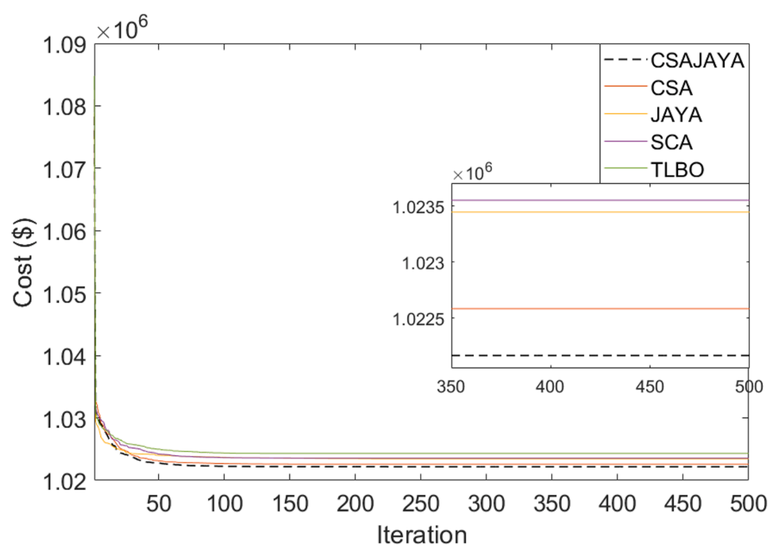

Fig. 8. Cost convergence curves for 10 unit system without RES.

$$P = \begin{bmatrix} P^1_{1,DER1}, P^2_{1,DER1}, \ldots P^{24}_{1,DER1}, P^1_{1,DER2}, P^2_{1,DER2}, \ldots P^{24}_{1,DER2} \ldots P^1_{1,DER10}, P^2_{1,DER10}, \ldots P^{24}_{1,DER10} \\ P^1_{2,DER1}, P^2_{2,DER1}, \ldots P^{24}_{2,DER1}, P^1_{2,DER2}, P^2_{2,DER2}, \ldots P^{24}_{2,DER2} \ldots P^1_{2,DER10}, P^2_{2,DER10}, \ldots P^{24}_{2,DER10} \\ P^1_{3,DER1}, P^2_{3,DER1}, \ldots P^{24}_{3,DER1}, P^1_{3,DER2}, P^2_{3,DER2}, \ldots P^{24}_{3,DER2} \ldots P^1_{3,DER10}, P^2_{3,DER10}, \ldots P^{24}_{3,DER10} \\ \ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots \\ P^1_{80,DER1}, P^2_{80,DER1}, \ldots P^{24}_{80,DER1}, P^1_{80,DER2}, P^2_{80,DER2}, \ldots P^{24}_{80,DER2} \ldots P^1_{80,DER10}, P^2_{80,DER10}, \ldots P^{24}_{80,DER10} \end{bmatrix} \tag{19}$$

Step 6: Evaluate the fitness function
Step 7: Create a new generation according to Eq. (18)
Step 8: Check updated DERs of the new position matrix for constraints violations.
Step 9: Calculate the fitness function of new position
Step 10: Update memory matrix according to Eq. (16)
Step 11: Steps 7 to 10 have be repeated until the termination conditions are met.

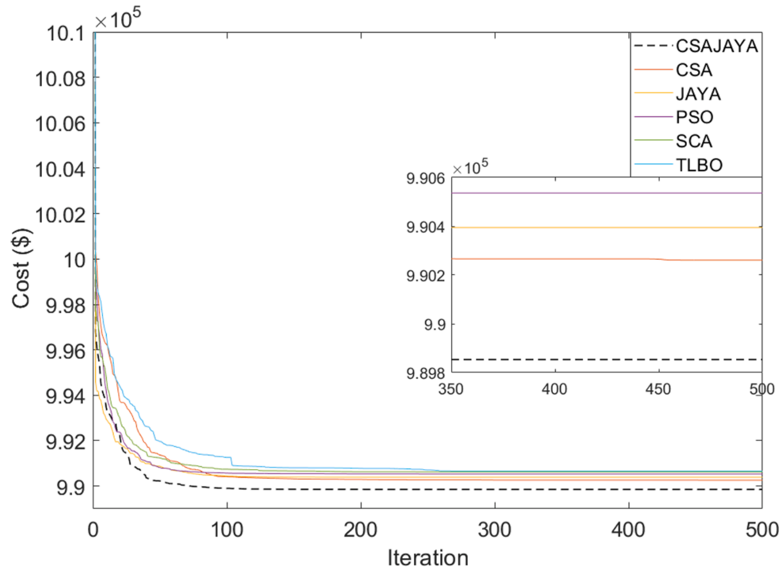

Fig. 9. Cost convergence curves for 10 unit system with RES.

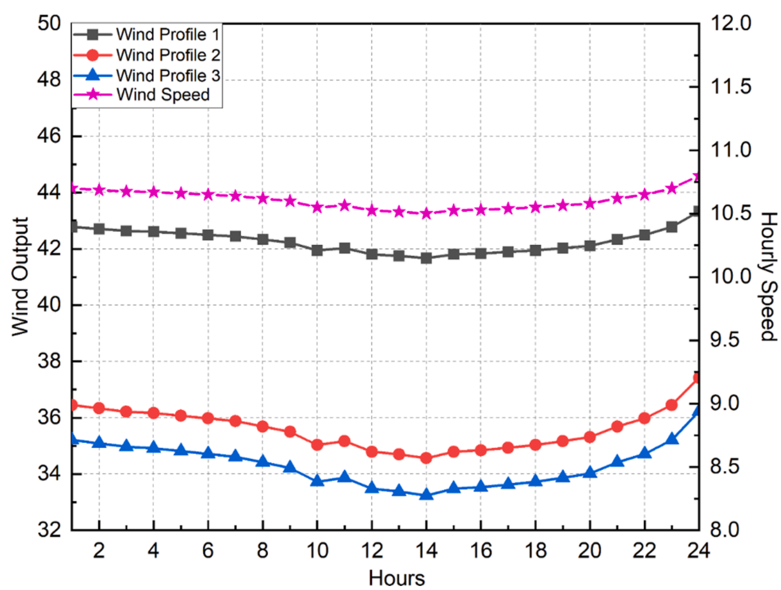

Fig. 10. Wind profiles for the 15 unit system.

Table 7
Comparative analysis of cost without and with wind profiles.

Algorithms	Without Wind Profile	With WP1	With WP2	With WP3
TLBO [S]	722261.2662	699881.7368	702557.4775	703293.9354
SCA [S]	721505.8826	699854.1756	702558.7822	703307.1034
PSO [S]	721197.6280	699680.2771	702600.3076	703318.1597
JAYA [S]	720610.3051	699640.2783	702815.5542	703324.7463
CSA [S]	720512.3399	699600.1384	702874.0740	703366.7042
CSAJAYA [P]	720492.4969	699463.1594	702906.3097	703439.1076

S=STUDIED; P=PROPOSED.

4. Results and discussions

4.1. Test system description

Two different test systems are considered for the study. The number of conventional fossil fuelled generators in the system are 10 and 15, respectively. The 10-unit system considered valve point loading effect in the fuel cost function, thus making its fitness function convex and non-linear in nature. Three profiles of wind power generation, formulated in Section 2, are evaluated based on their parameters. The necessary system descriptions to get a brief idea on the analytical study done in this paper is mentioned in Table 1. Table 2 and Table 3 displays the parameters of the wind systems considered in the study for test system 2. Figs. 5 displays the hourly load demands of 10 and 15 unit systems. For 15 unit system, the load demand is calculated from the dynamic ratio available in Table A2 by considering the peak demand, 2630 kW. Fig. 6 stands for the RES output for the test system 1. Two wind turbines with same parameters are considered for test system 2 while evaluated the wind profiles. The generator parameters are mentioned in Table A1 for both test system. A long list of algorithms were considered to carry on the study, all of which are cited and their tuning parameters mentioned in Table A3 of the Appendix section. The optimization were coded and executed in MATLAB 2021b environment on a laptop of 8GB RAM and Ryzen 5 5600H processor clocking at 3.3GHz. To perform an unbiased study population size of 80 was considered for all the algorithms. The

Table 8
Hourly outputs of 15 unit system without wind profiles.

Hour	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15
1	358.93	288.39	130.00	130.00	150.00	358.93	465.00	60.00	25.00	25.00	20.00	37.76	25.00	15.00	15.00
2	362.63	293.94	130.00	130.00	150.00	362.63	465.00	60.00	25.00	25.00	20.00	37.96	25.00	15.00	15.00
3	366.32	299.49	130.00	130.00	150.00	366.32	465.00	60.00	25.00	25.00	20.00	38.16	25.00	15.00	15.00
4	372.24	308.37	130.00	130.00	150.00	372.24	465.00	60.00	25.00	25.00	20.00	38.49	25.00	15.00	15.00
5	381.12	321.68	130.00	130.00	150.00	381.12	465.00	60.00	25.00	25.00	20.00	38.97	25.00	15.00	15.00
6	392.05	441.68	130.00	130.00	150.00	460.00	465.00	60.00	25.00	25.00	20.00	39.57	25.00	15.00	15.00
7	455.00	455.00	130.00	130.00	150.00	460.00	465.00	60.00	25.00	25.00	37.02	51.48	25.00	15.00	15.00
8	455.00	455.00	130.00	130.00	199.54	460.00	465.00	60.00	25.00	25.00	38.86	52.70	25.00	15.00	15.00
9	455.00	455.00	130.00	130.00	271.76	460.00	465.00	60.00	25.00	25.00	42.87	55.37	25.00	15.00	15.00
10	455.00	455.00	130.00	130.00	223.60	460.00	465.00	60.00	25.00	25.00	40.23	53.57	25.00	15.00	15.00
11	452.64	453.61	125.60	129.07	289.25	456.05	463.42	63.47	34.17	28.36	22.87	54.53	26.75	15.15	15.06
12	451.89	455.00	130.00	130.00	279.74	376.05	465.00	60.00	25.00	25.00	44.57	53.85	25.00	15.00	15.00
13	454.79	432.18	130.00	130.00	199.74	454.79	465.00	60.00	25.00	25.00	24.01	42.99	25.00	15.00	15.00
14	432.31	398.47	130.00	130.00	150.00	432.31	465.00	60.00	25.00	25.00	22.14	41.76	25.00	15.00	15.00
15	435.93	403.89	130.00	130.00	150.00	435.93	465.00	60.00	25.00	25.00	22.44	41.96	25.00	15.00	15.00
16	454.98	325.01	130.00	130.00	177.31	459.99	464.99	60.01	25.00	25.00	36.06	49.94	25.00	15.00	15.00
17	400.89	445.01	130.00	130.00	150.00	460.00	465.00	60.00	25.00	25.00	20.00	80.00	25.00	15.00	15.00
18	454.99	365.01	129.99	130.00	150.01	460.00	464.99	60.01	25.00	25.00	26.99	20.00	25.00	15.00	15.00
19	451.21	441.96	129.37	128.38	174.91	452.08	463.80	68.37	31.88	25.34	23.80	20.75	25.30	18.19	16.85
20	455.00	455.00	130.00	130.00	150.00	460.00	465.00	60.00	25.00	25.00	61.10	80.00	25.00	15.00	15.00
21	436.92	406.88	97.67	124.05	236.55	415.99	429.98	144.95	72.22	42.48	47.30	73.40	39.78	28.39	33.45
22	446.72	420.08	130.00	130.00	156.55	446.72	465.00	79.95	25.00	25.00	23.34	42.55	25.00	15.00	15.00
23	422.32	383.46	130.00	130.00	150.00	460.00	465.00	60.00	25.00	25.00	20.00	41.21	25.00	15.00	15.00
24	447.55	378.72	130.00	130.00	270.00	424.24	465.00	60.00	25.00	25.00	22.25	39.44	25.00	15.00	15.00

Table 9
Hourly outputs of 15 unit system With WP1.

Hour	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15
1	334.86	252.28	130.00	130.00	150.00	334.86	465.00	60.00	25.00	25.00	20.00	36.45	25.00	15.00	15.00
2	343.35	265.03	130.00	130.00	150.00	343.35	465.00	60.00	25.00	25.00	20.00	20.00	25.00	15.00	15.00
3	342.33	263.50	130.00	130.00	150.00	342.33	465.00	60.00	25.00	25.00	20.00	36.85	25.00	15.00	15.00
4	348.27	272.40	130.00	130.00	150.00	348.27	465.00	60.00	25.00	25.00	20.00	37.18	25.00	15.00	15.00
5	357.18	285.77	130.00	130.00	150.00	357.18	465.00	60.00	25.00	25.00	20.00	37.66	25.00	15.00	15.00
6	380.91	405.77	130.00	130.00	150.00	381.62	465.00	60.00	25.00	25.00	20.00	80.00	25.00	15.00	15.00
7	445.16	408.98	130.00	130.00	150.00	460.00	465.00	60.00	25.00	25.00	20.00	39.46	25.00	15.00	15.00
8	454.99	329.03	129.93	129.95	200.07	459.84	464.86	60.16	25.12	25.02	79.87	52.48	25.04	15.08	15.01
9	454.96	448.81	129.85	129.88	237.70	379.84	464.93	60.17	25.17	25.11	79.96	54.08	25.03	15.03	15.05
10	454.32	406.67	87.13	92.73	328.48	366.70	400.42	63.44	70.61	31.69	44.52	52.17	51.44	20.07	23.12
11	455.00	326.67	130.00	130.00	374.27	460.00	465.00	60.00	25.00	25.00	20.00	20.00	25.00	15.00	15.00
12	420.28	380.42	130.00	130.00	294.27	420.28	465.00	60.00	25.00	25.00	21.13	41.11	25.00	15.00	15.00
13	427.84	391.76	130.00	130.00	214.27	427.84	465.00	60.00	25.00	25.00	21.76	41.52	25.00	15.00	15.00
14	409.41	364.11	130.00	130.00	150.00	409.41	465.00	60.00	25.00	25.00	20.23	40.51	25.00	15.00	15.00
15	412.95	369.42	130.00	130.00	150.00	412.95	465.00	60.00	25.00	25.00	20.52	40.71	25.00	15.00	15.00
16	399.86	349.78	130.00	130.00	150.00	460.00	465.00	60.00	25.00	25.00	20.00	39.99	25.00	15.00	15.00
17	430.97	396.46	130.00	130.00	150.00	430.97	465.00	60.00	25.00	25.00	22.03	41.69	25.00	15.00	15.00
18	409.32	363.97	130.00	130.00	150.00	409.32	465.00	60.00	25.00	25.00	20.00	40.51	25.00	15.00	15.00
19	427.54	391.32	130.00	130.00	150.00	427.54	465.00	60.00	25.00	25.00	21.74	80.00	25.00	15.00	15.00
20	446.75	420.13	130.00	130.00	150.00	460.00	465.00	60.00	25.00	25.00	20.00	80.00	25.00	15.00	15.00
21	454.93	454.08	129.12	129.12	244.20	380.23	464.86	60.29	25.46	25.80	41.60	79.52	25.48	15.32	15.32
22	426.73	390.10	130.00	130.00	164.20	426.73	465.00	60.00	25.00	25.00	21.67	41.46	25.00	15.00	15.00
23	418.71	455.00	130.00	130.00	150.00	346.73	385.00	60.00	25.00	25.00	21.00	80.00	25.00	15.00	15.00
24	447.92	375.00	130.00	130.00	150.00	460.00	465.00	60.00	25.00	25.00	20.00	42.61	25.00	15.00	15.00

maximum number of iterations was set as 500 both test systems.

Historical data collected from literatures (Kayal and Chanda, 2015) are utilized to gather the hourly values of mean and standard deviation of wind speed and are mentioned in Table 2. Thereafter the shape factor and scale factor for every hour are evaluated using the formula mentioned in Section 2. Utilizing these values Weibull probability density function is evaluated for every hour for 12 different states (rated speed) and are plotted graphically as shown in Fig. 4(a), 4(b) and 4(c).

4.2. 10 units system

Initially with the dynamic RES outputs are shown in Fig. 6 for the 10 units system, while the dynamic load demand is presented in Fig. 5. The fuel cost of the system was minimized using a diverse variety of meta-heuristic optimization techniques. Table 4 displays the fuel cost of the 10-units test system with and without wind for both without RES and with RES. It is clearly visible that for the both cases CSAJAYA has out-performed a long list of algorithms. The hourly outputs of the operation using CSAJAYA for the both cases are shown in Table 5 and Table 6. This also shows that there are no violation of equality and inequality constraints which are mentioned in problem formulation part of this current article. A representation of the utilization percentages are displayed through Fig. 7. Fig. 8 and Fig. 9 shows the convergence curves for the cases, without and with RES, respectively, wherein the black dotted lines represents the proposed CSAJAYA algorithm.

4.3. 15 unit system

For this test system, hourly wind power were evaluated for different wind profiles. The total load demand (summation of 24-hour load

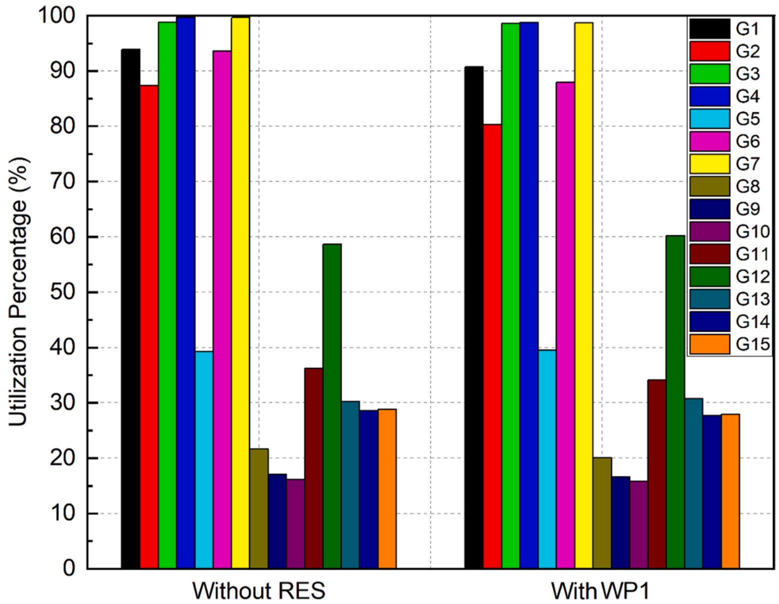

Fig. 11. Utilization percentage of 10 unit system without and with RES.

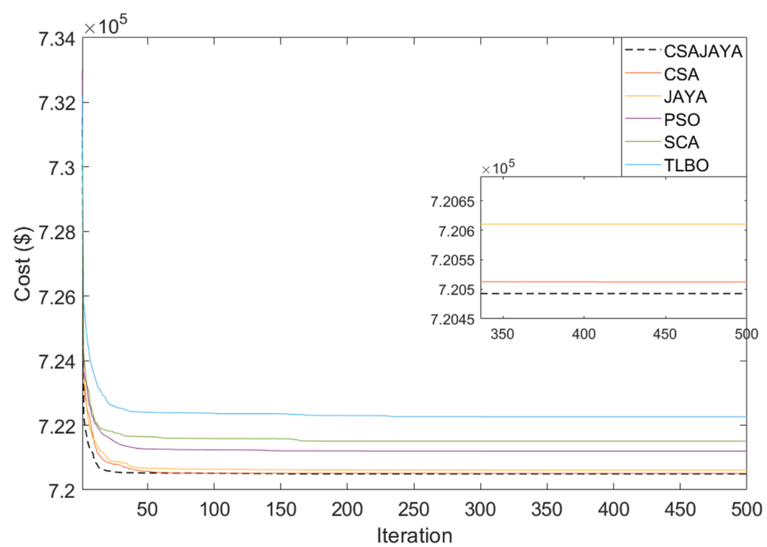

Fig. 12. Cost convergence curves without RES.

demand) of the day is 57907.34 kW. The total wind power generated throughout the day (summation of 24-hour wind power output) by linear, quadratic and cubic wind profiles are 2029.083 kW, 1708.31 kW and 1646.91 kW, respectively. This means that the corresponding contribution to address the total load demand of wind profiles are 3.50%, 2.95% and 2.84%, respectively. The various wind profiles evaluated per hour for the 15 units test system is shown in Fig. 10.

Thereafter, utilizing the cost coefficients of the fossil fuel generators, the fuel cost of the 15-units test system was evaluated without wind support and with the three wind profiles shown in Table 7. Six different algorithms were implemented for the same.

A few pellucid facts that can be envisaged from the table above are listed below point wise:

i A maximum of 2.92% savings was realized in the fuel cost when wind power generation was incorporated in the 15-units system.

ii Due to its maximum penetration level, wind profile 1 reduced the generation cost to as much as 2.92% compared to 2.44% and 2.37% of wind profile 2 and 3, respectively.

The hourly outputs of the various generators when the fuel cost of the system was minimized in case of without wind profile and with WP1 using the proposed hybrid method is displayed in Table 8 and Table 9. Table 8 and Table 9 shows the hourly outputs for without wind and with WP1, respectively. Fig. 11 shows that generating units [G1, G2, G3 G4, G6 and G7] were maximum utilized which are more than 80%, as these generators have low-cost coefficients compared to the rest of the generators for this level of load demand. To quantify and visualize the usage of the generators, we evaluate their utilization percentage. Likewise it is also clear from Fig. 11 that due to their high cost coefficients, specially for this level of load demand, [G5, G8, G9, G10, G11, G13, G14 and G15] were least used generators utilizing below 40% of their capacity. Fig. 12 and 13 exhibit the cost convergence curves for both cases, without considering wind and considering WP1 where black dotted lines

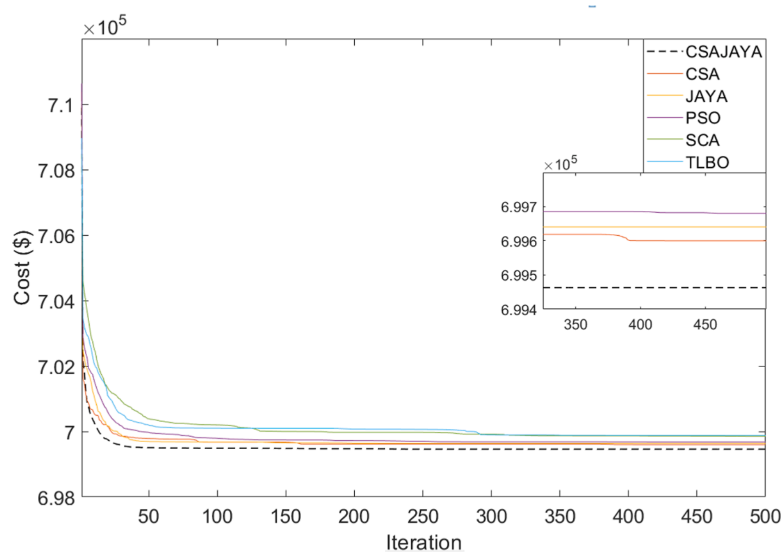

Fig. 13. Cost convergence curves with WP1.

Table 10
Statistical parameters of the algorithms implemented for 15-units system.

Algorithms	Best Cost ($)	Worst Cost ($)	Mean Cost ($)	SD	RE	MAE	RMSE	efficiency	Time (s/100 iteration)
Without RES									
TLBO	722261.27	722975.44	722451.72	321.22	0.000989	23.805667	130.3890	99.9012	0.124
SCA	721505.88	722193.13	721689.15	309.11	0.000953	22.908333	125.4741	99.9048	0.117
PSO	721197.63	721658.90	721289.88	187.66	0.000640	15.375667	84.2160	99.9361	0.107
JAYA	720610.31	721022.43	720692.73	167.67	0.000572	13.737333	75.2425	99.9428	0.107
CSA	720512.34	720896.48	720563.56	132.81	0.000533	12.804667	70.1340	99.9467	0.087
CSAJAYA	720492.50	720696.95	720512.95	62.38	0.000284	6.815000	37.3273	99.9716	0.069
With WP1									
TLBO	699881.74	700578.19	700044.25	299.60	0.000995	23.215000	127.1538	99.9006	0.118
SCA	699854.18	700555.63	699994.47	285.38	0.001002	23.381667	128.0667	99.8999	0.111
PSO	699680.28	700081.52	699733.78	138.73	0.000573	13.374667	73.2561	99.9427	0.984
JAYA	699640.28	700046.52	699694.45	140.46	0.000581	13.541333	74.1689	99.9420	0.985
CSA	699600.14	699954.29	699635.56	108.06	0.000506	11.805000	64.6586	99.9494	0.713
CSAJAYA	699463.16	699655.40	699475.98	48.77	0.000275	6.408000	35.0981	99.9725	0.062

Table 11
Wilcoxon's signed rank test for 15-units test system.

Comparison	p-value (*10^{-07})	Difference
TLBO vs CSAJAYA	4.11	+
SCA vs CSAJAYA	3.32	+
PSO vs CSAJAYA	1.98	+
JAYA vs CSAJAYA	1.98	+
CSA vs CSAJAYA	1.44	+

represent CSAJAYA like previous test system.

4.4. Statistical analysis of the quality of results obtained by various optimization techniques

Performing a non-parametric statistical analysis Hassan et al., 2021) is a quintessential step when multiple number of optimization algorithms are taken into consideration for solving a fitness function. For the 15-units test system a total of 6 algorithms were implemented including the proposed hybrid CSAJAYA approach. Statistical parameters such as mean, standard deviation (SD), relative error (RE), mean absolute error (MAE), root mean square error (RMSE) and efficiency, mentioned in Eqs. (20), (21), (22) and((23), were evaluated for the algorithms after executing each algorithm for 30 individual trials and their values are displayed in Table 7 below.

$$RE = \sqrt{\frac{\sum_{ii=1}^{NOT}(FFV_{ii} - FFV_{\min})}{FFV_{\min}}} \tag{20}$$

$$MAE = \sqrt{\frac{\sum_{ii=1}^{NOT}(FFV_{ii} - FFV_{\min})}{NOT}} \tag{21}$$

$$RMSE = \sqrt{\frac{\sum_{ii=1}^{NOT}(FFV_{ii} - FFV_{\min})^2}{NOT}} \tag{22}$$

$$Efficiency = \frac{FFV_{\min}}{FFV_{ii}} * 100\% \tag{23}$$

Non-parametric analysis such as Wilcoxon's signed rank test was conducted based on the results displayed in 2^{nd} part of Table 10. For this test, we name a hypothetical situation H_0 according to which there is no difference between the algorithms used and they are all one and the same. A contradictory hypothetical situation H_1 states that there are distinct differences between the algorithms used. If the p-value generated by the non-parametric statistical tests is more than significance level i.e. 0.05, the hypothesis H_0 is discarded. All the algorithms studied in this paper for test system 15 are compared one by one with the proposed CSAJAYA algorithm and the p-value is evaluated and displayed in

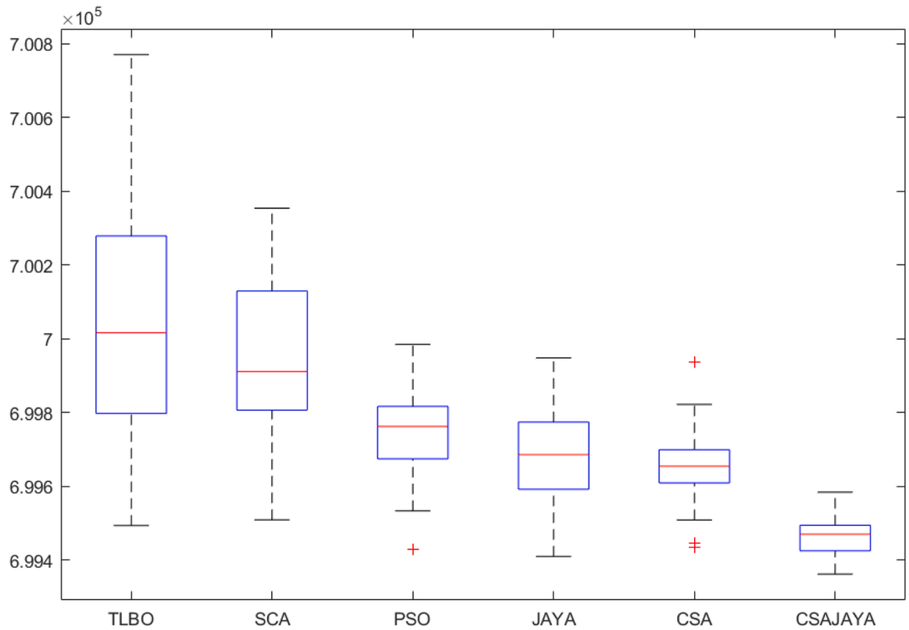

Fig. 14. box plot representation for 15 unit system with WP1.

Table 11. It can be clearly seen that the p-values are way below the threshold value 0.05, thus discarding our hypothesis H_0. This means there's a distinct difference between the algorithms implemented to evaluate the fitness function of the test system. Symbols +/-/~ signifies that the minimum value obtained using CSAJAYA algorithm is better than/worse than/approximately equal to the minimum value with which it is compared. It can be seen from Table 7 that the minimum value of the fitness function obtained using CSAJAYA ($699463.16) is better than all the other algorithms.

Convergence curve is a mean to display the performance of the algorithm per iteration and highlights the time taken by the algorithm to converge to the minimum possible value. The box plot representation with six aforementioned algorithms is shown through Fig. 14 for the extensive comparison and it is clearly visible that proposed CSAJAYA has performed better.

5. Conclusions

Two different dynamic test systems were considered in this paper for day-ahead optimal scheduling of the fossil fuelled generating units in such a way so as to minimize the fuel cost of the systems. Three different wind profiles were analyzed so as to select the one which has the highest penetration level. Maximum penetration of wind relaxes the demand on the conventional fossil fueled generators which in turn reduces the fuel cost of the system. Also, renewable energy sources like wind delivers clean and green energy thereby reducing the amount of harmful pollutants emitted from the combustion of fuels in the fossil fuelled generation units.

- It was observed from detailed and descriptive analysis that among the three different types of wind profile, the linear variant yielded wind power of maximum penetration level. Therefore the cost of generation of the dynamic systems supported by linear wind profile incurred a low fuel cost compared to the quadratic and cubic wind profile.
- Proposed novel hybrid CSAJAYA consistently yielded the minimum value of fitness function with maximum efficiency and within lowest execution time without being affected by the dimension and size of the test systems. Owing to its advantages as mentioned in the paper, CSAJAYA may be utilized to solve complex engineering optimization problems of any dimension and may also be tested on multi-objective problems.

As a future scope of research work, different wind profiles evaluated may be utilized to perform combined economic dispatch on these test systems to study the effect of renewables in obtaining a balanced trade off solution between fuel cost and pollutants emitted. Unit commitment based dynamic economic dispatch considering transmission losses can be performed on these test systems to reduce the load on the generating units with more than 80-90% utilization throughout the day. Also demand side management may be considered to deal with more complex and futuristic problem with this novel algorithm and thereafter the ability of this algorithm can be explored to handle more complex constraints problem.

Data availability

Data will be available by the authors upon reasonable request.

CRediT authorship contribution statement

Sourav Basak: Data curation, Writing – original draft, Writing – review & editing. **Biplab Bhattacharyya:** Supervision. **Bishwajit Dey:** Conceptualization, Methodology, Software.

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1 contains the detailed parameters of all the generators of 10 and 15 units test system. Table A2 displays the ration of hourly load demand with respect to the peak demand. Table A3 displays the various tuning parameters of the optimization algorithms used.

Table A1
Generator cost-coefficients of the test systems.

Test Systems	Units	Fuel cost coefficients			VPE coefficients		Operating Range		Ramp Rate	
		a ($/kW2)	b ($/kW)	c ($)	d	e	Min (kW)	Max (kW)	UR (kW)	DR (kW)
10 units (Victoire and Ebenezer Jeyakumar, 2005)	G1	0.000430	21.6	958.2	450	0.041	470	150	80	80
	G2	0.000630	21.05	1313.6	600	0.036	460	135	80	80
	G3	0.000390	20.81	604.97	320	0.028	340	73	80	80
	G4	0.000700	23.9	471.6	260	0.052	300	60	50	50
	G5	0.000790	21.62	480.29	280	0.063	243	73	50	50
	G6	0.000560	17.87	601.75	310	0.048	160	57	50	50
	G7	0.002110	16.51	502.7	300	0.086	130	20	30	30
	G8	0.004800	23.23	639.4	340	0.082	120	47	30	30
	G9	0.109080	19.58	455.6	270	0.098	80	20	30	30
	G10	0.009510	22.54	692.4	380	0.0943	55	55	30	30
15 units (Dasgupta et al., 2015)	G1	0.0003	10.1	671	-	-	150	455	80	120
	G2	0.0002	10.2	574	-	-	150	455	80	120
	G3	0.0011	8.8	374	-	-	20	130	130	130
	G4	0.0011	8.8	374	-	-	20	130	130	130
	G5	0.0002	10.4	461	-	-	150	470	80	120
	G6	0.0003	10.1	630	-	-	135	460	80	120
	G7	0.0004	9.8	548	-	-	135	465	80	120
	G8	0.0003	11.2	227	-	-	60	300	65	100
	G9	0.0008	11.2	173	-	-	25	162	60	100
	G10	0.0012	10.7	175	-	-	25	160	60	100
	G11	0.0036	10.2	186	-	-	20	80	80	80
	G12	0.0055	9.9	230	-	-	20	80	80	80
	G13	0.0004	13.1	225	-	-	25	85	80	80
	G14	0.0019	12.1	309	-	-	15	55	55	55
	G15	0.0044	12.4	323	-	-	15	55	55	55

Table A2
Ratio of dynamic demand (Kavousi-Fard et al., 2018).

Hour	Ratio	Hour	Ratio
1	0.8	13	0.95
2	0.805	14	0.9
3	0.81	15	0.905
4	0.818	16	0.91
5	0.83	17	0.93
6	0.91	18	0.9
7	0.95	19	0.94
8	0.97	20	0.97
9	1	21	1
10	0.98	22	0.93
11	1	23	0.9
12	0.97	24	0.94

Table A3
Algorithms implemented and their tuning parameters.

Algorithms	Full form	Tuning Parameters	Ref.
CSA	Crow Search Algorithm	fl=2; AP=0.165	(Askarzadeh, 2016)
JAYA	JAYA	No parameters	(Rao, 2016)
PSO	Particle Swarm Optimization	C1=C2=2; wmax = 0.9; wmin=0.4	(Kennedy and Eberhart, 1995)
TLBO	Teaching Learning Based Optimization	No parameters	(Rao et al., 2011)
SCA	Sine Cosine Algorithm	No parameters	(Mirjalili, 2016)
CSAJAYA	Crow Search Algorithm JAYA	fl=2; AP=0.165	This paper

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