Electrical Power and Energy Systems 128 (2021) 106632

Contents lists available at ScienceDirect

International Journal of Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Chaotic darwinian particle swarm optimization for real-time hierarchical congestion management of power system integrated with renewable energy sources

Namilakonda Srilatha*, Guduri Yesuratnam

Department of Electrical Engineering, Osmania University, Hyderabad, India

A R T I C L E I N F O

Keywords:
Real-time hierarchical congestion management
Chaotic darwinian particle swarm optimization
Demand response
Renewable energy sources
Generation rescheduling

A B S T R A C T

The increasing penetration of renewable energy sources that have intermittent outputs challenge the Independent System Operator while managing transmission congestion. A new Real-Time Hierarchical Congestion Management (RHCM) technique is proposed that reschedules generators in two stages based on Available Congestion Clearing Time (ACCT) of the transmission lines in presence of renewable energy sources. Chaotic Darwinian Particle Swarm Optimization (CDPSO) is used for determining the optimal schedules of demand response loads and reschedules of conventional generators to mitigate congestion. The solar and wind energy sources are modelled using Rayleigh and Beta probability density functions; Latin Hyper cube sampling is adopted for sampling. IEEE 39 bus system is simulated for cases of overloads and contingencies and RHCM using CDPSO is tested to ensure the security of the system. The benefit of RHCM incorporating demand response is presented in terms of reduced congestion relieving costs and decreased power loss.

1. Introduction

Ensuring continuous and reliable power supply through a congestion free transmission network under all operating conditions is quite challenging to the Independent System Operator (ISO) in a deregulated environment. Transmission congestion may prevent the existence of new contracts, leads to additional outages, increases the electricity prices in some regions of the electricity markets, and can threaten system security and reliability [11,18]. Although Generation Rescheduling (GR) is being adopted to manage congestion, deregulated market structure imposes a restriction on the quantity of power that can be rescheduled in the process of managing congestion to maintain security of the system. Moreover, the ramp rates of the generators confine the amount of power that can be ramped up to mitigate congestion within the available time.

There is an increasing participation of Renewable Energy Sources (RES) and this complicates the task of dispatching the conventional generators during different blocks of time in a day-ahead market. Output power of these RES is very intermittent and volatile in nature, and varies according to the time of the day and season of the year [23]. Demand Response (DR) is also devised as one of the strategies to ensure secure and reliable operation of the system during times of emergency. Market operations need to schedule the participation of DR loads while addressing contingencies. Hence, an efficient congestion management procedure needs to be designed that reschedules the generators within the available time limits considering accurately forecasted power outputs of RES and optimal participation of DR loads in a day-ahead power market.

Management of congestion deals with the set of procedures conceived and executed by the ISO in a deregulated market scenario in order to maintain system reliability and security during emergencies. Generation rescheduling, transmission switching, demand response, load shedding, deploying Flexible AC Transmission Systems (FACTS) devices and phase shifters are some of the methods using which congestion management is implemented [10,27]. Rescheduling of generator real and reactive powers is done for managing congestion using a zonal or cluster-based approach. The generators with strongest and non-uniform distribution indices, in the most sensitive zones are chosen for rescheduling in this approach [2]. Relative Electrical Distance concept has been utilized by Yesuratnam et al. for rescheduling of generators to manage congestion. This method results in minimum transmission losses and better voltage stability profile of the system [27]. Though all these works involve rescheduling of generators, the ramp rates of the generators were not considered to increase or decrease

* Corresponding author.
E-mail address: srilatha.n@uceou.edu (S. Namilakonda).

https://doi.org/10.1016/j.ijepes.2020.106632
Received 22 May 2020; Received in revised form 21 September 2020; Accepted 3 November 2020
Available online 13 January 2021

the output powers in a specific amount of time. The safe amount of time available for rescheduling was never a constraint in rescheduling process.

1.1. Literature survey

Most of the literature handles mitigating of congestion using generation rescheduling, utilizing various optimization algorithms [18,17]. Multi objective congestion management is proposed to optimize congestion mitigation cost, voltage security and dynamic security simultaneously by Esmaili et al. [14] using augmented ε-constraint method. Each of the market participants can obtain maximum benefits using the decentralized approach in the process of managing congestion as presented by Brijesh Singh et al. [4], that uses Interior point procedure of optimization. Hybrid of Firefly optimization and Differential evolution optimization has been used for location and placement of Distributed generation in order to manage congestion [9]. Constriction based Particle Swarm Optimization (PSO) is utilized by Jagadeesh et al. in [7] to reschedule the generators considering critical constraint violations. Satin Bowerbird Optimization is opted to minimize the congestion cost while rescheduling the generators for congestion management in [5]. Glow worm swarm optimization is utilized for minimizing congestion rentals and transmission losses in the system for rescheduling of generators in [21]. Most of these optimization algorithms, used for transmission congestion management, have convergence problems for large systems and local optima trapping is found after few iterations. To this end, to improve upon convergence and reaching near global optimal values, Chaotic Darwinian PSO (CDPSO) has been proposed recently in [25] that proves to be addressing the above problems in an efficient way. The random sequences are replaced by chaotic sequences for a better searching capability, and the Darwinian model further helps in avoiding premature local convergence. Authors in [13] re-iterate the advantages of CDPSO that is based on Darwinian principle of natural selection.

The process of congestion management is aided by the contribution of DR loads. It is used as a cheaper alternative compared to load shedding in a highly capital-intensive power system in order to ensure security under all operating conditions. The authors in [1] have analyzed various methods of DR and ascertained the advantages of DR to be reduced electricity prices, improved system reliability and reduced-price volatility. In this direction, Dehnavi and Abdi in [6] have illustrated the method of finding the optimal location and time of the loads willing to participate in DR. While power transfer distribution factors and Available Transfer Capacity of the system are used as basis for optimal location, numerous benefits of implementing optimal DR strategy is envisioned in terms of improving load curve characteristics, mitigating congestion, ease of ISO operation and reduction of contingencies and blackouts in the long run. But DR alone cannot completely be responsible for handling congestion, as the amount of congestion is quite large in a transmission system.

Another important aspect that needs attention of the ISO is the various RES that are increasingly becoming part of the power system. Output power from RES like solar and wind systems is uncertain and hence needs to be forecasted accurately using appropriate mathematical models for use in day-ahead scheduling. Mazidi et al. in [15] have modelled forecast errors of wind, solar generation using probability density functions, and have generated samples of close correlation to actual values. GR for managing congestion has been implemented in a smart grid environment where wind sources, DR and Gridable vehicles are considered in [12]. Moreno et al. [19] have developed an integrated OPF model for demand response incorporating wind power for day ahead markets. The loads that are willing to be flexible and bid day-ahead are incorporated as demand response models, thus resulting in an enormous saving in generation costs [8]. Prajapati and Mahajan [26] have demonstrated the effect of various types of demand response strategies in an uncertain environment created by renewable sources while managing the congestion during certain times of the day. However, all these strategies may fail to keep up security levels of operation during unforeseen contingencies

Therefore, this paper proposes an efficient GR methodology using Real-Time Hierarchical Congestion Management (RHCM) technique that reschedules the generators in two stages based on ACCT, owing to intensity of the congestion in transmission lines, with presence of uncertain RES. Optimal participation strategy of DR loads is determined to aid the GR in a deregulated environment using CDPSO algorithm that is based on Darwinian Theory of natural selection. Uncertainty in generated power output of RES are modelled using probability density functions to enable forecast of the schedules of generators in the day-ahead electricity markets. Congestion is simulated for contingencies and sudden overloads over a 24-hour period considering typical load variation throughout the day.

1.2. Contributions

(1) The optimal schedules of Demand Response (DR) loads and Generation Rescheduling (GR) are determined in presence of uncertain Renewable Energy Sources (RES) using a novel two-stage Real-Time Hierarchical Congestion Management (RHCM) for ensuring security of the power system during times of congestion that aim for minimum congestion relieving cost and better system performance.
(2) Optimization is implemented using Chaotic Darwinian Particle Swarm Optimization (CDPSO) algorithm to ensure better searching capability and to avoid premature local convergence.
(3) The uncertainties of RES, wind and solar energy sources are modelled using probability density functions, utilizing Latin Hypercube sampling (LHS) to generate samples of wind speed and solar irradiation uniformly.
(4) Two-stage RHCM using GR is implemented considering ramp rates of the generators and Available Congestion Clearing Time (ACCT) to clear congestion well before thermal failure of the line and avoid cascading outages.

IEEE 39 bus system is considered as a case study to present the findings of the above-mentioned proposals. The paper is organized as follows. Section 2 deals with the mathematical background of the optimization problem formulation and presents modelling of demand response and renewable energy sources. Section 3 presents the proposed methodology for congestion management and Section 4 provides results and discussion. Conclusions are presented in Section 5.

2. Problem formulation

The objective is to relieve the congestion by re-dispatching the active power of generating units and including demand response in presence of uncertain RES, with minimum cost of relieving congestion. Congestion is modelled as a non-linear problem and solved through OPF based method. Thus, the objective function for this work may be modelled as

$$Minimize\left(\sum_{p=1}^{n_g}\left(a_p + b_pP_{gp} + c_pP_{gp}^2\right) + \sum_{n=1}^{n_{DR}} inc_n\right) \quad (1)$$

$a_p,\ b_p\ and\ c_p \rightarrow cost\ coefficients\ of\ generators$

$P_{gp} \rightarrow real\ power\ generation\ of\ p^{th}\ unit$

$n_g \rightarrow number\ of\ generating\ units$

$n_{DR} \rightarrow number\ of\ loads\ in\ demand\ response$

$inc_n \rightarrow net\ incentive\ rewarded\ to\ n^{th}\ bus$

The first part of the objective function corresponds to reduction of the cost of rescheduling/ re-dispatch and the second part of the objective function corresponds to having effective demand side response with minimum incentives.

The equality and inequality constraints for the above objective function can be defined as follows.

2.1. Equality constraints

The equality constraints guarantee the balance in power at every node during power flow. The equality constraints of the model are described by the real and reactive power equations as described. Also, the active power of generator and demand has to be adhered as per the equations for market equilibrium.

(a) Active and Reactive Power balance

$$P_{gk} - P_{dk} = \sum_{j=1}^{n_b} |V_j||V_k||Y_{kj}|\cos(\delta_k - \delta_j - \theta_{kj}) \quad (2)$$

$$Q_{gk} - Q_{dk} = \sum_{j=1}^{n_b} |V_j||V_k||Y_{kj}|\sin(\delta_k - \delta_j - \theta_{kj}) \quad (3)$$

$P_{gk}, Q_{gk} \rightarrow$ *real and reactive power generated at bus k*

$P_{dk}, Q_{dk} \rightarrow$ *real and reactive power demands at bus k*

$Y_{kj} \rightarrow$ *bus admittance between nodes k and j*

$V_j,\ V_k \rightarrow$ *voltages of buses j and k*

$\delta_j, \delta_k \rightarrow$ *voltage angles of buses j and k*

$\theta_{kj} \rightarrow$ *admittance angle of line connected between j and k*

$n_b \rightarrow$ *number of buses*

$n_g \rightarrow$ *number of generators*

$n_d \rightarrow$ *number of demands*

(b) Market Equilibrium

$$P_{gk} \;=\; P^C_{gk} + \Delta P^+_{gk} - \Delta P^-_{gk}; \qquad k = 1, 2, ..., n_g \quad (4)$$

$$P_{dj} \;=\; P^C_{dj}; \qquad j = 1, 2, ..., n_d \quad (5)$$

$P^C_{gk} \rightarrow$ *active power generated by generator k, through market clearing*

$P^C_{dj} \rightarrow$ *active power consumed by load j, through market clearing*

$\Delta P^+_{gk} \rightarrow$ *incremental power of generator k*

$\Delta P^-_{gk} \rightarrow$ *decremental power of generator k*

2.2. Inequality constraints

The inequality constraints govern the operating bounds of the system pertaining to the line flow (active and reactive power), voltages (generators and load buses) and the apparent power of transmission lines and transformers. Also, they enforce limits on the controlling variables.

(c) Generator Active Power Limits

$$P_{gimin} \leq P_{gi} \leq P_{gimax} \quad (6)$$

$gi \rightarrow$ *number of generator buses*

(d) Generator Reactive Power Limits

$$Q_{gimin} \leq Q_{gi} \leq Q_{gimax} \quad (7)$$

(e) Generation Voltage Limits

$$V_{gimin} \leq V_{gi} \leq V_{gimax} \quad (8)$$

(f) Load Bus Voltage Limits

$$V_{Limin} \leq V_{Li} \leq V_{Limax} \quad (9)$$

$Li \rightarrow$ *number of load buses*

(g) Line Flow Limits

$$S_L \leq S_{Lmax} \quad (10)$$

2.3. Demand response modelling

Demand response (DR) is an approach to reduce or shift load from peak hours of the day, when the demand for electricity is the greatest to leaner demand periods. It is utilized only during congestion in the network in this paper. This comes under the category of market-based Incentive-type DR program according to Albadi and El-Saadany [1]. DR services can be utilized by the ISO only during emergencies, or during ancillary service requirement. The maximum allowable reduction in DR loads is limited to 20% of their maximum demand. Few loads are selected to contribute for DR depending on their influence on transmission line loading and willingness. Penalty will be levied on the DR load that is non-responsive during critical loading, once the contract has been signed. The penalty and incentives are specific to a particular market and are prescribed by the ISO. In this work, it is supposed that DRs are encouraged to participate consistently for longer periods if the penalty imposed is zero.

The difference in load at nth bus after executing the Demand Responsive Program is represented as,

$$\Delta_{Ln} = L_{0n} - L_n \quad (11)$$

$L_{0n} \rightarrow$ *load at the n^{th} responsive bus prior to demand response*

$L_n \rightarrow$ *load at the n^{th} responsive bus after demand response*

The total incentive rewarded to the demand response at n^{th} bus is given by,

$$inc_n = inc \times \Delta_{Ln} \quad (12)$$

$inc \rightarrow$ *incentive factor*

$inc_n \rightarrow$ *net incentive rewarded to the n^{th} bus*

The load reduction is determined by the ISO for the n^{th} responsive demand and is denoted as LR_n. In case, if the consumers of contributing DR are not committing to the previously agreed load as per the contract, then a penalty will be levied from them. The overall penalty of n^{th} load to respond can be calculated by the use of the following formula.

$$Pen_n = Pen \times [LR_n - \Delta_{Ln}] \quad (13)$$

$Pen \rightarrow$ *penalty factor*

$Pen_n \rightarrow$ *factor of penalty of the n^{th} responsive bus*

The revenue for participating in demand response to the consumer could be stated via different functions that include power, logarithmic, linear and exponential functions. A linear model is considered in this work, which can be described through the following equation:

$$L_n = L_{0_n} \times \left[1 + E \times \left(\frac{\rho - \rho_0 + inc - pen}{\rho_0}\right)\right] \quad (14)$$

$E \rightarrow$ *elasticity of load*

$\rho,\ \rho_0 \rightarrow$ *price for using electricity after using DR and before use of DR*

$inc \rightarrow incentive\ factor$

$L_{0n} \rightarrow load\ at\ the\ n^{th}\ responsive\ bus\ prior\ to\ demand\ response$

$L_n \rightarrow load\ at\ the\ n^{th} responsive\ bus\ after\ demand\ response$

The incentive coefficient is assigned a value between 0.1 and 10 times of the price fixed for electricity before applying DR and the penalty factor is made zero to encourage the commitment for load response.

2.4. Renewable energy sources modelling

Distributed energy resources like the renewable energy from solar and wind sources are assumed to be placed at certain buses in the system. As the wind speed and solar irradiation have uncertain behaviour and are probabilistic in nature, the output power of these units is uncertain. To mathematically model the uncertain sources of power, probability density functions are used.

2.4.1. Solar power

The output power of a solar cell mostly depends on irradiance of the sun. The distribution of hourly irradiance at a particular location usually follows a bimodal distribution that is actually a linear combination of two unimodal distribution functions [15]. A Beta PDF is utilized for a unimodal function in the given range of si, α and β and its value is zero for other values of si, α and β. It can be described as follows:

$$fb(si) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \times si^{(\alpha-1)} \times (1-si)^{(\beta-1)}; \quad for\ 0 \le si \le 1,\ \alpha \ge 0,\ \beta \ge 0 \tag{15}$$

$si \rightarrow$ solar irradiance $\left(\mathrm{kW}/m^2\right)$

α and β, the parameters of Beta distribution function are determined from the mean (μ) values and standard deviation (σ) values at different instants of time.

$$\beta = (1-\mu) \times \left(\frac{\mu \times (1+\mu)}{\sigma^2} - 1\right) \tag{16}$$

$$\alpha = \frac{\mu \times \beta}{1-\mu} \tag{17}$$

The amount of solar power is calculated by using irradiation distribution and irradiation to power conversion function is given as

$$Ppv(si) = \eta^{pv} \times S^{pv} \times si \tag{18}$$

$P_{pv}(si) \rightarrow solar\ output\ power\ for\ irradiance\ si\ (kW)$

$\eta \rightarrow efficiency\ of\ solar\ panel\ (\%)$

$S_{pv} \rightarrow total\ area\ of\ solar\ panel\ (m^2)$

2.4.2. Wind power

Rayleigh probability density function (PDF) is applied for uncertainty modelling of the wind speed patterns Mazidi et al. [15] and is defined as follows:

$$f_w(v) = \left(\frac{2v}{c^2}\right) exp\left[-\left(\frac{v}{c}\right)^2\right] \tag{19}$$

$f_w(v) \rightarrow Rayleigh\ PDF$

$c \rightarrow Rayleigh\ scale\ index$

$v \rightarrow wind\ speed$

If the mean speed of the wind is known, the scale index, c is calculated as

$$v_m = \int_0^\infty v f_w(v) dv = \int_0^\infty \left(\frac{2v^2}{c^2}\right) exp\left[-\left(\frac{v}{c}\right)^2\right] dv = \frac{\sqrt{\pi}}{2} c \tag{20}$$

$$c \simeq 1.128 v_m \tag{21}$$

The output power of the wind turbine for an actual wind speed of v_{aw} is calculated using the following equation:

$$\begin{aligned} &P_w(v) = P_{rated} \times \frac{(v_{aw} - v_{ci})}{(v_r - v_{ci})}; \ for\ v_r \le v_{aw} \le v_{co}, v_{ci} \le v_{aw} \le v_r \\ &P_w(v) = 0; \quad for\ 0 \le v_{aw} \le v_{ci}\ and\ v_{co} \le v_{aw} \end{aligned} \tag{22}$$

$v_{ci} \rightarrow cut - in\ speed\ of\ the\ wind\ turbine$

$v_r \rightarrow rated\ speed\ of\ the\ wind\ turbine$

$v_{co} \rightarrow\ cut - off\ speed\ of\ the\ wind\ turbine$

3. Proposed real-time hierarchical congestion management

A two-stage real-time hierarchical congestion management (RHCM) scheme is proposed in this work wherein real power outputs of the generators are rescheduled optimally depending upon two important criteria:

- Available Congestion Clearing Time (ACCT)
- Most Sensitive Generators (MSG)

ACCT depends on the extent of overload in the congested line. The extent of overload determines the time available to manage the congestion by considering generator ramp rates and quasi dynamic thermal ratings of the transmission lines. MSG are the set of generators that highly effect the flow in the congested line. The rescheduling of real power outputs of highly sensitive generators enables the power flow through the congested line to be redirected to other transmission lines so that power flow through it reduces.

3.1. Available congestion clearing time (ACCT)

ACCT is the longest duration of time slot available for the transmission line to withstand an overload. There is a thermal failure of the transmission line after the end of this time limit due to persistent overload. Temperature and weather conditions also have an influence on this time. During overload, current through the conductor increases, thermal inertia allows this increase to certain extent for a specific amount of time before the temperature reaches the maximum value. The Short Term Rate (STR) is 118% and the Emergency Term Rate (ETR) is 147% of the long-term rate [16]. STR can last up to 15 min and ETR can last up to 5 min before thermal breakdown. Any loading beyond ETR cannot be tolerated for any time and overload relay trips instantaneously.

These times are clear indicators of the congestion clearing time limits. Congestion should be cleared within the mentioned STR or ETR times, to avoid thermal breakdown. This clearing time should also include the time of execution of the optimization algorithm. Considering these limits as basis, a two-stage hierarchical congestion management process is adopted here.

If the overload in the congested line comes under ETR region, amount of change in generation is limited to 5 min. Hence, in the first stage, optimization algorithm reduces the overload such that the flow in the line is about 118%. This should also include the execution time of the optimization algorithm.

The second stage of the overload relieving process now comes into picture after first 5 min. At this instant the overload comes under STR region. The optimization algorithm now aims at reducing congestion in the line to the possible extent in 15 min time. The rescheduling power quantity is now more compared to ETR region as the available time is more. In both the stages, real power output of few generators is increased, while output of few other generators is decreased as explained in the next section.

3.2. Most sensitive generators (MSG)

Generation rescheduling is the most sought-after method of managing congestion, and is a non-cost-free means, particularly in the deregulated environment [18]. For a given operating condition, power flow tracing is done initially to determine the set of generators that actually contribute to the flow through the congested line. The decrease of generation on these generators reduces the flow through the congested line, as these are contributing generators. Similar amount of power is increased on the other set of generators, depending on their available margins, so that the load balance is achieved. Both these actions together result in reduction of flow in the congested line owing to the physical laws of power flow through the network. Hence, these conditions are included as one of the constraints in the optimization problem formulation. The set of contributing generators are only allowed to decrease their generation, whereas non-contributing generators are allowed to increase their generation according to the margins available.

Among the non-contributing generators, only the generators that are highly sensitive are chosen for increasing their output, rather than all the generators in that group. The sensitivity values are obtained from the Generation Shift Sensitivity factors using [22]. The most sensitive generators (MSG) are hence selected for the purpose of rescheduling to reduce the number of control actions to be implemented and to minimize the time and cost involved in the process.

3.3. Methodology for RHCM aided by demand response

In a restructured environment, the power from a generator flows in accordance to contractual arrangements and the generators are restricted to change their output in order to mitigate congestion. Hence, Demand Response (DR) is chosen to aid the process of congestion management that is implemented using GR. This work focuses on determining the schedules of loads participating in demand response and GR of conventional generators to mitigate congestion. Presence of RES like solar and wind farms in the system supply power at the place of their installation, but the nature of power generated is uncertain. So, LHS sampling of density functions of RES helps to forecast power from these sources to determine the schedules of DR and GR. Fig. 1 indicates the flow of simulation process in order to implement RHCM using both GR and DR in presence of RES.

3.4. Algorithm of CDPSO for RHCM

Particle Swarm Optimization (PSO) is used as the tool for optimally deciding the DR strategy and GR for mitigating congestion.

Traditional PSO, one of the evolutionary computing techniques, mimics the swarm intelligence of birds and fishes. The particles are initialized with random values and move through the search space for an optimal solution. In the process, the coordinates of the best solution (fitness) of a particle is saved as Pbest. The best solution among the total swarm is saved as Gbest. The positions of all the particles are updated to reach the best fitness through velocities, so that particles can move in the desired direction. The position and velocity are depicted and updated as follows in a search space.

$$x_p = (x_{p1}, x_{p2}, \cdots, x_{pn}) \tag{23}$$

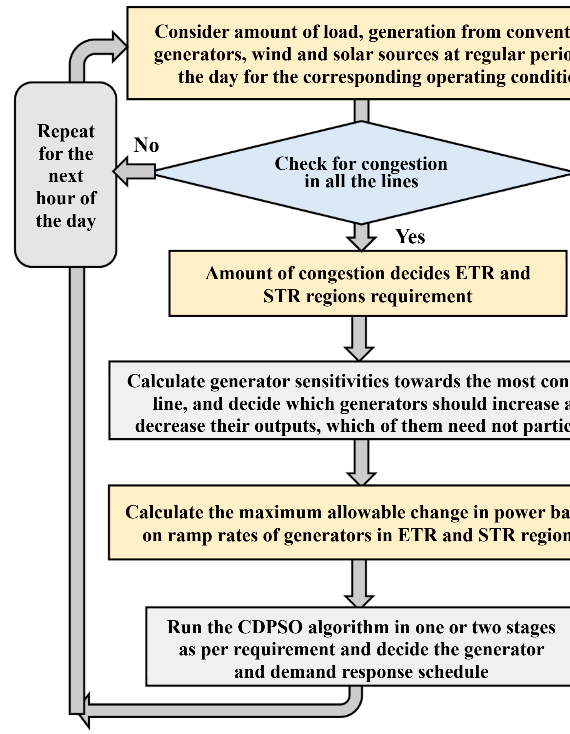


Fig. 1. Flowchart for RHCM aided by DR using CDPSO.

$$v_p = (v_{p1}, v_{p2}, \cdots, v_{pn}) \tag{24}$$

$$v_p^{(iter)} = wv_p^{(iter-1)} + r_1\phi_1\left(x_{pbest}^{(iter-1)} - x_p^{(iter-1)}\right) + r_2\phi_2\left(x_{gbest}^{(iter-1)} - x_p^{(iter-1)}\right) \tag{25}$$

$$x_p^{(iter)} = x_p^{(iter-1)} + v_p^{(iter)} \tag{26}$$

here, w is the inertia weight meant for limiting velocity changes and controls the balance between the global exploration and the local search ability. Global search is enhanced by large value of inertia, while a small inertia weight enhances the local search. Hence, w is considered to be a linearly decreasing value from 0.9 to 0.4 through the iterations. r1 and r2 are the acceleration coefficients for exploration and exploitation search capabilities respectively. ϕ1 and ϕ2 are random positive numbers derived from uniform distribution.

The positions and velocities of particle p are assigned randomly in the beginning denoted by x_p and v_p. These are updated using equations (25) and (26) respectively. As the particles keep moving from one location to another depending on velocities, their values of position and velocity are referred to on time basis, or mathematically in iterations. But it is observed that PSO results in premature convergence. Hence, CDPSO is used for overcome such difficulties. Here, particles and velocities are initialized with chaotic values in place of random numbers. Logistic chaotic function provides best features of searching capability among others and helps to avoid premature local convergence [25]. The position and velocity are initialized and updated as follows for CDPSO.

$$x_p = x_{pmin} + chaos(0,1)\left(x_{pmax} - x_{pmin}\right) \tag{27}$$

$$v_p = v_{pmin} + chaos(0,1)\left(v_{pmax} - v_{pmin}\right) \tag{28}$$

$$v_p^{(iter)} = wv_p^{(iter-1)} + r_1 chaos(0,1)\left(x_{pbest}^{(iter-1)} - x_p^{(iter-1)}\right) + r_2 chaos(0,1)\left(x_{gbest}^{(iter-1)} - x_p^{(iter-1)}\right) \tag{29}$$

Table 1
Pseudo code of the proposed CDPSO algorithm.

```
Initialize particle positions and velocities x, v via eqn. (23,24);
Calculate fitness values of all particles;
  While (t < Maxiter) do
      Compute p_best and G_best
      Calculate velocity vector via eqn. (25)
      Update particle positions via eqn. (26)
      Evaluate the fitness values
          If  fitness_new > fitness_old then
               Spawn new particle
               Update S
        else
               Update swarm cycle
                 If SC = SCmax
                     Delete worst particle
                     Increment n_kill by one
                     Re-initialize SC, Update S
                 end
                 If S < Smin
                     Delete swarm
                     Update Ns
                 end
        end
        If n_kill = 0 and Ns < N_max
               Spawn new swarm
               Update Ns
        end
      Update iteration count
  End
```

$$x_p^{(iter)} = x_p^{(iter-1)} + v_p^{(iter)} \tag{30}$$

Here, chaos (0,1) is the logistic chaotic operator. x_{pmax} and x_{pmin} represent maximum and minimum values of the particle x_p. Incorporating Darwinian principle of natural selection in PSO for finding the fittest candidate is realized by the use of multiple number of swarms and this helps in improving its search capacity to a better extent. CDPSO that combines the chaotic maps to the algorithm helps in improving convergence efficiency.

In CDPSO for every iteration, the new fitness value is checked against the fitness of the previous iteration. If the new fitness is better, a new particle is spawned to indicate swarm is increasing its adaptability by increasing number of particles in the swarm. In case of a bad fitness, Swarm Cycles (SC) are executed. For a count of SC_{max}, starting from zero, if there are particles that are continuously resulting in bad fitness value, the worst particle with least fitness in the swarm will be deleted at the end of SC_{max}. This is the way in which the number of particles in swarm keep varying between S_{min} and S_{max}. If the particle count has reached S_{min}, and still there are particles to be deleted, this results in deletion of the swarm itself, indicating this particular swarm is not adaptable. If no particles of a swarm are deleted in a given iteration, a new swarm can be spawned until the count reaches N_{smax}, indicating multiple swarms can co-exist as long as they are adaptable. The swarm cycle count (SC) is updated to zero once it reaches maximum after the execution of swarm cycle. The pseudo code of the CDPSO algorithm for spawning and deleting particles and swarms is presented in Table 1.

Table 2
Parameters used in CDPSO.

Parameter	Description	Value
S	Population of a swarm (No. of particles)	30
Ns	No. of swarms	4
Nsmin	Min. No. of swarms	2
Nsmax	Min. No. of swarms	6
Maxiter	No. of iterations	100
Smin	Min. population in a swarm	10
Smax	Max. population in a swarm	50
w	Inertia weight	$0.9 < w < 0.4$
r1, r2	Acceleration coefficients	1.2, 0.8
SCmax	Max. Swarm cycles	10

4. Simulation results and discussion

In order to demonstrate the effectiveness of the proposed method, IEEE 39 bus system is chosen as the case study. This system consists of 10 generators, 29 load buses and 46 transmission lines. Of these buses, loads present at 18, 23, 28 and 35 are selected as DR loads. 20% of the load present at each of the DR Loads will be available in response to the congestion clearing procedure. A wind farm of 100 MW installed capacity (20 wind turbines each of 5 MW capacity) is present at bus 14. A solar generation of 100 MW (400,000 solar panels each of 250 W) is present at bus 22. The load present in the system varies throughout the day that follows a considered daily load curve. The power from wind and solar energy are modelled and incorporated on an hourly basis all through the day. The system is analyzed for the effect of the proposed congestion management procedure using the following cases.

Case. ***A***: *Critical contingency condition* (*outage of line connecting buses* 14 *and* 34).

Case. ***B***: 2% *and* 5% *increase in load during peak hour*.

In Case-A, congestion is result of contingency that is simulated and in Case-B, congestion is observed because of sudden increase in loading. Both these cases are further analyzed in the following possible scenarios.

Table 3
Comparison of GR using RHCM and other techniques.

	Results using RED [27]	Results using PSO [24]	Results using FA[20]	Results of proposed RHCM using PSO	Results of proposed RHCM using CPSO	Results of proposed RHCM using TECMPSO	Results of proposed RHCM using CDPSO
ΔG1 (MW)	−99.59	−149.1	−75.34	−222.9	−220.58	−224.87	−217.79
ΔG2 (MW)	98.75	65.6	−33.61	42	130	105	103
ΔG3 (MW)	−159.64	−129.0	−45.45	−50	−50	−45	−50
ΔG4 (MW)	12.34	*	*	*	*	*	*
ΔG5 (MW)	24.69	*	*	*	*	*	*
ΔG6 (MW)	24.69	*	*	*	*	*	*
ΔG7 (MW)	12.34	*	*	*	*	*	*
ΔG8 (MW)	24.69	75.4	18.33	47	0	18	0
ΔG9 (MW)	12.34	52.1	−105.03	20	20	20	0
ΔG10 (MW)	49.38	83.0	250.00	171	122	130	166
Rescheduled Power (MW)	518.45	554.2	527.77	552.86	542.58	542.87	**536.79**
Cost of Rescheduling ($/hr)	6795.5	6093.2	5781.4	6205.2	6114.6	6160.7	**5642.5**

*Not participating (least sensitive generators).

Table 4
Characteristics of Generators.

Generator Bus	Ramp Rate MW/min	Ramp Power in ETR (MW)	Ramp Power in STR (MW)	Sensitivity	Remarks
1	10	50	150	NA	Contributing generator
2	9	45	135	−0.53	High
3	9	45	135	NA	Contributing generator
4	9	0	0	−0.36	Moderate
5	8	0	0	−0.36	Moderate
6	6	0	0	−0.37	Moderate
7	8	40	120	−0.37	Moderate
8	8	40	38	−0.49	High
9	8	0	0	−0.42	High
10	9	45	135	−0.52	High

- **Scenario-I:** Mitigation of congestion using only optimal GR through RHCM technique. This scenario is considered when the DR loads fail to respond / unavailable.
- **Scenario-II:** Mitigation of congestion using optimal schedules of both GR and DR loads through RHCM technique.

In all the above cases and scenarios, CDPSO is used for optimization purpose. The values of parameters used in CDPSO algorithm for case study are listed in Table 2.

In order to analyze the performance of the proposed RHCM using CDPSO, the example of outage of line connecting the buses 14 and 34 in the test system is considered, that results in overflow of line between 15 and 16 buses. RES and DR loads are not considered in this example. This is to enable comparison of the proposed technique with techniques available in literature. The results of the proposed RHCM technique for reducing the overload in line 15–16 is compared with the results of various methods applied as mentioned in Yesuratnam and Thukaram [27], Dutta and Singh [24], Sadhan [20]. The results obtained are also compared with recently proposed efficient methods like Chaotic Particle Swarm Optimization (CPSO) and Twin Extremity Chaotic Map Adaptive Particle Swarm Optimization (TECMPSO) [3] as illustrated in Table 3. CDPSO is utilized to implement RHCM technique in this work and the algorithm is developed in MATPOWER [28]. Observations reveal that the proposed method gives better results in terms of the optimized variable, the total rescheduling cost of GR compared all the listed methods.

The system behaviour is now analyzed using Case-A and Case-B, as mentioned earlier in this section. Table 4 gives the calculated sensitivity

Table 5
Load details of DR Load buses.

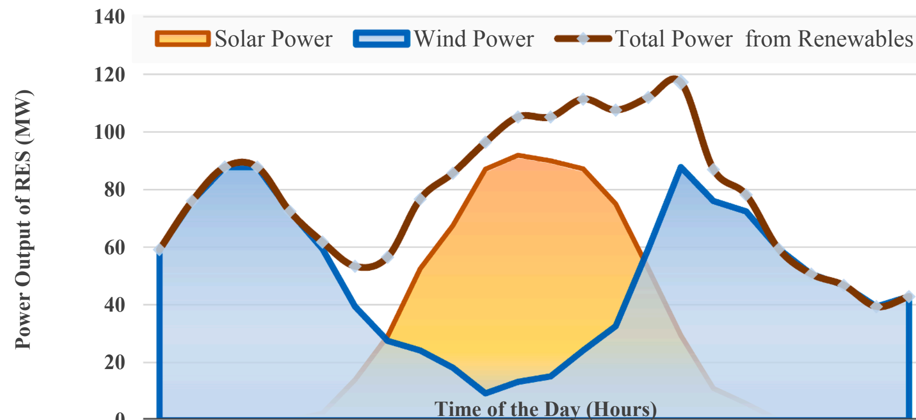
Bus	Power Demand (MW)	Available power for DR Loads (MW)
18	522	104.4
23	247.5	49.5
28	206	41.2
35	320	64

values of all the generators with respect to the congested line (15–16) and generator ramp rates Esfahani et al. [16]. The sensitivities of the contributing generators [22] to the overloaded line are specified to be Not Applicable (NA). The non-contributing generators only with high sensitivity are considered for GR to increase their generation as mentioned in Section 3.2. Ramp powers in ETR and STR regions indicate the limit of rescheduling power for respective generators depending on their ramp rates. Table 5 lists the buses selected [19] for demand response.

Solar and wind powers are modelled using Beta and Rayleigh probability density functions to justify the uncertainty as explained in the previous section. The mean values and standard deviation are provided on an hourly basis, for a 24-hour period. These values are used to develop the database consisting of wind speeds and solar irradiance, based on the designed probability density functions Mazidi et al. [15]. LHS is utilized to generate uniformly distributed samples from the considered probability density functions. The LHS method is highly beneficial in terms of increased sampling efficiency and reduced execution time compared to the traditional Monte Carlo sampling method. 1000 random and uniform samples per hour are generated using LHS to represent the actual wind speed and solar irradiance to have more accurate representation of the actual system parameters. The quantity of wind power and solar power generated for the corresponding 24,000 samples are calculated based on Mazidi et al. [15]. Considering these calculated powers, Fig. 2 represents the availability of RES power throughout the day. Solar power and wind power are together represented in terms of the produced power at different instances in a day.

In a day ahead dispatching market framework, a typical daily load curve of IEEE 39-bus New England system is shown in Fig. 3. The peak load of 6100 MW occurs at 20.00 hours in the system, the morning peak is approximately identical to the load throughout the active working hours of the day with slight variation [19]. This load pattern is considered as one of the inputs for determining the contributions of DR loads while mitigating congestion. The generators are dispatched economically for varying load conditions and there is no congestion observed during normal operating schedules.

In Case-A, outage of line between 14 and 34 buses leads to



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Solar Power	0	0	0	0	0	2.4	14	29	53	68	87	92	90	87	75	53	29	11	5.8	0	0	0	0	0
Wind Power	59	76	88	88	72	59	39	28	24	18	9.3	13	15	24	33	59	88	76	72	59	51	47	39	43
Total Power from Renewables	59	76	88	88	72	62	53	57	77	86	96	105	105	111	108	112	117	87	78	59	51	47	39	43

Fig. 2. Renewable Power availability throughout the day.

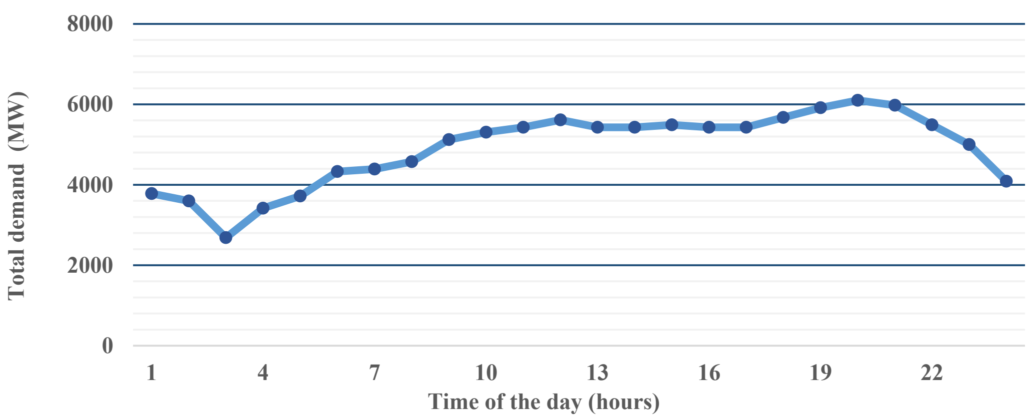


Fig. 3. Typical Daily Load curve.

congestion during some of the highly loaded periods of the day. In Case-B, the increase in loading of the system beyond the value predicted in daily load curve causes congestion in the network. Hence increase of 2% and 5% load during the peak loading hour is considered for analysis in this case. The congestion particulars of both these cases is listed in Table 6. In all the instances of these cases, line between 15 and 16 gets overloaded, and the ACCT values are given based on severity of the overload.

The results of congestion management in Case-A analyzed for peak hour 20.00 in all the possible scenarios are presented in Table 7. The quantity of rescheduling power of conventional generators and the share of DR loads in appropriate scenarios are listed in this table. The effect of single-stage optimization is also included to highlight the advantages of two-stage optimization. It is evident from the results that single-stage optimization results in sub-optimal solution, as the time available for managing congestion is limited by ACCT and ramp rates of the generators. The time of execution of the proposed CDPSO algorithm is also provided to understand the time available for congestion management process.

Table 8 provides a comparison of efficiency of the proposed method with existing method like PSO, for scenarios in Case-A in terms of rescheduling power and costs. Scenario-I reveals that if DR loads fail to contribute as per the contract, only conventional generators are rescheduled. In this scenario, the rescheduling of generators is maximum when compared to the other scenarios. Scenario-II schedules the conventional generators and DR loads optimally such that all the conditions of the system like load, RES availability and extent of congestion are taken into account. In this scenario, it can be observed that the share from DR is optimally utilized to mitigate congestion. The share of the GR is also reduced when compared to Scenario-I, enabling the ISO to allow the rescheduling of conventional generators in rescheduled market within defined limits. It can be observed that the total congestion relieving cost is optimal in Scenario-II compared to Scenario-I. This is a combination of the rescheduling cost of GR and the incentives offered to DR loads. The system losses also have reduced in this scenario compared to others resulting in better performance of the system. The result of the proposed method is further compared with the analytical Interior Point method to demonstrate that the fast and robust analytical methods cannot provide a global optimal solution for a complex problem that has multiple peaks in its search space. Hence, the usage of metaheuristic method like CDPSO is advantageous in terms of better quality of solution.

Similar analysis has been carried out for all the congestion instances in Case-A. Congestion is observed from Hour 9 to Hour 22 in presence of the mentioned contingency. Fig. 4 presents the cost components of congestion relieving cost for all the congestion instances in Scenario- I & II to demonstrate the advantage of reduced GR cost in Scenario-II. It can be observed that in Scenario-I, the cost of relieving congestion is

Table 6
Congestion particulars in Case A and Case B.

Case under Study	Time of the Day (in Hours)	Percentage of Overload (in Line 15–16)	No. of stages required for RHCM	Available Congestion Clearing Time (ACCT)
Case-A	9	18	2	5 min from ETR to STR in stage1 15 min from STR to safe loading in stage 2
	10	16	1	15 min from STR to safe loading in stage 1
	11	17	1	15 min from STR to safe loading in stage 1
	12	28	2	5 min from ETR to STR in stage1 15 min from STR to safe loading in stage 2
	13	27	2	5 min from ETR to STR in stage1 15 min from STR to safe loading in stage 2
	14	26	2	5 min from ETR to STR in stage1 15 min from STR to safe loading in stage 2
	15	23	2	5 min from ETR to STR in stage1 15 min from STR to safe loading in stage 2
	16	16	1	15 min from STR to safe loading in stage 1
	17	14	1	15 min from STR to safe loading in stage 1
	18	16	1	15 min from STR to safe loading in stage 1
	19	32	2	5 min from ETR to STR in stage1 15 min from STR to safe loading in stage 2
	20	29	2	5 min from ETR to STR in stage1 15 min from STR to safe loading in stage 2
	21	28	2	5 min from ETR to STR in stage1 15 min from STR to safe loading in stage 2
	22	23	2	5 min from ETR to STR in stage1 15 min from STR to safe loading in stage 2
Case-B	20 with 2% extra load	12	1	15 min from STR to safe loading in stage 1
	20 with 5% extra load	30	2	5 min from ETR to STR in stage1 15 min from STR to safe loading in stage 2

Table 7
Congestion Management Results of proposed RHCM using CDPSO for Case-A.

	Case-A, Scenario-I (Only optimal GR using RHCM)		*Case-A, Scenario-I* (Only optimal GR using RHCM)	*Case-A, Scenario-II* (optimal GR and DR using RHCM)		*Case-A, Scenario-II* (optimal GR and DR using RHCM)
	Stage-1	Stage-2	*Only one stage*	Stage-1	Stage-2	*Only one stage*
ΔG1 (MW)	−63.1	−142.3	−71.9	−72.9	−50.1	−240.9
ΔG2 (MW)	50.0	87.0	33	0.0	50.0	48
ΔG3 (MW)	−45.0	−44.0	−45	−45.0	−135.0	−43
ΔG4 (MW)*	–	–	0	–	–	0
ΔG5 (MW)*	–	–	0	–	–	0
ΔG6 (MW)*	–	–	0	–	–	0
ΔG7 (MW)*	–	–	0	–	–	0
ΔG8 (MW)	25.0	18.0	40	0.0	0.0	19
ΔG9 (MW)	0.0	0.0	0	0.0	0.0	0
ΔG10 (MW)	33.0	82.0	45	0.0	135.0	16
ΔL18 (MW)	0.0	0.0	0	104.0	0.0	100
ΔL23 (MW)	0.0	0.0	0	0.0	0.0	0
ΔL28 (MW)	0.0	0.0	0	0.0	0.0	39
ΔL35 (MW)	0.0	0.0	0	12.0	0.0	62
Time of execution of CDPSO (seconds)	14.15	14.85	9.7	14.26	14.97	9.2
Reschedule of Conventional Generation (MW)	589.5		234.9	488.1		366.9
Load Reduction by DR Loads (MW)	0		0	116.0		201
Total cost of relieving congestion ($/hr)	6147.3		3120.6	6808.1		6971.9
Flow in congested line after Congestion Management	No overload		**17% overload**	No overload		**3% overload**
System Loss after Congestion Management (MW)	52.7		53.3	49.7		52.2

* Not Participating (Least sensitive generators).

Table 8
Comparison Results of Case-A Scenarios.

	Scenario-I using PSO	Scenario-I using CDPSO	Scenario-II using PSO	Scenario-II using CDPSO	Scenario-II using Interior Point Method
System Loss after Congestion Management (MW)	54.8	**52.7**	49.3	**49.7**	52.7
Reschedule of Conventional Generation (MW)	623.4	589.5	489.5	488.1	507.1
Rescheduling Cost ($/hr)	6747.1	6147.3	5225.1	5133.6	5769.1
Load Reduction by DR Loads (MW)	0	0	115.0	116.0	94
Incentives for DR Loads($/hr)	0	0	1668.0	1674.4	1530
Total power rescheduled (MW)	623.4	589.5	604.5	604.1	601.1
Total cost of relieving congestion ($/hr)	6747.1	**6147.3**	6893.1	**6808.1**	7299.1
Flow in congested line before Congestion Management	129% (ETR)				
System Loss before Congestion Management	52.2 MW				

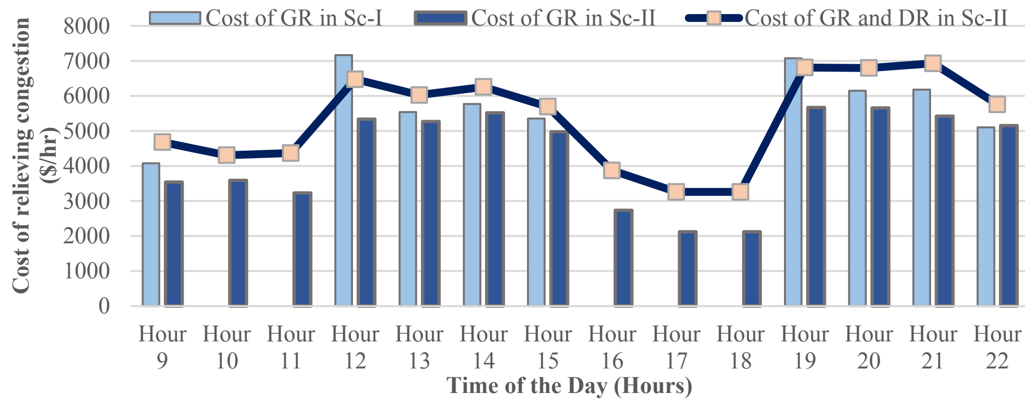


Fig. 4. Comparison of scenarios for Case-A.

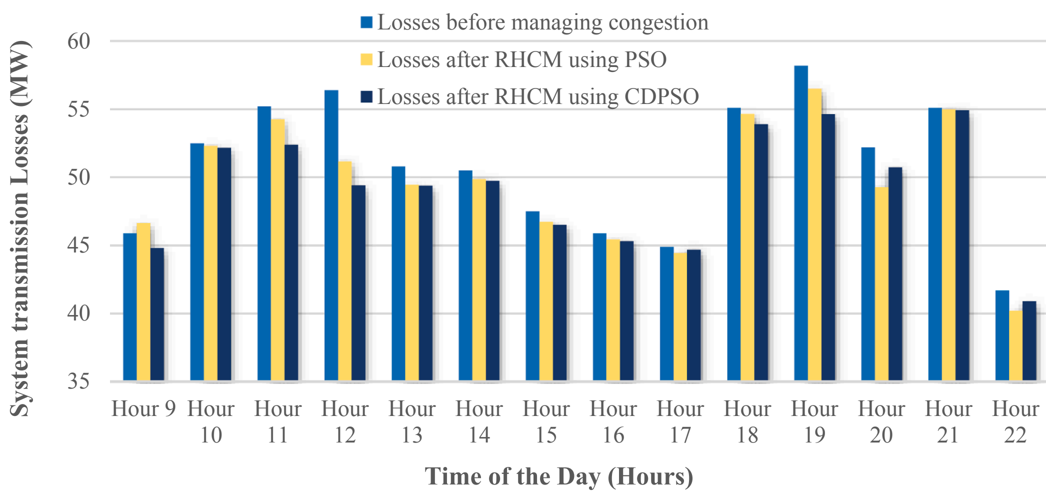


Fig. 5. Comparison of transmission losses using PSO and CDPSO.

Table 9
Congestion Management Results of proposed RHCM using CDPSO for Case-B.

	102% Loading at Hour 20 *Case-B, Scenario - I* (Only optimal GR using RHCM)	*Case-B, Scenario-II* (optimal GR and DR using RHCM)	105% Loading at Hour 20 *Case-B, Scenario-I* (Only optimal GR using RHCM)		*Case-B, Scenario-II* (optimal GR and DR using RHCM)	
			Stage-1	Stage-2	Stage-1	Stage-2
ΔG1 (MW)	−84.7	−92.1	−89.2	−92.4	−96.8	−90.8
ΔG2 (MW)	50.0	0.0	50.0	73.0	0.0	59.0
ΔG3 (MW)	−45.0	−45.0	−45.0	−135.0	−45.0	−123.0
ΔG4 (MW)*	–	–	–	–	–	–
ΔG5 (MW)*	–	–	–	–	–	–
ΔG6 (MW)*	–	–	–	–	–	–
ΔG7 (MW)*	–	–	–	–	–	–
ΔG8 (MW)	35.0	13.0	39.0	20.0	37.0	20.0
ΔG9 (MW)	0.0	0.0	0.0	0.0	0.0	0.0
ΔG10 (MW)	45.0	19.0	45.0	135.0	0.0	135.0
ΔL18 (MW)	0.0	104.0	0.0	0.0	104.0	0.0
ΔL23 (MW)	0.0	0.0	0.0	0.0	0.0	0.0
ΔL28 (MW)	0.0	0.0	0.0	0.0	0.0	0.0
ΔL35 (MW)	0.0	0.0	0.0	0.0	0.0	0.0
Reschedule of Conventional Generation (MW)	259.7	169.1	723.6		606.6	
Load Reduction by DR LOADS(MW)	0	104.0	0		104.0	

* Not Participating (Least sensitive generators)

Table 10
Comparison Results of Case-B Scenarios for 2% sudden increase of load.

	102% Loading at Hour 20 Scenario-I using PSO	Scenario-I using CDPSO	Scenario-II using PSO	Scenario-II using CDPSO
System Loss after Congestion Management (MW)	50.3	**49.7**	49.1	**48.3**
Reschedule of Conventional Generation (MW)	261.1	**259.7**	170.3	**169.1**
Rescheduling Cost ($/hr)	3749.7	**3334.6**	2417.6	**2309.2**
Load Reduction by DR Loads (MW)	0	**0**	104.0	**104.0**
Incentives for DR Loads ($/hr)	0	**0**	1138.4	**1138.4**
Total power rescheduled (MW)	261.1	**259.7**	274.3	**273.1**
Total cost of relieving congestion ($/hr)	3749.7	**3334.6**	3555.6	**3447.6**
Flow in congested line before Congestion Management	112% (STR)			
System Loss before Congestion Management	49.37			

Table 11
Comparison Results of Case-B Scenarios for 5% sudden increase of load.

	105% Loading at Hour 20 Scenario-I using PSO	Scenario-I using CDPSO	Scenario-II using PSO	Scenario-II using CDPSO
System Loss after Congestion Management (MW)	49.6	**50.4**	48.2	**48.9**
Reschedule of Conventional Generation (MW)	700.3	**723.6**	596.4	**606.6**
Rescheduling Cost ($/hr)	7455.9	**7246.2**	6132.4	**6211.8**
Load Reduction by DR Loads (MW)	0	**0**	123.0	**104.0**
Incentives for DR Loads($/hr)	0	**0**	1716.2	**1138.4**
Total power rescheduled (MW)	700.3	**723.6**	719.4	**710.6**
Total cost of relieving congestion ($/hr)	7455.9	**7246.2**	7848.5	**7350.2**
Flow in congested line before Congestion Management	130% (ETR)			
System Loss before Congestion Management	49.97			

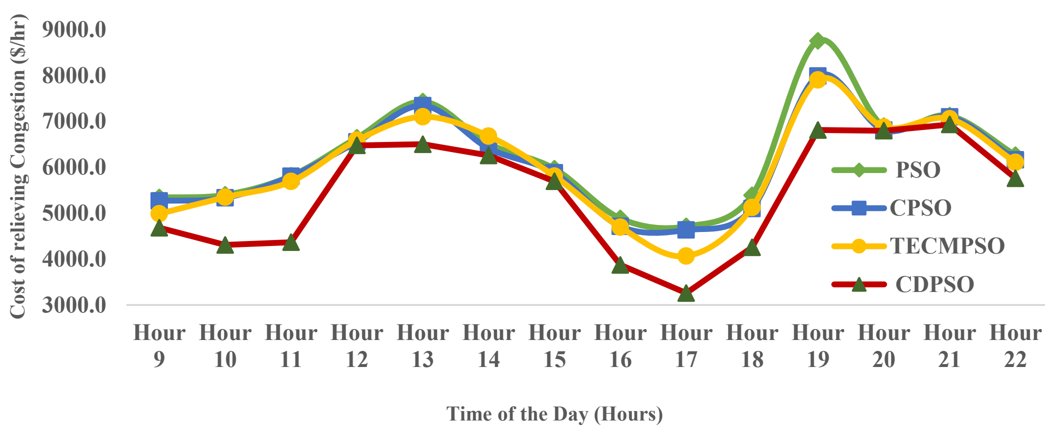


Fig. 6. Performance of various optimization techniques for Case-A.

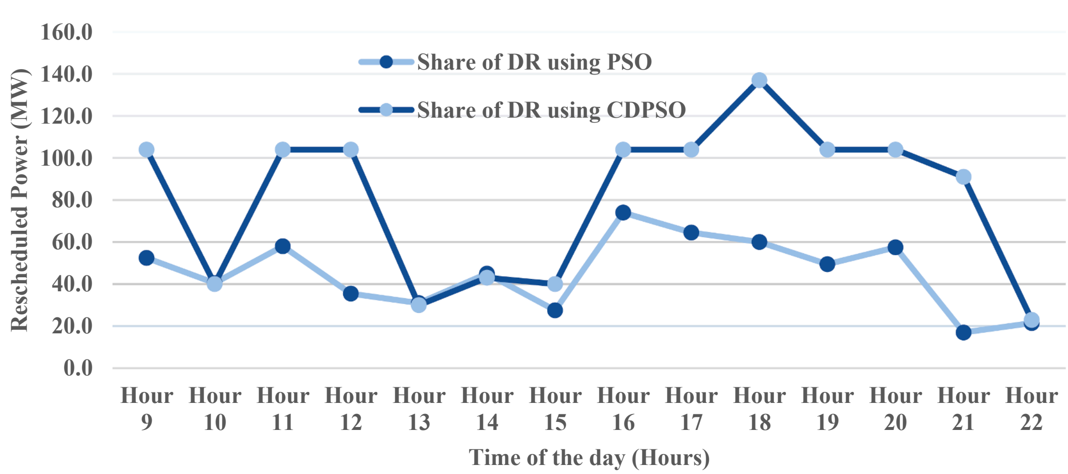


Fig. 7. Share of DR in PSO and CDPSO.

minimum, but all of the rescheduling is done using GR only. This is the scenario where generators may not be allowed to reschedule beyond certain limits. To ease this situation, DR is introduced, but DR when optimally scheduled along with GR in Scenario-II gives better results in terms of congestion relieving cost as well as system losses. For Hours 10, 11, 16, 17 and 18, it can be seen that share of GR is zero in Scenario-I, indicating that GR alone cannot mitigate the congestion completely. It is even in such cases, DR becomes inevitable.

The comparison of losses in the system are shown in Fig. 5, indicating the values before and after managing the congestion, using different optimization techniques, PSO and CDPSO. It is clearly concluded from this figure that introduction of DR not only reduces the burden of conventional generators, but also improves the system performance by reduction in losses when compared to other scenarios and other algorithms.

The system is also analyzed for increase of load during peak hour in Case-B. Table 9 provides the results of congestion management for Case-B. It can be observed that the management of congestion is implemented efficiently using Scenario-II. If the amount of congestion corresponds to STR, one stage is required and two stages are required if congestion amount falls in ETR respectively. The cost comparison of various scenarios reveal that Scenario-II gives an optimal mix of GR and DR loads. These comparisons are also presented with respect to PSO and CDPSO in Table 10 and Table 11 for 2% and 5% increase in loading respectively. It is clear from these statistics that CDPSO performs better than PSO, and is better in Scenario-II compared to others.

Fig. 6 gives the comparison of various optimization techniques in terms of the final objective, the congestion relieving cost. It is clear from the comparison that CDPSO fares fairly well for all the loading conditions. Fig. 7 depicts the participation of DR loads at various instants of loads. It can be observed that for more optimal relieving of congestion the share of DR participation is more. That is evident from PSO and CDPSO comparison of DR share.

5. Conclusion

A new real-time Hierarchical Congestion Management (RHCM) method using Chaotic Darwinian Particle Swarm Optimization (CDPSO) has been proposed in this work that is aided by demand response mechanism in the presence of Renewable energy sources (RES). HCM is achieved by rescheduling of the most sensitive generators in multiple stages and optimal scheduling of Demand Responsive Loads (DR Loads). Furthermore, the modelling of RES that vary according to the time of the day and its incorporation has realized the mitigation of congestion in real time environment. All the market participants can make use of the proposed two-stage RHCM in providing congestion management as an ancillary service in a deregulated environment. Different cases of congestion and various scenarios of exploring the performance of RHCM technique using CDPSO has revealed through numerical examples that the optimal mix of Generation Rescheduling (GR) and Demand Responsive Loads (DR Loads) using RHCM is feasible and cost-effective technique of mitigating congestion in a deregulated environment. CDPSO performs better than other optimization methods without converging in local optima. The proposed technique proves to improve the security and reliability of the system when GR alone fails to mitigate the congestion for certain loading conditions. The proposed two-stage RHCM method provides feasible solution to ISO to mitigate congestion in terms of reduced rescheduling power of conventional generators and minimum cost of relieving congestion.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

6. Data availability

Solar Irradiation and Wind speed Data:

[15]. "Integrated Scheduling of Renewable Generation and Demand Response Programs in a Microgrid." *Energy Conversion and Management,* 86: 1118–1127. https://doi.org/10.1016/j.enconman.2014.06.078.

Generator cost data of case study:

[19]. "An Integrated OPF Dispatching Model with Wind Power and Demand Response for Day-Ahead Markets." *International Journal of Electrical and Computer Engineering (IJECE)* 9 (4). http://ijece.iaescore.com/index.php/IJECE/article/view/15173.

Declaration of Competing 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.

References

[1] Albadi MH, El-Saadany EF. A Summary of Demand Response in Electricity Markets. Electr Power Syst Res 2008;78:1989–96.
[2] Kumar Ashwani, Srivastava SC, Singh SN. A Zonal Congestion Management Approach Using Real and Reactive Power Rescheduling. IEEE Trans Power Syst 2004;19(1).
[3] Batra Indu, Ghosh Smarajit. A Novel Approach of Congestion Management in Deregulated Power System Using an Advanced and Intelligently Trained Twin Extremity Chaotic Map Adaptive Particle Swarm Optimization Algorithm. Arabian Journal for Science and Engineering 2018.
[4] Singh Brijesh, Mahanty R, Singh SP. Centralized And Decentralized Optimal Decision Support For Congestion Management. Electrical Power and Energy Systems 2015;64:250–9.
[5] Chintam, Jagadeeswar Reddy, and Mary Daniel. 2018. "Real-Power Rescheduling of Generators for Congestion Management Using a Novel Satin Bowerbird Optimization Algorithm." energies.
[6] Dehnavi E, Abdi H. Determining Optimal Buses for Implementing Demand Response as an Effective Congestion Management Method. IEEE Trans Power Syst 2017;32(2):1537–44.
[7] Gunda Jagadeesh, Harrison Gareth P, Djokic Sasa Z. Remedial Actions for Security Constraint Management of Overstressed Power Systems. Transactions on Power Systems 2018;33(5):5183–93.
[8] Jiasi Wu, Zhang Buhan, Jiang Yazhou. Optimal Day-Ahead Demand Response Contract For Congestion Management in the Deregulated Power Market Considering Wind Power. IET Gener Transm Distrib 2018;12(4).
[9] Kashyap Mohan, Kansal Satish. Hybrid approach for congestion management using optimal placement of distributed generator. Int J Ambient Energy 2018:132–42.
[10] Kumar A, Sekhar C. Congestion Management with FACTS Devices in Deregulated Electricity Markets Ensuring Loadability Limit. Int J Electr Power Energy Syst 2013;46:258–73.
[11] Kumar A, Srivastava S, Singh SN. Congestion Management in Competitive Power Market: A Bibliographical Survey. Electr Power Syst Res 2005;76(1):153–64.
[12] Govardhan Manisha, Roy Ranjit. Generation Scheduling in Smart Grid Environment using Global Best Artificial Bee Colony Algorithm. Electrical Power and Energy Systems 2015;64:260–74.
[13] Di Martino Ferdinando, Sessab Salvatore. PSO image thresholding on images compressed via fuzzy transforms. Inf Sci 2020:308–24.
[14] Masoud Esmaili, NimaAmjady, and Heidar Ali Shayanfara. 2011. "Multi-Objective Congestion Management by Modified Augmented ε-Constraint Method." Applied Energy 88 (3).
[15] Mazidi M, Zakariazadeh A, Jadid S, Siano P. Integrated Scheduling of Renewable Generation and Demand Response Programs in a Microgrid. Energy Convers Manage 2014;86:1118–27.
[16] Esfahani Mohammad Mahmoudian, Sheikh Ahmed, Mohammed Osama. Adaptive Real-Time Congestion Management in Smart Power Systems using A Real-Time Hybrid Optimization Algorithm. Electr Power Syst Res 2017;150:118–28.
[17] Narain Aishvarya, Srivastava SK, Singh SN. Congestion management approaches in restructured power system: Key issues and challenges. The Electricity J 2020.
[18] Pillay A, Karthikeyan SP, Kothari D. Congestion Management in Power Systems - A Review. Int J Electr Power Energy Syst 2015;70:83–90.
[19] Moreno Ricardo, Obando Johan, Gonzalez Gabriel. An Integrated OPF Dispatching Model with Wind Power and Demand Response for Day-Ahead Markets. Int J Electrical Comput Eng (IJECE) 2019;9(4).
[20] Gope Sadhan, Goswami Arup Kumar, Tiwari Prashant Kumar, Deb Subhasish. Rescheduling of Real Power for Congestion Management with Integration of Pumped Storage Hydro Unit Using Firefly Algorithm. Electrical Power and Energy Systems 2016;83:434–42.

[21] Salkuti, Surender Reddy, and Seong–Cheol Kim. 2019. "Congestion Management Using Multi–Objective Glowworm Swarm Optimization Algorithm." Journal of Electrical Engineering & Technology 1565-1575.
[22] Srilatha N, Yesuratnam G, and Shiva Deepthi M. 2014. "RBF Neural Network Approach for Security Assessment and Enhancement." IEEE Transmission & Distribution Conference & Exposition. Chicago.
[23] Gumpu Srinivasulu, Pamulaparthy Balakrishna, Sharma Ankush. Review of Congestion Management Methods from Conventional to Smart Grid Scenario. Int J Emerg Electr Power Syst 2019;20(3).
[24] Dutta Sudipta, Singh SP. Optimal Rescheduling of Generators for Congestion Management Based on Particle Swarm Optimization. IEEE Trans Power Syst 2008; 23(4).
[25] Suresh Shilpa, Lal Shyam. Multilevel Thresholding based on Chaotic Darwinian Particle Swarm Optimization for Segmentation of Satellite Images. Appl Soft Comput 2017.
[26] Prajapati Vijaykumar K, Mahajan Vasundhara. Demand Response Based Congestion Management of Power System with Uncertain Renewable Resources. Int J Ambient Energy 2019.
[27] Yesuratnam G, Thukaram D. Congestion Management in Open Access Based on Relative Electrical Distances Using Voltage Stability Criteria. Electr Power Syst Res 2007;77:1608–18.
[28] Zimmerman RD, Murillo-Sanchez CE, Thomas RJ. MATPOWER:steady-state operations, planning, and analysis tools for power systemsresearch and education. IEEE Transactions on Power Systems 2011.