Congestion Management Using an Optimized Deep Convolution Neural Network in Deregulated Environment

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***Abstract*.** The technical issue of congestion, which is predominantly found in deregulated power systems, is caused by the failure of transmission networks to satisfy load power demands. This failure is primarily caused due to an increase in loads or loss of transmission lines or generators in modern restructured power networks. This work introduces a CM approach using Deep Convolution Neural Network (DCNN) for minimizing congestion and supporting Independent System Operators (ISOs). The purpose of the work is to generate enhanced prediction outputs for congestion management with reduced error values. These objectives were achieved through the actual power rescheduling of generators. The proposed work adopts DCNN which is optimized using an Improved Lion Algorithm (LA) and aids in providing significant outcomes for congestion management with reduced error. By implementing customized IEEE 57-bus, IEEE 30-bus, and IEEE 118-bus test systems, the suggested approach has been successfully verified for its performance on test systems of varied sizes. This analysis incorporates restrictions such as line loads, bus voltage influence, generator, line limits, etc. The most important results for the test system indicating convergence profile, congestion cost, and change in real-power and voltage magnitude are obtained by the simulation in MATLAB, and on the basis of the obtained simulation outcomes, it is evident that the proposed Improved Lion Algorithm optimized Deep Convolution Neural Network displays phenomenal computation performance in minimizing congestion losses at minimum congestion costs. When compared to several contemporary optimization techniques, the suggested technique performs better in terms of congestion cost and losses by generating improved prediction outputs with reduced errors.
Keywords: congestion management, DCNN, ISO, improved Lion Algorithm, deregulated power.

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Controlul congestiei folosind o rețea neuronală de convoluție profundă optimizată într-un mediu dereglementat

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***Rezumat*.** Problema tehnică a congestiei, care se găsește predominant în sistemele de energie dereglementate, este cauzată de eșecul rețelelor de transport de a satisface cerințele de putere a sarcinii. Această defecțiune este cauzată în primul rând din cauza creșterii sarcinilor sau a pierderii liniilor de transport sau generatoarelor din rețelele de energie restructurate moderne. Scopul lucrării este de a genera rezultate de predicție îmbunătățite pentru gestionarea congestiei cu valori reduse de eroare. Aceste obiective au fost atinse prin reprogramarea efectivă a puterii generatoarelor. Lucrarea propusă adoptă DCNN, care este optimizat folosind un algoritm Lion (LA) îmbunătățit și ajută la furnizarea de rezultate semnificative pentru gestionarea congestiei cu erori reduse. Prin implementarea sistemelor de testare personalizate IEEE 57-bus, IEEE 30-bus și IEEE 118-bus, abordarea sugerată a fost verificată cu succes pentru performanța sa pe sisteme de testare de dimensiuni variate. Această analiză încorporează restricții, cum ar fi sarcinile de linie, influența tensiunii magistralei, generatorul, limitele de linie etc. Cele mai importante rezultate pentru sistemul de testare care indică profilul de convergență, costul de congestie și modificarea puterii reale și a mărimii tensiunii sunt obținute prin simulare în MATLAB și pe baza rezultatelor simulării obținute, este evident că Rețeaua neuronală de convoluție profundă optimizată cu algoritmul îmbunătățit Lion afișează performanțe de calcul fenomenale în reducerea la minimum a pierderilor de congestie la costuri minime de congestie. În comparație cu mai multe tehnici de optimizare contemporane, tehnica sugerată are performanțe mai bune în ceea ce privește costul de congestie și pierderile prin generarea de rezultate de predicție îmbunătățite cu erori reduse.
***Cuvinte-cheie*:** controlul congestiei, algoritm leu îmbunătățit, putere dereglementată.

Управление перегрузками с использованием оптимизированной нейронной сети глубокой свертки в дерегулируемой среде

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Аннотация. Техническая проблема перегрузки, которая в основном встречается в нерегулируемых энергосистемах, вызвана неспособностью передающих сетей удовлетворить потребности в мощности нагрузки. Этот сбой в первую очередь вызван увеличением нагрузки или потерей линий электропередачи или генераторов в современных реструктурированных электрических сетях. Таким образом, управление перегрузками (УП) считается незаменимым аспектом в нынешнюю эпоху дерегулирования, поскольку оно обеспечивает бесперебойную работу системы передачи. В этой работе представлен подход УП с использованием нейронной сети глубокой свертки (DCNN) для минимизации перегрузки и поддержки независимых системных операторов (НСО). Цель работы состоит в том, чтобы генерировать расширенные выходные данные прогнозирования для управления перегрузками с уменьшенными значениями ошибок. Эти цели были достигнуты за счет фактического перераспределения мощности генераторов. Предлагаемая работа использует DCNN, который оптимизирован с использованием улучшенного львиного алгоритма (УЛА) и помогает обеспечить значительные результаты для управления перегрузкой с уменьшенной ошибкой. Путем реализации настраиваемых систем тестирования с шиной IEEE 57, IEEE 30 и IEEE 118 предложенный подход был успешно проверен на эффективность на тестовых системах различных размеров. Этот анализ включает в себя такие ограничения, как нагрузка на линию, влияние напряжения на шине, генератор, ограничения на линию и т. д. Наиболее важные результаты для тестовой системы, указывающие на профиль конвергенции, стоимость перегрузки и изменение реальной мощности и величины напряжения, получены путем моделирования в MATLAB, и на основе полученных результатов моделирования становится очевидным, что предложенная улучшенная нейронная сеть глубокой свертки, оптимизированная с помощью УЛА, демонстрирует феноменальную производительность вычислений при минимальных потерях из-за перегрузки при минимальных затратах на перегрузку. По сравнению с несколькими современными методами оптимизации предлагаемый метод работает лучше с точки зрения стоимости перегрузки и потерь за счет создания улучшенных выходных данных прогнозирования с меньшим количеством ошибок.

***Ключевые слова*: управление перегрузками, улучшенный львиный алгоритм, нерегулируемая мощность.

INTRODUCTION

Electric energy is the driving force behind the functioning of the modern world and its rise in prominence is mainly because of industrialization, urbanization and enhanced life style. Consequently, the overdependence and ever-increasing demand for electric energy has led to several rapid advancements in the power sector. Previously, vertically integrated utilities were used to operate the power grids, and the government mostly controls this regulated power system. Thus, both incurred expenditure and the resultant revenue of the power system are both handled by the government [1-3]. However, the excessive demand for power in recent times effectuated the deregulation and privatisation of electric power system. This in turn has contributed to the restructuring of the power system with the inclusion of numerous smaller generation plants, comprising of sustainable power sources to meet the booming number of loads [4]. As a result of excessive power requirements, transmission systems are operating beyond their thermal and stability limits, placing strain on the current power system architecture. Moreover, in a deregulated environment, the DISCOs, GENCOs and TRANCOs are not controlled by a common institution, instead different organizations manage these companies and the establishment of coordination between these companies is left to an ISO. The transactions made by the DISCOs and GENCOs are unpredictable, abrupt and ahead of time, resulting in transmission line congestion [5, 6]. The issue of transmission line congestion mainly occurs due to rise in load demand, generation outages and equipment failure. The vital task of relieving this congestion and ensuring a safe and secured working of power system, is entrusted to ISO. The major techniques followed by ISO to relieve congestion are cost free and not cost-free methods [7]. The former involves Flexible AC Transmission (FACTS) devices, transformer taps, network reconfiguration, phase shifters or congestion lines out-ageing. The latter entails approach like curtailment of loads, generation prioritization and generation rescheduling. In certain situations, ISO informs the consumers about the specific line congestion and facilitate load adjustment inside the limits of system constraints. In severe cases, the CM is carried out by physically restricting the transaction, irrespective of the inconvenience to consumers [8, 9]. FACTS devices are regarded as technology that, lowers transmission congestion and improves grid infrastructure use. The usage of FACTS controllers has some drawbacks, including challenges with placement, size, cost, and modelling that are ideal. In order to manage congestion in reorganized electricity markets, this article discusses the application and ideal position of the FACTS device series [10, 11]. Through the creation of an algorithm to improve working measure of contingency analysis as well as positioning and control of Thyristor-Controlled Series Compensator (TCSC) [12], and operation of TCSC for transmission line optimization and congestion is explored. The best location for TCSC [13] in terms of increasing power transmission efficiency, limiting steady-state instability, and preserving power system voltage stability. TCSC is used in power systems to enhance transient response and congestion control. The explanation of the objective models for minimising expense and load shedding involved optimising welfare of society, limiting load shedding, as well as increasing load served. Two generators and bus sensitivity factors were presented along with Particle Swarm Optimization (PSO) technique. However, PSO exhibits demerits including sensitivity to parameters, lack of diversity and premature convergence leading to inaccurate outputs [14]. In [15], Genetic algorithm is engaged for finding best generation schedule for CM in an unregulated power system but shows challenges in the improvement of congestion management performance. The Grey Wolf Algorithm (GWO) is employed for congestion management due to its ability of enhanced convergence speed yet gets trapped on local optimum value [16]. Firefly Algorithm (FA) is another metaheuristic algorithm employed for handling congestion management but exhibits inability in handling optimization problems with constraints [17]. The line overload problem during congestion management is eliminated in power system by grasshopper algorithm (GA), however, the inappropriate selection of parameters may lead to premature convergence of the algorithm [18]. The differential algorithm is adopted the hourly congestion management but demands increased consumption of resources leading to resource shortage [19]. Bat algorithm is also deployed for the congestion management in power systems but faces issues related to computational complexity [20]. Several studies introduce deep neural networks together with metaheuristic algorithms for congestion control in response to these problems. In [21], glow worm swarm optimization is adopted for the optimization of DCNN which in turn adjusts the weight initialization. Anyway, with the increase in data size, slight fluctuations occur in memory usage of the algorithm.

In [22], atrous convolution algorithm is used for the optimizing of DCNN but the accuracy results attained are not high. In [23] swarm intelligent based algorithms are adopted for the optimizing of DCNN. However, these algorithms face issues related to convergence and accuracy. Considering these shortcomings, the novelty of the work engages a DCNN network with Improved Lion Optimization, which is a recent optimization strategy showing remarkable performance towards congestion management.

Contributions of the study are,

- An Improved LA optimized DCNN is proposed for relieving congestion in a deregulated environment.
- The presented CM approach is tested for its effectiveness in IEEE 118-bus, 57-bus, and 30-bus systems.
- The proposed methodology is effective in minimizing congestion cost and losses.

PROPOSED SYSTEM MODELLING.

A. Problem Formulation

The primary goal is to lower the systems z cost, which is taken into account.

$$\text{Minimize } \sum_{k=1}^{N_k} C_k^n \left(\Delta P_k^n\right) \Delta P_k^n \quad (1)$$

From above equation, rescheduling power cost in accordance with price bids at interval n is represented as c_k^n ,as incremental adjustment of generators active power is given by ΔP_k^n for interval n . N_K represent the number of buses used and the generation of maximum and minimum limits is denoted as $P_k^{\max}$ and $P_k^{\min}$ Subject to the limitations are listed as follows

$$P_{gj} - P_{dj} = \sum_{k=1}^{n} |V_J||V_K||Y_{jk}| \cos(\partial_i - \partial_k - \theta_{jk}) \quad (2)$$

$$Q_{gj} - Q_{dj} = \sum_{k=1}^{n} V_J ||V_K||Y_{jk}| \cos\left(\delta_i - \delta_k - \theta_{jk}\right), \quad j = 1, 2, ..., n \quad (3)$$

$$P_{gk}^{\min} \le P_{gk} \le P_{gk}^{\max} \quad (4)$$

$$Q_{gk}^{\min} \le Q_{gk} \le Q_{gk}^{\max} k = 1,2,..., N_g \quad (5)$$

Here, V_j, V_k denotes the voltage for j^{th} bus and k^{th} bus respectively, Y denotes the shunt admittance, θ_{jk} represents the admittance angle between j^{th} bus and k^{th} bus, $\delta_i.\delta_k$ denote bus voltage angle of the i^{th} bus and k^{th} bus, $P_{gj,}Q_{gj}$ denote the real and reactive powers for j bus while, $P_{dj,}Q_{dj}$ indicate a real and reactive load powers for j bus, N_g denote the number of generators, $P_{gk}^{\min}, Q_{gk}^{\min}$ denote the minimum value of real and reactive power of k^{th} bus, $P_{gk}^{\max}, Q_{gk}^{\max}$ represent the maximum of real and reactive power of k^{th} bus. The following additional limits are taken into account once the bus is linked to pumped storage units for lowering the system's congestion costs:

$$e^n = e^{initial} n = 0, e^n = e^{final} n = 24 \quad (6)$$

$$e^{n+1} = e^n + t(\eta p) \quad (7)$$

$$P_{Ps}^{\min} \le p_{ps}^n \le P_{ps}^{\max} \quad (8)$$

$$P_{Hs}^{\min} \le P_{Hs}^n \le P_{Hs}^{\max} \quad (9)$$

$$e^l \le e^n \le e^u \quad (10)$$

Here, $P_{Ps}^{\min}, P_{Hs}^{\min}$ and $P_{Ps}^{\max}, P_{Hs}^{\max}$ represent the minimum and maximum values of power.

B. ***Bus Sensitivity Factor (BSF)***

BSF is defined as ratio of incremental changes occurring in m^{th} power of the bus to an incremental change in real power flowing through bus "i" which is linked to buses "j" and "$k,$" as shown below. On the basis of greatest negative sensitive indexes, BSF offers the best location for pumped hydro storage unit deployment.

$$BSF_m^i = \frac{\Delta p_{jk}}{\Delta p_m} \quad (11)$$

From the expression above, the degree to which the amount of real power changes in accordance with amount of real power injected at bus m in a transmission line is represented by BSF_m^i . ΔP_{jk} indicates the incremental changes in real power that flows in bus i which is connected between j and k buses, Δ_{pm} represents an incremental change in m^{th} power of the bus.

Equation (12) is used to derive BSF, as shown below

$$\Delta P_{jk} = \frac{\partial P_{jk}}{\partial \delta_i}\Delta\delta_j + \frac{\partial P_{jk}}{\partial \delta_k}\Delta\delta_k + \frac{\partial P_{jk}}{\partial V_i}\Delta V_j + \frac{\partial P_{jk}}{\partial V_k}\Delta V_k$$

(12) $\Delta P_{jk} = a_{jk}\Delta\delta_j + b_{jk}\Delta\delta_k + c_{jk}\Delta V_j + d_{jk}\Delta V_k$

(13) $\Delta P_{jk} = a_{jk}\Delta\delta_j + b_{jk}\Delta\delta_k + c_{jk}\Delta V_j + d_{jk}\Delta V_k$ (14)

From Equation the expression for a_{jk}, b_{jk} and c_{jk} is given by,

$$a_{jk} = V_j V_k V_{jk} \sin(\theta_{jk} + \delta_k - \delta_j) \quad (15)$$

$$b_{jk} = -V_j V_k V_{jk} \sin(\theta_{jk} + \delta_k - \delta_j) \quad (16)$$

$$c_{jk} = -V_k Y_{jk} \cos(\theta_{jk} + \delta_k - \delta_j) - 2V_k Y_{jk} \cos\theta_{jk} \quad (17)$$

$$d_{jk} = V_j Y_{jk} \cos(\theta_{jk} + \delta_k - \delta_j) \quad (18)$$

Here, V_j, V_K denotes the voltage across the j and k buses, Y_{jk} represents equation (19) provides the Jacobian Matrix using Newton-Raphson (NR) technique.

$$\begin{pmatrix} \Delta P \\ \Delta Q \end{pmatrix} = [J]\begin{pmatrix} \Delta\delta \\ \Delta V \end{pmatrix} = \begin{pmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{pmatrix}\begin{pmatrix} \Delta\delta \\ \Delta V \end{pmatrix} \quad (19)$$

Here,

$$\Delta\delta = [J_{11}]^{-1}[\Delta P] = [M][\Delta P] \quad (20)$$

$$\Delta\delta_j = \sum_{l=1}^{n} m_{jl}\Delta P_l j = 1,2,...,n, j \ne s \quad (21)$$

Hence, the expression of BSF becomes

$$BSF_m^i = a_{jk} m_{jl} + b_{jk} m_{jl} \quad (22)$$

The Improved LA-optimized DCNN is employed for congestion management in this work and the presented approach is shown in Figure 1.

C. ***Optimized DCNN with Improved Lion Algorithm (LA) for classification***

In this work, DCNN is adopted in which the automatic optimization of hyperparameters is carried out by improved LA. In Figure 2, the general flow diagram of DCNN with optimization is indicated. Here, back propagation is used for the learning process. The obtained prediction output from the fully connected layer is compared with an actual value and subsequently, the loss function calculates the error value. The Stochastic Gradient Update (SGD) function is used in the training procedure of DCNN. Consider, the n samples of the training dataset and assume $f_i(x)$ as the loss function in which i denotes the index and x denotes the parameter vector. The objective function is given by,

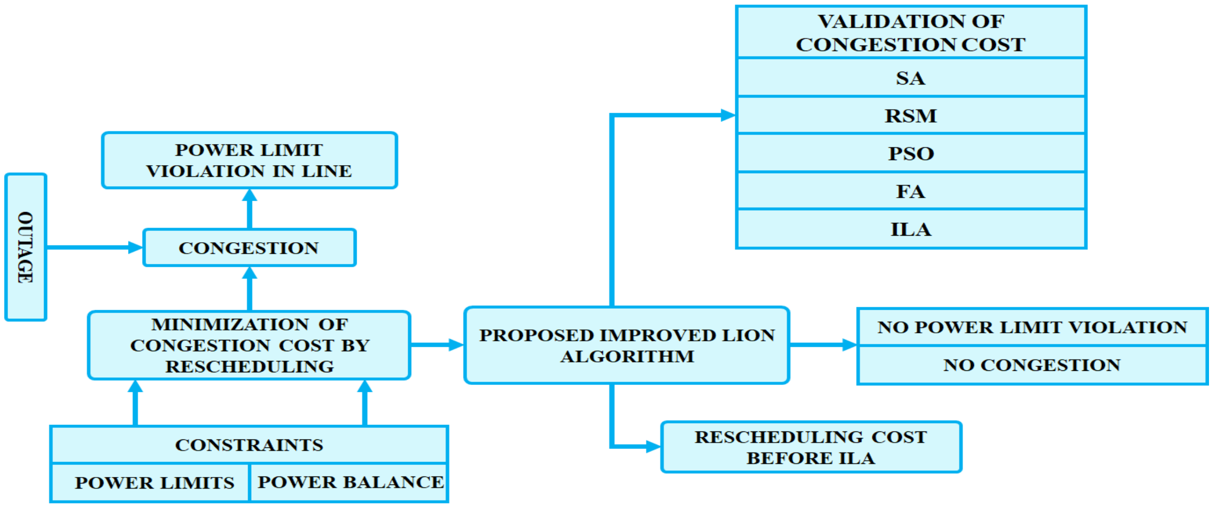


Fig.1. Congestion management using Improved LA-optimized DCNN

$$f(x)=\frac{1}{n}\sum_{i=1}^{n} f_i(x) \qquad (23)$$

The following expression denotes the objective function gradient at x.

$$\nabla f(x)=\frac{1}{n}\sum_{i=1}^{n}\nabla f_i(x) \qquad (24)$$

The computational cost for each independent variable iteration, if gradient descent is used, is given by $O(n)$ An index $i\in\{1,.........,n\}$ is uniformly sampled at each iteration of SGD for updating x by computing $\nabla f_i(x)$.

$$x\leftarrow x-\eta\nabla f_i(x) \qquad (25)$$

Here, η indicates the learning rate.

The DCNN structure used in the proposed work is AlexNet which is an updated architecture generating improved accuracy with less computational time. Table 1 represents the Alexnet DCNN layer architecture used in the proposed work.

The convolutional layer extracts the features from the data and is normalized by ReLU. Subsequently, the pooling layer of size 3×3 reduces the number of sizes thereby minimizing the complexity. In this DCNN, categorical cross-entropy is adopted as the loss function DCNNs are trainable architectures with biological inspiration that acquire on invariant aspects. Filter banks, certain non-linearities, and feature pooling layers are present in all stages of a DCNN. Multiple-stage multilevel hierarchical features are learned by a DCNN. The combined input features fe in DCNN are characterised by a function as shown in Equation (26), where fe is given a size of m_1Xm_2 and A indicates the 8-bit channel ranging from $\{0,............,250\}$.

Table 1

Alexnet DCNN layer architecture

Layers	Filters	Filter size	Strides
Convolutional layer 1 Max. pooling	96	11×11 3×3	4
Convolutional layer 1 Max. pooling	256	5×5 3×3	1
Convolutional layer 1 Max. pooling	384	3×3 3×3	1
Convolutional layer 1 Max. pooling	384	3×3 3×3	1
Convolutional layer 1 Max. pooling	256	3×3 3×3	1

$$lm_{Se}:\{1,...,m_1\}\times\{1,...,m_2\}\rightarrow A\subseteq R,(i,j)\rightarrow fe_{i,j} \qquad (26)$$

(Considering filter $L\in\Re^{2g_1+2g_2+1}$, where the discrete convolution $(*)$ w h filter H is specified by Equation (27) for the best image features fe. L is modelled as per Equation (28),

$$\left(fe_i * L\right)_{p,r} = \sum_{v=g_1}^{g_1} \sum_{u=-g_2}^{g_2} L_{v,u}\, fe_{p+v,r+u} \tag{27}$$

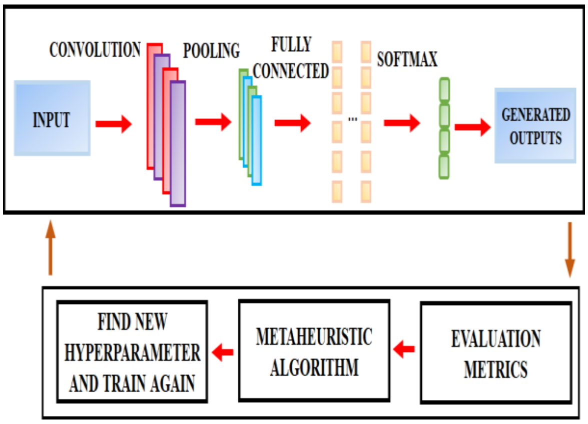


Fig .2. Deep CNN.

$$\begin{pmatrix} L_{-g_1,-g_2}; & \cdots & L_{-g_1,-g_2} \\ \vdots & L_{0,0} & \vdots \\ L_{g_1,-g_2} & \cdots & L_{g_1,g_2} \end{pmatrix} \tag{28}$$

A commonly used smoothing filter is the discrete Gaussian filter $L_{H(\alpha)}$, which is shown in Eq. (29), where σ stands for "standard deviation of Gaussian distribution".

$$\left(L_{H(\sigma)}\right)_{p,r} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{p^2+r^2}{2\sigma^2}\right) \tag{29}$$

Assume convolutional layer with feature maps $n_1^{(s)}$ and output dimensions a $n_2^{(s)} X n_3^{(s)}$ The ith feature map of s layer is illustrated in expression 30. The bias matrix and filter dimensions are given by $W_i^{(s)}$ and $L_{i,j}^{(s)}$ that links ith and jth feature map of s and $(s-1)$ layer.

$$X_i^{(s)} = W_i^{(s)} + \sum_{v=g_1}^{n_{11}^{x-1}} L_{i,j}^{(s)} * X_j^{(s-1)} \tag{30}$$

The output feature map retains a dimension by utilising discrete convolution at specific locations on input feature maps and is expressed as

$$n_2^{(s-1)} - 2g_1^s = n_2^{(s)} and\ n_3^{(s-1)} - 2g_2^s = n_3^{(s)} \tag{31}$$

The convolutional layer with its membership function including multilayer perceptron is expressed as

$$\left(X_i^s\right)_{p,r} = \left(W_i^s\right)_{p,r} + \sum_{j=1}^{n_1^{x-1}} \left(L_{i,j}^{(s)} * X_j^{(s-1)}\right)_{p,r} \tag{32}$$

$$\left(W_i^{(s)}\right)_{p,r} + \sum_{j=1}^{n^{(s-1)}{}_1} \sum_{v=-g_1{}^s}^{g_1{}^s} \sum_{u=-g_2{}^s}^{g_2{}^s} \left(L^{(s)}{}_{i,j}\right)_{v,u} \left(L^{(s)}{}_{i,j}\right)_{p,r} \left(X^{(s-1)}{}_j\right)_{p+v,r+u} \tag{33}$$

The position (p,r) achieved by output computation unit is illustrated in Equation 33. The trainable weight of network is represented as $L_{i,j}^{(s)}$ and $W_i^{(s)}$ indicates bias matrix. Consider fully connected layer as s. If s-1 is also fully connected s takes as input feature map $n_1^{(s-1)}$ with size $n_2^{(s-1)} X n_3^{(s-1)}$ and is given by,

$$X_i^{(s)} = f(V_i^s)\ with\ V_i^s = \sum_{j=1}^{n_1^{(s-1)}} \sum_{p=-1}^{n_2^{(s-1)}} \sum_{r=-1}^{n_3^{(s-1)}} We*_{i,j,p,r}^s \left(X_j^{s-1}\right)_{p,r} \tag{34}$$

$We*_{i,j,p,r}^s$ clarifies the weight which links unit at position (g,h) in layer $s-1$ feature map and ith unit in s. The weights are updated with the backpropagate of error in the network after the calculation of network error. The optimization algorithm updates the weights till the minimized value of error is obtained and the error does not get reduced further. For better prediction outcomes, it is preferable to make the values ideal rather than generating some random evaluation values. However, the automatic finding of hyperparameters of DCNN is crucial and requires the involvement of metaheuristic algorithms. The tuning in this work is done using the optimization idea, specifically, a novel tuning approach is presented.

Solution Encoding and Objective Function

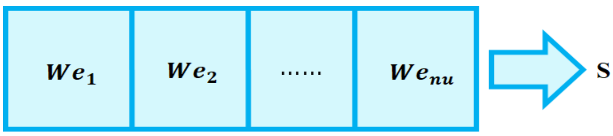


Fig. 3. Solution encoding.

Figure 3 shows the solution provided by the suggested algorithm, where nu represents total number of weights. An objective function (OF) of research that is being presented is described in Equation (32), where Er denotes error.

$$OF = Min(E_r) \tag{35}$$

$$E_r = \frac{1}{N} \sum_i^n (L^A - L^P) \tag{36}$$

From the above expression N indicates the number of samples, and actual and predicted outcomes of the ground truth table are specified as L^A and L^P

Proposed Improved LA.

The Improved LA model is used in the work is presented to optimise a weight of DCNN. Here, the current LA method is enhanced so that it is

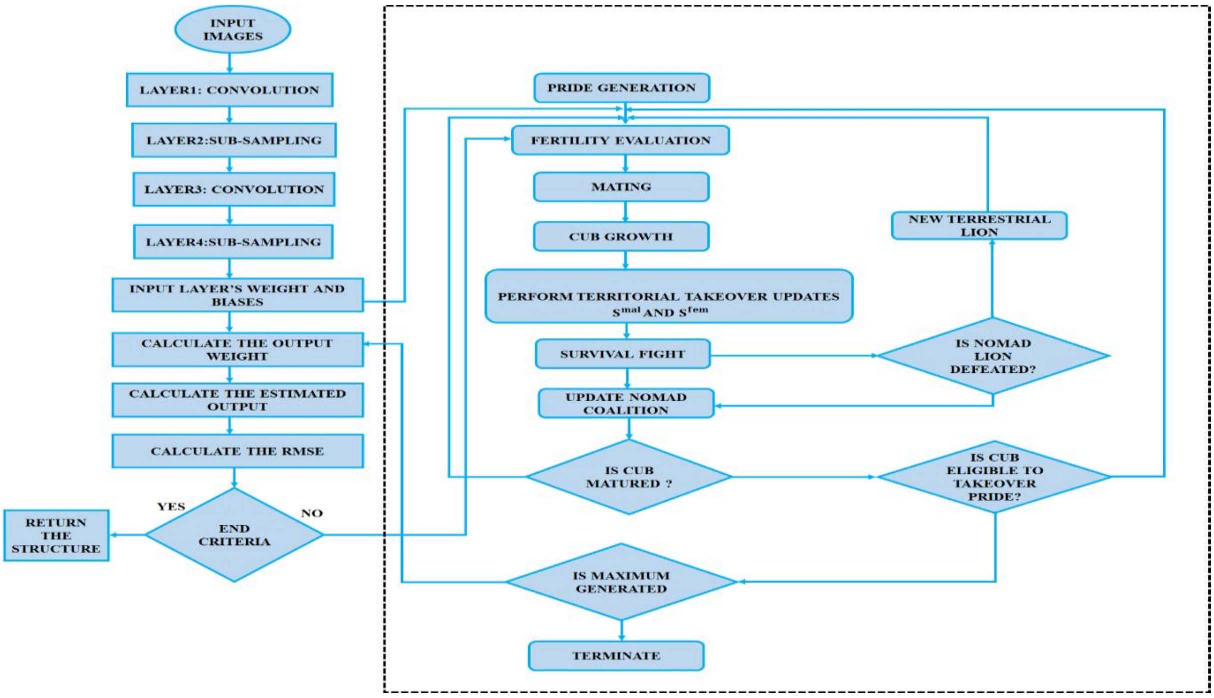


Fig. 4. Adopted Improved LA Flow Diagram.

capable of handling the difficult optimization problems. Self-improvement has generally been shown to be promising in conventional optimization techniques. The live nature of lion species served as the basis for LA model. It consists of four stages, including "mating, pride-generating, improved territorial takeover and territorial defence". The proposed Improved LA adopts the improved territorial takeover phase in which the lions are updated based on the maximum age of cubs. In contrast, conventional LA do not have specific updating process. The solution vector of Improved LA is referred as $S=[S_1, S_2, ..., S_M]$.

Pride Generation.

The pride formulation is initiated by nomadic lion, territorial lion, and lioness which are indicated as s^{mal}, S^{nd} and s^{fem} the vector components are specified as s^{mal}_{len}, s^{nd}_{len} and, s^{fem}_{len} with $len = 1, 2, 3, ..., Len;$ that lies within the limits of random integers, when $\hat{m} \rangle 1$.The length of lion is specified as Len and variables are denoted by $\hat{n}$ and $\hat{m}$ .Simultaneously, when $\hat{m}=1$,the expression for $V(S_{ten})$ is written by,

$$Len = \begin{cases} m; m>1 \\ n; \text{otherwise} \end{cases} \quad (37)$$

$$V(S_{len}) \in \left(S^{min}_{len}, S^{max}_{len}\right) \quad (38)$$

$$n\%2 = 0 \quad (39)$$

$$V(S_{len}) = \sum_{len=1}^{Len} S_{len\,2\left(\frac{len}{2}-len\right)} \quad (40)$$

Fertility Estimation.

If s^{fem} and s^{mal} become saturated, they may have reached a local or global optimum and so failed to find the ideal solution. In the proposed technique

$$S^{fem+}_{len} = \begin{cases} S^{fem+}_{d} \ \ if \ len = d \\ S^{fem}_{len} \ \ otherwise \end{cases}$$

(41)

$$S_d^{fem+} = \min\left[S_d^{\max}, \max\left(S_d^{\max}, \nabla_d\right)\right]$$
(42)

The process of mating is performed when s^{fem+} is considered as s^{fem}. From the expressions above $d^{th}$and len^{th} component vectors of s^{fem+} is specified as S_d^{fem} and s_{len}^{fem+}.

$$\nabla_d = \left[S_d^{fem+} + \left(0.1r_2 - 0.05\right)\left(S_d^{mal} - r_1 S_d^{fem}\right)\right] \quad (43)$$

The random constraints are specified by variables $\breve{r}_1, \breve{r}_2$ and d, which are produced and lie between [$[0,1]$ and $[1, Len]$, respectively. Also, female update process is indicated as ∇ .

Matching

Gender-based clustering occurs as a result of the crossover and mutation processes that occur during mating. Cubs are generated by mutation and crossover process and are referred as, s^{cubs} which are produced by cross over process and s^{new} by mutation process. Thus, a lioness gives birth to four cubs when it is pregnant, and another four cubs are created through the crossover process. These four cubs are used to carry out mutation procedure in order to create four further cubs.

Lion Operators.

The territorial defensive and coalition developments are covered in survival fight. If the conditions in Equation (44 to 46) is satisfied is S^{e-nd} selected.

$$\mathrm{h}\left(\mathrm{S}^{\text{e-nd}}\right) < \mathrm{h}\left(\mathrm{S}^{\text{mal}}\right)$$
(44)

$$\mathrm{h}\left(\mathrm{S}^{\text{e-nd}}\right) < \mathrm{h}\left(\mathrm{S}^{\text{mal}_{\text{cub}}}\right) \quad (45)$$

laggardness, laggard is specified as L_{ar} and s^{mal} ,while $h\left(s^{mal}\right)$ beyond h^r specifies the fitness reference. The sterility rate st_r indicates s^{fem} fertility. While $St_r \rangle St_r^{\max}$ tolerance, the expression becomes

$$\mathrm{h}\left(\mathrm{S}^{\text{e-nd}}\right) < \mathrm{h}\left(\mathrm{S}^{\text{fem}_{\text{cub}}}\right) \quad (46)$$

The nomadic coalition upgrade happens after the failure of S^{nd}, while a pride update happens after failure of s^{mal}.

Territorial Takeover.

The process of upgrading s^{mal} and s^{fem} based on maximum cub age $A_{\max}$ takes place in this phase. In the proposed work, the territorial takeover uses the algorithm to upgrade s^{mal} and s^{fem} as mentioned in (47) and (48) which is absent in conventional LA. In other words, the territorial updating is based on size of male and female cubs and a random variable called $rann$.

$$S^{mal} = \left[S^{mal_{cub}} + \left(S^{fem_{cub}} \times ran\ n\left(size\left(S^{fem_{cub}}\right)\right)\right)\right] \quad (47)$$

$$S^{fem} = \left[S^{fem_{cub}} + \left(S^{mal_{cub}} \times ran\ n\left(size\left(S^{mal_{cub}}\right)\right)\right)\right] \quad (48)$$

Termination.

The design gets terminated only when Equations (49) and (50) are satisfied.

$$it > it_{\max} \quad (49)$$

$$h\left(S^{mal}\right) - h\left(S^{opt}\right) \le er_{th} \quad (50)$$

Figure 4 shows the flow chart for the suggested Improved LA model. From the expression above count of generation is indicated by it, which is set to zero at initial and further increased to 1, during the territorial takeover. $it_{\max}$ and er_{th} stands for maximum generation and error threshold, respectively. The list of hyperparameters for the evaluation selected with the help of improved LA is mentioned in Table 2.

Table 2

List of hyperparameters.

Hyperparameters	Range	Optimal Value
No. of epoch	[1-200]	100
No. of filters	[1-400]	16
Batch size	[10-100]	32
Pooling size	[1×1-7×7]	2×2
Filter size	[1×1-11×11]	3×3

RESULTS AND DISCUSSION

In this study, an Improved LA optimized DCNN is used for resolving congestion issue in unregulated environment. The optimized Deep CNN facilitates the active power rescheduling of generators with reduced congestion cost. Around 500 loading scenarios are being generated among which 78% of patters are adopted for training and 22% of patterns are adopted for testing. Out of the 390 loading scenarios of training set, the number of congested scenarios identified is 378 while the non-congested cases is 12. Among 110 loading scenarios of testing set, the number of congested loading scenarios is identified as 100 whereas the number of non-congested loading scenarios is identified as 10. An apparent power load, active power load and reactive power load are applied as inputs to DCNN in which the dimension of the input layer is given by 3×21×1.

In order to apply power load, active power load and reactive power load as inputs, data requires pre-processing. Initially, the data has to be collected at regular intervals and further pre-processed which involves removal of outliers and conversion of data into time-series format. The data could then be formatted into a tensor or array, where each row represents a time step and each column represents a feature, such as active power load. Finally, the formatted data can be fed as input to the DCNN.The proposed work is verified by implementing in MATLAB and is tested under variety of networks including IEEE 30-bus, IEEE 57-bus and IEEE 118-bus. An upper voltage of the load bus is 1.1 p.u, while the lower voltage of the load bus is 0.9 p.u. Table 3 lists the test systems considered for evaluating the performance of Improved LA optimized DCNN for CM, while the congestion line details are presented in Table 4.

Table 3

Test System details

Test system	Modified	IEEE 30-bus	Modified	IEEE 57-Bus	IEEE 118-bus
Test case	1A	1B	2A	2B	3
Considered Contingency	Line outage between 1 and 2.	Line outage between 1 and 7.	Reduction of line capacity from 50-35 MW and 200 to 175MW between 6-12 and 5-6.	Reduction of line capacity between lines 2 and 3 from 85 to 20 MW.	Line outage between 5 and 8.

Table 4

Congestion line flow details of test system

Test Case		**1A**		**1B**			**2A**		**2B**	**3**		
Congested Lines		1-7	7-8	1-2	2-8	2-9	5-6	6-12	2-3	16-17	30-17	8-30
Line Flow	**Before CM**	147.5	140.2	314	97.8	103.6	188.7	49.5	36.6	209.2	580.2	363.5
	After CM	130	123.5	130	61.4	64.39	168.4	16.8	16.7	97.6	496.8	143
Specified line limit (MW)		130	130	130	65	65	175	35	20	175	500	175

IEEE 30-Bus Test System

For comprehending the potential of proposed DCNN based CM approach, a revised version of IEEE 30-bus system that comprises of 24 load buses, 6 generator buses and 41 transmission lines is considered. The two different cases considered here are: Case 1A – power outage causes congestion between lines 1-7 and 7-8; Case 1B – load rises to 50% at every bus and the lines 1-2, 2-8 and 2-9 are congested. Table 3 gives the details about the obtained results from which it is noted that the proposed work generates improved outputs of 18.707 for case1A and 161.14 for case 1B.

Table 5

Test system results

	Techniques	$TC,\$/h$	ΔP_{G1}	ΔP_{G2}	ΔP_{G3}	ΔP_{G4}	ΔP_{G5}	ΔP_{G6}	TRRG
Case 1A	SA [24]	719.86	-9.076	3.133	3.234	2.968	2.954	2.443	23.809
	RSM [24]	716.25	-8.808	2.647	2.953	3.063	2.913	2.952	23.33
	PSO [24]	538.95	-8.61	10.4	3.03	0.02	0.85	-0.01	22.93
	FA [25]	511.87	-8.778	15	0.106	0.065	0.1734	-0.618	24.74
	Proposed	421.58	-8.596	7.57	0.352	1.096	0.568	0.5228	18.707
Case 1B	SA [24]	6068.7	-	-	-	-	-	-	164.53
	RSM [24]	5988	-	-	-	-	-	-	164.5
	PSO [24]	5335.5	-	-	-	-	-	-	168
	FA [25]	5304.4	-8.579	75.99	0.057	42.99	23.83	16.51	167.9
	Proposed	5238.9	-9.001	62.9	34.24	2.059	29.45	23.47	161.14

TRRG-Total Real power Rescheduling Generator, TC-Total

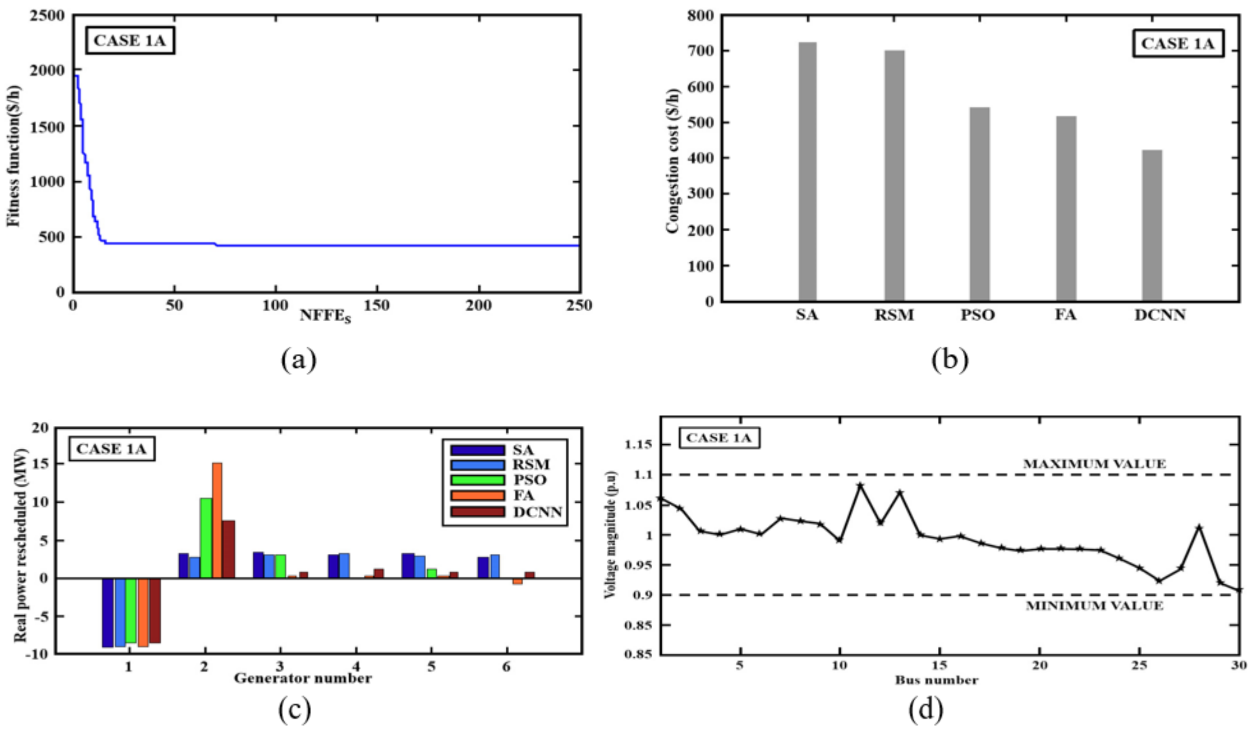


Fig. 5. Case 1A simulation outcomes (a) Convergence profile (b) Congestion cost (c) change in real-power and (d) Voltage magnitude.

The simulation results for case 1A are provided in Figure 5. On analyzing the figure, it is detected that a congestion cost is minimum for the proposed CM approach using Improved LA optimized DCNN.

Further, real-power losses are significantly reduced to 12.65 MW from 16.13 MW, indicating the effectiveness of the proposed methodology. The voltage magnitude is also maintained within a reasonable range (0.9 to 1.1) after CM

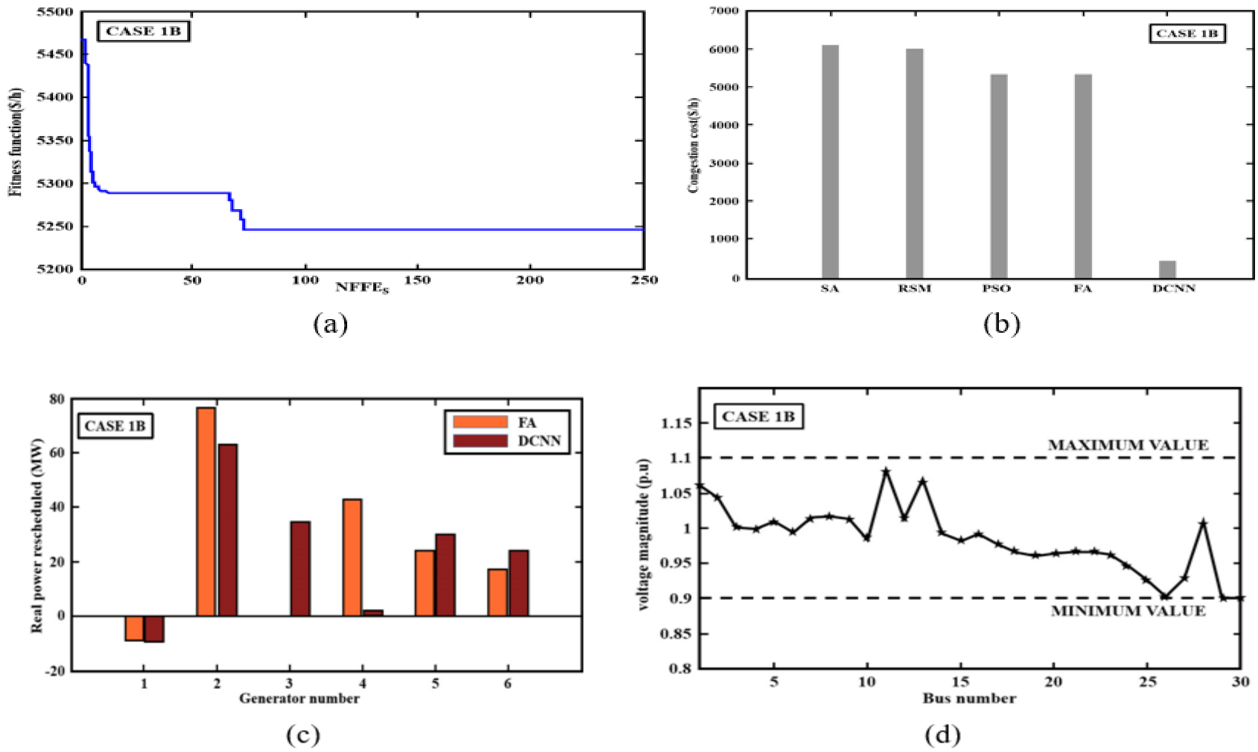


Fig. 6. Case 1B simulation outcomes (a) Convergence profile (b) Congestion cost (c) change in real-power and (d) Voltage magnitude.

From Figure 6, which gives the simulation outcomes for case-1B, deduces that the congestion cost is comparatively lower for the proposed DCNN based CM approach. In this case, increase in load along with the outage of line between 1 and 7 results in overloading Moreover, the system losses are also reduced to 14.59 MW from 37.24 MW after CM using Improved LA optimized DCNN.

IEEE 57-Bus Test System

Next, a revised topology of IEEE 57-bus test system considered for CM is made up of80 transmission lines, 50 load buses and7 generator buses. Its reactive and real power values, 336 MVAR and 1250.8 MW respectively. Moreover, the details and results of the two cases coming under this test system is provided in Table 6.

Table 6

Test system results.

	Techniques	$TC, \$/h$	ΔP_{G1}	ΔP_{G2}	ΔP_{G3}	ΔP_{G4}	ΔP_{G5}	ΔP_{G6}	ΔP_{G7}	TRRG
Case 2A	SA [24]	7116.8	76.4	0	-2.64	9.98	-87.3	0	0	172.9
	RSM [24]	7876.4	59.3	0	38.7	-48.6	-63.7	0	0	197.3
	PSO [24]	6735.2	24.7	13.5	8.54	-6.49	-82.3	0	39.7	164.4
	FA [25]	6214.4	5.72	2.75	0.63	0.21	-39.2	-35.1	62.2	146.82
	Proposed	5324.6	-0.05	-11.7	-5.81	-45.2	-51.3	-34.8	-0.53	144.57
Case 2B	SA [24]	4274.3	-	-	-	-	-	-	-	98.74
	RSM [24]	4123.6	-	-	-	-	-	-	-	89.67
	PSO [24]	3856.1	-	-	-	-	-	-	-	76.43
	FA [25]	2987.9	0.37	-27.5	31.4	0.44	-2.32	-1.87	-0.63	65.87
	Proposed	2012.3	0.76	0.08	22.044	0.17	-10.5	-0.00	16.07	49.583

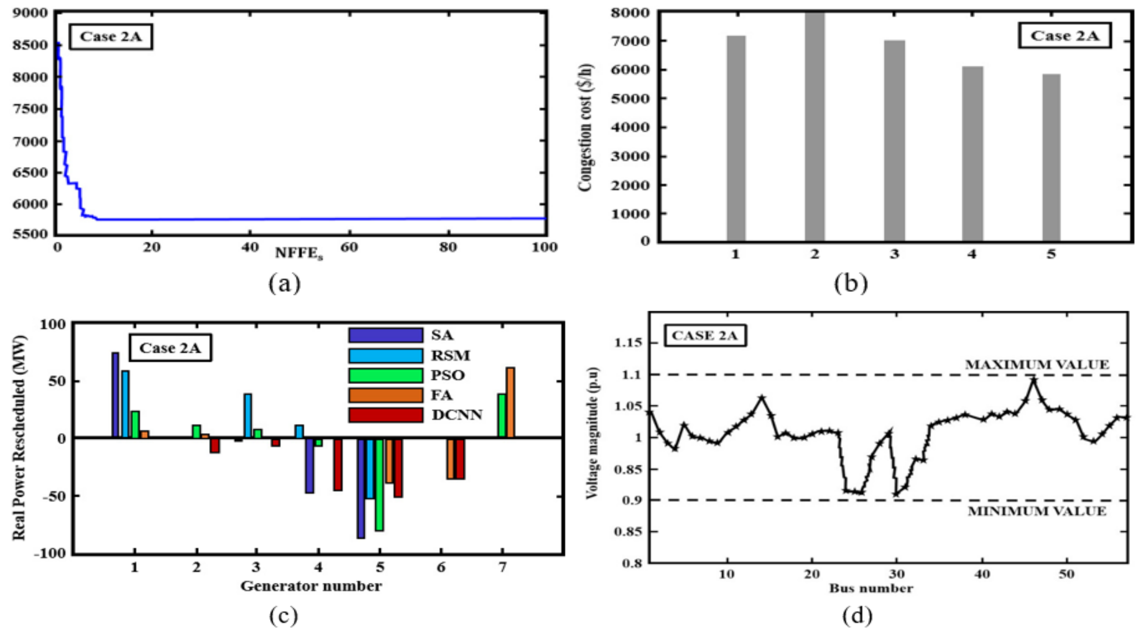


Fig. 7. Case 2A simulation outcomes (a) Convergence profile (b) Congestion cost (c) change in real-power and (d) Voltage magnitude.

The simulation outcomes for case 2A are illustrated in Figure 7, In case 2A, for lines 6-12 and 5-6, line limits are lessened from 50 MW to 35 MW and 200 MW to 175 MW respectively. With the occurrence of congestion, there is an overloading between lines 6-12 and 5-6. After CM using the proposed methodology in case 2A, the system loss is significantly reduced to 24.558 MW from 69.64 MW.

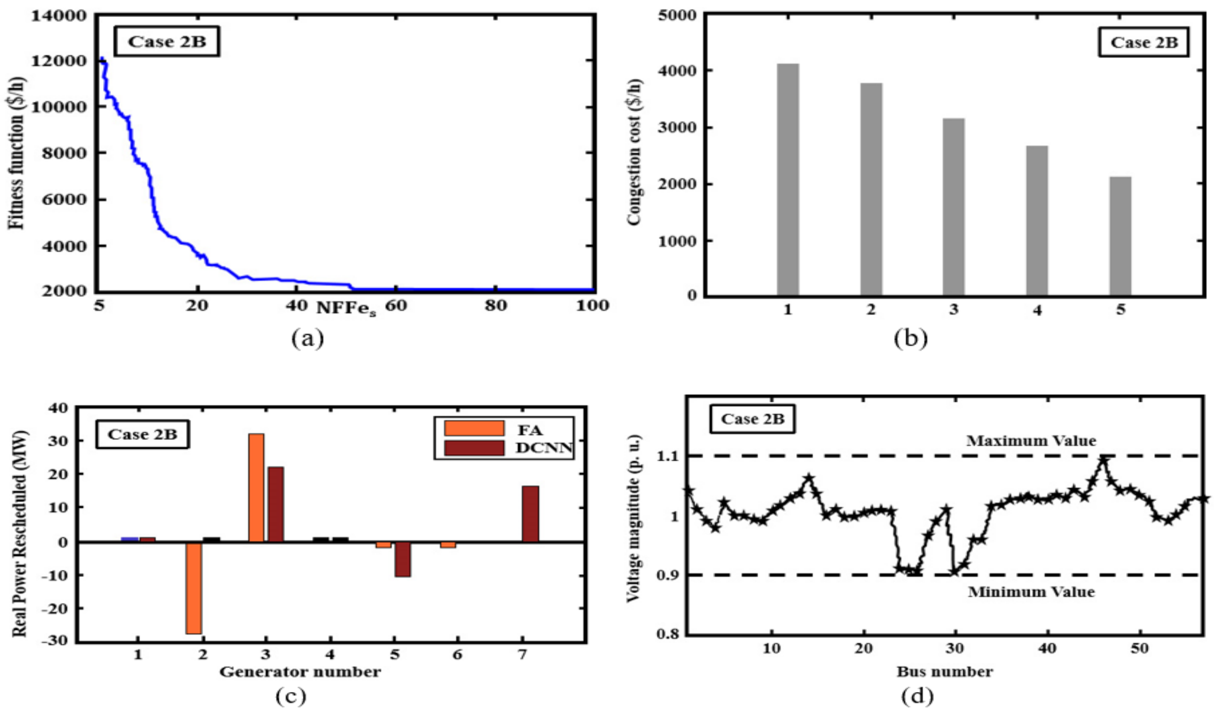


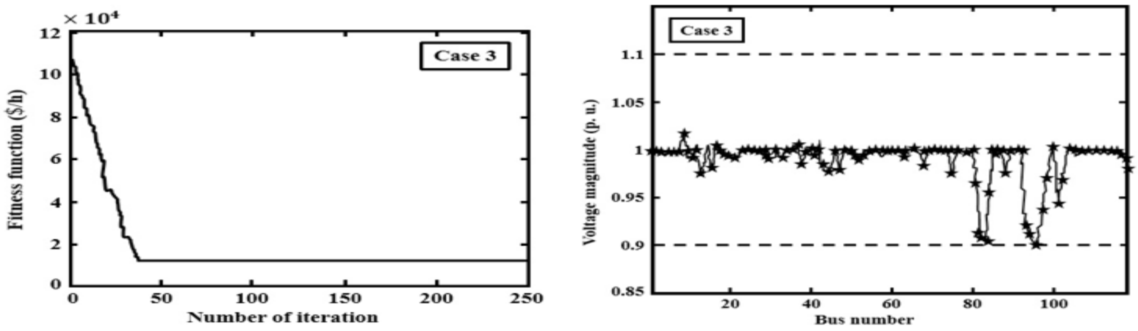
Fig. 8. Case 2B simulation outcomes (a) Convergence profile (b) Congestion cost (c) change in real-power and (d) Voltage magnitude.

whereas simulation outcomes for case 2B are illustrated in Figure 8. In case 2B, line overloading is created by reducing line limit to 20 MW from 85 MW between lines 2-3. From analyzing Table 4, it is observed that the proposed approach delivers comparatively better performance in Case 2A also.

In this case the system losses are greatly reduced to 28.22 MW from a primary value of 78.23 MW before CM. On the whole, the violation of overloading lines is alleviated by the optimized real-power rescheduling.

IEEE 118-Bus Test System

The proposed DCNN based CM is also evaluated for its effectiveness in a larger test system by deploying it in a revised topology of 118-bus test system, made up of 54 generator buses, 64 load buses and one 186transmission lines. In this case, the lines between 5 and 8 are disconnected, while the loads between lines 20 and 11 are increased 1.57 times. Figure 8 gives the simulation resultsforCase3



(a) (b)

Fig. 9. Case 3 simulation results (a) Convergence profile and (b) voltage magnitude.

In this case, the total system loss becomes 230.505 MW after CM using DCNN. The value of system loss before CM is 277.301 MW. Thus, it is significantly apparent that the proposed DCNN methodology is effective at minimizing congestion in any test system, regardless of its size. Figure 10 represents the comparison of convergence in terms of cost and iteration. From the curve it is clear that the Improved LA exhibits rapid convergence rate when compared to conventional LA.

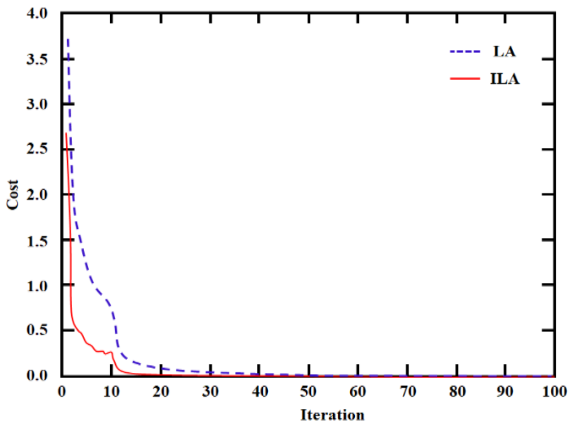


Fig. 10. Comparison of convergence.

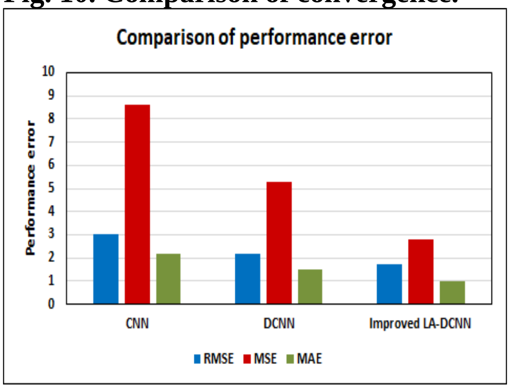


Fig. 11. Comparison of performance error.

Figure 11 represents the comparison of performance error obtained using CNN, DCNN and Improved LA optimized DCNN related to mean absolute error (MAE), mean squared error (RMSE) and root mean squared error (RMSE). The comparison outputs indicate reduced error for the proposed neural network indicating improved computational performance.

Table 7

Comparison of generator rescheduling for IEEE 30-bus system

Networks	Outputs	G1	G2	G3	G4	G5	G6
Cascaded DCNN[26]	Actual	40.882	54.409	16.485	21.747	16.083	29.902
	Predicted	40.469	54.222	16.299	21.692	16.073	29.775
	% Error	1.008	0.344	1.128	0.253	0.064	0.307
DNN[27]	Actual	179.098	45.973	21.831	23.637	19.086	-
	Predicted	179.111	46.416	21.605	23.640	18.901	-
	% Error	0.007	0.964	1.038	0.014	0.970	-
Proposed ILA-DCNN	Actual	161.149	55.946	19.627	22.676	18.384	32.916
	Predicted	161.146	55.740	18.707	22.671	18.342	32.775
	% Error	0.003	0.206	0.920	0.005	0.042	0.141

Table 6 represents the comparison of the proposed ILA-DCNN for generator rescheduling with existing works. The listed values indicate that the proposed work outperforms other ones with enhanced prediction outputs indicating reduced error percentage.

CONCLUSION.

This study suggests a novel robust methodology for CM in an unregulated open access electricity environment. In order to satisfy several electrical constraints, problem was developed as multiple-objective function, with losses and congestion costs as vital factors. Conventionally, FACTS devices or nature-inspired algorisms were prominently employed for CM in many works. Meanwhile, in this work, DCNN is chosen for congestion minimization in an unregulated environment for solving the tasks of issues in congestion management due to uncertainties in load. The working of the DCNN is enhanced further by using Improved LA optimization. The proposed DCNN-based generator rescheduling approach is put to test for its performance in three different test systems of varied sizes. Moreover, its performance is evaluated by analogizing with other existing methodologies in these test systems. The proposed work is simulated in MATLAB and on the basis of the obtained simulation outcomes, it is evident that the proposed Improved LA optimized DCNN displays phenomenal performance in minimizing congestion losses at minimum congestion costs. Moreover, it also outperforms other techniques in terms of its superior performance in managing congestion. The future extension of this work can include the adoption of hybrid optimization algorithms for the enhancement of neural network parameters. Moreover, the effects of optimization over multi-objective functions have to be analyzed in a detailed manner.

Conflict of interest. The authors declare that they have no conflicts of interest.

References

[1] Yadav A. K., Srivastava S. K. and Narain A."A Review on Congestion Management in Power System," *International Conference on Electrical and Electronics Engineering (ICE3),*2020, pp. 359_364, doi: https://doi.org/10.1109/ICE348803.2020.9122988.

[2] R. Ciavarella, M. Di Somma, G. Graditi and M. Valenti, "Congestion Management in distribution grid networks through active power control of flexible distributed energy resources," *2IEEE Milan PowerTech*, Milan, Italy, 2019, pp. 1-6, doi: https://doi.org/10.1109/PTC.2019.8810585.

[3] Jagadeeswar Reddy., and Mary Daniel. "Real-power rescheduling of generators for congestion management using a novel satin bower bird optimization algorithm." *Energies* 11, no.1,2018. doi:https://doi.org/10.3390/en11010183.

[4] Sankar Murthy Padmini., Bharati raja Chokkalingam., Sanjeev Kumar Padmanabhan., Zbigniew Leonowicz., and Yusuff Adedayo. "Rescheduling of generators with pumped hydro storage units to relieve congestion incorporating flower pollination optimization." *Energies* 12, no. 8, 2019.doi:https://doi.org/10.3390/en12081477.

[5] Dhegihan Moslem., Mohammad Ghiasi., Taher Niknam., Abdollah Kavousi-Fard., Mokhtar Shasadeghi., Noradin Ghadimi, and Farhad Taghizadeh-Hesary. "Blockchain-based securing of data exchange in a power transmission system considering congestion management and social welfare." *Sustainability* 13, no. 1, 2020. doi:https://doi.org/10.3390/su13010090.

[6] Saravanan C, and Anbalagan P. "Multi-objective dragonfly algorithm for congestion management in deregulated power systems." *Journal of Ambient Intelligence andHumanizedComputing* 12,no.7,2021.doi:https://doi.org/10.1007/s12652-022-04282-1.

[7] Prajapati, Vijaykumar K., and Vasundhara Mahajan. "Reliability assessment and congestion management of power system with an energy storage system and uncertain renewableresources." *Energy* 215,2021.doi:https://doi.org/10.1016/j.energy.2020.119134.

[8] A. Asrari, M. Ansari, J. Khazaei and P. Fajri, "A Market Framework for Decentralized Congestion Management in Smart Distribution Grids Considering Collaboration Among Electric Vehicle Aggregators," in *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1147-1158, 2020,doi:https://doi.org/10.1109/TSG.2019.2932695.

[9] Nguyen Thang Trung., and Fazel Mohammadi. "Optimal placement of TCSC for congestion management and power loss reduction using multi-objective genetic algorithm." *Sustainability* 12, no. 7, 2020. doi:https://doi.org/10.3390/su12072813.

[10] Sarwar, Md, and Anwar Shahzad Siddiqui. "A novel approach for optimal allocation of series FACTS device for transmission line congestion management." *Engineering Reports* 3, no. 6, 2021.doi:https://doi.org/10.1002/eng2.12342.

[11] Bagheri A., A. Rabiee, S. Galavani., and F. Fallahi. "Congestion management through optimal allocation of FACTS devices using Dig SILENT-based DPSO algorithm-a real case study." *Journal of Operation and Automation in Power Engineering* 8, no. 2, 2020.https://doi.org/10.22098/joape.2019.6094.1462.

[12] Kalaimani P., and Mohana K. Sundaram. "Congestion management with improved real power transfer using TCSC in 30 bus system." *International Journal of Information Technology and Management* 20, no. 1-2, 2021. doi: https://doi.org/ 10.1504/ijitm.2021.114155.

[13] Gautam Anubha., Parsh Ram Sharma., and Yogendra Kumar. "Sensitivity Based Congestion Management in a Deregulated Power System by Optimal Allocation & Parameter Setting of TCSCusingGreyWolfOptimization." *International Journal on Electrical Engineering and Informatics* 12, no.4,2020.doi:http://dx.doi.org/10.15676/ijeei.2020.12.4.12.

[14] Vijaykumar K Prajapati., Vasundhara Mahajan, and Narayan Prasad Padhy. "Congestion management of integrated transmission and distribution network with RES and ESS under stressed condition." *International Transactions on Electrical Energy Systems* 31, no. 2, 2021. doi: https://doi.org/10.1002/20507038.12757.

[15] Papun Biswas, and Bijay Baran Pal. "A fuzzy goal programming method to solve congestion management problem using genetic algorithm." *Decision Making: Applications in Management and Engineering* 2, no. 2, 2019. doi:http://dx.doi.org/10.31181/dmame1902040

[16] Roy, Rupam Gupta. "Rescheduling based congestion management method using hybrid Grey Wolf optimization-grasshopper optimization algorithm in power system." *J. Compute. Mech. Power Syst. Control* 2, no. 1, 2019.doi: https://doi.org/10.46253/jcmps.v2i1.a2.

[17] Basha A., Ahamed Jeelani., M. Anitha, and E. B. Elanchezhian. "Optimal placement of TCSC for congestion management in deregulated power system using firefly algorithm." *International Journal of Process Systems Engineering* 5, no. 1, 2019.doi:https://dx.doi.org/10.1504/IJPSE.2019.10017448.

[18] Chatuanramtharnghaka. Benjamin, and Subhashish Deb. "Transmission congestion management in deregulated electricity market using multi-objective grasshopper optimization algorithm." *EAI Endorsed Transactions on Energy Web* 8, no. 33, 2020. doi:https://doi.org/10.1504/ijitm.2021.114155.

[19] Sharma Vatsala., Pratima Walde., and Anwar Shahzad Siddiqui. "Hourly congestion management by adopting distributed energy storage system using hybrid optimization." *Journal of Electrical Systems* 16, no.2, 2020.doi:http://dx.doi.org/10.1016/j.ref.2020.10.006

[20] Kaushik Paul., Niranjan Kumar, and Poulami Dalapati. "Bat algorithm for congestion alleviation in power system network." *Technology and Economics of Smart Grids and Sustainable Energy, vol.* 6, no. 1, 2021.doi: https://doi.org/10.1007/s40866-020-00100-9.

[21] Ye Le, Yaser Ahangari Nanehkaran, Deborah Simon Mwakapesa, Ruipeng Zhang, Jianbing Yi, and Yimin Mao. "FP-DCNN: a parallel optimization algorithm for deep convolutional neural network." *The Journal of Supercomputing* 78, no. 3,2022, pp: 3791-3813.doi: https://doi.org/10.1007/s11227-021-04012-y.

[22] Yanyi Li, Jian Shi, and Yuping Li. "Real-Time Semantic Understanding and Segmentation of Urban Scenes for Vehicle Visual Sensors by Optimized DCNN Algorithm." *Applied Sciences* 12, no. 15 (2022): 7811. https://doi.org/10.3390/app12157811.

[23] Pradipta Kumar Mishra, Suresh Chandra Satapathy, and Minakhi Rout. "Segmentation of mri brain tumor image using optimization based deep convolutional neural networks (dcnn)." *Open Computer Science* 11, no. 1 2021, pp: 380-390. doi: https://doi.org/10.1515/comp-2020-0166.

[24] Mahdad B., Srairi K. Interactive artificial ecosystem algorithm for solving power management optimizations. Electrical Engineering

[25] & Electromechanics, 2022, no. 6, pp. 53-66. doi: https://doi.org/10.20998/2074-272X.2022.6.09

[26] Mahdad B., Srairi K. Interactive artificial ecosystem algorithm for solving power management optimizations. Electrical Engineering

[27] & Electromechanics, 2022, no. 6, pp. 53-66. doi: https://doi.org/10.20998/2074-272X.2022.6.09

[28] Mahdad B., Srairi K. Interactive artificial ecosystem algorithm for solving power management optimizations. Electrical Engineering & Electromechanics, 2022, no. 6, pp. 53-66. doi: https://doi.org/10.20998/2074-272X.2022.6.09

[29] M. Lindner *et al.*, "Corrective Congestion Management in Transmission Grids Using Fast-Responding Generation, Load and Storage," *2021 IEEE Electrical Power and Energy Conference (EPEC)*, Toronto, ON, Canada, 2021, pp. 1-6, doi: https://doi.org/10.1109/EPEC52095.2021.9621491.

[30] M. Lindner *et al.*, "Corrective Congestion Management in Transmission Grids Using Fast-Responding Generation, Load and Storage," *2021 IEEE Electrical Power and Energy Conference (EPEC)*, Toronto, ON, Canada, 2021, pp. 1-6, doi: https://doi.org/10.1109/EPEC52095.2021.9621491.

[31] Verma., Summit., and V. Mukherjee. "Firefly algorithm for congestion management in deregulated environment." *Engineering Science and Technology, an International Journal* 19, no.3,2016. doi:https://doi.org/10.1016/j.jestch.2016.02.001

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