International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

A Comprehensive Analysis of Various Optimization Algorithm Approaches for Efficiently Handling Congestion in Transmission Networks

Gajendrakumar R. Patel[1], Dr. Sweta J. Shah[2]

Submitted: 29/01/2024 **Revised**: 07/03/2024 **Accepted**: 15/03/2024

Abstract: Congestion management is a critical issue in the process of deregulated power structure. This articles suggest a comparison of different methodologies for a Traffic Management speak to, specifically focusing on the best true power adjourn of power structure generators. The selection of the most acute generators to endure in Traffic Management is based on the Generator Sensitivity Factors (GSF). To minimize congestion costs, an Updated Whale Optimization Algorithm (UWOA) has been developed. The proposed methodology has two main objectives. Firstly, it aims to solve congestion problems in power systems using a differential method, such as the Differential Evolution Algorithm (DE), Crow Search Algorithm (CSA), Genetic Algorithm (GA), Whale Optimal Algorithm (WOA), Modified Whale Optimal Algorithm (MWOA), and Updated Whale Optimal Algorithm (UWOA). Secondly, it aims to compare the congestion cost results achieved by various methods for the IEEE 118-bus structure. The findings indicate that the reworking of UWOA stint Traffic Management charge surpasses the different ways utilized for Traffic Management.

Keywords: *Congestion Management, crow search Algorithm, whale optimal Algorithm, Optimization*

1. Introduction:

The pattern of the electric power society has brought about significant changes in the actual control activities of power grids. Among these activities, managing dispatch is crucial in ensuring the smooth operation of a power system. In a competitive market environment, an independent system operator plays a vital role in facilitating the efficient dispatch of contracted power among market players. However, with the increasing number of bilateral contracts in the electricity market, there is a possibility of insufficient resources leading to network congestion. In such cases, congestion management becomes a critical issue. One commonly used technique for managing congestion is to reschedule the power outputs of generators in the system.

As real-world scientific and engineering problems become more complex, optimization poses a major challenge in the field of soft computing. Traditional mathematical methods often fall short in solving and addressing these problems. This is where Metaheuristics Algorithms (MA) excel, as they are capable of solving NP problems and finding optimal or near-optimal solutions in real-time. These algorithms have gained popularity due to their ease of implementation, ability to avoid local optima, and flexibility.

One such algorithm is the Crow Search Algorithm (CSA), developed in 2016. It imitate the conduct of crows in storing and retrieving food, and has been successfully applied to address complex multimodal issues in determine the parameters for induction motors and distribute capacitors in distribution networks. An enhanced CSA variant called the Improved Crow Search Algorithm (ICSA) has been suggested in an effort to boost performance even more. The awareness probability (AP) and the random perturbation are two aspects of the original CSA that are altered by this new method.

Genetic algorithms (GAs) have gained widespread acceptance as an efficient optimization method for solving various types of large-scale engineering problems. References [5-9] present different congestion management methods based on genetic algorithms. Additionally, the challenge of creating the best bidding tactics for generation businesses has been framed as a stochastic optimization model, and it has been resolved with the use of genetic algorithms and the well-known Monte Carlo simulation technique. [5, 10].

Over the past few decades, several techniques have been applied to regulate traffic flow on road networks, such as deep neural networks [11] and improved particle swarm optimization [12]. However, these conventional approaches are not effective in managing large datasets. Consequently, a novel method created especially to manage and reduce road traffic congestion is introduced in

[1] *Ph.D Research Scholar Electrical Engineering Indus Institute of Technology and Engineering, Indus University, Ahmedabad*
ORCID ID: 0009-0005-9860-8245
[2] *Asst. Prof. – Electrical Engineering Department OSD Research Development & Innovation, Indus Institute of Technology and Engineering, Indus University, Ahmedabad*
1.patelgajendra.20.rs@indusuni.ac.in

this research study. The goal is to reduce commuters' exposure to vehicle pollution at traffic signals, both in terms of severity and duration. The study's input data was gathered from the Beibei Tunnel and subjected to pre-processing procedures, such as data normalisation, in order to bring the diverse collection of numerical data into proportion. The best qualities were chosen using the Whale Optimisation Algorithm (WOA) following pre-processing. The characteristics that were most important for categorising the various phases of traffic congestion on roads are indicated by the WOA output.

The structure of this research study is as follows: The proposed system is explained in Section II. The suggested system is evaluated and contrasted with the Updated WOA in part III. Section IV presents the conclusion at the end.

2. Methodology:

2.1 Different Evolution Algorithm (DEA)

One heuristic optimisation technique for minimising nonlinear and non-differentiable continuous space functions with real-valued parameters is Differential Evolution. Three basic actions comprise the optimisation process in differential evolution: crossover, selection, and mutation. In DE methods, the population size (Np), crossover constant (CR), and scaling factor (mf) are the three most important control factors. The scaling factor, whose value falls between 0 and 2, regulates how perturbed the mutation process is. The crossover constant, which has a value between 0 and 1, regulates the population's diversity. The population size establishes how many people are in the population and gives the algorithm enough diversity to investigate the solution space. [17].

The incorporation of the DE algorithm into the proposed problem is described as follows:

Step 1: Enter the DE's parameters and system data.

Step 2: Assign k = 1 as the iteration count and kmax as the maximum iteration.

Step 3: Within the upper and lower boundaries, construct parent vectors at random.

$$Y_i^k = (\Delta P_{Gij}^{+} \ and \ \Delta P_{Gij}^{-} \ ; i = 1,2,..Np \ , j = 1,2,..,Ng) \quad (1)$$

Run the Newton Raphson (NR) power flow for each person and determine their slack bus power. Look for any instances where limits have been broken. In the event of a violation, regenerate the relevant particle.

Step 4: Vector X* should contain the differential evolution member that fits the best.

Step 5: Using the distance between two additional parameter vectors, create a candidate child vector Mi (k+1) for each parent vector Yik.

Step 6: Use the crossover procedure to create a trial vector Ti (k+1) from the parent and child vectors.

Step 7: The process of selection is what makes an offspring superior. Compare the fitness value of the vector Ti(k+1) with that of the corresponding vector Yik to decide whether or not it should be a part of the future generation's population. As Yi(k+1), save the vector that fits the model the best.

Step 8: Update vector X* and evaluate the fitness values for Yi (k+1). Check to see whether there is any queue traffic. Move on to the next phase if the congestion is fully eased or if the maximum number of iterations is reached. In every other case, go back to step 5 and set k = k+1.

Step 9: Print the best value of X* to show the optimal answer.

2.2 Crow Search Algorithm

The Crow Search Algorithm (CSA), a revolutionary algorithm suggested by Askarzadeh, which emulates the food-hiding behavior of crows [18]. Crows are intelligent birds that possess the ability to recognize faces and alert their species to potential dangers. One remarkable demonstration of their intelligence is their capability to hide food and remember its location.

Furthermore, the exploration and exploitation aspects of CSA can be understood by referring to Figure 1. Algorithm 1 can be used to express the pseudo code of CSA, and Figure 2 shows the CSA flowchart. The following is a summary of the primary CSA phases:

1) A random initialization is performed on the crows swarm in a d-dimensional space.

2) A fitness function is employed to evaluate each crow, and the resulting value is stored as the initial value.

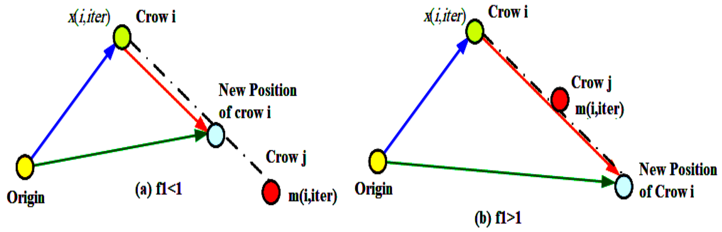

Fig 1 Exploration and Exploitation of CSA

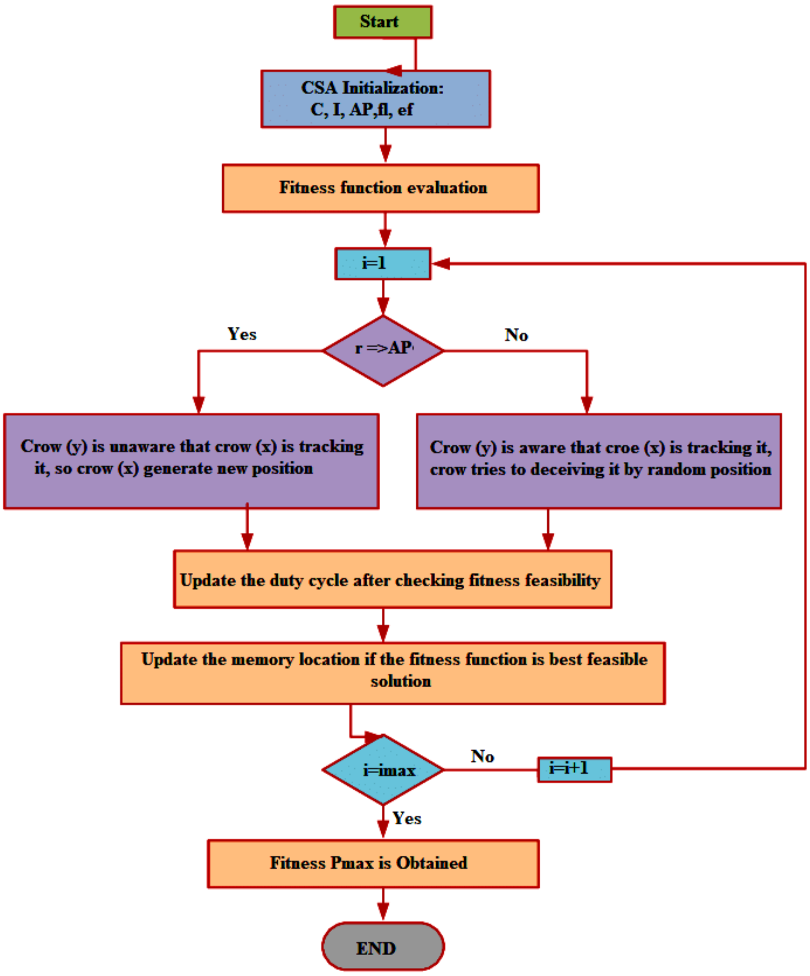

Fig 2 Flowchart of CSA

2.3 Improved Crow Search Algorithm (ICSA)

The CSA has demonstrated that it can determine the best option for particular search space configurations [13–15]. However, because of its search strategy's inadequate investigation, its convergence cannot be assured. When high multi-modal formulations are present, the CSA search technique faces considerable difficulties. Two main factors impact the search process in the original CSA method: the awareness probability (AP) and the random movement (evasion). Finding a balance between diversification and intensification is the responsibility of the AP value. On the other hand, because the random movement re-initializes candidate solutions, it directly affects the exploration process. Both the awareness probability (AP) and the random movement are redefined in the suggested ICSA technique.

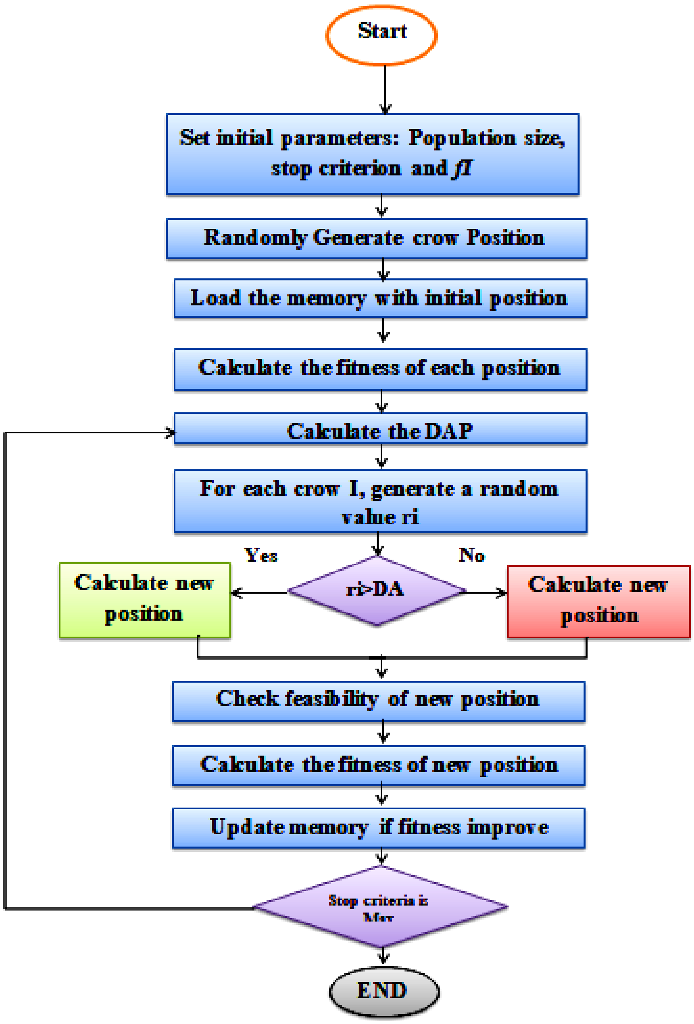

Fig 3 Flowchart of ICSA

2.4 Genetic Algorithm (GA)

In order to efficiently find and arrive at a superior solution that is near the global optimum, genetic algorithms make use of the concepts of population genetics and natural evolution. A binary string that represents a set of genes that correlate to chromosomes in biological systems is used to encode the design variables needed for the optimisation process. Genetic algorithms use a group of points called chromosomes as the initial conditions, as opposed to conventional optimisation methods that depend on a single starting point. A population is created when these chromosomes are grouped together. Between 30 and 300 chromosomes make up the average population size. Genes, or binary codes, make up each chromosome, and substrings may be present. The quality is assessed using the fitness function, which is derived from the objective function.

The cost reduction challenge is resolved by applying the genetic algorithm that this study suggests. The steps that the algorithm takes are as follows:

Step 1: Enter the parameters of the system, including the topology of the system, load and line specifications, maximum and minimum generation limitations, and flow limits for the lines. Add Nchrom chromosomes to the original population as well.

Step 2: Configure the parameter settings and start counter. For instance, set Fmin to a high value and Nch=Nit=NR=1.

Step 3: The Process of Fitness

Step 3A: Execute each chromosome's DC power flow and store the results.

Step 3B: Using the DC power flow's outputs, calculate the suggested penalty functions. Compute the fitness functions associated with every chromosome. Assign Nch to Nch+1.

Step 3C: Return to step 3A if Nch is less than or equal to Nchrom.

Step 4: The Process of Reproduction:

Step 4A: As the total of all fitness values for each chromosome, define the total fitness.

Step 4B: Determine a proportion of "roulette wheels" according to the fitness value of each chromosome relative to the total fitness value.

Step 4C: Roll the "roulette wheel" Nchrom times to enhance the generation. Choose a different set of chromosomes.

The Crossover Process, Step 5:

Choose a random number (RND1) for the mating of two parent chromosomes in step 5A.

Step 5B: Combine the two parents, produce two offspring, and move on to Step 5D if RND1 is between 0.01 and 0.3.

Step 5C: If not, move the chromosome without crossing over.

Step 5D: For each chromosome, repeat steps 5A through 5C.

Step 6: The Process of Mutation

Step 6A: For the mutation of one chromosome, choose a random number (RND2).

Step 6B: Apply the mutation process at a random location and move on to Step 6D if RND2 is between 0.01 and 0.1.

If not, transfer the chromosome without mutation (Step 6C).

Step 6D: For each chromosome, repeat Steps 6A through 6C.

Step 7: Updating Populations: Substitute the previous population with the enhanced one produced by Steps 2 through 6. Examine each chromosome to see whether there are any that have FL=1, FG=1, and FF <Fmin= FF, then note them. Nu=Nu+ 1 should be set.

Step 8 (Convergence): The answer will be printed and the process will end if all chromosomes are identical or if Nu = Nmax, the maximum number of iterations, is reached. If not, move on to Step 2.

2.5 Whale Optimization Algorithm (WOA)

Pre-processing the data entails turning unstructured data into structured data and enhancing the quality of the original data. Addressing the "curse of dimensionality" requires converting the typically high dimensional acquired data into low dimensional data. An acceptable strategy is selected for this research study out of the many possible approaches for data pre-processing. After preprocessing, the numerical data is used for classification and optimisation. This instance involves the pre-processing technique known as data normalisation, which turns the unstructured data into structured data. The heterogeneous set of numerical data is scaled via data normalisation, which sets the baseline to zero and the maximum value to one.

The Whale Optimisation Algorithm is used to optimise the pre-processed data (WOA). WOA is a meta-heuristic method that draws inspiration from humpback whale behaviour. The first step in the optimisation procedure is to generate a random population of whales. Then, these whales look for the best place to catch their prey and employ either an encircling or bubble-net technique [15].

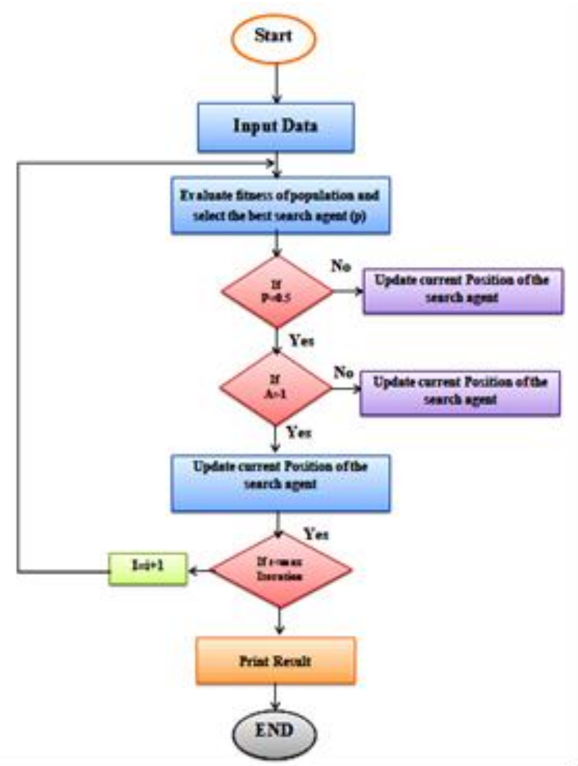

Fig 4 Flowchart of WOA

2.6 Updated Whale Optimization Algorithm (UWOA)

The target prey in the Whale Optimisation Algorithm (WOA) is the current fitness solution. As a result, the most recent fittest solution is used to update the placements of the remaining search agents.

The ideal position of the search agent is not defined in the original WOA at the outset of the procedure. The process may be limited to a local optimal location as a result of this information shortage. In order to overcome this constraint, the WOA has been improved by adding two correction factors, I F1 and I F2. These corrective variables are intended to overcome the previously described constraints in order to enhance performance.

The whales' ability to approach the prey in little stages thanks to the application of these corrective variables enhances the exploring stage. Figure 5 [16] shows the flowchart for the Updated Whale Optimization Algorithm (UWOA) for Congestion Management.

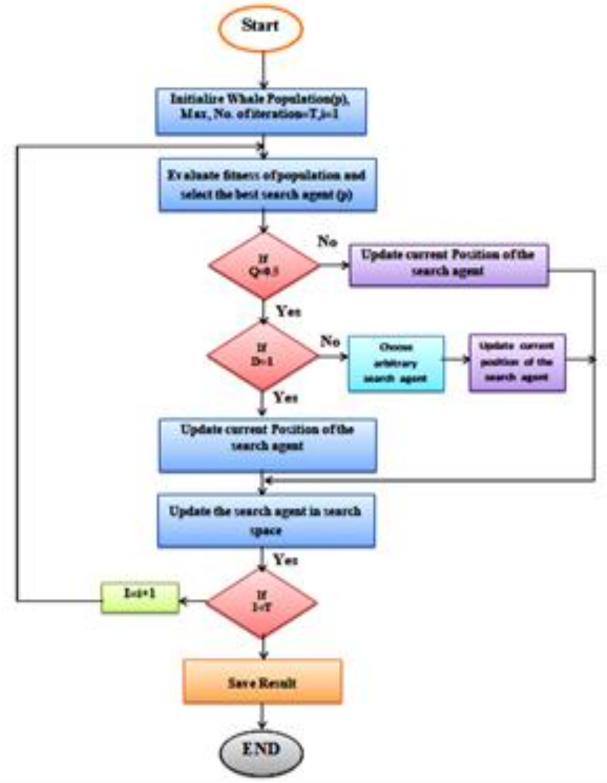

Figure 5 Flow chart of MWOA

3. Result Analysis

The suggested UWOA technique has been applied to In order to reduce the cost of congestion and ease transmission channel congestion, the UWOA technique was applied. It is apparent that the application of UWOA reduced transmission line congestion and allowed power flow to drop from 420.87 MW to 208.97 MW. The congestion costs attained by a number of algorithms—DE, CSA, ICSA, GA, WOA, MWOA, and UWOA—were compared. To compare the congestion costs attained by different methods, a graphical depiction was given. This section focuses on the use of UWOA on the 118-bus system, which is a sizable power system network.

Optimization algorithms for 118 bus system

When the UWOA is connected, the CM problem is mitigated. The optimal rescheduling of the chosen generators using UWOA alleviates the obstruction in line L8-30. Table 1 shows the yield that was attained for the 118 Bus structure with UWOA. In addition, the line flow is decreased from 209.63MW to 165.32MW previously. The cost of the blockage incurred by UWOA is 3032.27 \$/h. When compared to alternative optimization procedures, it is clear that UWOA has the lowest cost of obstruction. Figure 6 displays a comparative graphical representation of the obstruction cost.

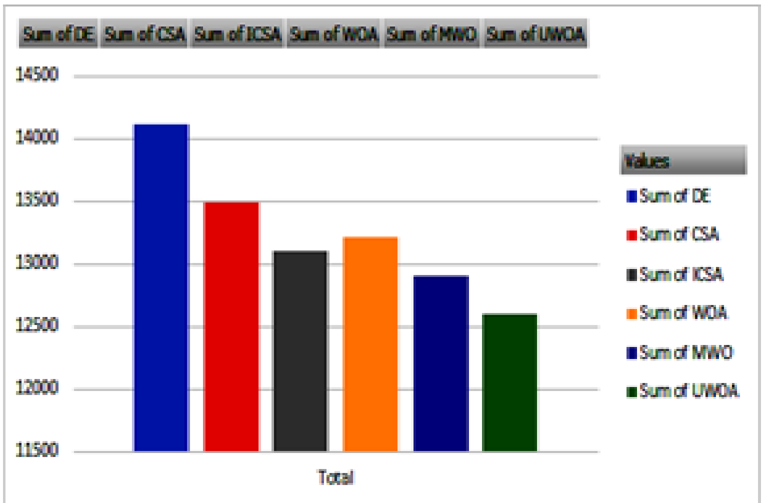

Fig 6 Comparison of congestion cost with various Optimization Algorithms

Figure 4 shows the merging feature of WOA as well as additional optimization techniques from the CM problem. When different optimization techniques were used to the CM fetched problem, UWOA obtained the 38th highest emphasis number. A comparison of the structure losses and voltages following the CM scenario is shown in Table 2. With UWOA, the structure loss is seen to have dropped from 140.78 MW to 131.846 MW (congested scenario). The reduction in structure losses realized using UWOA is significant when compared to other optimization methodologies provided in Table 2. Figure 6 shows the comparative structure losses following CM using the applied optimization algorithm for the 118 Bus structure. In addition, Table 2 shows that the average voltage at the buses.

Table 1 Comparison Chart for 118-bus System

	DE	CSA	ICSA	WOA	MWO	UWOA
Approx. congestion cost ($/h)	**3361.51**	**3190.69**	**3110.56**	**3178.02**	**3115.81**	**3032.27**
Best cost ($/h)	**3361.51**	**3190.69**	**3110.56**	**3178.02**	**3115.81**	**3032.27**
Worst cost ($/h)	**3559.16**	**3380.91**	**3167.56**	**3300.67**	**3163.42**	**3121**
Mean value	**3463.71**	**3364.7**	**3354.64**	**3201.64**	**3156.47**	**3076.64**
Standard Deviation	**8.4893**	**7.324**	**6.235**	**4.6842**	**2.3602**	**0.38026**
Power flow Post Obtained (MW)	**170.01**	**174.9**	**173.46**	**168.98**	**168.03**	**165.32**
Total Amount (MW)	**182.37**	**182.25**	**176.88**	**179.82**	**175.14**	**168.97**

Table 2 Survey of system mislaying and voltage for 118 bus system

Structure Parameter	**Before Rescheduling**	**CSA**	**ICSA**	**WOA**	**MWO**	**UWOA**
Loss (MW)	140.36	137.02	136.71	131.846	136.71	**131.846**
V (p.u.)	0.955	0.972	0.979	0.98814	0.979	**0.98814**

4. Conclusion

With just a few parameters needed, the Updated Whale Optimal approach (UWOA) is a straightforward and simple approach to use. It has demonstrated beneficial practical application effects and has been implemented successfully in a number of fields. It is therefore advised to investigate algorithm combinations in more detail in order to balance the capabilities of local and global search, increase convergence speed, and boost population diversity.

In order to reduce the overall cost of power generation in power systems, we present the Updated Whale Optimal Algorithm (UWOA) in this paper and evaluate it against alternative algorithmic approaches. The marginal cost at each bus is calculated using the nodal pricing method. The reference bus's marginal cost and the cost of congestion are added to determine each bus' locational marginal cost. The 118-bus IEEE test system's simulation results show that the suggested solutions significantly lower the system's overall cost, which benefits the users (Tables 1 and 2).

References

[1] Zeng HB, Liu XG, Wang W. "A generalized free-matrix-based integral inequality for stability analysis of time-varying delay systems", Applied Mathematics and Computation, 354 (2019), pp. 1-8

[2] Zeng, H., Liu, X., Wang, W., Xiao, S. "New results on stability analysis of systems with time-varying delays using a generalized free-matrix-based inequality", Journal of the Franklin Institute, 356(13) (2019), pp.7312- 7321. doi: 10.1016/j.jfranklin.2019.03.029

[3] Moayedi, H. Hayati, S. "Modelling and optimization of ultimate bearing capacity of strip footing near a slope by soft computing methods", Applied Soft Computing, 66 (2018), pp. 208-219 https://doi.org/10.1016/j.asoc.2018.02.027

[4] Weibiao Qiao, Hossein Moayedi, and Loke Kok Foong. "Natureinspired hybrid techniques of IWO, DA, ES, GA, and ICA, validated through a k-fold validation process predicting monthly natural gas consumption", Energy and Buildings 217 (2020), pp.110023. https://doi.org/10.1016/j.enbuild.2020.110023

[5] M. Li, F. Wen, N. Yixin and F.F Wu, "Optimal bidding strategies for generation companies in electricity markets with transmission capacity constraints taken into account", IEEE Power Engineering Society General Meeting, 2003, Vol. 4, pp. 13-17, July 2003

[6] J.M. Ramirez and G.A. Marin, "Alleviating congestion of an actual power system by genetic algorithms", Power Engineering Society General Meeting, 2004. IEEE, 6-10 June 2004, Vol. 2, pp. 2133-2141

[7] M. Saguan, S. Plumel, P. Dessante, J.M. Glachant and P. Bastard, "Genetic algorithm associated to game theory in congestion management"; Probabilistic Methods Applied to Power Systems, 2004 International Conference on, 12-16 Sept. 2004 pp. 415-420

[8] M. Shahidehpour, H. Yamin and Z. Li, "Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management", John Wiley & Sons, Inc., 2002, ISBNs: 0-471-44337-9 (Hardback); 0-471-22412-X (Electronic)

[9] A.J. Wood and B.F. Wollenberg, "Power Generation, Operation, and Control", New York: Wiley, 1996

[10] Seyed Abbas Taher, Muhammad Karim Amooshahi, "Optimal Load Frequency Control Using PSO Algorithm in Deregulated Power Systems", Vol. 2. n. 6, pp. 708-714

[11] H. Zhang, X. Wang, J. Cao, M. Tang, and Y. Guo. (2018). A hybrid short-term traffic flow forecasting model based on time series multifractal characteristics. Applied Intelligence, 48(8). Pp.2429-2440, 2018.

[12] Y. Wu, H. Tan, L. Qin, B. Ran, and Z. Jiang. (2018) "A hybrid deep learning based traffic flow prediction method and its understanding". Transportation Research Part C: Emerging Technologies, 90, pp.166-180.

[13] Askarzadeh, A, "Capacitor placement in distribution systems for power loss reduction and voltage improvement" A new methodology. IET Gener. Transm. Distrib. **2016**, 10, 3631–3638.

[14] Askarzadeh, A, "A novel metaheuristic method for solving constrained engineering optimization problems" Crow search algorithm. Comput. Struct. **2016**, 169, 1–12.

[15] X. Yu, S. Xiong, Y. He, W. E. Wong, and Y. Zhao. (2016). Research on campus traffic congestion detection using BP neural network and Markov model. Journal of Information Security and Applications, 31. Pp.54-60.

[16] Mirjalili, S.; Lewis, A.: The whale optimization algorithm. Adv. Eng. Softw. **95**, 51–67 (2016). https://doi.org/10.1016/j. advengsoft.2016.01.008.

[17] Gamperie, R. &, Muller,S. (2002) "A parameter study for Differential Evolution. Advances in Intelligent systems, Fuzzy systems, Evolutionary computation", WSEAS Press., 293 - 298.

[18] A. Askarzadeh, A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm, Computers & Structures 169 (2016) 1-12.