Bulletin of Electrical Engineering and Informatics
Vol. 15, No. 6, December 2026, pp. 4755~4765
ISSN: 2302-9285, DOI: 10.11591/eei.v15i6.11546

Hybrid SNGNN–BKOA framework for intelligent congestion management in renewable-integrated power systems

Venkateswarlu Tata[1], Tenali Nagamani[2], Maddukuri Venkata Ramesh[3], Kotikala Narayana Rao[4], Manam Ravindra[5], Jampani Satish Babu[6]
[1]Department of Computer Science and Engineering-Artificial Intelligence and Machine Learning, Kallam Haranadhareddy Institute of Technology, Guntur, India
[2]Department of Computer Science and Engineering, Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, India
[3]Department of Electrical and Electronics Engineering, Prasad V. Potluri Siddhartha Institute of Technology, Vijayawada, India
[4]Department of Computer Science and Engineering, Dhanekula Institute of Engineering and Technology, Ganguru, India
[5]Department of Electrical and Electronics Engineering, Aditya University, Surampalem, India
[6]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India

Article Info

Article history:

Received Oct 4, 2025
Revised Sep 11, 2026
Accepted Oct 4, 2026

Keywords:

Congestion management
Energy storage system
Graph neural network
Hybrid optimization
Renewable energy integration

ABSTRACT

The rapid integration of renewable energy sources (RES), such as wind and solar, introduces significant variability and uncertainty in modern power systems, which often leads to transmission congestion and operational inefficiencies. This paper proposes a hybrid congestion management framework that combines a similarity-navigated graph neural network (SNGNN) with the black-winged kite optimization algorithm (BKOA). The SNGNN model captures complex spatial relationships within the power network to accurately forecast load demand, while BKOA optimizes congestion mitigation by coordinating generator rescheduling and energy storage system (ESS) operations. The proposed framework was evaluated through MATLAB simulations under different renewable penetration levels. Results demonstrate that the SNGNN–BKOA approach achieves superior performance compared with benchmark algorithms such as grey wolf optimizer (GWO) and salp swarm algorithm (SSA). The proposed method reduces system power loss to 48.4 MW, achieves a forecasting RMSE of 0.164%, and lowers congestion mitigation costs to $5800.09/h at 10% renewable penetration and $6823.71/h at 40% penetration. These results indicate that the proposed hybrid learning–optimization framework improves grid stability, reduces operational cost, and enhances decision-making for congestion management in renewable-dominated smart grids.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Tenali Nagamani
Department of Computer Science and Engineering, Seshadri Rao Gudlavalleru Engineering College
Gudlavalleru, Andhra Pradesh, India
Email: tenalinagamani@gmail.com

1. INTRODUCTION

Renewable energy sources (RES) are increasingly used in electrical power systems due to their economic and environmental benefits. Wind and solar power reduce fossil fuel use and help the globe transition to low-carbon energy systems. These are beneficial benefits, but RES' erratic and intermittent behaviour produces uncertainty that can make systems less reliable and increase the demand for reserve capacity [1]. When meteorological variables like solar radiation and wind speed fluctuate, renewable unit output might be influenced, making system balance difficult. The increased demand for power and limited transmission line capacity worsen transmission network congestion, which reduces efficiency and endangers

current grids. Energy storage systems (ESS) are one of the most promising technologies for lowering RES fluctuation, but high capital costs limit their utilization, therefore they must be used efficiently [2]–[5]. Independent system operators (ISOs) are crucial to grid reliability in competitive power markets. They must also manage voltage instability, unit commitment, loss minimization, and transmission expansion planning [6]. In the previous decade, much research has been done to improve wind energy integration issues such network stability, demand response (DR), and generation sufficiency in distribution networks [7]. Researchers have examined solar-based systems' energy sufficiency, smart home energy management, and DR roles [8], [9]. Wind and solar remain unclear, making power system planning harder and transmission congestion more likely. Many people have suggested adopting ESS to prevent these impacts, but system planners must compare investment costs against system reliability to identify the optimum size and operation [10].

Many scholars have introduced optimization-based methods to progress this discipline. El-Azab *et al.* [11] introduced a probabilistic multi-objective congestion management model that lowered generating costs, enhanced system dependability, and prevented islanding by incorporating transmission switching scenarios. In hybrid systems with thermal and renewable units, Ali *et al.* [12] suggested the white shark optimizer (WSO) to solve optimal power flow (OPF) concerns. Their research demonstrated that new bio-inspired metaheuristics could cut costs, but RES only produce energy at particular periods, making integration difficult. A differential evolution-based multi-objective framework improved Ghiasi *et al.* [13] smart microgrid model. This model lowered operating expenses and environmental impact. Other studies have examined multi-energy carrier hybrid solutions. A more flexible virtual energy storage system (VESS) was developed by Aghdam *et al.* [14] using hydrogen, batteries, and power-to-hydrogen conversion. Gupta *et al.* [15] used a mixed-integer nonlinear programming problem to build a wind-hydro bidding mechanism to reduce rescheduling costs to manage congestion. Prashant *et al.* [16] optimized distributed generator sizing using harmony search optimization (HSO) and particle swarm optimization (PSO) to reduce congestion and operational expenses. Suresh and Meenakumari [17] combined DR tactics with hybrid optimization algorithms to improve smart grid renewable resource inclusion. Their adaptive whale optimization–tabu search (AWOTS) hybrid algorithm had potential, but parameter tweaking and computing cost prevented its widespread use.

These experiments demonstrate that heuristic and metaheuristic optimization approaches work, however there are issues. PSO converges too early and becomes caught in local optima, making it unsuitable for complicated, high-dimensional power system problems. Teacher learning-based optimization (MOTLBO) is computationally demanding and struggles to balance conflicting goals in large systems. Hybrid approaches like AWOTS improve exploration and exploitation, but they need more work and are sensitive to parameter changes. These constraints demonstrate the need for better frameworks that may manage RES fluctuation, reduce congestion, and improve energy management [18]–[20]. Recently improved artificial intelligence (AI) and machine learning (ML) give us new solutions to solve these difficulties. Graph neural networks (GNNs) are promising for modelling complex systems like power grids' structural and topological dependencies. The similarity-navigated graph neural network (SNGNN) dynamically acquires graph structure and node properties to improve prediction precision [21]. SNGNN improves load demand estimates, lowering congestion management uncertainty. Adding a robust optimization algorithm to this prediction ability helps system operators decide. This work improves congestion mitigation tactics using the newly developed nature-inspired metaheuristic black-winged kite optimization algorithm (BKOA). BKOA, which models black-winged kite predatory and migratory behaviours, provides improved global search and convergence qualities for engineering optimization issues [22]. It and SNGNN create a hybrid strategy with data-driven forecast accuracy and significant optimization. The SNGNN–BKOA framework balances renewable uncertainty, optimizes ESS scheduling, and lowers congestion costs, filling major gaps in earlier techniques. Congestion management and dependability are more important due to power system changes [23]–[25]. Emerging uncertainties, such as electric vehicle charging erraticness, stress system operators trying to maintain grid resilience [26], [27]. Thus, congestion control in RES-dominated grids requires proactive operational efficiency and uncertainty management solutions.

This work is novel because it uses SNGNN to model complex grid interactions and accurately predict load demand under different renewable penetration levels and BKOA to optimize congestion management by minimizing costs and losses while following system rules. The methodology is tested and compared to the grey wolf optimiser (GWO) and salp swarm algorithm (SSA) using MATLAB simulations. The hybrid technique consistently reduces congestion costs, system losses, and calculation times compared to benchmark algorithms. However, the SNGNN–BKOA approach has a minimal system loss of 48.4 MW and an RMSE of 0.164%. It is more accurate and reliable than other methods. At varying renewable penetration levels, the suggested framework is powerful and flexible. This suggests it could help system operators manage power networks with lots of renewable energy. This research presents an effective hybrid learning-

optimization strategy for congestion management, optimizes ESS operation to better integrate renewable resources, and outperforms current optimization methods in various situations. This work improves congestion management methods for modern power systems and enables intelligent, hybrid solutions in future smart grids with renewable energy dominance.

Despite significant advances in renewable-integrated congestion management, existing approaches commonly treat load forecasting and congestion mitigation as separate tasks. Moreover, many optimization-based methods do not explicitly exploit the similarity and topological relationships among power system components when predicting future operating conditions. The proposed SNGNN–BKOA framework addresses this gap by integrating similarity-based spatial learning with adaptive congestion optimization. SNGNN captures complex relationships among buses, generators, and load nodes to improve demand prediction, while BKOA utilizes the forecasted operating information to coordinate generator rescheduling, DR, and ESS operation. Thus, the novelty of the proposed framework lies in the direct integration of predictive network intelligence and bio-inspired optimization for proactive congestion management under renewable uncertainty.

System configuration for congestion management with res integration: the incorporation of RES like wind and solar has fundamentally altered the configuration of contemporary power systems. But because they are not always reliable and can change, they often cause imbalances between generation and demand, which can lead to transmission congestion and threaten the stability of the grid. To solve these problems, a framework for managing congestion has been made that uses both hybrid modelling and optimisation. Figure 1 shows how the proposed congestion management in power systems (CMPS) will work with RES integration. The model has traditional thermal generation units, renewable energy plants (like wind and solar), and an ESS. The ISO is in charge of running the grid. It keeps an eye on network status, load demand, and power flows all the time to make sure that both operational and market constraints are met.

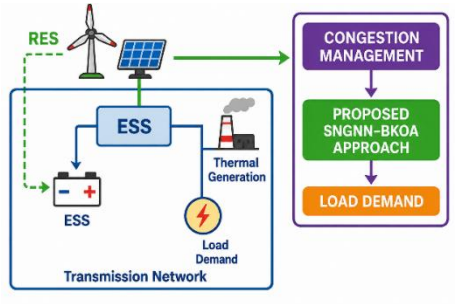


Figure 1. Proposed SNGNN–BKOA framework for congestion management

The ESS plays a key role in mitigating the uncertainty associated with RES. During periods of excess renewable generation, the ESS stores surplus power to prevent transmission congestion, while during high demand or low renewable output, it releases stored energy to maintain supply balance. This charge–discharge mechanism improves system reliability and reduces congestion mitigation costs. The proposed SNGNN–BKOA framework supports this process by combining accurate load forecasting with efficient optimization. The SNGNN captures nonlinear relationships among buses, generators, and loads to improve demand prediction. Based on the forecasted demand, the BKOA optimizes generator scheduling, DR participation, and ESS operation, ensuring both technical feasibility and economic efficiency. Despite significant progress in congestion management using optimization techniques and AI methods, existing studies often treat load forecasting and congestion mitigation as separate problems. Furthermore, many hybrid optimization approaches do not explicitly consider the spatial dependencies of power networks or the coordinated scheduling of ESSunder renewable uncertainty. These limitations motivate the need for an integrated predictive–optimization framework capable of simultaneously improving forecasting accuracy and congestion mitigation performance.

2. METHOD

To handle congestion in modern power systems with a lot of renewable energy, you need a plan that can both accurately predict how the load will behave and make the best decisions for reducing congestion quickly. To accomplish this, a hybrid methodology is formulated by amalgamating a SNGNN with the BKOA. The SNGNN's job is to improve load demand forecasting by taking into account the nonlinear and

topological connections between buses, generators, and demand nodes, which traditional forecasting methods often miss. The SNGNN uses a similarity-driven aggregation mechanism to improve representation learning, which lets the network predict load changes more accurately. This is different from traditional graph convolutional networks, which only use adjacency-based propagation. Being able to accurately predict demand is very important for being able to anticipate possible congestion situations before they happen. This lets the system operator take proactive steps. After the demand forecast is made, the BKOA is used to improve congestion management by changing the times when generators produce power, changing DR programs, and coordinating the operations of ESS. BKOA goes through phases of exploration (attacking behaviour) and exploitation (migration behaviour), just like black-winged kites do when they hunt and move around. The algorithm searches new solution spaces aggressively during exploration to avoid premature convergence. During exploitation, it improves candidate solutions based on the most promising areas found in earlier iterations. This balanced process makes sure that everything comes together and reduces the chances of getting stuck in local minima, which are common problems with algorithms like PSO and GWO. The overall objective function is set up to find the lowest cost for relieving congestion while still meeting the requirements for power balance, generators, and transmission lines. Figure 2 shows how BKOA works, starting with population initialisation and fitness evaluation, going through attacking and migration phases for iterative position updates, and ending with finding the global optimum. The proposed framework can lower congestion management costs, cut down on transmission losses, and make computations more efficient by combining the predictive intelligence of SNGNN with the optimisation power of BKOA. Simulation results show that the SNGNN–BKOA method always works better than benchmark algorithms like the SSA and the GWO. This makes it a strong and scalable way to reduce congestion in power systems that use renewable energy.

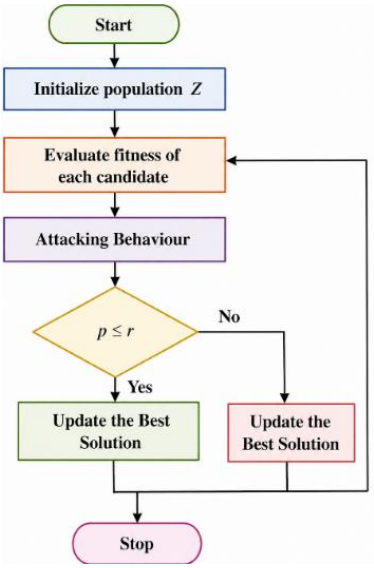


Figure 2. Flowchart of the proposed BKOA optimization process

The SNGNN architecture consists of multiple graph convolution layers followed by nonlinear activation functions and fully connected layers for load prediction. The network parameters were trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. The BKOA algorithm was configured with a population size of 50 and a maximum iteration count of 100. The exploration and exploitation phases follow the attacking and migration strategies described in the original BKOA formulation. For reproducibility, the SNGNN architecture consists of graph-based feature aggregation layers followed by nonlinear activation and fully connected prediction layers. The network was trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. For congestion optimization, BKOA was configured with a population size of 50 and a maximum iteration limit of 100. The optimization process combines exploration through attacking behaviour and exploitation through migration behaviour to search for feasible solutions while satisfying power balance, generator operating, transmission, ESS, and DR constraints.

3. RESULTS AND DISCUSSION

The proposed congestion management framework was evaluated using MATLAB simulations on a modified IEEE power network test system. The system consists of multiple generation units, transmission lines, and load buses that represent a renewable-integrated power network. Renewable generation was modeled using photovoltaic (PV) and wind turbine (WT) profiles. PV generation follows a typical diurnal solar irradiance curve, while wind generation was generated using stochastic wind speed profiles. The proposed framework was evaluated using MATLAB simulations on a modified renewable-integrated IEEE power network containing conventional generation, transmission lines, load buses, PV generation, wind generation, and energy storage resources. Two renewable penetration scenarios, namely 10% and 40%, were considered to analyze system performance under different levels of renewable variability. The proposed SNGNN–BKOA method was compared with GWO and SSA. Each optimization algorithm was executed independently for 30 runs, and the mean performance values were used to evaluate system loss, congestion relief cost, load forecasting error, and computation time. Standard deviation was also calculated to assess the consistency and stability of the optimization results. The suggested SNGNN–BKOA hybrid framework for managing congestion in renewable-integrated power systems was put into action and tested in MATLAB. The primary aim of this study was to decrease system losses, lower congestion relief costs, and enhance forecasting accuracy amid varying degrees of renewable energy integration. Simulation studies were performed utilising solar PV, WT, and integrated renewable profiles in conjunction with traditional generation units and ESS. The findings are illustrated via graphical analysis and comparative studies against benchmark algorithms, including the GWO and the SSA.

Figure 3 shows how much renewable energy was available during the simulation period. Figure 3(a) shows the output of the PV system, which changes a lot depending on how much sunlight it gets. It has its highest output in the middle of the day and almost none at night. Figure 3(b) shows the output of the WT, which changes because the wind speed is random. The output has many peaks and troughs over time. Figure 3(c) shows the total amount of renewable power available by combining these two sources. The fact that solar and wind power are both used means that even though PV stops working at night, wind power often keeps working, which makes the renewable contribution more stable. The fact that both types of power are available at the same time shows how important it is to have good scheduling and congestion management plans, since the natural variability can easily put stress on transmission lines.

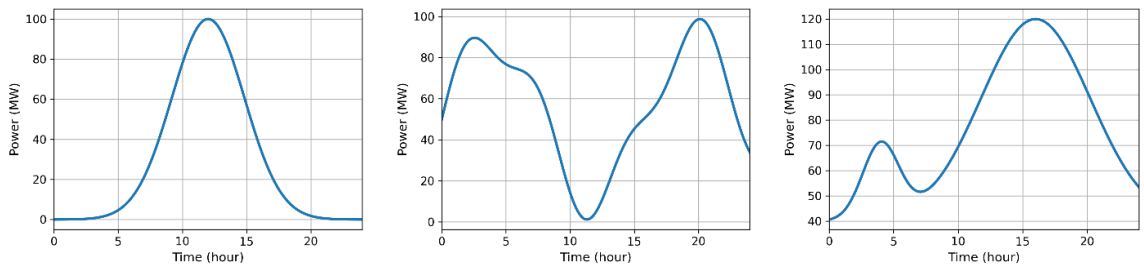
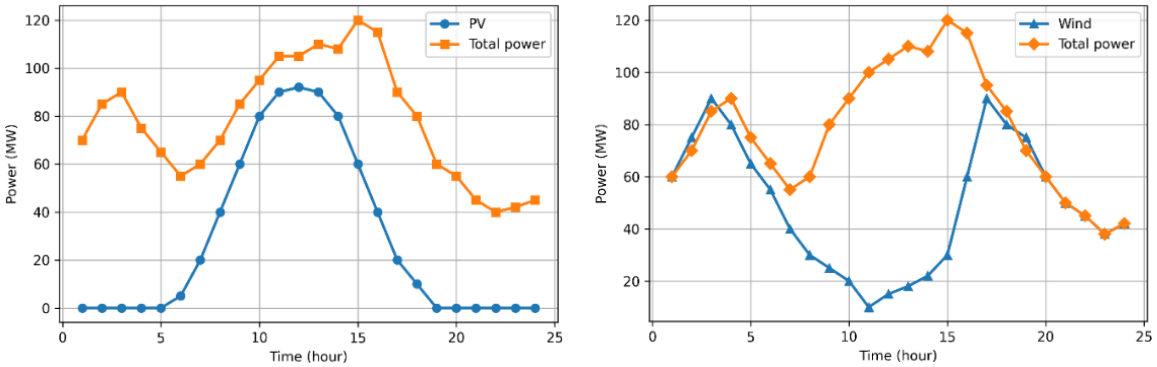


Figure 3. Renewable power availability analysis: (a) PV power, (b) wind power, and (c) combined renewable power

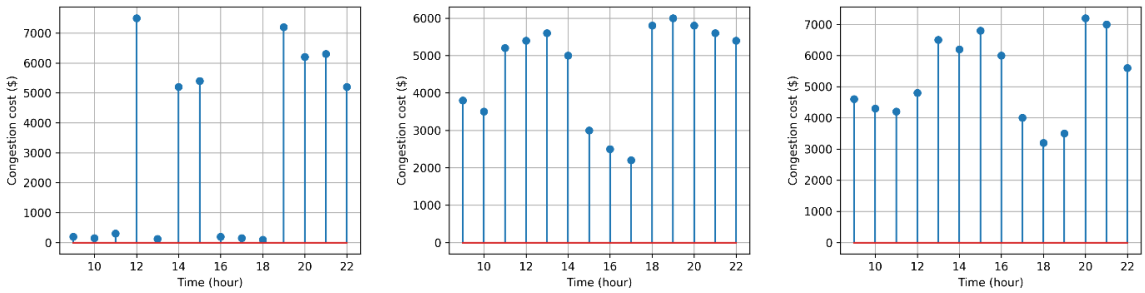
Figure 4 goes into more detail about how much energy each renewable source contributes. Figure 4(a) shows PV power, Figure 4(b) shows wind power, and the two together are used to figure out how much energy is available for scheduling. It is evident that while PV output is relatively predictable, displaying a distinct diurnal pattern, wind generation demonstrates considerable irregularities. The complementary behaviour of solar and wind is what drives the need for hybrid congestion management systems that can balance their combined uncertainty with ESS support.

Figure 5 shows the effect of congestion pricing by looking at how the market reacts in different situations. The price for grid-only response in the first scenario, where the grid takes on all congestion costs, is shown in Figure 5(a). Figure 5(b) shows the grid-only response in the second scenario. This causes congestion prices to go up because there are more renewable sources and they change more often. Figure 5(c) shows a strategy that combines the grid and DR in the second scenario. This strategy gets much lower congestion prices by getting consumers involved. The findings underscore the significance of amalgamating DR with congestion management strategies, as it mitigates price volatility and bolsters overall system resilience.



(a) (b)

Figure 4. Analysis of total power availability: (a) PV power and (b) wind power

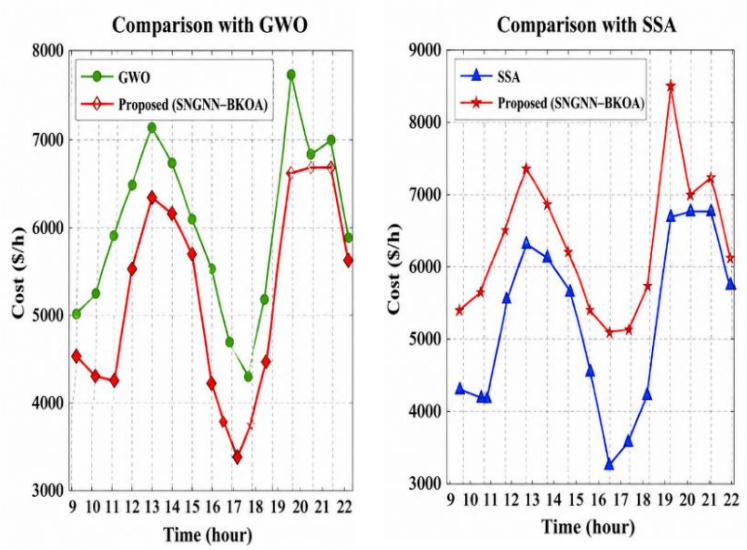


(a) (b) (c)

Figure 5. Congestion price analysis: (a) grid response–scenario 1, (b) grid response–scenario 2, and (c) grid+DR–scenario 2

Figure 6 shows how the proposed SNGNN–BKOA framework works compared to other algorithms. The proposed method is compared to the GWOin Figure 6(a) and the SSA in Figure 6(b). In both cases, the proposed method works better because it consistently lowers the costs of congestion mitigation. The proposed method has a minimum congestion relief cost of $5800.09/h at 10% penetration and $6823.71/h at 40% penetration. This is better than GWO and SSA, which have higher costs under the same conditions. The lower cost of congestion relief is a direct result of SNGNN's ability to make accurate predictions and BKOA's ability to balance exploration and exploitation. The comparative results indicate that BKOA achieves improved convergence behaviour by balancing global exploration and local exploitation during the optimization process. During the attacking phase, the algorithm explores alternative solution regions to reduce the possibility of premature convergence, whereas the migration phase refines promising candidate solutions. This mechanism enables BKOA to obtain lower congestion relief costs than GWO and SSA. The proposed framework achieved congestion relief costs of $5800.09/h at 10% renewable penetration and $6823.71/h at 40% penetration, while also maintaining computational times of 5.6 s and 13.4 s, respectively.

Figure 7 shows how the costs of congestion relief change from day to day by comparing system performance over a full day of operation. The suggested hybrid approach clearly keeps congestion costs lower all day than current methods. This is especially important when the load is at its highest, when renewable variability can make congestion risks worse. The proposed framework gets rid of the extreme peaks that are common in baseline methods by optimising ESS scheduling and using DR strategies. In general, the results show that the main goals of the proposed work-lowering costs, minimising losses, and improving accuracy-have been met. The system loss is down to 48.4 MW, and the root mean square error (RMSE) in load forecasting is down to 0.164%. This shows how accurate the SNGNN forecasting component is. Also, the proposed framework is computationally efficient, which means it converges faster than GWO and SSA. This is important for real-time grid operations.



(a) (b)

Figure 6. Comparison of congestion relief costs for SNGNN–BKOA, GWO, and SSA: (a) low renewable energy penetration and (b) high renewable energy penetration

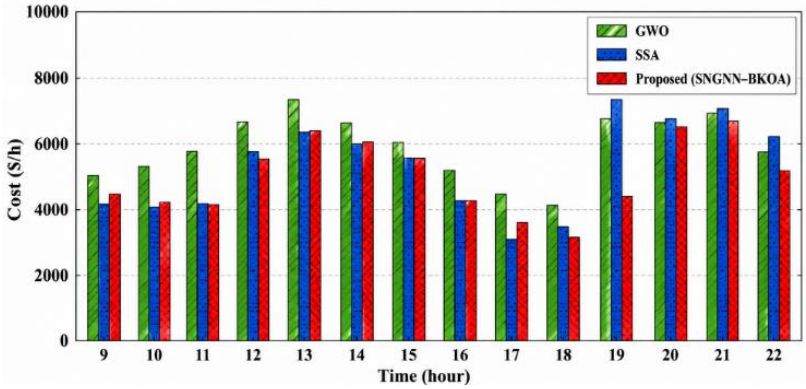


Figure 7. Daily variation in congestion relief cost under changing operating conditions

Discussion: the results show that hybrid methods work very well for managing congestion in grids with a lot of renewable energy. When combined with ESS, the complementary qualities of solar and wind can create stable supply profiles. However, because they are inherently uncertain, they need advanced predictive and optimisation tools. SNGNN successfully solves the problem of making predictions by capturing complicated spatial and temporal dependencies. BKOA, on the other hand, effectively lowers congestion costs by intelligently scheduling resources for generation, storage, and DR. The proposed method is more accurate, has fewer losses, and works better on computers than traditional metaheuristics. This makes the SNGNN-BKOA framework a good choice for use in future smart grids with a lot of renewable energy, where managing congestion well will be important for both technical reliability and economic sustainability.

As shown in Table 1, the proposed SNGNN–BKOA framework achieved low system loss and forecasting error while maintaining effective congestion relief performance under different renewable penetration levels. The results also demonstrate its computational efficiency, supporting its suitability for renewable-integrated congestion management. Sensitivity analysis was performed by examining the behaviour of the proposed framework under different renewable penetration levels and load variations. The results demonstrate that the proposed method maintains low system losses and stable congestion management performance under changing operating conditions. The system loss was reported as 48.4 MW under the main operating scenario, while losses of 46.7 MW and 47.8 MW were obtained for 2% and 5% load variations, respectively. These results indicate that the proposed framework maintains stable operational performance despite variations in system demand.

The proposed framework also demonstrates potential scalability because the forecasting and optimization stages are designed to support changing operating conditions and increasing renewable penetration. However, the present evaluation is conducted on a medium-scale power network. Therefore, further validation using larger benchmark systems, such as IEEE 57-bus and IEEE 118-bus networks, is required to establish the computational scalability and performance of the framework under larger network dimensions and more complex operating conditions. From a practical perspective, the proposed SNGNN–BKOA framework can support decision-making within ISO and energy management system environments. The SNGNN component can provide short-term operating information based on the predicted demand and network relationships, while BKOA can generate congestion mitigation decisions involving generator rescheduling, ESS scheduling, and DR. In practical deployment, the framework would need to operate together with existing market rules, security constraints, communication infrastructure, and real-time operational requirements.

Table 1. Overall performance comparison of the proposed SNGNN–BKOA framework

Performance metric	SNGNN–BKOA
System loss	48.4 MW
Load forecasting RMSE	0.164%
Congestion relief cost at 10% RES	$5800.09/h
Congestion relief cost at 40% RES	$6823.71/h
Computation time at 10% RES	5.6 s
Computation time at 40% RES	13.4 s

4. CONCLUSION

This study introduced a hybrid framework for CMPS characterised by significant integration of RES. The suggested method combines the BKOA for lowering congestion relief costs with the SNGNN for precise load forecasting. The method uses predictive intelligence and metaheuristic optimisation to deal with the nonlinear and uncertain nature of RES while making sure that ESS and DR are scheduled efficiently. The SNGNN–BKOA model consistently outperforms other optimisation methods like the GWO and the SSA, as shown by the simulation results. The proposed method had the lowest gearbox system loss of 48.4 MW and the lowest RMSE of 0.164%, which shows how accurate and reliable it is. The system also stayed stable with very little loss when the load changed. For example, it only recorded 46.7 MW when the load increased by 2% and 47.8 MW when the load increased by 5%. The suggested method also had the lowest costs for relieving congestion, bringing them down to $5800.09/h at 10% renewable penetration and $6823.71/h at 40% penetration. The method also worked better because it took 5.6 seconds at 10% penetration and 13.4 seconds at 40% penetration, making it good for real-time grid applications. The combining SNGNN and BKOA has worked to reduce traffic, lower costs, and make the system more resilient when renewable energy generation is uncertain. This hybrid strategy makes the grid more reliable and encourages the use of renewable energy. Future research directions encompass the expansion of the model to encompass larger and more heterogeneous power networks, the enhancement of robustness in the face of extreme variability, and the investigation of lightweight optimisation algorithms to further diminish computational complexity.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to their respective institutions and colleagues for providing the necessary resources and support to carry out this research.

FUNDING INFORMATION

The authors did not receive any specific grant or financial support from funding agencies in the public, commercial, or not-for-profit sectors for this research

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Venkateswarlu Tata	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	✓
Tenali Nagamani	✓	✓			✓	✓		✓	✓	✓	✓	✓	✓	
Maddukuri Venkata Ramesh	✓		✓	✓			✓			✓	✓		✓	✓
Kotikala Narayana Rao	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Manam Ravindra		✓				✓		✓	✓	✓	✓	✓		
Jampani Satish Babu	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing -**O**riginal Draft
E : Writing - Review &**E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest regarding the publication of this research work.

ETHICAL APPROVAL

This article does not contain any studies involving human participants or animals performed by any of the authors.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] S. Deb *et al*., "Charging coordination of plug-in electric vehicle for congestion management in distribution system integrated with renewable energy sources," *IEEE Transactions on Industry Applications*, vol. 56, no. 5, pp. 5452–5462, Sep. 2020, doi: 10.1109/TIA.2020.3010897.

[2] S. Namilakonda and Y. Guduri, "Chaotic darwinian particle swarm optimization for real-time hierarchical congestion management of power system integrated with renewable energy sources," *International Journal of Electrical Power & Energy Systems*, vol. 128, Jun. 2021, doi: 10.1016/j.ijepes.2020.106632.

[3] V. K. Prajapati and V. Mahajan, "Reliability assessment and congestion management of power system with energy storage system and uncertain renewable resources," *Energy*, vol. 215, Jan. 2021, doi: 10.1016/j.energy.2020.119134.

[4] H. Doagou-Mojarrad, H. Rezaie, and H. Razmi, "Probabilistic integrated framework for AC/DC transmission congestion management considering system expansion, demand response, and renewable energy sources and load uncertainties," *International Transactions on Electrical Energy Systems*, vol. 31, no. 12, Dec. 2021, doi: 10.1002/2050-7038.13168.

[5] B. N. Bhukya, P. R. Chinda, S. R. Rayapudi, and S. R. Bondalapati, "Congestion management of power transmission line with advanced interline power flow controller," *Journal of Mechatronics, Electrical Power, and Vehicular Technology*, vol. 16, no. 1, pp. 52-68, 2025, doi: 10.55981/j.mev.2025.795.

[6] J. Hu, X. Liu, M. Shahidehpour, and S. Xia, "Optimal operation of energy hubs with large-scale distributed energy resources for distribution network congestion management," *IEEE Transactions on Sustainable Energy*, vol. 12, no. 3, pp. 1755–1765, Jul. 2021, doi: 10.1109/TSTE.2021.3064375.

[7] S. Kim and J. Hur, "Probabilistic power output model of wind generating resources for network congestion management," *Renewable Energy*, vol. 179, pp. 1719–1726, Dec. 2021, doi: 10.1016/j.renene.2021.08.014.

[8] X. Yan, C. Gu, X. Zhang, and F. Li, "Robust optimization-based energy storage operation for system congestion management," *IEEE Systems Journal*, vol. 14, no. 2, pp. 2694–2702, Jun. 2020, doi: 10.1109/JSYST.2019.2932897.

[9] D. Singh, N. Pal, S. K. Sinha, and B. Singh, "Allocation of reserved green energy transmission corridors to secure power purchase agreements in smart power networks during congestion management," *Electric Power Systems Research*, vol. 209, Aug. 2022, doi: 10.1016/j.epsr.2022.108006.

[10] M. Pantoš, "Market-based congestion management in electric power systems with exploitation of aggregators," *International Journal of Electrical Power & Energy Systems*, vol. 121, Oct. 2020, doi: 10.1016/j.ijepes.2020.106101.

[11] M. EL-Azab, W. A. Omran, S. F. Mekhamer, and H. E. A. Talaat, "Congestion management of power systems by optimizing grid topology and using dynamic thermal rating," *Electric Power Systems Research*, vol. 199, Oct. 2021, doi: 10.1016/j.epsr.2021.107433.

[12] M. A. Ali, S. Kamel, M. H. Hassan, E. M. Ahmed, and M. Alanazi, "Optimal power flow solution of power systems with renewable energy sources using white sharks algorithm," *Sustainability*, vol. 14, no. 10, May 2022, doi: 10.3390/su14106049.

[13] M. Ghiasi, T. Niknam, M. Dehghani, P. Siano, H. H. Alhelou, and A. Al-Hinai, "Optimal multi-operation energy management in smart microgrids in the presence of RESs based on multi-objective improved DE algorithm: Cost-emission based optimization," *Applied Sciences*, vol. 11, no. 8, Apr. 2021, doi: 10.3390/app11083661.

[14] F. H. Aghdam, M. W. Mudiyanselage, B. Mohammadi-Ivatloo, and M. Marzband, "Optimal scheduling of multi-energy type virtual energy storage system in reconfigurable distribution networks for congestion management," *Applied Energy*, vol. 333, Mar. 2023, doi: 10.1016/j.apenergy.2022.120569.
[15] A. Gupta, Y. P. Verma, and A. Chauhan, "Wind-hydro combined bidding approach for congestion management under secured bilateral transactions in hybrid power system," *IETE Journal of Research*, vol. 69, no. 1, pp. 354–367, Jan. 2023, doi: 10.1080/03772063.2020.1822216.
[16] Prashant, M. Sarwar, A. S. Siddiqui, S. S. M. Ghoneim, K. Mahmoud, and M. M. F. Darwish, "Effective transmission congestion management via optimal DG capacity using hybrid swarm optimization for contemporary power system operations," *IEEE Access*, vol. 10, pp. 71091–71106, 2022, doi: 10.1109/ACCESS.2022.3187723.
[17] M. Suresh and R. Meenakumari, "Optimum utilization of grid connected hybrid renewable energy sources using hybrid algorithm," *Transactions of the Institute of Measurement and Control*, vol. 43, no. 1, pp. 21–33, Jan. 2021, doi: 10.1177/0142331220913740.
[18] L. Lind, R. Cossent, J. P. Chaves-Ávila, and T. G. S. Román, "Transmission and distribution coordination in power systems with high shares of distributed energy resources providing balancing and congestion management services," *WIREs Energy and Environment*, vol. 8, no. 6, Nov. 2019, doi: 10.1002/wene.357.
[19] M. Numan, A. Z. Khan, M. Asif, S. M. Malik, and K. Imran, "Exploiting the inherent flexibility in transmission network for optimal scheduling, wind power utilization, and network congestion management," *IEEE Access*, vol. 9, pp. 88746–88758, 2021, doi: 10.1109/ACCESS.2021.3090089.
[20] A. Navon, P. Kulbekov, S. Dolev, G. Yehuda, and Y. Levron, "Integration of distributed renewable energy sources in Israel: Transmission congestion challenges and policy recommendations," *Energy Policy*, vol. 140, May 2020, doi: 10.1016/j.enpol.2020.111412.
[21] M. Zou, Z. Gan, R. Cao, C. Guan, and S. Leng, "Similarity-navigated graph neural networks for node classification," *Information Sciences*, vol. 633, pp. 41–69, Jul. 2023, doi: 10.1016/j.ins.2023.03.057.
[22] J. Wang, W. Wang, X. Hu, L. Qiu, and H. Zang, "Black-winged kite algorithm: a nature-inspired meta-heuristic for solving benchmark functions and engineering problems," *Artificial Intelligence Review*, vol. 57, no. 4, Mar. 2024, doi: 10.1007/s10462-024-10723-4.
[23] P. Rajesh, R. Kannan, J. Vishnupriyan, and B. Rajani, "Optimally detecting and classifying the transmission line fault in power system using hybrid technique," *ISA Transactions*, vol. 130, pp. 253–264, Nov. 2022, doi: 10.1016/j.isatra.2022.03.017.
[24] V. P. Moorthy, S. S. Subramanian, V. Tamilselvan, S. Muthubalaji, P. Rajesh, and F. H. Shajin, "A hybrid technique based energy management in hybrid electric vehicle system," *International Journal of Energy Research*, vol. 46, no. 11, pp. 15499–15520, Sep. 2022, doi: 10.1002/er.8248.
[25] S. Muthubalaji, S. Srinivasan, and M. Lakshmanan, "IoT based energy management in smart energy system: A hybrid SO2SA technique," *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, vol. 34, no. 5, Aug. 2021, doi: 10.1002/jnm.2893.
[26] S. Muthubalaji, M. A. Kareem, N. Karuppiah, and M. G. Sugirtha, "An enhanced analysis of two diode model PV module under various weather conditions," in *2017 IEEE International Conference on Circuits and Systems (ICCS)*, Dec. 2017, pp. 162–167, doi: 10.1109/ICCS1.2017.8325982.
[27] S. Rajalingam, N. Karuppiah, S. Muthubalaji, and J. Shanmugapriyan, "Power quality improvement in the distribution system by interconnecting PV using hybrid DSTATCOM," *International Journal of Advanced Technology and Engineering Exploration*, vol. 9, no. 88, pp. 310–325, Mar. 2022, doi: 10.19101/IJATEE.2021.875154.

BIOGRAPHIES OF AUTHORS



Dr. Venkateswarlu Tata is a faculty member in the Department of Computer Science and Engineering (AIML), with research and teaching interests in machine learning, data science, artificial intelligence, and advanced computing. His research focuses on developing intelligent and data-driven solutions for real-world applications, with particular emphasis on machine learning, deep learning, cloud computing, and emerging computational technologies. He has published research articles in international journals and conferences and actively contributes to academic teaching, research, and professional activities. He was completed his M.Tech. at Acharya Nagarjuna University, Guntur and Ph.D. in Computer Science and Engineering at Annamalai University Chidambaram, Tamilnadu, India. His research interests are primarily in the area of machine learning, deep learning, and IoT. He can be contacted at email: venkat543@gmail.com.



Dr. Tenali Nagamani is an esteemed academician, currently serving as an associate professor in the Department of Computer Science and Engineering at Seshadri Rao Gudlavalleru Engineering College, Andhra Pradesh, India. She received her Ph.D. in Computer Science and Engineering from Acharya Nagarjuna University and holds an M.Tech. from JNTUK, Kakinada. Her research interests include data science, big data analytics, data mining, machine learning, deep learning, quantum computing, web technologies, and cryptography, and network security. She has published several research papers in reputed journals and conferences, and has authored books and holds several patents in her areas of expertise. She is an active member of professional bodies including IEEE, ACM, CSI, ISTE, CSTA, and MIEA. She can be contacted at email: tenalinagamani@gmail.com.



Dr. Maddukuri Venkata Ramesh working as an associate professor in Prasad V. Potluri Siddhartha Institute of Technology, Vijayawada, India. He received a Bachelor of Technology in Electrical and Electronics Engineering from Nagarjuna University, Master of Science in Electrical Engineering/System Design and Technology from University of Darmstadt, Germany and Ph.D. in Electrical and Electronics Engineering from JNTUH, Hyderabad. His research interests include power electronics, industrial drives, electric vehicles and charging stations, and robotics. He can be contacted at email: vrameshmaddukuri@gmail.com.



Dr. Kotikala Narayana Rao is an associate professor in Computer Science and Engineering, Dhanekula Institute of Engineering and Technology, Ganguru, Andhra Pradesh, India. He can be contacted at email: narayanarao2@gmail.com.



Dr. Manam Ravindra is an associate professor in the Department of Electrical and Electronics Engineering at Aditya University, Surampalem, Andhra Pradesh, India. He completed his Ph.D. at JNTU Kakinada. He has more than 25 publications, which are published in reputed journals indexed in the Scopus and Web of Science databases. His areas of interest include power system state estimation, power systems operation and control and electric power distribution systems. He can be contacted at email: ravieeejntu@gmail.com.



Jampani Satish Babu is an associate professor in the Department of Computer Science and Engineering at KL Deemed to be University, Guntur, Andhra Pradesh, India. He received his B.Tech. and M.Tech. degrees in Computer Science and Engineering with First Class and obtained his Ph.D. in Cyber-Physical Systems. His research interests include artificial intelligence, machine learning, intelligent systems, cyber-physical system security, IoT security, and data-driven analytics. His research focuses on developing secure and intelligent frameworks for cyber-physical systems, machine learning-based remote sensing analysis, intelligent data analytics and computer vision techniques, aiming to advance AI-enabled solutions for real-world technological challenges. He can be contacted at email: jampanisatishbabu@gmail.com.