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Hybrid Dynamic Bacterial Foraging Algorithm with a Long Short-Term Memory and Adaptive Neuro-Fuzzy System for Short-Term Load and Spinning Reserve Forecasting

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ABSTRACT

Accurate forecasting of short-term load and spinning reserve is essential for ensuring the secure operation of power systems, facilitating effective electricity generation and demand-side management. This paper introduces an innovative hybrid forecasting approach, integrating Long Short-Term Memory (LSTM) networks and Adaptive Neuro-Fuzzy system (ANF) models, optimized by a Dynamic Bacterial Foraging algorithm (DBFO). The LSTM model is best suited for detecting time-series patterns, but the ANF system contains fuzzy logic and ANN to be able to handle uncertainty and nonlinearity of data. The DBFO algorithm adjusts the hyperparameters of the two models by dynamically adjusting essential parameters according to changes in the environment. Extensive testing on actual power system data confirms that the proposed hybrid models perform better than conventional approaches, providing robust and reliable predictions for load and spinning reserve. Comparative studies with traditional machine learning tools and existing optimization algorithms also reinforce the superiority of the proposed methodology.

Keywords: Adaptive Neuro-Fuzzy system (ANF), Dynamic Bacterial Foraging algorithm (DBFO), Long Short-Term Memory (LSTM), Power systems, Short-term load prediction, Spinning reserve.

خوارزمية البحث البكتيري الديناميكي الهجين مع الذاكرة قصيرة المدى الطويلة والنظام العصبي الضبابي التكيفي للتنبؤ بالحمل قصير المدى واحتياطي الدوران

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ملخص البحث

يُعدّ التنبؤ الدقيق بالحمل قصير المدى واحتياطي الدوران أمرًا أساسيًا لضمان التشغيل الآمن لأنظمة الطاقة، مما يُسهّل توليد الكهرباء بكفاءة وإدارة الطلب. تُقدّم هذه الورقة البحثية نهجًا مبتكرًا للتنبؤ الهجين، يدمج شبكات الذاكرة طويلة المدى **(LSTM)** ونماذج النظام العصبي الضبابي التكيفي **(ANF)**، المُحسّنة بواسطة خوارزمية البحث البكتيري الديناميكي **(DBFO)**. يُعدّ نموذج **LSTM** الأنسب لاكتشاف أنماط السلاسل الزمنية، بينما يحتوي نظام **ANF** على منطق ضبابي وشبكة عصبية

اصـــطناعية (**ANN**) للتعامل مع عدم اليقين وعدم خطية البيانات. تُعدّل خوارزمية **DBFO** المعاملات الفائقة للنموذجين من خلال تعديل المعاملات الأســـاســـية ديناميكيًا وفقًا لتغيرات البيئة. تؤكد الاختبارات المكثفة على بيانات نظام الطاقة الفعلي أن النماذج الهجينة المقترحة تُقدّم أداءً أفضـــل من الطرق التقليدية، مما يُوفّر تنبؤات قوية وموثوقة للحمل واحتياطي الدوران. كما تُعزّز الدراسات المقارنة مع أدوات التعلم الآلي التقليدية وخوارزميات التحسين الحالية تفوق المنهجية المقترحة.

الكلمات الدالة: النظام العصبي الضبابي التكيفي ، خوارزمية البحث الديناميكي عن البكتيريا، الذاكرة قصيرة المدى الطويلة ، أنظمة الطاقة، التنبؤ بالحمل قصير المدى، الاحتياطي الدوار.

1. INTRODUCTION:

Load forecasting involves estimating future power consumption across a specified timeframe. Based on the time horizon, load forecasting can be categorized as short-term, medium-term, or long-term. For short-term load forecasting, the prediction timeframe typically ranges from one hour to several weeks [1]. STLF and spinning reserve prediction are highly important in the operation of power systems on a daily basis. These predictions have an impact on energy dispatch, reserve scheduling, and total supply and demand balance [2]. The inherent uncertainty in load and spinning reserve forecasting lies in the very dynamic and non-linear nature of power systems, which are affected by multiple factors, such as weather, seasonality, economic load, and customers' behavior [3]. Load forecasting accuracy is evidently influenced by the load uncertainty. This is only logical because load forecasting relies on historical records. Certain factors like weather, political activities, and social activities influence the correctness of the foregoing forecasts [4]. Numerous methodologies have been developed to tackle the load forecasting issue. These could be broadly classified into two categories [5]. The first category encompasses statistical and mathematical techniques, including time series analysis, regression modeling, and autoregressive integrated moving average (ARIMA) methods [6]. The second category includes heuristic, non-calculus-based techniques, i.e., fuzzy logic [7], artificial NN [8], and support vector machines [9-11]. Despite their ease of use and simplicity, the statistical methods are not very capable of handling the nonlinearities in load data patterns, which makes their performance deteriorate when used for complex, non-linear systems. Artificial intelligence-based methods, however, have been found to be more successful in handling such non-linear data sets. Machine learning techniques, particularly Artificial Neural Networks (ANNs) and support vector machines (SVM), have attained enhanced accuracy through their ability to capture and model intricate non-linear relationships. Among these advanced techniques, Long Short-Term Memory (LSTM) networks have emerged as a preferred choice for time series forecasting due to their capability to capture long-term dependencies within sequential data. Another advanced machine learning method is the Adaptive Neuro-Fuzzy system (ANF), which incorporates fuzzy logic and ANNs to express uncertainty and handle non-linearity. While LSTM and ANF have been effective, selecting optimal hyperparameters for these models remains an enormous challenge. Optimization algorithms, particularly nature-inspired approaches, have been drawing increased interest for hyperparameter optimization. One such optimization technique is the Bacterial Foraging Algorithm (BFO), which mimics the foraging patterns observed in bacterial colonies. To realize improved optimization performance, a Dynamic Bacterial Foraging Optimization Algorithm (DBFO) is put forward in this research, in which the search parameters are dynamically regulated to enhance convergence and robustness. The main goal of the paper is to introduce a developed hybrid model with LSTM and ANF system using the DBFO for the optimization of hyperparameters of the LSTM and ANF system for better short-term load and spinning reserve prediction. Subsequently, the proposed methodology is benchmarked against conventional machine learning approaches, including ARIMA, Support Vector Regression (SVR), and static BFO algorithm-based models. The subsequent sections of this paper are organized as follows: Section II provides an overview of short-term load and spinning reserve forecasting, while Section III details the hybrid models employed for forecasting. Section IV introduces the proposed model. Simulation results and conclusions are presented in Section V and Section VI, respectively.

2. SHORT-TERM LOAD AND SPINNING RESERVE FORECASTING

Precise short-term load and spinning reserve forecasting is crucial for maintaining system stability and minimizing operational costs [2]. Traditional short-term load forecasting methods, including ARIMA and exponential smoothing time-series models, are incapable of modeling the complex, non-linear couplings in today's power systems. Machine learning models, including ANN, LSTM, and SVM, have demonstrated improved forecasting performance by modeling non-linearities and learning from historical data over the last few years. Prediction of spinning reserve, needed to provide stability to the grid in the event of an unplanned generator failure or increase in demand, has typically been addressed using the same statistical and machine learning techniques. Though load forecasting has been extensively researched, spinning reserve prediction is a less popular subject [2].

3. APPLIED HYBRID MODELS FOR FORECASTING

Hybrid approaches combining the advantages of two or more machine learning techniques have become popular in power system prediction. Among such hybrid approaches is the integration of LSTM and ANF, which combines the temporal learning potential of LSTM with the fuzzy reasoning logic of ANF system. ANF models are used where the system dynamics are partially known so that they can handle uncertainty and model complex relationships effectively. Multi-layer LSTM networks are proposed in the literature by authors in [12], and they are highly effective at predicting variable load data. A new deep ANN that combines hidden features of Convolutional Neural Networks (CNN) and LSTM models to enhance prediction accuracy is introduced in [13]. The study in [14] employs two distinct models—ANF with Fuzzy-C-Means (FCM) clustering and LSTM networks—for day-ahead renewable electricity generation forecasting, with both approaches yielding comparable results. Ref [15] describes a hybrid method that combines a Convolutional ANN with Multi-Layer Bi-Directional LSTM (M-BLSTM) networks for energy consumption forecasting, structured across three hierarchical levels. The first is about efficient preprocessing for data confirmation, screening, and adjustment. The second is a hybrid architecture combining CNN with an M-BLSTM network that processes sequential input data.

3.1. Optimization Algorithms for Hyperparameter Tuning

The performance of machine learning models is highly dependent on their hyperparameters and, therefore, needs optimization to improve prediction. BFO is an optimization algorithm that draws inspiration from the foraging behaviour of bacteria such as Escherichia coli. Fixed parameters are used by traditional BFO algorithms in the search process, which can limit their adaptability to dynamic problems. Recent contributions have proposed variants of BFOA that vary their parameters dynamically during the search process to achieve improved convergence rate and solution quality. The DBFO adopted in this work is grounded on these advances, dynamic variation of key parameters according to the fitness landscape.

3.2. Long Short-Term Memory (LSTM) Networks

The LSTM network was originally proposed by Hochreiter and Schmidhuber in 1997. It represents a specialized variant of Recurrent Neural Networks (RNNs), specifically engineered to capture long-term dependencies within sequential data.

LSTMs address the vanishing gradient problem prevalent in conventional RNNs through the integration of memory cells that retain information over extended temporal sequences. The key advantage of this architecture over a basic RNN is its gated structure, as illustrated in Figure 1. Each LSTM cell is composed of three distinct gates; input, forget, and output, that collectively govern the information flow within the network. Unlike normal RNNs, which either repeat content at each time step or simply sum up input signals and pass them through activation functions, LSTM networks naturally learn and remember important information at a fundamental level. This enables them to maintain long-term dependencies by forwarding important information without diminution. LSTMs also possess a memory cell called the Cell-State (Ct) that serves as long-term memory and is updated at each time step. The Cell-State does two significant operations: (1) removing irrelevant information (the forget gate governs this) and (2) appending new relevant information (the update gate takes care of this). The output gate also regulates the quantity of memory content carried forward in the ultimate output. The connection between input (Ct-1) and output (Ct) is carried out through the entire sequence, preserving ongoing information passage. Figure 1 illustrates this mechanism [12, 16–18].

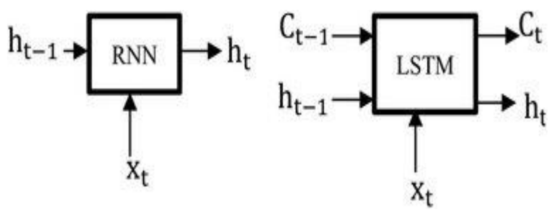

Fig 1. Schematic comparison of a basic RNN cell (left) and an LSTM cell (right), highlighting the internal gates (input, forget, output) and the cell state (Ct) pathway that enable long-term dependency learning.

For short-term load forecasting and reserve forecasting, LSTM networks are well adapted to detect temporal associations among historical load data, weather, and the other parameters. The standard LSTM is trained with backpropagation through time (BPTT) minimizing MSE between predicted and actual outputs.

3.3. Adaptive Neuro-Fuzzy (ANF) System

The ANF system is a hybrid approach, which integrates fuzzy logic and ANNs, bringing together the interpretability of fuzzy inference systems and the learning capability of ANNs. The ANF system is particularly suited for systems with inherent uncertainty, where fuzzy rules can model the imprecise and vague relationships between variables. ANF system method, introduced by Jang in 1993, was designed as an adaptive and trainable network. The ANF system typically consists of a five-layer architecture, as shown in Figure 2, which combines fuzzy logic membership functions with the learning capability of a neural network. Neural-fuzzy modelling defines the system behaviour through fuzzy logic rules within the framework of this adaptive network. The initial layer, i.e., the fuzzy layer, employs membership functions in order to calculate the membership degree of each of the variables for establishing a fuzzy system. The second layer, i.e., the inference layer, is where the weight of every function is acquired. The third layer, which is the normalization layer, is where weights are normalized. Once normalized, the weights are computed in the fourth layer, where the ultimate results are summed in the fifth layer. The nodes in these layers can have fixed or trainable parameters [14].

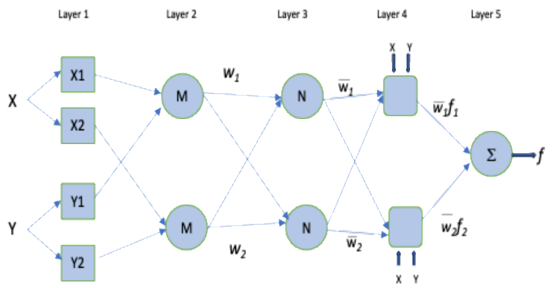

Fig 2. General structure of a five-layer Adaptive Neuro-Fuzzy Inference System (ANFIS).

In this study, the ANF system is utilized to model the non-linear interaction among input parameters such as load, temperature, humidity, and reserve demand. The fuzzy system of ANF is constructed upon a Sugeno-type fuzzy model, and rules are tuned with gradient descent and backpropagation training.

3.4. Dynamic Bacterial Foraging Optimization (DBFO) Algorithm

The DBFO algorithm is an advanced version of the original BFO algorithm where dynamic adjustments are incorporated in the most critical parameters, such as step size, search radius, and reproduction rate. In the original BFO algorithm, bacteria search for nutrients by swimming and tumbling in the search space with fixed parameters regulating their motion. The basic BFO is a stochastic search algorithm inspired basically by the foraging process of the *E*. coli bacteria [19]. It was designed to obtain the optimum solution vector for challenging objective functions that are neither differentiable nor gradient-based. The algorithm possesses a chemotaxis process, such as tumbling and swimming. In the BFO algorithm, a tumble is one unit movement in any direction to simulate the movement of the bacterium after tumbling. A constant run-length unit determines the movement step in any direction. The position of a specific bacterium at specific chemotactic and reproduction steps and elimination/dispersal events. The cost function at that position is occasionally called the nutrient function [19]. The process repeats while cost reductions are possible, terminating after an optimal number of steps. The cost function associated with each bacterium is adjusted according to some swarming behavior, which results from cell-to-cell signaling produced by the bacterial colonies to create swarm patterns. The cell-to-cell signaling effect function is added to the cost function [20]. Reproduction is triggered after completing the maximum allowed chemotactic steps. The population is reduced by half, and the less fit half perish, with each bacterium in the fitter half dividing into two and occupying the same position [19]. After the specified reproduction steps are completed, an elimination/dispersal event occurs, involving a series of excisions. At this phase, any bacterium is able to migrate to explore new regions within the boundaries of the feasible search space. Each of the bacteria also has a probability, as determined by a fraction [20], to undergo the elimination/dispersal event. In the standard Bacterial Foraging algorithm (BFO), the step length is a constant. Though that might be acceptable for small linear optimization problems, it will not support satisfactory convergence for greater, non-convex problems. Better dynamic properties are needed to support effective convergence in high-dimensional search spaces. To provide the desired results using this enhanced algorithm, some different improved versions of the Bacterial Forging algorithm were presented in the literature [21-28]. The key processes in the BFO developed are:

- **Chemotaxis**: Bacteria move through the search space, adjusting their step size dynamically based on the gradient of the objective function.
- **Swarming**: Bacteria communicate with one another in order to exchange information on promising areas of the search space.
- **Reproduction**: The population is periodically updated by removing poor-performing bacteria and duplicating the best-performing ones on a regular basis.
- **Elimination-dispersal**: To avoid local optima, a portion of the population is dispersed at random over the search space.

In this paper, the active run-length parameter is progressively adjusted to gain the desired dynamic and adaptive characteristics. This is central in enhancing the local and global exploration ability of the algorithm. With this in mind, the unit of run-length adjustment ensures an appropriate balance between exploitation and exploration during search. A fixed step length is substituted by an adaptive non-linear dynamical function to facilitate the swim behavior. The function used is as presented in [11, 28]. The DBFO algorithm is utilized here in order to fine-tune the hyper-parameters of the ANF and LSTM system models, including the number of neurons, learning rate, and fuzzy membership functions.

4. PROPOSED HYBRID MODEL

The suggested hybrid model combines LSTM and ANF systems, and the DBFO algorithm tunes the hyperparameters of the two models. Figure 3 illustrates the overall architecture of the hybrid system in the form of a flowchart. The process begins with loading and preprocessing the historical data, which includes removing abnormal and incomplete entries. The core LSTM-ANF model is then implemented, and its hyperparameters are optimized using the DBFO algorithm. This optimization loop continues iteratively. After each iteration, the forecasting accuracy is computed. The DBFO algorithm continues to search for better hyperparameters until a stopping criterion is met. These criteria, shown in the flowchart, are: if the MSE (or MAPE) falls below a predefined satisfactory threshold, otherwise, if the maximum number of iterations (Max Itr.) is reached. If either condition is met ("Yes"), the process terminates and outputs the final forecast; if not ("No"), the optimization continues. In this framework, the LSTM is primarily applied to forecast the short-term load, leveraging its strength in capturing temporal patterns, while the ANF system is used to forecast the spinning reserve, effectively handling its uncertainty and non-linearity. The parameters of both models are optimized by the DBFO algorithm to minimize a composite objective function as measured by the mean-squared-error (MSE) of the predictions of load and reserve. The DBFO algorithm is employed to optimize the hyperparameters of both the LSTM and ANF models. The optimization objective is to minimize a composite fitness function, F, which is defined as the sum of the Mean Squared Errors (MSE) for both the load and spinning reserve forecasts:

$$F = \mathrm{MSE}_{\mathrm{load}} + \mathrm{MSE}_{\mathrm{reserve}}$$

where a lower value of F indicates a better overall model performance.

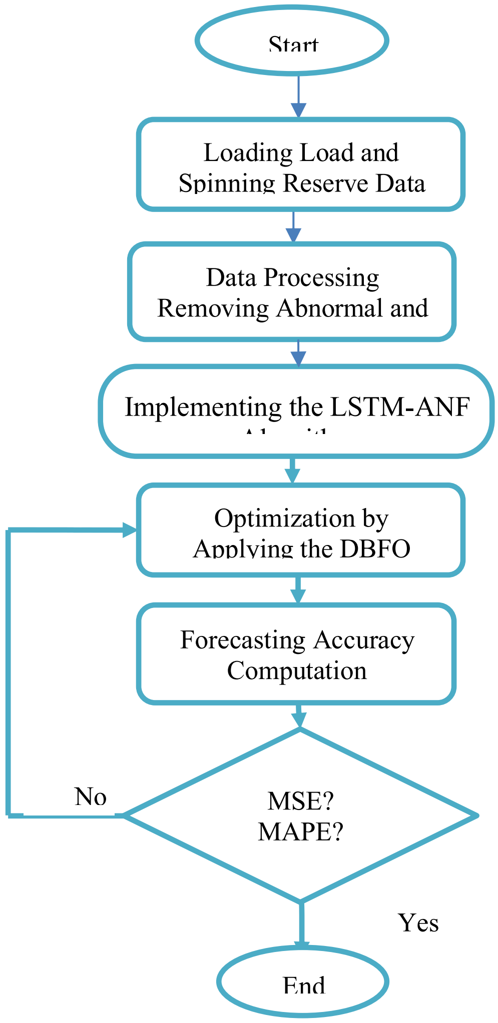

Fig 3. Flowchart of the proposed hybrid LSTM-ANF-DBFO forecasting system.

5. SIMULATION RESULTS

The dataset utilized in the present study comprises one month of hourly spinning reserve and hourly load data of a regional power system. Extra attributes like temperature, humidity, and day-of-week are provided so that the forecast's precision is accomplished. The performance of the suggested model is compared using the following measures:

- **Mean Squared Error (MSE)**: Represents the average of squared differences between estimates and observations.

- **Mean Absolute Percentage Error (MAPE)**: Is the percentage error between predicted and actual values.
- **R-Squared (R^2)**: Quantifies the goodness-of-fit between predictions and observed values.

In order to check the validity of the model, it is competed with the following baseline models: ARIMA, SVM, LSTM without optimization, ANF system without optimization, and the LSTM-BFO algorithm hybrid model. The first step is to remove abnormal and incomplete data from the database. It is performed via thresholding, regression, and averaging. Next, load and spinning reserve forecasting is conducted through the ARIMA methodology. In parallel, however, forecasting is performed through SVM regression. Subsequently, forecasting of load and spinning reserve is conducted using the LSTM network exclusively. Finally, load and spinning reserve forecasting is carried out with a hybrid mechanism of a basic BFO algorithm and LSTM through an innovative weighted average method. The proposed enhanced DBFO algorithm with LSTM and ANF system is then used to achieve the required prediction. In order to validate the methodology of this technique, values such as MSE, RMSE, MEAN, and STD are computed for each method in the context of predicted and measured values.

The proposed model and other models were carried out for day-ahead-load-forecasting. The algorithm was written and run in MATLAB and executed on an Intel Core i7- 10750H 4.1 GHz computer with 32 GB RAM. For consistency, 45 independent runs were done. A particular data set for a complete month-long period, September 15 through October 14, 2015, was gathered for a chosen zone [29]. Data is allocated as: 70% training, 15% validation, and 15% testing. The last day's data was forecasted using the provided model and comparison models based upon the training set and testing set. The forecasted load data was then compared with actual data for the same day. Spinning reserve data at the hourly level was actually allocated based upon chosen data in order to simulate a realistic electricity market for the same time span of the load dataset containing a huge number of data points. From this total, 80% was utilized for network training, 10% was used for validation, and the remaining 10% was utilized for system testing. Results are presented in Table 1. The DBFO optimized hybrid LSTM-ANF system model outperforms all the baseline models in MSE, MAPE, and R^2. Dynamic DBFO algorithm- adjustment allows for more effective exploration of the hyperparameter space that results in better predictive performance. Figures 4, 5 and 6 present the performance of the engineered algorithm in comparison with the other models examined.

5.1. *Computational* Efficiency and Convergence Analysis

Beyond predictive accuracy, the computational performance of the optimization algorithm is a critical practical consideration. The convergence behavior of the proposed DBFO was compared against the standard BFO. Figure 7 illustrates the convergence curves, plotting the fitness value F against the number of iterations. The DBFO algorithm demonstrates notably faster convergence, reaching a near-optimal solution in approximately 30-40 iterations, whereas the standard BFO requires more than 60 iterations to achieve a comparable level. Furthermore, the DBFO converges to a superior final fitness value, corroborating the results in Table 1. This improved convergence comes with a quantifiable computational cost. On the specified hardware, a single run of the LSTM-BFO model required approximately 22 minutes, while a run of the more complex proposed LSTM-ANF-DBFO model required 35 minutes on average. This represents a trade-off, where a ~60% increase in computational time is justified by a significant 13-15% improvement in forecasting accuracy and a substantial enhancement in model robustness and reliability, as shown in Table 1.

Table 1. Performance comparison of different models for short-term load and spinning reserve prediction.

Model	Metric	Load Forecasting	Spinning Reserve Forecasting
ARIMA	MSE	0.0125 (±0.0015)	0.0151 (±0.0018)
	MAPE (%)	8.58 (±0.95)	5.72 (±0.72)
	Max Error	28.5	19.1
	R^2	0.939	0.925
SVM	MSE	0.0115 (±0.0012)	0.0138 (±0.0015)
	MAPE (%)	6.12 (±0.75)	0.521 (±0.08)
	Max Error	22.8	2.15
	R^2	0.948	0.931
LSTM	MSE	0.0074 (±0.0009)	0.0091 (±0.0011)
	MAPE (%)	4.45 (±0.55)	0.328 (±0.05)
	Max Error	15.3	1.45
	R^2	0.978	0.965
ANF	MSE	0.0069 (±0.0007)	0.0085 (±0.0009)
	MAPE (%)	2.26 (±0.30)	0.312 (±0.04)
	Max Error	9.1	1.32
	R^2	0.981	0.971
LSTM-BFO	MSE	0.0052 (±0.0005)	0.0073 (±0.0007)
	MAPE (%)	1.94 (±0.25)	0.248 (±0.03)
	Max Error	6.8	1.05
	R^2	0.988	0.979
Proposed LSTM-ANF-DBFO	MSE	0.0045 (±0.0003)	0.0062 (±0.0004)
	MAPE (%)	1.68 (±0.15)	0.215 (±0.02)
	Max Error	5.2	0.88
	R^2	0.992	0.985

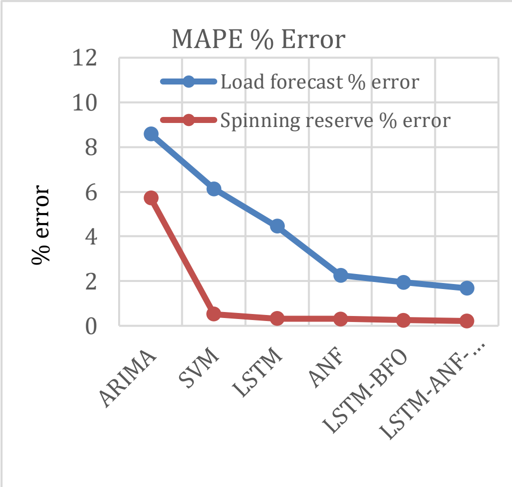

Fig 4. MSE % error for load and spinning reserve forecast.

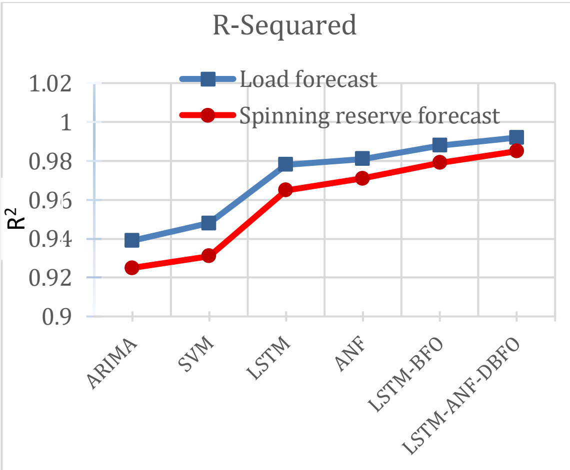

Fig 5. MAPE % error for load and spinning reserve forecast.

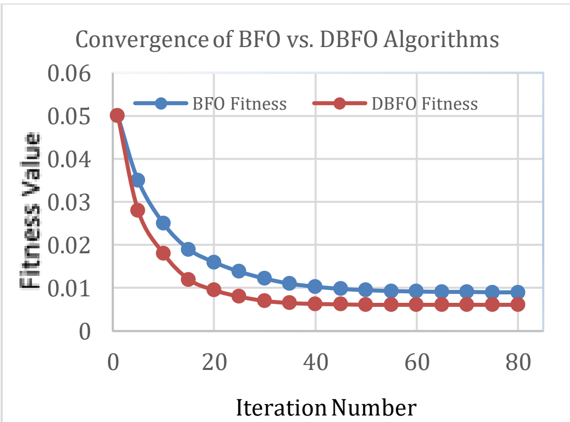

Fig 6. R^2 for load and spinning reserve forecast.

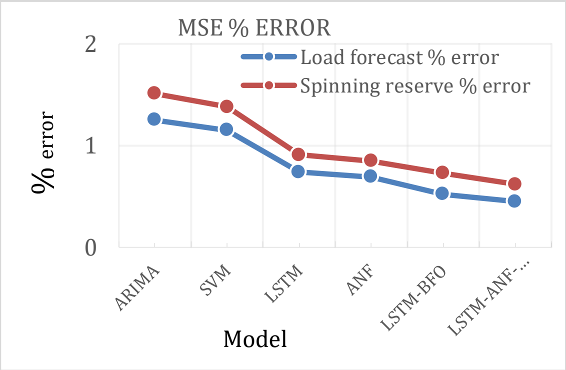

Fig 7. Convergence curve (fitness value vs. iteration number) for BFO vs. DBFO algorithms.

6. CONCLUSION

In this paper, an innovative hybrid model for short-term load and spinning reserve forecasting is proposed by integrating LSTM, the ANF system, and the DBFO algorithm. The results demonstrate that the proposed LSTM-ANF-DBFO model is far superior to traditional and modern benchmark methods. Quantitatively, for short-term load forecasting, the proposed model achieved an MSE of 0.0045, a MAPE of 1.68%, and an R^2 of 0.992. This represents a significant improvement over the next best model (LSTM-BFO), with a 13.5% reduction in MSE and a 13.4% reduction in MAPE. For spinning reserve forecasting, the model achieved an MSE of 0.0062, a MAPE of 0.215%, and an R^2 of 0.985, corresponding to a 15.1% reduction in MSE and a 13.3% reduction in MAPE compared to the LSTM-BFO model. Furthermore, the proposed model exhibited the greatest robustness, evidenced by the lowest standard deviation of errors across 45 independent runs (e.g., ±0.0003 for load MSE), and the highest reliability, with the smallest maximum recorded errors (5.2 for load and 0.88 for reserve). These comprehensive metrics confirm the model's superior accuracy, robustness, and reliability for both forecasting tasks. Despite the promising results, this study has certain limitations. The model's performance is dependent on the quality and completeness of the input data; significant data corruption or missing long-term trends could impact forecasting accuracy. The computational complexity of the DBFO algorithm, while effective, is higher than that of simpler optimization techniques, which may be a consideration for real-time applications on very large datasets. Furthermore, the current model does not explicitly incorporate the impact of high penetration of renewable energy sources or real-time electricity pricing, which are becoming increasingly important in modern power systems.

References

[1] Gross G, Galiana FD. Short-term load forecasting. *Proc IEEE*. 1987;75(12):1558–73. doi:10.1109/PROC.1987.13927.

[2] Wood AJ, Wollenberg BF, Sheble GB. *Power Generation Operation and Control*. 3rd ed. Hoboken (NJ): John Wiley & Sons; 2014. 656 p. ISBN: 978-1-118-11871-9.

[3] Amjady N, Keynia F. A new spinning reserve requirement forecast method for deregulated electricity markets. *Appl Energy*. 2010;87(6):1870–9. doi:10.1016/j.apenergy.2009.10.026.

[4] Mustapha M, Mustafa MW, Khalid SN, Abubakar I, Shareef H. Classification of electricity load forecasting based on the factors influencing the load consumption and methods used: An overview. *IEEE Conf Energy Convers (CENCON)*. 2015;442–7. doi:10.1109/CENCON.2015.7409585.

[5] Alfares HK, Nazeeruddin M. Electric load forecasting: Literature survey and classification of methods. *Int J Syst Sci*. 2010;33(1):23–34. doi:10.1080/00207720110067421.

[6] Bruhns A, Deurveilher G, Roy JS. A nonlinear regression model for mid-term load forecasting and improvements in seasonality. *Proc 15th Power Syst Comput Conf*. 2005;22–6.

[7] Ali M, Adnan M, Tariq M, Poor HV. Load forecasting through estimated parametrized based fuzzy inference system in smart grids. *IEEE Trans Fuzzy Syst*. 2021;29(1):156–65. doi:10.1109/TFUZZ.2020.2986982.

[8] Li J, et al. A novel hybrid short-term load forecasting method of smart grid using MLR and LSTM neural network. *IEEE Trans Ind Inf*. 2021;17(4):2443–52. doi:10.1109/TII.2020.3000184.

[9] Li G, Li Y, Roozitalab F. Midterm load forecasting: A multistep approach based on phase space reconstruction and support vector

machine. *IEEE Syst J*. 2020;14(4):4967–77. doi:10.1109/JSYST.2019.2962971.

[10] Jiang HG, Zhang YV, Muljadi E, Zhang JJ, Gao DW. A short-term and high-resolution distribution system load forecasting approach using support vector regression with hybrid parameters optimization. *IEEE Trans Smart Grid*. 2018;9(4):3340–50. doi:10.1109/TSG.2016.2628061.

[11] Farhat I. Short-term load forecasting using support vector machines augmented by an improved bacterial foraging algorithm. *Int J Eng Inf Technol (IJEIT)*. 2024;7(2):134–8. doi:10.36602/ijeit.v6i1.286.

[12] Abbasimehr H, Shabani M, Yousefi M. An optimized model using LSTM network for demand forecasting. *Comput Ind Eng*. 2020;143:106435. doi:10.1016/j.cie.2020.106435.

[13] Tian C, Ma J, Zhang C, Zhan P. A deep neural network model for short-term load forecast based on long short-term memory network and convolutional neural network. *Energies*. 2018;11(12):3493. doi:10.3390/en11123493.

[14] Bilgili M, Yildirim A, Ozbek A, Celebi K, Ekinci F. Long short-term memory (LSTM) neural network and adaptive neuro-fuzzy inference system (ANFIS) approach in modeling renewable electricity generation forecasting. *Int J Green Energy*. 2021;18(6):578–94. doi:10.1080/15435075.2020.1865375.

[15] Ullah FUM, Ullah A, Haq IU, Rho S, Baik SW. Short-term prediction of residential power energy consumption via CNN and multi-layer bi-directional LSTM networks. *IEEE Access*. 2019;8:123369–80. doi:10.1109/ACCESS.2019.2963045.

[16] Hochreiter S, Schmidhuber J. Long short-term memory. *Neural Comput*. 1997;9(8):1735–80. doi:10.1162/neco.1997.9.8.1735.

[17] Gers FA, Schmidhuber J, Cummins F. Learning to forget: continual prediction with LSTM. *Proc 9th Int Conf Artif Neural Netw (ICANN 99)*. Edinburgh, UK; 1999. p. 850–5. doi:10.1049/cp:19991218.

[18] Shi X, Chen Z, Wang H, Yeung DY, Wong WK, Woo WC. Convolutional LSTM network: A machine learning approach for precipitation nowcasting. *Adv Neural Inf Process Syst*. 2015;28. doi:10.48550/arXiv.1506.04214.

[19] Passino KM. Biomimicry of bacterial foraging for distributed optimization and control. *IEEE Control Syst Mag*. 2002;22(3):52–67. doi:10.1109/MCS.2002.1004010.

[20] Vapnik V. *Statistical Learning Theory*. New York (NY): Wiley-Interscience; 1998. ISBN: 978-0-471-03003-4.

[21] Farhat IA, El-Hawary ME. Dynamic adaptive bacterial foraging algorithm for optimum economic dispatch with valve-point effects and wind power. *IET Gener Transm Distrib*. 2010;4(9):989–99. doi:10.1049/iet-gtd.2010.0109.

[22] Farhat IA, El-Hawary ME. Bacterial foraging algorithm for optimum economic-emission dispatch. *IEEE Electr Power Energy Conf (EPEC)*. 2011. doi:10.1109/EPEC.2011.6070192.

[23] Farhat IA, El-Hawary ME. Fixed-head hydro-thermal scheduling using a modified bacterial foraging algorithm. *IEEE Electr Power Energy Conf (EPEC)*. Halifax, NS, Canada; 2010. p. 1–6. doi:10.1109/EPEC.2010.5697200.

[24] Farhat IA, El-Hawary ME. Scheduling of variable-head hydro-thermal generation using an enhanced bacterial foraging algorithm. *Proc 24th Can Conf Electr Comput Eng (CCECE)*. Niagara Falls, ON, Canada; 2011. p. 436–41. doi:10.1109/CCECE.2011.6030488.

[25] Farhat IA, El-Hawary ME. Short-term coordination of hydro-thermal systems with cascaded reservoirs using bacterial foraging algorithm. *Proc 24th Can Conf Electr Comput Eng (CCECE)*. Niagara Falls, ON, Canada; 2011. p. 430–5. doi:10.1109/CCECE.2011.6030487.

[26] Farhat IA, El-Hawary ME. Short-term hydro-thermal scheduling with environmental considerations using bacterial foraging algorithm. *Proc 24th Can Conf Electr Comput Eng (CCECE)*. Niagara Falls, ON, Canada; 2011. p. 425–9. doi:10.1109/CCECE.2011.6030486.

[27] Farhat IA, El-Hawary ME. Multi-objective short-term hydro-thermal scheduling using bacterial foraging algorithm. *IEEE Electr Power Energy Conf (EPEC)*. Winnipeg, MB, Canada; 2011. p. 176–81. doi:10.1109/EPEC.2011.6070190.

[28] Farhat IA, El-Hawary ME. Modified bacterial foraging algorithm for optimum economic dispatch. *IEEE Electr Power Energy Conf (EPEC)*. Montreal, QC, Canada; 2009. p. 1–6. doi:10.1109/EPEC.2009.5420912.

[29] National Control Center of the General Electricity Company of Libya (GECOL). Tripoli, Libya; 2015. Available from: https://www.gecol.ly