Novel bat algorithm for short-term peak load forecasting in Sulselrabar electricity system

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ABSTRACT

This study addresses short-term load forecasting (STLF) in the South, Southeast, and West Sulawesi (Sulselrabar) power system, Indonesia, using interval type-2 fuzzy logic (IT2FL) optimized by the proposed novel bat algorithm (NBA). The NBA is employed to optimize the footprint of uncertainty (FOU) of the fuzzy membership functions for both antecedent (X and Y) and consequent (Z) variables. The forecasting model utilizes daily peak load data from the previous four days (d−4 to d−1) to predict the peak load of the forecast day (d). To evaluate the effectiveness of the proposed approach, NBA is benchmarked against particle swarm optimization (PSO), firefly algorithm (FA), and cuckoo search algorithm (CSA). The results demonstrate that the proposed IT2FL–NBA model provides the highest forecasting accuracy among the evaluated methods, achieving a mean absolute percentage error (MAPE) of 1.5650%. In comparison, IT2FL–PSO, IT2FL–FA, and IT2FL–CSA achieve MAPEs of 1.6353%, 1.6451%, and 1.6353%, respectively. For type-1 fuzzy logic (IT1FL), the NBA, PSO, FA, and CSA optimization methods produce MAPEs of 1.6668%, 1.6842%, 1.6805%, and 1.6768%, respectively. These findings demonstrate that optimizing the FOU of IT2FL using the proposed NBA significantly improves forecasting accuracy and provides a robust and reliable approach for STLF in power systems.

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1. INTRODUCTION

Short-term load forecasting (STLF) is a vital tool for predicting electricity demand over a time horizon ranging from a few hours to one week [1]. The forecasts generated by STLF provide critical information that supports decision-making in load management, pump storage scheduling, unit commitment, and load dispatching. By providing accurate and timely predictions, STLF enables utility companies to optimize steady-state operations, enhance system reliability, prevent overloading or underutilization of resources, and reduce overall operational costs [2]. Moreover, precise short-term forecasts help in planning for peak demand periods and mitigating potential risks associated with unexpected fluctuations in load [3].

Conversely, inaccuracies in load forecasting can result in suboptimal use of reserves, directly increasing operational costs [4]. Underestimating load may necessitate the activation or purchase of costly peaking units, while also raising the risk of network overload or even system failures. Conversely, overestimating load can lead to the allocation of excessive reserves, causing unnecessary waste and further elevating operational costs [5]. Accurate forecasting is therefore critical to balancing reliability and efficiency in power system operations.

Over the past few decades, STLF techniques have evolved significantly, progressing from manual methods to advanced computerized models [6]. Broadly, STLF techniques can be categorized into two main types: conventional methods and modern methods. Conventional methods typically rely on statistical approaches that use historical load data and account for specific events, such as holidays or special occasions, to generate daily or weekly load forecasts [7]. These methods are generally simpler and easier to implement but may struggle to capture complex or nonlinear load patterns.

Statistical approaches are typically implemented as offline forecasting methods using time functions and have proven effective in modeling linear relationships. However, since electricity load inherently exhibits nonlinear and complex behavior, these methods often produce lower accuracy compared to modern techniques [8]. Additionally, the growing uncertainty and complexity of modern power systems further exacerbate forecasting errors when relying on traditional methods. Contributing factors include weather variability, seasonal fluctuations, changes in customer composition, and the impacts of climate change, all of which make electricity load patterns increasingly dynamic and challenging to predict accurately.

Feasible and promising solutions can be effectively obtained using artificial intelligence (AI) techniques, such as fuzzy logic, artificial neural networks (ANN), and evolutionary algorithms (EA) [9], [10]. These methods are particularly well-suited for capturing complex nonlinear relationships that are difficult to model using traditional mathematical approaches, making them widely adopted in load forecasting. A rapidly growing branch of AI is swarm intelligence (SI), which is inspired by the collective and decentralized behavior of individuals interacting with their environment. Several SI-based methods have been applied successfully to load forecasting, including particle swarm optimization (PSO) [11], firefly algorithm (FA) [12], cuckoo search algorithm (CSA) [13], grey wolf optimization (GWO) [14], and artificial bee colony [15]. These algorithms offer advantages in efficiently exploring complex solution spaces and improving forecasting accuracy.

In classical AI methods based on interval type-1 fuzzy logic (IT1FL), mathematical computations derived from set theory are used to represent ambiguity through linguistic variables. IT1FL has been widely applied in STLF [16]. However, a key limitation of IT1FL lies in its crisp membership functions, which are less capable of handling high levels of uncertainty. To overcome this limitation, Tian *et al.* [17] introduced the concept of interval type-2 fuzzy logic (IT2FL), which generalizes the interval sets of IT1FL and allows for modeling uncertainty both linguistically and numerically. Building on this concept, the authors [18], [19] developed IT2FL systems that incorporate inference rules specifically designed to manage the uncertainty inherent in membership functions, improving their flexibility and robustness in complex forecasting applications.

The application of IT2FL in forecasting problems has demonstrated strong performance. Moyo *et al.* [20] highlighted the use of IT2FL for STLF, showing that it can produce accurate and consistent load estimates, even during high-load periods, with performance comparable to ANNs. This underscores IT2FL's potential as a reliable solution for STLF. Almaraashi [21] applied IT2FL to address uncertainties in weather and solar radiation forecasts in Saudi Arabia, achieving improved prediction accuracy compared to T1FLSs while reducing computational costs by up to 93.7%, demonstrating both efficiency and practicality. Li *et al.* [22] developed a short-term load prediction model using an IT2FLS and compared algorithms based on interval type-1 and type-2 fuzzy sets. The results indicated that IT2FLS provides higher prediction accuracy, effectively handling chaotic time series and meeting the operational needs of power systems. Eyoh *et al.* [23] further advanced IT2FL for very short- and STLF by incorporating membership functions, non-membership functions, and hesitation indices, with parameters optimized via a gradient descent method. Experimental results showed that this model outperforms traditional fuzzy logic systems and neural networks across various load scenarios, highlighting IT2FL's robustness and adaptability in complex forecasting tasks.

The footprint of uncertainty (FOU) is a fundamental component in characterizing IT2FL [24], [25], making its accurate representation a critical issue in IT2FL theory. The FOU is uniquely defined by the upper membership function (UMF) and lower membership function (LMF). Consequently, IT2FL studies typically focus on analyzing the LMF and UMF, each represented as an IT1FL set within the same IT2FL universe [26], [27]. While the FOU can be specified through the UMF and LMF, its representation cannot be directly derived from these functions alone. To properly characterize the FOU in a general IT2FL, the principal membership levels must first be established, ensuring an accurate depiction of the uncertainty inherent in the system.

A new SI approach known as the novel bat algorithm (NBA) was introduced [28], [29]. This algorithm is inspired by the echolocation behavior of bats for navigation and prey searching. The NBA extends the classical bat algorithm by integrating more adaptive exploration and exploitation mechanisms through the adjustment of frequency, velocity, loudness, and pulse emission rate, thereby enhancing the balance between local and global search and accelerating convergence toward the optimal solution. NBA is recognized as a fast and robust optimization algorithm [30], [31] and has been widely studied in various power system optimization applications. Eltamaly *et al.* [32] proposed NBA for maximum power point tracking (MPPT) in photovoltaic systems with partial shading by improving initialization, re-initialization mechanisms, and global peak memory updating. Simulation and experimental results demonstrated that NBA is faster and more reliable than PSO and GWO in tracking the global maximum power. Lin *et al.* [33] applied the NBA for unmanned aerial vehicle (UAV) path planning by combining an improved artificial potential field, an optimal success rate strategy, and a chaos strategy within the bat algorithm. Simulation results showed increased convergence rate, success rate, and robustness compared to the bat algorithm and differential evolution bat algorithm, while effectively avoiding local optima. Nguyen *et al.* [34] proposed an NBA variant that combines parallel and compact approaches to reduce the number of stored variables in optimization problems. Benchmark testing and wireless sensor network (WSN) energy balance problems showed that NBA is more efficient in terms of memory usage and computational time compared to other methods.

One of the power systems in Indonesia, the South, Southeast, and West Sulawesi system (Sulselrabar), exhibits complex and highly variable load characteristics due to seasonal influences and societal behavior [4], [5]. Accurate load forecasting in this system is essential for estimating electricity consumption over specific periods and for supporting the safe and reliable operation of the power network, including power flow management, generator maintenance, and unit commitment. These challenges provide a strong motivation for authors to investigate peak load forecasting specifically within Sulselrabar system.

The main contributions of this research are as follows: i) the application of the NBA method to optimize the FOU membership functions of IT2FL for STLF in the Sulselrabar electricity system; and ii) the testing and validation of the IT2FL-NBA approach for accurate STLF in the Sulselrabar system. The paper is organized as follows. Section 2 describes the research methodology. Section 3 presents the results and analysis. Lastly, section 4 concludes the study.

2. METHOD

2.1. Interval type-2 fuzzy logic

An IT2FL set, denoted as Ã, has membership function μÃ, where x belongs to X and u belongs to Jx, a subset of [0,1]. Its properties can be described by (1) [35].

$$\tilde{A} = \int_{x \in X} \int_{x \in J_X} \frac{\mu \tilde{A}(x,u)}{(x,u)} Jx \subseteq [0,1] \tag{1}$$

The variable x is the primary variable with domain X, while u, belonging to U, serves as the secondary variable with domain Jx for each x in X. The set Jx is referred to as the primary membership function of x. The uncertainty in Ã is captured by the collection of all primary membership functions Jx, which collectively constitutes the FOU of Ã, as defined in (2) to (4).

$$FOU(\tilde{A}) = \cup_{\forall x \in X} Jx = \{(x,u); u \in Jx \subseteq [0,1]\} \tag{2}$$

$$Jx = \left\{(x,u); u \in \left[\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)\right]\right\} \tag{3}$$

$$FOU(\tilde{A}) = \cup_{\forall x \in X} \left[\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)\right] \tag{4}$$

Jx serves as the primary membership function of x, while $\underline{\mu}$Ã and $\bar{\mu}$Ã denote the LMF and UMF of Ã, respectively, as illustrated in Figure 1.

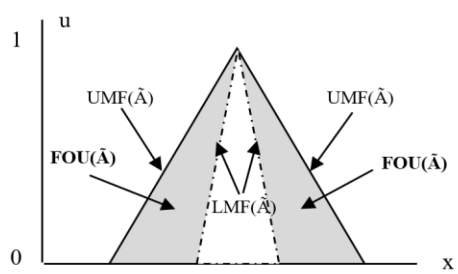


Figure 1. IT2FL membership function

2.2. Novel bat algorithm

Yang and He [28] introduced the bat algorithm, a population-based metaheuristic inspired by how bats hunt and navigate using echolocation. The algorithm mimics the bats' prey-searching behavior, particularly their use of frequency adjustment, velocity, and pulse emission rate, to explore the search space and identify optimal solutions. The bat algorithm is designed to blend exploration and exploitation, balancing broad global searches with focused local convergence. This design helps the algorithm escape local optima and converge more quickly toward the best solution. To translate these natural behaviors into a computational model, the algorithm relies on several simplifying assumptions and idealized rules.

i) All bats are assumed to have the ability to detect and locate prey or potential solutions using echolocation mechanisms.
ii) Each bat flies from its current position x_i with a velocity v_i and emits sound pulses with varying frequencies, where the minimum frequency is set to f_{min}. This frequency variation enables the bats to explore the search space adaptively.
iii) The loudness of each bat is dynamic and varies within a certain range, from a minimum value A_{min} to an initial maximum value A_0. Changes in loudness reflect the transition from the exploration phase to the exploitation phase during the optimization process.

The algorithm imitates the echolocation behavior of bats, where key parameters such as wavelength (λ) and loudness (A_0) are adaptively varied to enhance the search process for optimal solutions. These variations enable the bats to dynamically adjust their search behavior, facilitating an effective balance between global exploration and local exploitation. In this process, each bat modifies its movement in the search space by updating its frequency (f_i) and velocity (v_i). The frequency parameter controls the step size of the search, while the velocity determines the direction and speed of movement toward promising regions. By continuously updating these parameters, the algorithm enhances its capability to converge toward the optimal solution while avoiding premature convergence to local optima.

The frequency f_i and velocity $v_i$of the i-th bat are updated using (5) and (6).

$$f_i = f_{min} + (f_{max} - f_{min})\delta \tag{5}$$

$$v_i^t = v_i^{t-1} + \left(X_i^t - X_{gbest}^t\right)f_i \tag{6}$$

The new candidate solutions are generated by updating the position of each bat in the search space based on its current velocity. This movement reflects the adaptive echolocation behavior of bats as they navigate toward promising regions. Consequently, the new solutions can be obtained using (7).

$$X_i^t = X_i^{t-1} + v_i^t \tag{7}$$

With δ [0,1] represents a random vector generated from a uniform distribution over the interval [0,1]. f_{min} and f_{max} are functions of the domain size.

Each bat is randomly assigned a frequency within the range $[f_{min}, f_{max}]$. To further enhance the global search capability, the proposed algorithm incorporates a Lévy flight–based bat algorithm, which allows bats to perform long-distance movements in the search space. This mechanism significantly improves exploration and helps prevent premature convergence to local optima.

Through Lévy flight, each bat performs a random walk to generate a new candidate solution by perturbing its current position with respect to the best solution obtained so far. Accordingly, the new solution for each bat is generated based on the current global best solution, as given by (8).

$$X_{new} = X_{old} + A.|s|^{1/\beta} \tag{8}$$

With $A = \beta\Gamma(\beta)sin\left(\frac{\beta\pi}{2}\right)\frac{1}{\pi}$; β is the spatial exponent; α is temporal exponent; and $\Gamma(\beta)$ is a Gamma function.

As a bat moves closer to its prey, the loudness gradually decreases, while the pulse emission rate correspondingly increases, as defined in (9) and (10). This adaptive behavior enables a smooth transition from global exploration to local exploitation during the optimization process. Furthermore, the incorporation of a Lévy flight–based randomization parameter significantly accelerates the convergence rate by allowing occasional long-distance jumps in the search space, thereby enhancing the algorithm's ability to escape local optima and improve overall solution quality.

$$A_i^{t+1} = \propto + A_i^t \tag{9}$$

$$r_i^{t+1} = r_i^0 |1 - e^{-\gamma t}| \quad (10)$$

Where α and γ are constants.

3.3. Objective function

The objective function is evaluated through a forecasting procedure consisting of three main stages, namely pre-processing, processing, and post-processing, as described as follows.

i) Pre-processing: in the pre-processing stage, daily electricity load data from 2010 to 2016 are collected, and the data are then grouped to extract the electricity load corresponding to January 4th of each year within this period.

ii) Processing: the processing stage consists of modeling STLF using the proposed IT2FL-NBA method, as described as follows:
   - Define the IT2FL input membership functions, denoted as X, and the output membership function, denoted as Z, for the day to be forecasted:
     X1-X6 : load data from the years 2010–2015
     Z1 : forecasted load for the predicted day
   - Optimize the IT2FL membership functions, including the antecedents and the consequent, using the NBA to obtain the optimal FOU.
   - Construct IT2FL fuzzy rules in the following form:
     IF X is A_i AND Y is B_i THEN Z is C_i
   - Apply the AND operation to combine IT2FL rules.
   - Use the MIN implication function for the fuzzy rules.
   - Apply the MAX composition operation to aggregate the rules.

iii) Post-processing: next, the mean absolute percentage error (MAPE) for STLF is calculated using (11).

$$MAPE\% = \left|\frac{P_{forecast} - P_{actual}}{P_{actual}}\right| \times 100 \quad (11)$$

The MAPE value is then compared with the forecasting errors obtained from IT1FL-PSO, IT1FL-FA, IT1FL-NBA, IT2FL-PSO, IT2FL-FA, and IT2FL-NBA methods.

3.4. Load data profile

This study examines the Sulselrabar electricity system in Indonesia, which links the main load centers across Sulselrabar. For forecasting purposes, 24-hour load data from January 4, 2016, were used as the target. Accordingly, load data from January 4 of each year from 2010–2015 were grouped to serve as input for the fuzzy logic model. The following section presents the results of this data grouping for the period 2010–2015.

3.5. Fuzzy logic design

Based on the load data profile presented in Figure 2, the next step is to construct the forecasting model inputs for both IT1FL and IT2FL. Six input variables are employed, representing the daily peak load data from the same calendar date during the previous six years (2010–2015). Figure 3 illustrates the input structure of the proposed fuzzy logic forecasting models. Specifically, Figure 3(a) presents the input design of the IT1FL model, while Figure 3(b) shows the corresponding input design of the IT2FL model.

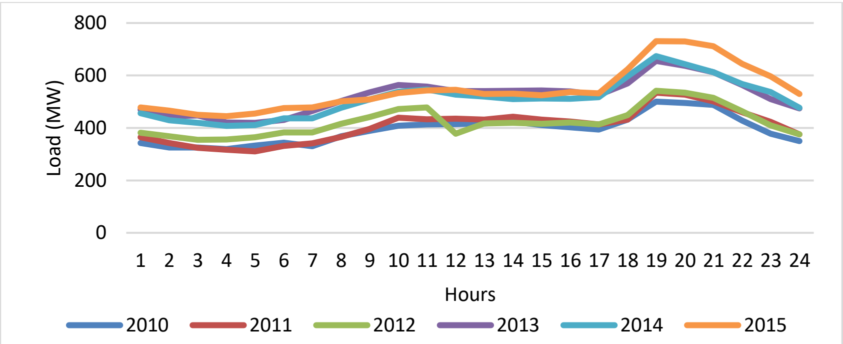
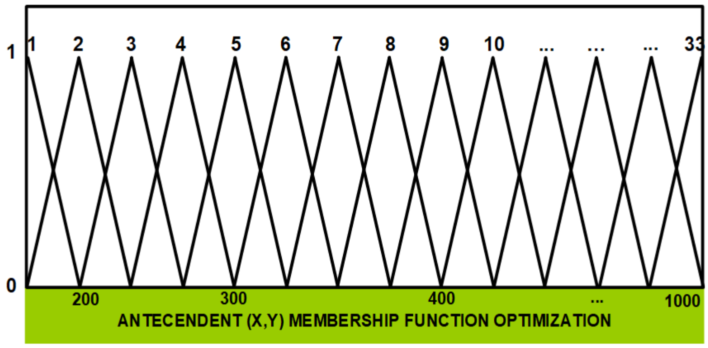
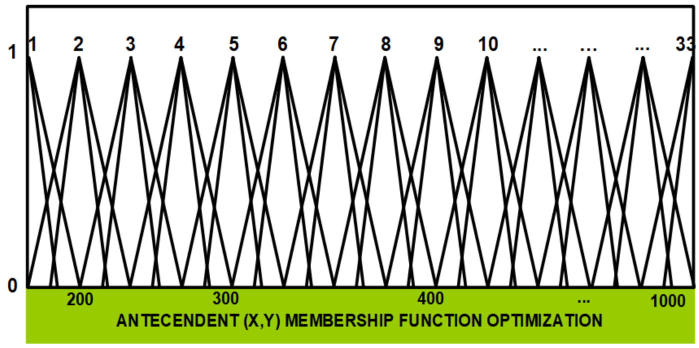


Figure 2. Electrical load profile January 4, 2010-2015



(a)



(b)

Figure 3. Input membership function designs for STLF: (a) IT1FL and (b) IT2FL input design

3. RESULTS AND DISCUSSION

3.1. Benchmarking analysis

Before implementing the NBA optimization method, a comprehensive benchmark analysis was conducted using PSO, FA, and the CSA as comparative algorithms. This preliminary evaluation aimed to systematically assess the exploration and exploitation capabilities of each algorithm under identical experimental conditions, with carefully selected parameter settings to ensure a fair and unbiased comparison. Six benchmark functions, consisting of unimodal and multimodal optimization problems, were employed to evaluate algorithm performance. Unimodal functions were used to assess exploitation capability by testing the ability to converge toward a single global optimum, whereas multimodal functions evaluated exploration performance and robustness against premature convergence. In addition, fixed-dimension multimodal functions were included to investigate algorithm effectiveness in low-dimensional optimization problems, which are often challenging due to limited search-space diversity [28]–[31].

Each algorithm, including NBA, PSO, FA, and CSA, was independently executed 30 times to account for stochastic variability and ensure statistical reliability. The best, mean, and standard deviation values obtained from these runs were used as performance indicators. The experimental results demonstrated that NBA consistently achieved competitive and, in most cases, superior performance compared with PSO, FA, and CSA across the benchmark functions. NBA exhibited an effective balance between exploration and exploitation, enabling rapid convergence toward high-quality solutions while maintaining the ability to escape local optima. Furthermore, the relatively low standard deviation values obtained by NBA indicate greater stability, consistency, and robustness throughout the optimization process. These findings confirm the effectiveness of the proposed NBA algorithm and highlight its potential as a reliable optimization tool for solving complex engineering and power-system optimization problems characterized by diverse search-space landscapes. The parameter settings adopted for PSO, FA, CSA, and NBA are summarized in Table 1. These parameters were selected according to recommendations from the literature and preliminary experiments to ensure a fair and consistent comparison among the evaluated optimization algorithms.

The search process toward the optimal solution for each algorithm is illustrated through convergence curves, which represent the evolution of the best fitness value at each iteration. Figure 4 presents the normalized average convergence curves of NBA, PSO, FA, and CSA, obtained from 30 independent runs on both unimodal and multimodal benchmark functions. Figure 4(a) illustrates the convergence behavior on the f1 benchmark function, while Figure 4(b) presents the corresponding convergence curves for f2. Figure 4(c) shows the convergence performance on f3, followed by Figure 4(d), which illustrates the convergence behavior on f4. The convergence curves for f5 and f6 are presented in Figures 4(e) and 4(f), respectively. These curves provide valuable insights into the convergence characteristics, search efficiency, and optimization performance of the evaluated algorithms. The benchmark functions used in this study are listed in Table 2. The selected test suite covers a variety of optimization landscapes, including unimodal, multimodal, and fixed-dimension multimodal problems, allowing a comprehensive assessment of the exploration and exploitation capabilities of the evaluated algorithms [30], [31].

Table 1. Parameters of the algorithms

Algorithm	Parameter	Value
PSO	Particles, most iterations, the quantity of variables, C2 social constant, C1 cognitive constant, W moment inertia	30; 50; 8; 2; 2; 0.9
FA	Alpha, beta, gamma, dimension, number of fireflies	0.25; 0.2; 1; 80; 80
CSA	Population size (number of nests), discovery rate of alien eggs, Lévy flight step size, Lévy distribution exponent	25; 0.25; 0.01; 1.5
NBA	Alpha (loudness) = Gamma (pulse rate), $f_{min}, f_{max}, A_0 = R_0, G, P, w, C, \theta$	0.9; 0; 1.5; 0.1; 10; [0.5, 0.9]; [0.4, 0.9]; [0.1, 0.9]; [0.5, 1]

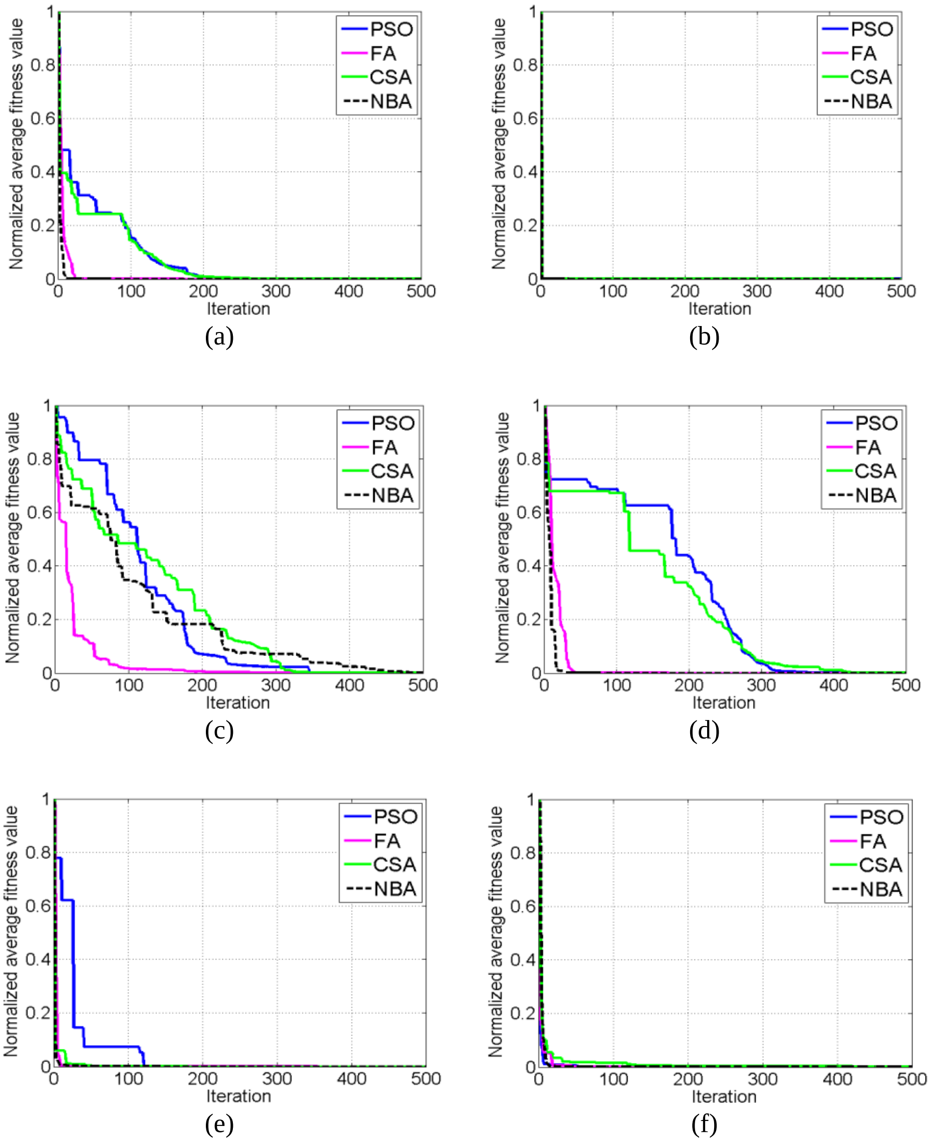


Figure 4. The convergence curves: (a) f1, (b) f2, (c) f3, (d) f4, (e) f5, and (f) f6

Table 2. Benchmark test function

Category	Test function	Range	*Dim*	f_{min}
Unimodal functions	$f_1(x)=\sum_{i=1}^{D} x_i^2$	(-100,100)	30	0
	$f_2(x)=\sum_{i=1}^{D} \lvert x_i\rvert+\prod_{i=1}^{D} \lvert x_i\rvert$	(-10,10)	30	0
Multimodal functions	$f_3(x)=\sum_{i=1}^{n} -x_i \sin\left(\sqrt{\lvert x_i\rvert}\right)$	(-500,500)	30	-418.9 *n*
	$f_4(x)=\sum_{i=1}^{n} [x_i^2-10\cos(2\pi x_i)+10]$	(-5.12,5.12)	30	0
Fixed-dimension multimodal functions	$f_{14}(x)=\left(\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}(x_i-a_{ij})^6}\right)^{-1}$	(-65,65)	2	1
	$f_{15}(x)=\sum_{i=1}^{11}\left[a_i-\frac{x_1(b_i^2+b_i x_2)}{b_i^2+b_i x_3+x_4}\right]^2$	(-5,5)	4	0.0003

The statistical results obtained from 30 independent runs of each algorithm are summarized in Table 3. The reported best, average, median, and standard deviation values provide a comprehensive evaluation of optimization accuracy, convergence consistency, and robustness. To further evaluate the overall performance of the optimization algorithms, a non-parametric Friedman test was conducted using the average results obtained from the six benchmark functions. The Friedman ranking results are presented in Table 4, while the corresponding statistical test results are summarized in Table 5.

As shown in Table 4, the proposed NBA achieved the best average rank of 1.7500, followed by FA (2.1667), CSA (3.0000), and PSO (3.0833). These results indicate that NBA consistently provided superior performance across the benchmark functions compared with the other algorithms. The improved ranking can be attributed to the balanced exploration and exploitation mechanisms incorporated in the NBA search strategy, enabling effective convergence toward high-quality solutions.

The Friedman test yielded a test statistic of 4.55 with a p-value of 0.208, as shown in Table 5. Although the p-value is greater than the significance level of 0.05, indicating that the differences among the algorithms are not statistically significant, the average ranking results consistently favor NBA. Therefore, the Friedman analysis supports the benchmark and convergence results, demonstrating the competitive and robust performance of the proposed NBA across different optimization landscapes.

Table 3. Benchmarking results

f	Statistical parameter	Algorithm			
		PSO	FA	CSA	NBA
f_1	Best	1.04E-01	7.50E-77	1.11E-02	8.01E-109
	Avg	4.65E+03	7.08E+02	4.59E+03	2.44E+02
	Med	1.37E+02	1.33E-27	9.74E+01	2.67E-50
	Std.	8.24E+03	4.99E+03	8.34E+03	2.92E+03
f_2	Best	6.74E-01	5.57E-50	2.08E-01	6.26E-58
	Avg	2.64E+09	1.10E+10	1.74E+10	2.64E+09
	Med	1.53E+01	4.43E-16	8.98E+00	2.58E-28
	Std.	5.90E+10	2.47E+11	3.90E+11	5.90E+10
f_3	Best	-1.03E+04	-1.23E+04	-8.28E+03	-8.21E+03
	Avg	-8.56E+03	-1.19E+04	-7.60E+03	-7.00E+03
	Med	-1.01E+04	-1.23E+04	-8.28E+03	-7.74E+03
	Std.	2.44E+03	1.21E+03	1.28E+03	1.35E+03
f_4	Best	5.47E+01	5.68E-14	8.48E+01	0.00E+00
	Avg	1.71E+02	1.25E+01	1.87E+02	6.49E+00
	Med	1.35E+02	5.68E-14	1.45E+02	0.00E+00
	Std.	1.16E+02	5.76E+01	1.01E+02	4.27E+01
f_5	Best	9.98E-01	9.98E-01	9.98E-01	9.98E-01
	Avg	1.98E+00	1.97E+00	1.27E+00	1.50E+00
	Med	9.98E-01	9.98E-01	9.98E-01	9.98E-01
	Std.	2.94E+00	1.13E+01	1.08E+00	8.23E+00
f_6	Best	6.21E-04	7.30E-04	3.45E-04	3.07E-04
	Avg	3.41E-03	1.70E-03	2.42E-03	1.28E-03
	Med	7.83E-04	7.30E-04	6.56E-04	3.08E-04
	Std.	3.05E-02	9.11E-03	1.99E-02	9.56E-03

Table 4. Friedman ranking results of the optimization algorithms based on benchmark functions

Algorithm	Average rank	Rank
NBA	1.75	1
FA	2.1667	2
CSA	3	3
PSO	3.0833	4

Table 5. Friedman statistical test results

Parameter	Value
Number of benchmark functions (N)	6
Number of algorithms (k)	4
Friedman statistic	4.55
Degrees of freedom	3
p-value	0.208

3.2. Load forecasting optimization

The initial stage of the optimization process involves defining the parameters and constraints of the fuzzy membership functions to be optimized using PSO, FA, CSA, and the proposed NBA. The STLF model was developed for January 4, 2016, using historical load data from the corresponding date over the preceding six years. Optimization of the FOU in IT2FL was implemented in MATLAB through M-file programming, utilizing functions available in the IT2FL toolbox to generate forecasting outputs. The resulting forecasts were subsequently processed in Microsoft Excel to determine peak-load values and calculate forecasting errors. Comparisons of the forecasting results and corresponding STLF errors for IT2FL-PSO, IT2FL-FA, IT2FL-CSA, and IT2FL-NBA are presented in Figures 5 and 6. For completeness, the forecasting performances of IT1FL-PSO, IT1FL-FA, IT1FL-CSA, and IT1FL-NBA are also included. Figure 4 presents the convergence curves of the benchmark functions used to evaluate the optimization algorithms. The results demonstrate that NBA achieves superior convergence performance compared with PSO, FA, and CSA, characterized by a faster convergence rate, improved ability to avoid local optima, and greater consistency in locating high-quality solutions.

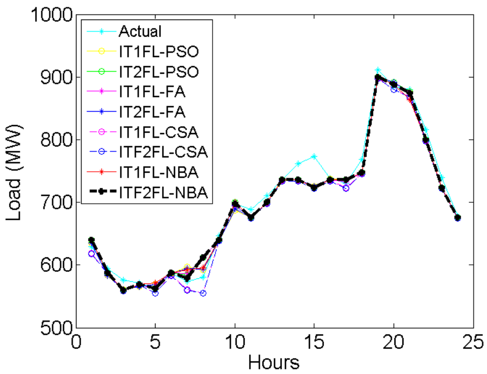


Figure 5. Comparison of STLF results

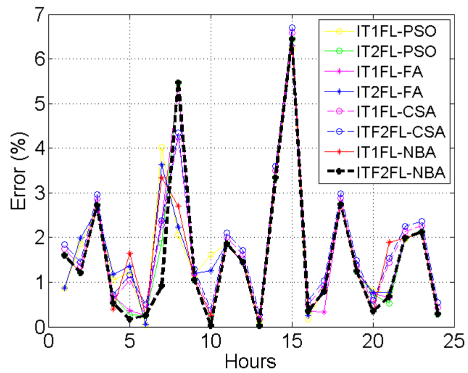


Figure 6. Comparison of error STLF results

This study demonstrates the effectiveness of applying the proposed bat-inspired SI algorithm to optimize the FOU parameters of fuzzy logic models for the Sulselrabar STLF system. NBA operates by minimizing the MAPE objective function, thereby improving forecasting accuracy. Based on both benchmark evaluations and practical implementation in the STLF problem, NBA consistently outperforms PSO, FA, and CSA. Its superior performance can be attributed to its balanced exploration and exploitation mechanisms, enhanced capability to escape local optima, and greater consistency in determining optimal FOU parameters. Consequently, the proposed IT2FL-NBA approach delivers more accurate and reliable STLF results for the Sulselrabar power system.

The proposed NBA-IT2FL forecasting framework has significant potential for deployment in information and communication technology (ICT)-enabled smart grid environments. In practical applications, historical and real-time load measurements can be collected through internet of thing (IoT)-enabled smart meters, sensors, and supervisory monitoring systems, providing continuous data streams for adaptive load forecasting. As an AI-driven predictive analytics approach, the proposed framework can generate accurate load predictions to support operational planning, demand-side management, generation scheduling, and decision-making processes. Furthermore, the NBA-IT2FL model can be implemented on cloud-based computing platforms, enabling scalable data processing, centralized forecasting services, and real-time access to forecasting results. The forecasting outputs can also be integrated into energy management systems (EMS), smart grid monitoring infrastructures, and cyber-physical energy systems to enhance situational awareness and operational efficiency. Therefore, the contribution of this work extends beyond the optimization of fuzzy logic parameters by providing an intelligent forecasting framework that supports emerging data-driven, interoperable, and ICT-enabled power system management technologies.

4. CONCLUSION

This study proposed the NBA, an SI optimization technique inspired by the echolocation behavior of bats. In the proposed approach, each bat represents a candidate solution that navigates the search space through adaptive adjustments of frequency, velocity, and position. The search process is regulated by pulse frequency, pulse emission rate, and loudness, enabling an effective balance between global exploration and local exploitation. NBA was applied to optimize the FOU in IT2FL for STLF in the Sulselrabar power system, Indonesia. The performance of NBA was evaluated using six benchmark functions to assess its exploration capability, exploitation efficiency, convergence characteristics, and ability to avoid local optima. The results demonstrated that NBA is highly competitive with well-established SI algorithms, including PSO, FA, and CSA. In particular, NBA exhibited strong exploitation performance in unimodal optimization problems and effective exploration capability in multimodal search spaces. For the STLF application, NBA-based FOU optimization improved the forecasting accuracy of IT2FL. The proposed IT2FL–NBA model achieved a MAPE of 1.5435%, outperforming IT2FL–PSO (1.6353%), IT2FL–FA (1.6451%), and IT2FL–CSA (1.6353%). For comparison, the IT1FL models optimized using NBA, PSO, FA, and CSA achieved MAPEs of 1.7196%, 1.6668%, 1.6842%, and 1.6768%, respectively. These results confirm that the proposed NBA effectively optimizes the FOU of IT2FL and enhances forecasting accuracy. Overall, the findings demonstrate that NBA is a reliable and promising optimization method for STLF and has strong potential for broader applications in power system optimization and intelligent energy management.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
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Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

INFORMED CONSENT

Informed consent was obtained from all participants included in this study.

DATA AVAILABILITY

The authors confirm that all data supporting the findings of this study are provided within the article.

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