Improving the Energy Management System with the Interval Type-2 Fuzzy Inference System – Zebra Optimization Algorithm (IT2FIS-ZOA) for Predicting the Load Consumption of Healthcare Facilities in National Holiday Season

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ABSTRACT

The improvement of Energy Management System (EMS) with a load consumption prediction feature is essential to the uninterrupted operation of medical equipment in healthcare facilities, such as hospitals. Accurately predicting their energy consumption demands leads to effective energy management. Additionally, the load consumption prediction is essential to achieve the energy-saving goals in the construction sector. This paper aims to improve the EMS of the Ulin Regional Public Hospital, one of the largest hospitals in South Kalimantan of Indonesia, by utilizing the Interval Type-2 Fuzzy Inference System – Zebra Optimization Algorithm (IT2FIS-ZOA) to predict the load consumption during the national holiday season. The IT2FIS-ZOA will enhance the exploration and exploitation processes to provide more accurate results. The load demand prediction is conducted based on the historical data of the Ulin Regional Public Hospital during 14 previous national holidays between 2020 and 2022. The accuracy of IT2FIS-ZOA is validated through a comparison of the prediction with actual data from 2023. Furthermore, IT2FIS-ZOA performance is compared to the Big Bang-Big Crunch Algorithm (BBBC), Firefly Algorithm (FA), and Cuckoo Search Algorithm (CSA). The findings indicate that the most accurate load consumption prediction is obtained from IT2FIS-ZOA with the lowest Mean Absolute Percentage Error (MAPE) of 2.49%, compared to a Fuzzy Type-1 of 2.74%, Fuzzy Type-2 of 2.55%, IT2FIS-BBBC of 3.91% , IT2FIS-FA of 2.51%, and IT2FIS-CSA of 2.50%. The results demonstrate the superiority of IT2FIS-ZOA in improving the EMS of the Ulin Regional Public Hospital.

Keywords-energy management system; load consumption prediction; interval type-2 fuzzy inference system; zebra optimization algorithm

I. INTRODUCTION

Global energy consumption has reached its unprecedented records, driven by factors, such as increased reliance on energy-intensive technologies, urbanization, population growth, and industrial expansion [1]. With the global population approaching 7.9 billion, energy demand continues to significantly rise with non-renewable resources, like fossil fuels, playing a dominant role in supplying load demand [2, 3]. The transportation, industrial, commercial, and residential sectors are the primary contributors to global energy consumption. The continuous reliance on fossil fuels raises concerns regarding the depletion of this limited resource and their adverse environmental impacts, including greenhouse gas emissions and climate change [4, 5]. To address the environmental and financial challenges posed by the current energy consumption demand requires an urgent transition to sustainable and renewable energy sources for improved energy efficiency, and the adoption of smart energy management systems [6].

One of the key components of an EMS is the load prediction [7, 8]. Given its significant economic impact, it remains a crucial element of the electricity industry [9]. It helps predict the energy market prices and ensures the stable operation and maintenance of the electricity grid [10]. However, safety constraints, such as reserve margins, system frequency, and reliability, can be compromised if the load exceeds the calculated projections [11]. Consequently, accurate prediction is critical to enhance management performance in the electricity sector and to reduce the frequency of outages. Five general categories of load prediction methods exist: Artificial Intelligence (AI) techniques, time series models, regression-based models, state-space technology and Kalman filtering, and Fuzzy Logic (FL) methods [12-17]. Among these, AI methods are becoming increasingly attractive due to their superior computational performance, particularly in optimizing the electric power systems in areas, such as stability, reliability, economic dispatch, and load forecasting [18-23].

In classic AI methods based on Interval Type-1 Fuzzy Inference Systems (IT1FIS), mathematical calculations derived from the set theory represent ambiguity through linguistic variables. IT1FIS is commonly applied in Short-Term Load Forecasting (STLF) [24]. However, the shape of its Membership Function (MF) is considered a significant challenge, as the sharp membership values are inadequate for handling high levels of uncertainty. To address this issue, the Interval IT2FIS is introduced with interval sets, which generalizes the interval sets of T1FIS [25]. Subsequently, IT2FIS can handle both the linguistic and numerical uncertainties. Authors in [26] proposed an IT2FIS system which includes rules that manage the uncertainty associated with its MF.

The application of IT2FIS in forecasting has demonstrated strong performance. Authors in [27] introduce a Mamdani-type IT2FIS designed to address forecasting challenges through Permanent Magnetic Drive (PMD) loss data. Simulation studies and convergence analysis are conducted to evaluate the effectiveness and feasibility of the proposed method, in comparison to IT1FIS. The use of STLF with IT2FIS is explored highlighting its high flexibility in the Java-Bali system [28]. The results indicate a low MAPE demonstrating the method's reliability. Similarly, authors in [29] investigate the application of IT2FIS for STLF in the Makassar system, Indonesia. The validation results confirm that the proposed method provides highly accurate predictions with an Absolute Error (AE) averaging less than 2%.

Healthcare facilities represent a key area for energy conservation studies due to their complexity, energy systems, and high energy consumption [30]. For instance, in [31], the energy consumption of a public hospital in Shanghai, China, is examined to demonstrate how ML models can provide detailed insights into the projected energy usage. Authors in [32] introduce two forecasting models that utilize regression analysis to estimate the hospital workloads in Istanbul. These models offer valuable insights for designers, allowing them to calculate the maximum energy requirements and determine the appropriate transformer and generator sizes in a single calculation. Similarly, authors in [33] forecast the future electrical loads for Ghanaian healthcare institutions using Model Predictive Control (MPC). A comprehensive analysis of a load forecasting algorithm, specifically designed for MPC applications in PV hybrid systems, is provided.

An often-overlooked aspect of STLF is the impact of special days [34]. In many cases, forecasting systems do not provide a detailed analysis of these periods, and the reported errors are not disaggregated to assess the forecasting accuracy, specifically for special days [35]. However, holidays and other special days often offer the highest contribution to the largest forecasting errors leading to significant losses. Authors in [36] analyzed the Spanish national system using linear regression to model the impact of social events, such as holidays. A combined method based on same-day matching for STLF during holidays is proposed in [37]. Similarly, authors in [38] explore STLF in a case study of Korean national holidays, comparing its forecasting accuracy with conventional methods. Additionally, authors in [39] examine STLF for the Qingdao system in China during special days, including national holidays, connecting days, and proximity days. Accurate electricity load forecasting enhances the safety and reliability of the power system operations, including load flow management, unit maintenance, and unit commitment.

This study develops an EMS to predict the power consumption during national holidays at Ulin Regional Public Hospital, which is part of a network of hospitals managed by the South Kalimantan government. The goal is to numerically model the electricity consumption in healthcare facilities. The IT2FIS and ZOA are utilized to optimize the Foot of Uncertainty (FoU) MF of the IT2FIS-ZOA. The ZOA is a novel metaheuristic approach that simulates the zebra foraging behavior and their defensive strategies against predators [40]. Several studies in the field of power systems have demonstrated the optimal performance of ZOA. Authors in [41] suggest that ZOA effectively solves optimization problems by achieving a suitable balance between exploration and exploitation, outperforming nine well-known competing algorithms. In [42], a solution to the Optimal Power Flow

(OPF) problem is proposed for an IEEE 30-bus test system, demonstrating that ZOA outperforms other algorithms. Authors in [43] introduce a ZOA-based approach to analyze Photovoltaic (PV) systems, utilizing block lookup tables for fast and efficient simulation. In [44], a ZOA is utilized to optimize the capacity of Distributed Energy System (DES) devices and the energy supply ratio of ground source heat pumps. This study verifies the effectiveness of ZOA in solving the DES configuration optimization problem.

The IT2FIS-ZOA approach is used to predict the electrical energy usage at Ulin Regional Public Hospital, with a comparison to other metaheuristic methods, such as the FA and CSA, which are also proposed for forecasting the electrical energy consumption. The high energy demands of healthcare facilities, the neglected impact of special dates on STLF, and the promising results achieved through the ZOA power system optimization motivated the investigation of the peak load prediction during national holiday periods at Ulin Regional Public Hospital.

II. INTERVAL TYPE-2 FUZZY INFERENCE SYSTEM

In type-1 FL systems, the knowledge base is used to create rules which can occasionally be unanticipated. Like IT1FIS, IT2FIS also includes MFs, FIS, and defuzzification. IT2FIS employs a type-reduction procedure for defuzzification, which includes algorithms like the Karnik-Mendel Algorithm (KMA), the Enhanced Karnik-Mendel Algorithm (EKMA), the Enhanced Karnik-Mendel Algorithm with Initialization (EKMANI), the Iterative Algorithm with a Stop Condition (IASC), and the Enhanced Iterative Algorithm with a Stop Condition (EIASC).

A. *Interval Type-2 Fuzzy Set*

An IT2FIS is defined by:

$$\tilde{A} = \int_{x\in X}\int_{x\in Jx}\frac{\pi\tilde{A}(x,u)}{(x,u)}Jx\subseteq[0.1] \quad (1)$$

where $\tilde{A}$ is represented by the MF $\mu\tilde{A}$ and $x\in X$ and $u\in Jx\subseteq[0, 1]$ characterize its properties. Let $u\in U$ be the secondary variable with domain Jx for each $x\in X$, where x is the primary variable with domain X. The set Jx is referred to as the primary membership of x. The FoU of $\tilde{A}$ represents the uncertainty in $\tilde{A}$ and is defined as the union of all primary memberships Jx, as depicted in Figure 1.

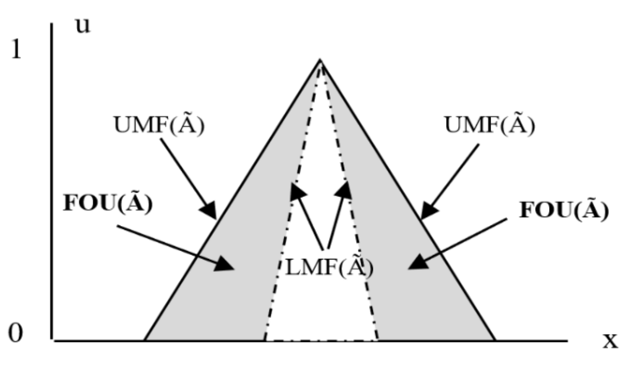


Fig. 1. FoU is illustrated in grey, LMF as a dotted line, and UMF as a solid line.

This relationship is formally expressed in:

$$FoU(\tilde{A}) = \cup_{\forall x\in X} Jx = \{(x,u); u \in Jx\subseteq[0.1]\} \quad (2)$$

Where Jx is an interval set, as defined by:

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

From (3), the FoU $(\tilde{A})$ can also be expressed as:

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

The Lower MF (LMF) of $\tilde{A}$ and the Upper MF (UMF) of $\tilde{A}$ are both represented as Jx, which corresponds to the primary membership of x [45].

B. *IT2FIS Structure*

The structure of the IT2FIS, displayed in Figure 2, illustrates the mapping process of the IT2FIS, where the input crisp value x is mapped to an output, as expressed in the equation $Y=f(x)$.

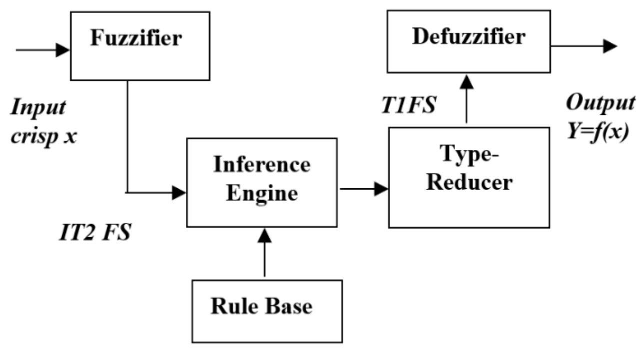


Fig. 2. Structure of IT2FLS.

C. *MF and Fuzzy Rules*

This method forecasts the maximum load consumption using fuzzy IF-THEN logic. In this study, X and Y stand for the input MFs (antecedents) and Z stands for the output MF (consequent). If X is A_i and Y is B_i, then Z is C_i. The fuzzy sets A_i, B_i, and C_i consist of eleven terms:

- Negative Very Big (UNVB and LNVB)
- Negative Big (UNB and LNB)
- Negative Medium (UNM and LNM)
- Negative Small (UNS and LNS)
- Negative Very Small (UNVS and LNVS)
- Zero (UZE and LZE)
- Positive Very Small (UPVS and LPVS)
- Positive Small (UPS and LPS)
- Positive Medium (UPM and LPM)
- Positive Big (UPB and LPB)
- Positive Very Big (UPVB and LPVB)

III. ZEBRA OPTIMIZATION ALGORITHM

ZOAis a novel bio-inspired metaheuristic algorithm, primarily influenced by the zebra behavior. It mimics their foraging habits and predator-avoidance strategies. The core principle of ZOA is the replication of the social dynamics observed in wild zebra herds.

A. Initialization

ZOA, a population-based optimization algorithm, consists of a population of zebras. Mathematically, each zebra represents a potential solution to the problem, while the area where the zebras reside corresponds to the problem's search space. Each zebra's position within this space defines the values of the decision variables. Initially, zebras are randomly distributed across the search space. The ZOA population matrix is specified by:

$$\mathrm{X} = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_n \end{bmatrix}_{Nxm} \quad (5)$$

Each zebra represents a potential solution to the optimization problem. Consequently, the proposed values assigned to each zebra for the problem variables are used to evaluate the objective function. The resulting objective function values are represented as a vector in:

$$\mathrm{F} = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_n \end{bmatrix}_{Nx1} \quad (6)$$

F_i represents the vector containing the objective function values, where F denotes the objective function value obtained for the third zebra. By comparing these values, the quality of the candidate solutions is assessed to identify the optimal solution for the given problem. The ZOA algorithm updates its members by incorporating two natural behaviors of zebras:

1. Foraging behavior.
2. Defense techniques against predators.

Consequently, in each iteration, the ZOA population is updated in two distinct phases based on these behaviors.

B. Phase 1: Foraging Behavior

In the first phase of the ZOA, the population members are updated by simulating the behavior of zebras during foraging. Zebras typically feed on grasses and sedges, but when these are scarce, they may also consume other food sources, such as buds, fruits, bark, roots, and leaves. Within the ZOA framework, the best member of the population is called the pioneer zebra. This pioneer zebra serves as a guide, leading the other zebras toward its position in the search space. To mathematically model this behavior, the process of updating the zebra positions during the foraging phase is represented by:

$$x_{1,j}^{new,PI} = x_{i,j} + r.\left(PZ_j - I.x_{i,j}\right) \quad (7)$$

$$X_i = \begin{cases} X_i^{new,P1}, & F_i^{new,P1} < F_i \\ X_i, & else \end{cases} \quad (8)$$

where $x_1^{new,PI}$ represents the new position of the *i-th* zebra after the first phase, and $x_{i,j}^{new,PI}$ denotes its value in the *j-th* dimension. $F_i^{new,PI}$ is the objective function value of the *i-th* zebra after the update. P_Z refers to the pioneer zebra, the best member of the population, and P_{Zj} is its value in the *j-th* dimension. r is a random number between [0,1], and I = *round (1+rand)*, where *rand* is a random number in the interval [0,1]. As a result, $I \in \{1,2\}$. If $I=2$, there will be more significant changes in the movement of the population.

C. Phase 2 : Defense Techniques Against Predators

In the second phase, the positions of the ZOA population members are updated in the search space by mimicking the zebras' defense mechanisms against predator attacks. The ZOA design assumes an equal probability for one of two scenarios to occur: (a) the lion attacks the zebra, prompting the zebra to adopt an escape strategy, or (b) other predators attack the zebra, causing it to adopt an offensive strategy.

The first strategy suggests that when zebras are attacked by lions, they flee from the attack site. This behavior is simulated using mode S_1 in (9). In the second strategy, the other zebras in the herd move toward the attacked zebra to form a defensive structure, aiming to confuse and intimidate the predator. Mode S_2 in (9) is used to mathematically model this defensive strategy. When the zebra positions are updated, the zebra with a higher objective function value at the new position is accepted. This update condition is represented by:

$$X_{i,j}^{new,P2} = \begin{cases} S_1 ;\ X_{i,j}+R.(2r-1).\left(1-\frac{t}{T}\right).X_{i,j} & P_S \leq 0.5 \\ S_2 ;\ X_{i,j}+r.\left(AZ-I.X_{i,j}\right), & else \end{cases} \quad (9)$$

$$X_i = \begin{cases} X_i^{new,P2}, & F_i^{new,P2} < F_i \\ X_i & else, \end{cases} \quad (10)$$

where $x_1^{new,P2}$ represents the new position of the *i-th* zebra after the second phase, while $x_{i,j}^{new,P2}$ denotes its value in the *j-th* dimension. $F_i^{new,P2}$ is the objective function value at the update position of the zebra. The iteration count is represented by t, and T is the maximum number of iterations. R is a constant equal to 0.01. P_s is the probability of selecting one of the two strategies, randomly generated within the interval [0,1]. Finally, A_Z represents the position of the attacked zebra, and AZ_j is its value in the *j-th* dimension

IV. PROPOSED LOAD CONSUMPTION PREDICTION METHODE

A. Pre-Processing

The quantitative data for this study are obtained from the daily electricity load values, in kWh, of the Ulin Regional Public Hospital electrical system. The single line diagram of Ulin Regional Public Hospital is presented in Figure 3. The dataset includes hourly measurements over a 24-hour period, covering a national holiday and the four preceding days, spanning a four-year period.

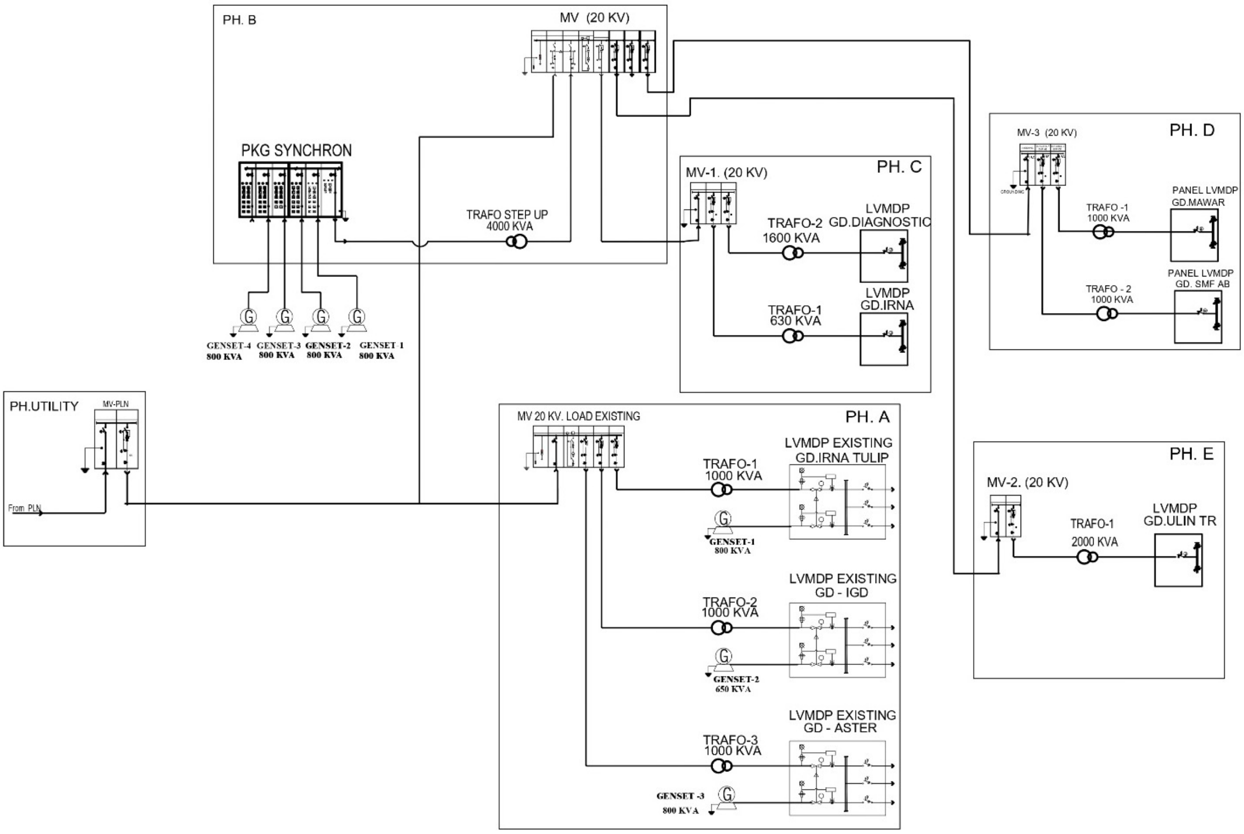


Fig. 3. Single line diagram of Ulin regional public hospital power system.

The date used to forecast the peak load for each holiday is applied to preprocess the load consumption data from Day-4 to *MaxSD* on the holiday.

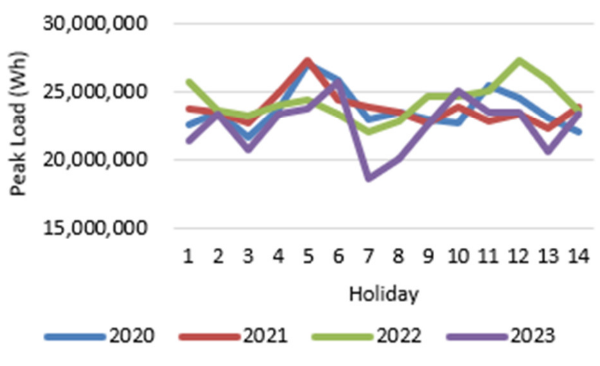


Fig. 4. Peak load consumption profile of Ulin Regional Public Hospital for 14 holidays in 2020-2023.

Using data from 2020 to 2023, which include totally load consumption data from Day-4 to *MaxSD* on the national holiday season, the peak demand for the same holiday season in 2023 is predicted. Initially, the data are preprocessed using (11) to calculate *MaxWD(i)*, which represents the average maximum load consumption for the four weekdays preceding the holiday. The difference between the holiday load (*MaxSD*) and *MaxWD*, as shown in (12), is referred to as the Load Difference (LDs) for the maximum loads on holidays.

$$MaxWD_{(i)} = \frac{WD_{(i)h-4} + WD_{(i)h-3} + WD_{(i)h-2} + WD_{(i)h-1}}{4} \quad (11)$$

$$LD_{MAX}(i) = \frac{MaxSD_{(i)} - MaxWD_{(i)}}{MaxWD_{(i)}} x100 \quad (12)$$

Based on past load data, the Typical Load Differences (TLDs) are calculated by averaging the LDs for the same special day within the same day type. The maximum load consumption for each unique day type are then predicted using the TLDs as baseline values. Regarding the Variation of Load Differences (VLDs), the distinction between the typical behavior of the same special days within the same day type and the load behavior of a special day. The VLD_{MAX} values are then calculated as indicated by:

$$VLD_{MAX}(i) = LD_{MAX}(i) - TLD_{MAX}(i) \quad (13)$$

VLD_{MAX} utilizes peak load data, resulting in the computations illustrated in Figure 4.

B. Processing

The processing stage of the EMS for healthcare facilities, using the proposed IT2FIS-ZOA for prediction, is described as follows:

1. The design of the MFs for type-2 fuzzy sets, with 50% FoU is presented in Figure 5. Next, A_i, B_i, and C_i are grouped

into 22 upper and lower regions of the triangular MFs. Within the range of -15 to 15 for the input variables, 11 triangular MFs are also employed for the antecedent inputs X and Y. Likewise, the subsequent output variable Z also uses all 11 triangular MFs. All input values for variables X, Y, and the output values of variable Z are defined and transformed into their respective values, where X represents $VLD_{MAX}(i)$ for the same holiday in the previous forecasted years, Y represents $VLD_{MAX}(i)$ for the previous holiday next to the forecasted year, and Z represents the forecasted $VLD_{MAX}(i)$.

2. The antecedent (X, Y) and the consequent (Z) are optimized through ZOA to obtain the best value of FoU.
3. Create fuzzy rules using the largest value of the membership degree. There are 14 fuzzy rules, as presented in Table I. An example of selecting the largest value of the corresponding membership degree (μ) for Idul Fitri is shown in Table II.
4. After determining the input and output variables, the implementation was carried out in the MATLAB software environment using the command line. The final crisp value obtained is called the Forecasted $VLD_{MAX}(i)$.

C. Post-Processing

During the post-processing phase, the maximum forecasted LD is calculated by (14), using the maximum forecasted VLDs and TLDs.

$$ForecastLD_{MAX}(i) = ForecastVLD_{MAX} + TLD_{MAX}(i) \quad (14)$$

The load consumption forecasted in the i^{th} year is calculated by:

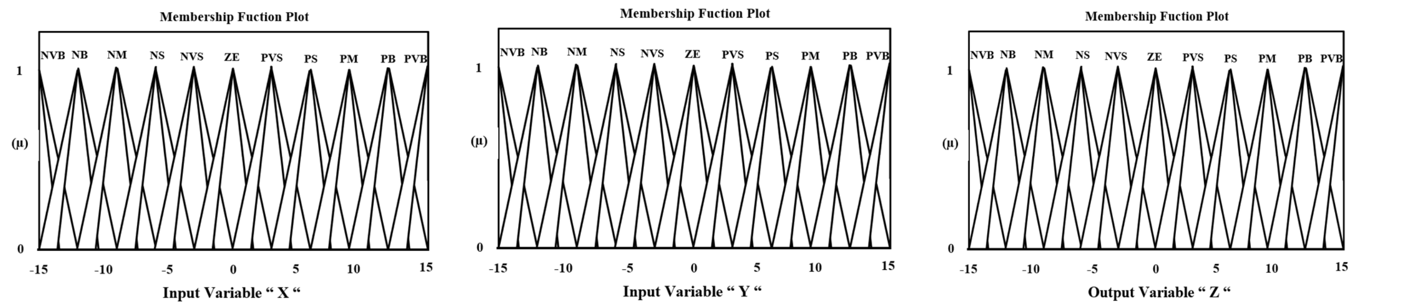
$$P'_{Max}(i) = MaxWD(i)\frac{(ForecastLD_{MAX}(i)\times MaxWD(i))}{100} \quad (15)$$

TABLE I. FUZZY RULES

Number of rules	X	Y	Z
New Year (1)	ZE	NM	NB
Independence Day (2)	NS	NB	NM
Idul Adha (3)	NM	NVS	NVB
Islamic New Year (4)	NB	NVB	NM
Maulid (5)	NM	NM	NB
Isra Mi'raj (6)	NM	NB	NVS
Idul Fitri I (7)	NM	NVS	NVB
Idul Fitri II (8)	NVS	NVB	NVS
Good Friday (9)	NM	NS	NM
Ascention (10)	NM	NM	NS
Christmas (11)	NVS	NS	NB
Silent Day (12)	PVB	NB	NM
Imlek (13)	PM	NM	NB
Waisak (14)	NS	NB	NVB

The difference between the calculated and real numbers is represented by the percentage of error, which is calculated using:

$$Error\% = \left|\frac{P'_{MAX}(i) - MaxSD(i)}{MaxSD(i)}\right| x100 \quad (16)$$



(a) (b) (c)

Fig. 5. Fuzzy type-2 membership fuction design.

TABLE II. RULE CREATION PROCESS FOR IDUL FITRI

Variable	VLD_{MAX}	MF degree of fuzzy set (μ)											Rules
		NVB	NB	NM	NS	NVS	ZE	PVS	PS	PM	PB	PVB	
X	-9.890031	0	0.8901	2.1099	0	0	0	0	0	0	0	0	NM
Y	-3.758399	0	0	0	0.7584	2.2416	0	0	0	0	0	0	NVS
Z	-15.60298	3	0	0	0	0	0	0	0	0	0	0	NVB

The results of the $MaxWD$ and LD_{MAX} calculations for 2020-2023 are presented in Table III, while the results of TLD_{MAX} and VLD_{MAX} for 2022-2023 are illustrated in Table IV. Across most cases, the $MaxWD$ values increase over the years from 2020 to 2023. However, mostly negative fluctuations in LD_{MAX} reveal that many holidays still experienced lower-than-expected levels, relative to historical norms. Notably, holidays, such as Christmas and Waisak, highlight significant increases in $MaxWD$ by 2023. On the contrary, holidays, such as Idul Fitri II and Imlek, exhibit sharp drops in LD_{MAX}. The contrasting trends between $MaxWD$ and LD_{MAX} emphasize that while the overall volumes may rise, they do not always align with historical expectations or typical patterns.

TABLE III. MAXWD AND LDMAX FOR 2020-2023

Holiday	2020		2021		2022		2023	
	MaxWD	LD_{MAX}	MaxWD	LD_{MAX}	MaxWD	LD_{MAX}	MaxWD	LD_{MAX}
New Year	23,715,232	-4.8407	25,023,089	-5.2145	27,226,531	-5.5077	25,600,450	-16.473
Independence Day	23,654,496	-0.9895	24,648,852	-4.8541	25,933,614	-9.0161	27,228,926	-14.176
Idul Adha	21,999,285	-1.6998	23,656,498	-4.0988	26,657,734	-12.889	25,801,574	-19.934
Islamic New Year	23,257,963	2.3842	24,460,998	1.9358	26,477,708	-9.3786	26,528,525	-11.739
Maulid	26,199,016	2.9757	28,776,341	-5.2206	27,453,191	-11.31	28,393,989	-16.186
Isra Mi'raj	25,354,336	2.1586	25,258,235	-3.3608	24,654,349	-5.2063	27,313,703	-5.8946
Idul Fitri I	22,677,528	1.2006	24,776,692	-3.7297	24,732,223	-11.155	23,242,761	-20.164
Idul Fitri II	22,877,005	2.5336	24,550,881	-4.5201	23,893,459	-4.6674	20,843,649	-3.7541
Good Friday	23,240,490	-1.0046	25,519,500	-10.8455	28,132,247	-12.468	27,317,614	-17.567
Ascention	23,902,581	-4.8523	24,776,692	-3.7297	27,738,289	-11.118	28,959,638	-13.345
Christmas	25,595,285	-0.5416	26,634,467	-14.3377	28,287,407	-11.468	30,104,863	-22.055
Silent Day	25,428,236	-3.2507	25,684,426	-9.3311	25,428,467	7.3560	26,472,321	-11.387
Imlek	28,534,700	-19.008	25,042,313	-11.1316	27,348,897	-5.5686	26,824,361	-23.21
Waisak	22,735,789	-3.0802	23,362,101	2.1412	25,510,283	-7.4479	28,678,328	-18.685

TABLE IV. TLDMAX AND VLDMAX 2022-2023

Holiday	2022		2023	
	TLD_{MAX}	VLD_{MAX}	TLD_{MAX}	VLD_{MAX}
New Year	-5.0276	-0.4801	-5.1876	-11.286
Independence Day	-2.9218	-6.0943	-4.9532	-9.2225
Idul Adha	-2.8993	-9.9893	-6,2291	-13.705
Islamic New Year	2.16006	-11.539	-1.6862	-10.053
Maulid	-1.1225	-10.188	-4.5183	-11.667
Isra Mi'raj	-0.6011	-4.6052	-2.1362	-3.7584
Idul Fitri I	-1.2646	-9.89	-4.5612	-15.603
Idul Fitri II	-0.9918	-3.6756	-2.27	-1.5372
Good Friday	-5.9251	-6.5433	-8.1062	-9.4613
Ascention	-4.291	-6.8269	-6.5666	-6.7785
Crismas	-7.4397	-4.0278	-8.7822	-13.273
Silent Day	-6.2909	13.647	-1.7419	-9.6447
Imlek	-15.07	9.5011	-11.903	-11.307
Waisak	-0.4695	-6.9784	-2.7956	-15.889

V. RESULTS AND DISCUSSION

A case study focusing on the historical load consumption data of Ulin Regional Public Hospital during 14 national holidays is utilized to test the effectiveness of the ZOA method.

A. Benchmarking Analysis

Prior to applying the ZOA approach for optimization, a benchmark analysis is carried out for comparison utilizing the FA, CSA, and BBBC methodologies. This investigation assesses each method's capacity for exploration and exploitation. Table V lists the parameters of the algorithm. The six benchmark test functions are listed below. The unimodal functions with a range from -100 to 100 are described by:

$$F_1(X) = \sum_{i=1}^{m} x_i^2 \quad (17)$$

$$F_2(X) = \sum_{i=1}^{m}\left(\sum_{j=1}^{i} x_i\right)^2 \quad (18)$$

Furthermore, the high-dimensional multimodal functions with a range of [-500, 500] and [-50, 50], respectively, are presented by:

$$F_3(X) = \sum_{i=1}^{m} -x_i sin\left(\sqrt{|x_i|}\right) \quad (19)$$

$$F_4(X) = 0.1\{sin^2(3\pi x_1) + \sum_{i=1}^{m}(x_i-1)^2[1 + sin^2(3\pi x_i+1)] + (x_n-1)^2[1 + sin^2(2\pi x_m)]\} + \sum_{i=1}^{m} u(x_i, 5,100,4) \quad (20)$$

The last set of the test functions includes fixed-dimensional multimodal functions with a range from -5 to 5, described by:

$$F_5(X) = \sum_{i=1}^{11}\left[a_i - \frac{x_i(b_i^2+b_i x_2)}{b_i^2+b_i x_3+x_4}\right]^2 \quad (21)$$

$$F_6(X) = 4x_1^2 - 2.1.x_1^4 + \frac{1}{3}x_1^6 + x_1 x_2 - 4x_2^2 + 4x_2^4 \quad (22)$$

This strategy offers a thorough assessment of the algorithms' performance on various optimization tasks. In particular, the fixed dimension multimodal functions evaluate the algorithm's performance in low-dimensional optimization scenarios. Table VII displays the results of the ZOA, which is run 30 times, along with the best values and standard deviations.

These statistical tests demonstrate the suggested algorithm's accuracy, consistency, and notable differences. The results show that ZOA performs better than the BBBC, CSA, and FA approaches, exhibiting better exploration and exploitation skills, as well as increased accuracy and consistency.

TABLE V. PARAMETER OF THE ALGORITHM

Algorithm	Parameter	Value
BBBC	Population size	25
	Number of parameter	15
CSA	Population size	25
	Dimension of the problem	15
	Discovery rate	0.25
FA	Number of fireflies	30
	Alpha	0.2
	Gamma	1.0
	Delta	0.97
ZOA	Number of zebras	30
	Dimension	30

The convergence curves, which monitor the evolution of the best solution at each iteration, serve as an illustration of how the algorithm finds the best solution. The analyzed algorithms' normalized average convergence curves over 30 runs for both unimodal and multimodal benchmark functions are shown in Figure 6. These curves provide information on how well each algorithm performs and how well it finds the best answers. In contrast to BBBC, CSA, and FA, ZOA has a superior convergence curve, demonstrating a stronger capacity to avoid the local optima and a faster convergence to the optimal solution. These findings highlight the benefits of using a ZOA-based method to solve optimization issues, especially when considering the FoU of IT2FIS.

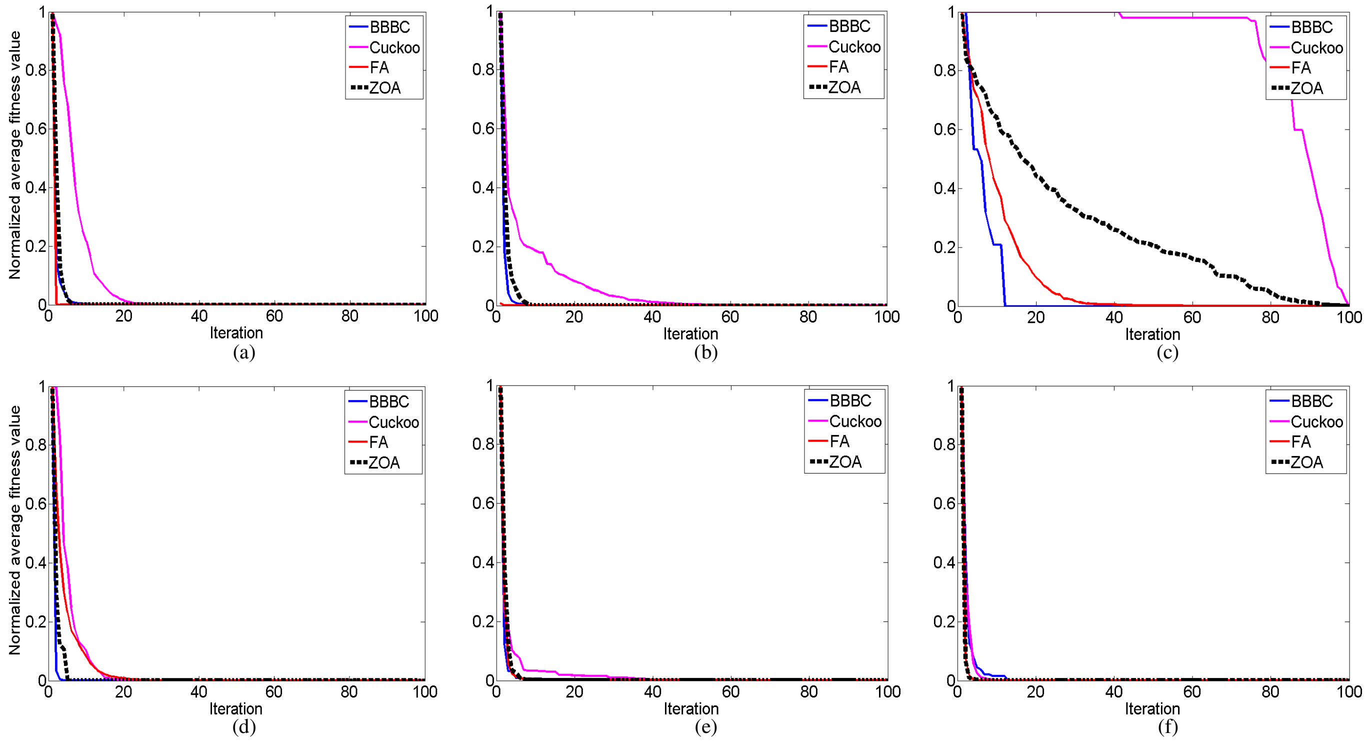


Fig. 6. Comparison of convergence curves for benchmark functions: (a) F_1, (b) F_2, (c) F_3, (d) F_4, (e) F_5, and (f) F_6.

TABLE VI. BENCHMARKING TEST RESULT

Statistical Parameter	Algorithm			
	BBBC	CSA	FA	ZOA
F_1 - Best	1.05E-05	3.09E-03	4.63E-10	1.24E-44
F_1 - Std.	2.64E-01	1.60E+03	8.05E-03	7.02E+03
F_2 - Best	3.87E+01	4.39E+01	3.86E-10	3.50E-29
F_2 - Std.	2.79E-04	9.49E+03	9.61E-03	1.74E+04
F_3 - Best	-5.50E+03	-8.44E+03	-5.96E+03	-4.22E+03
F_3 - Std.	3.18E+02	3.42E+02	7.84E+02	6.83E+02
F_4 - Best	3.65E+00	3.71E+00	3.80E+00	2.97E+00
F_4 - Std.	1.00E+08	3.65E+07	1.91E+08	2.48E+08
F_5 - Best	3.60E-02	5.91E-04	7.81E-04	4.40E-04
F_5 - Std.	2.26E-02	1.13E-02	3.38E-03	1.94E-02
F_6 - Best	-1.02E+00	-1.03E+00	-1.03E+00	-1.03E+00
F_6 - Std.	9.92E-02	1.15E-01	1.17E-02	1.85E-01

B. Load Prediction Result

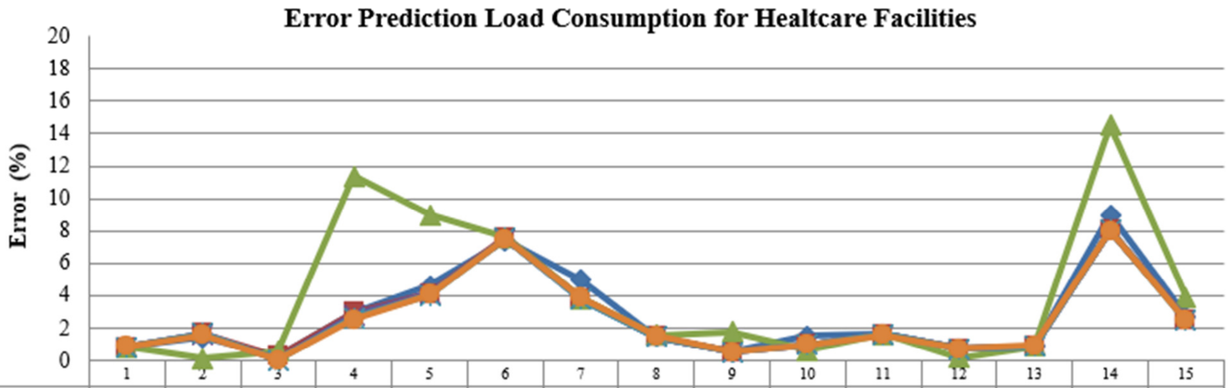
A MATLAB m-file program is used to optimize the FoU in IT2FIS along with ZOA and functions from the IT2FIS Toolbox are employed to obtain the forecast values. Subsequently, the forecast errors are calculated and the peak load projections are derived by processing the forecast results in Microsoft Excel.

Based on data from various load conditions during holidays, the comparison of the prediction results from IT2FIS, IT2FIS-BBBC, IT2FIS-FA, and IT2FIS-CSA is presented. The results, of the predicted load consumption for the year 2023 are shown in Table VIII. In addition, the prediction error in the load consumption is displayed in Figure 7.

This method has been applied to the historical load consumption data of Ulin Regional Public Hospital during 14 national holidays in 2023. The resulting MAPE for each method is: 2.74% for IT1FIS, 2.55% for IT2FIS, 3.91% for IT2FIS-BBBC, 2.51% for IT2FIS-FA, 2.50% for IT2FIS-CSA, and 2.49% for IT2FIS-ZOA. Therefore, the IT2FIS-ZOA method is the most accurate in predicting the electrical power consumption at Ulin Regional Public Hospital compared to the other methods.

VI. CONCLUSIONS

Healthcare buildings have high energy consumption and complex energy systems, and are considered pivotal in achieving the energy-saving goals within the building industry. Effective energy management in these buildings requires an accurate forecasting of the energy consumption demands. This study outlines the Energy Management System (EMS) and its application in numerically modeling the electricity consumption of healthcare facilities at Ulin Regional Public Hospital, which is managed by the South Kalimantan government. The improvement in load consumption prediction during national holidays for hospitals significantly enhances real-world operations by improving the safety and reliability of the hospital's power system. By accurately forecasting the energy consumption, the hospital can better manage the energy resources, plan for unit maintenance, and optimize the unit cost predictions. This leads to more efficient energy management, ensuring uninterrupted operations during the peak demand times, such as holidays, thereby enhancing the overall reliability and efficiency of the hospital's electrical systems. This improvement can also contribute to cost savings and more sustainable energy use in the long term.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Fuzzy Type -1	0.8553	1.4357	0.2687	2.9436	4.6141	7.3952	4.9545	1.5199	0.5596	1.5670	1.6331	0.7276	0.9025	8.9970	2.7410
Interval Type-2 FIS	0.8553	1.6882	0.2872	2.9904	4.1425	7.5973	3.8349	1.5199	0.5596	1.0058	1.6331	0.7276	0.9025	8.0496	2.5567
IT2FIS-BBBC	0.8553	0.1682	0.5887	11.3901	9.0228	7.5971	3.8134	1.5971	1.7922	0.6687	1.6331	0.1941	0.9025	14.5251	3.9106
IT2FIS-FA	0.8548	1.6454	0.0684	2.8337	4.1527	7.5182	3.7873	1.4829	0.5596	1.0058	1.6336	0.7431	0.9019	8.0622	2.5178
IT2FIS-CSO	0.8293	1.7139	0.0684	2.6215	4.0531	7.5619	3.8038	1.5001	0.5596	1.0058	1.6637	0.7363	0.8750	8.0756	2.5049
IT2FIS-ZOA	0.8930	1.6179	0.0684	2.5404	4.0921	7.5149	3.8881	1.5529	0.5596	1.0058	1.5884	0.7276	0.9413	8.0001	2.4993

Fig. 7. Error prediction load consumption for healthcare facilities on national holiday for year 2023 (case study of Ulin Regional Public Hospital, South Kalimanran in Indonesia).

TABLE VII. LOAD CONSUMPTION PREDICTION RESULTS

Holiday	Actual (Wh)	IT1FIS P'_{MAX} (Wh)	IT2FIS P'_{MAX} (Wh)	IT2FIS-BBBC P'_{MAX} (Wh)	IT2FIS-FA P'_{MAX} (Wh)	IT2FIS-CSA P'_{MAX} (Wh)	IT2FIS-ZOA P'_{MAX} (Wh)
New Year	21,383,235	21,200,344	21,200,344	21,200,344	21,200,446	21,205,899	21,192,280
Independence Day	23,369,011	23,033,510	22,974,505	23,329,705	22,984,497	22,968,487	22,990,923
Idul Adha	20,658,325	20,602,818	20,598,999	20,536,714	20,672,456	20,672,456	20,672,456
Islamic New Year	23,414,288	24,103,509	24,114,465	26,081,210	24,077,776	24,028,088	24,009,093
Maulid	23,798,221	24,896,300	24,784,059	25,945,486	24,786,500	24,762,791	24,772,076
Isra Mi'raj	25,703,680	23,802,837	23,750,886	23,750,940	23,771,234	23,759,981	23,772,081
Idul Fitri I	18,556,040	19,475,404	19,267,637	19,263,662	19,258,804	19,261,872	19,277,514
Idul Fitri II	20,061,148	19,756,239	19,756,239	20,381,548	19,763,659	19,760,220	19,749,610
Good Friday	22,518,593	22,644,616	22,644,616	22,115,009	22,644,616	22,644,616	22,644,616
Ascention	25,094,944	24,701,718	24,842,548	25,262,752	24,842,548	24,842,548	24,842,548
Christmas	23,465,167	23,848,366	23,848,366	23,848,365	23,848,486	23,855,560	23,837,889
Silent Day	23,458,006	23,628,680	23,628,680	23,412,481	23,632,333	23,630,718	23,628,680
Imlek	20,598,511	20,412,617	20,412,617	20,412,617	20,412,724	20,418,277	20,404,623
Waisak	23,319,886	25,417,975	25,197,037	26,707,122	25,199,990	25,203,116	25,185,508

This study employs the Interval Type-2 Fuzzy Inference System (IT2FIS) combined with the Zebra Optimization Algorithm (ZOA) to predict the electrical energy usage in hospitals. The method was applied to historical load consumption data from Ulin Regional Public Hospital during 14 national holidays in 2023 resulting in lower error rates compared to other methods. The Mean Absolute Percentage Error (MAPE) for the IT2FIS-ZOA method was 2.49% the lowest in comparison with the rest of studied methods. All MAPE values remain below the permissible tolerance threshold.

Future studies could explore how these predictions contribute to quantifiable cost savings and improvements in energy efficiency. By accurately forecasting the energy demand, healthcare facilities can optimize their energy usage, minimize waste, and adopt more efficient energy management practices. These improvements can ultimately lead to significant cost reductions and more sustainable operations

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