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Research paper

Peak load forecasting on national holiday using fuzzy-cuckoo for Jawa-Bali system in Indonesia

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Abstract

This paper discusses the peak load forecasting on national holiday. The forecasting is done by using Fuzzy Logic System Type 2 method, optimized with Cuckoo Search Algorithm (CSA). Cuckoo Search Algorithm is used to optimize Footprint of Uncertainty (FOU) on fuzzy logic which consisting of antecedent (X, Y) and consequent (Z). This method uses data from daily peak load during the holidays on the Jawa-Bali electricity system. The data is focused on load data from four days before holidays (h-4) and on holidays (h). Validation results indicate that the Fuzzy Logic System Type-2 method which is optimized with Cuckoo Search Algorithm provides a good enough forecasting with Mean Absolute Percentage Error (MAPE) is less than 2%.

Keywords: *Peak Load Forecasting; National Holiday; Fuzzy Logic Type-2; Cuckoo Search Algorithm; MAPE.*

1. Introduction

Load forecasting is very important in planning, analyzing, and operating in the energy market [1]. Accurate load estimates can provide effective information to support power system planning [2]. Load forecasting is classified into two categories that are short-term load forecasting and long-term load forecasting [2], but other sources divide into three categories that are short-term load forecasting, mid-term load forecasting and long-term load forecasting. Short-term load forecasting is very important in modern countries because of the highly competitive energy market [3]. Short-term load forecasting especially on holidays is a concern because holidays are different from ordinary days [4]. In implementing load forecasting there are many methods that have been used. In general, the method used is the classical method and the intelligent method [1, 5]. Classical method is statistical methods such as multiple regression [6], exponential smoothing [7], Box and Jenkins method [8], Kalman filter [9], and state estimation [10]. Intelligent method used in load forecasting such as expert system [11-13], neural networks [14-16], and fuzzy logic [17-18].

The main problem that is often experienced by the classical method is the difficulty to model a complex non-linear relationship between the load and he rhythm of daily and weekly times, which can cause a high error in forecasting the load [1]. The intelligent method has the ability to provide better performance in dealing with non-linear problems. For example, the fuzzy set and fuzzy logic solve the non-probabilistic information and uncertainty by manipulating data through a rule basis and adjusting membership function [17]. Therefore, this method is reliable for executing and modelling complex system with non-linear and non-exact characteristic.

In this research, we apply the fuzzy logic type 2 method which is optimized by using Cuckoo Search Algorithm (CSA) for forecasting the peak load of national holidays. Cuckoo Search Algorithm is an optimization method that is inspired by cuckoo bird behaviour [19-21]. Cuckoo Search (CS) has attracted great attention because of its promising efficiency in solving many optimization problems and real-world applications [20]. This method is superior than GA and PSO for multimodal objective functions [19].

2. Fuzzy logic type-2

Fuzzy logic system type 2 is the development of fuzzy logic system type 1. The membership function of fuzzy logic system type 2 has two membership degrees that is the degree of primary and secondary membership. Similar to FLS type-1, FLS type-2 also includes fuzzifier, rule base, fuzzy inference engine, and output processor. The difference lies in the output. The FLS type-2 output includes the type-reducer and defuzzifier. The type-reducer converts the fuzzy set type 2 to some fuzzy set type 1 and defuzzifier will produce an output crisp. The fuzzy logic system type 2 structure can be seen in figure 1.

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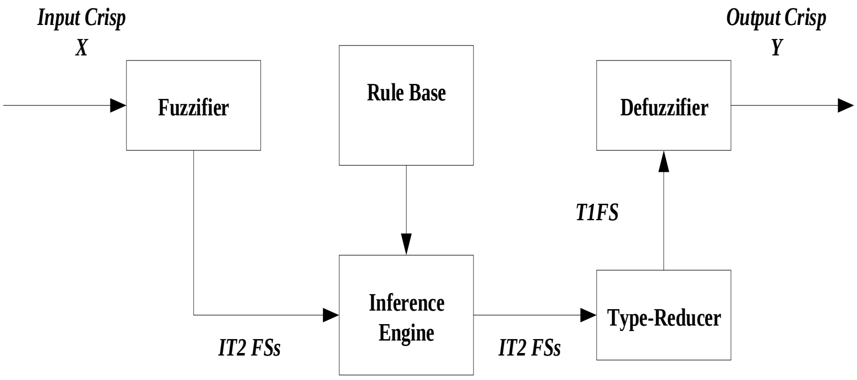

Fig. 1: Type-2 Fuzzy Logic System (T2fls) Structure.

2.1. Interval type-2 fuzzy set

Interval type-2 fuzzy set (IT2FS) is symbolized with $\tilde{A}$ and the membership function is given the symbol $\mu\tilde{A}$ With $x \in X$ andu $\in$ $Jx \subseteq [0,1]$, the characteristic can be seen in the following equation:

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

Uncertainty of $\tilde{A}$ is represented by a combination of primary membership (Jx) called the footprint of uncertainty (FOU) of $\tilde{A}$. x is the primary variable. x has X domain; u ∈ U, secondary variable, has Jx domain. Every x∈X; Jx is called the primary membership of x. The equation can be expressed as follows:

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

Jx interval can be seen in the following equation:

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

Thus from 2 FOU($\tilde{A}$) equation can be written with equation:

$$FOU(\tilde{A}) \equiv \bigcup_{\forall x \in X} \left[\underline{\mu}_{\tilde{A}}(x), \overline{\mu}_{\tilde{A}}(x)\right] \tag{4}$$

$\underline{\mu}\tilde{A}$ = Lower Membership Function (LMF) of $\tilde{A}$
$\overline{\mu}\tilde{A}$ = Upper Membership Function (UMF) of $\tilde{A}$
Jx = Primary membership of x

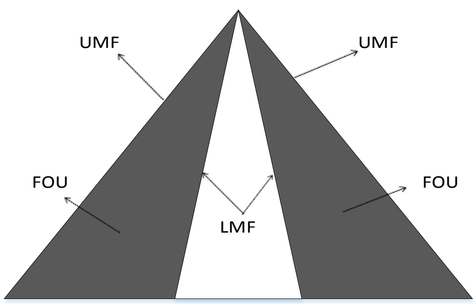

Fig. 2: FOU, LMF , and UMF.

2.2. Interval type-2 fuzzy membership function operations

Operations in the fuzzy type-2 set are enclosed between two intervals that are Upper Membership Function (UMF) and Lower Membership Function (LMF) or called Footprint of Uncertainty (FOU). The operation can be seen in the following figure:

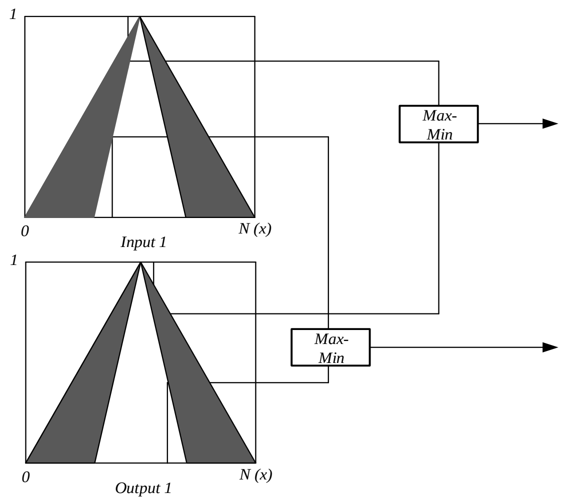

Fig. 3: Operation Interval Type-2 Fuzzy Set.

2.3. Karnik mendel algorithm

One of the centroid searching method on fuzzy interval type-2 is by using Karnik Mendel method. The formulation method is as follows:

$$Y_{Cos}(x') = \bigcup_{\substack{f^n \in F^n(x'),\\ y^n \in Y^n}} \frac{\sum_{n-1}^{N} f^n y^n}{\sum_{n-1}^{N} f^n} = [yl, yr] \tag{5}$$

$$y_l = \min_{k \in [1, N-1]} \frac{\sum_{n=1}^{k} \overline{f}^n \underline{y}^n + \sum_{n=k+1}^{N} \underline{f}^n \underline{y}^n}{\sum_{n=1}^{k} \overline{f}^n + \sum_{n=k+1}^{N} \underline{f}^n}$$

$$\equiv \frac{\sum_{n=1}^{L} \overline{f}^n \underline{y}^n + \sum_{n=L+1}^{N} \underline{f}^n \underline{y}^n}{\sum_{n=1}^{L} \overline{f}^n + \sum_{n=L+1}^{N} \underline{f}^n}$$

$$y_r = \max_{k \in [1, N-1]} \frac{\sum_{n=1}^{k} \underline{f}^n \overline{y}^n + \sum_{n=k+1}^{N} \overline{f}^n \overline{y}^n}{\sum_{n=1}^{k} \underline{f}^n + \sum_{n=k+1}^{N} \overline{f}^n} \tag{6}$$

$$\equiv \frac{\sum_{n=1}^{R} \underline{f}^n \overline{y}^n + \sum_{n=R+1}^{N} \overline{f}^n \overline{y}^n}{\sum_{n=1}^{R} \underline{f}^n + \sum_{n=R+1}^{N} \overline{f}^n}$$

Switch point of L and R as follows:

$$\underline{y}^L \le yl \le \underline{y}^{L+1}$$
$$\overline{y}^R \le yr \le \overline{y}^{R+1} \tag{7}$$

The value of centroid is expressed with the following equation:

$$Centroid = \frac{(yl + yr)}{2} \tag{8}$$

3. Cuckoo search algorithm

Cuckoo search is one of artificial intelligent type and modern heuristic algorithm which is based on cuckoo bird behaviour. Cuckoo bird has a unique reproductive strategy, where they will put their egg in other types of bird nest. To make it easier in describing Cuckoo Search, there are three ideal rules that are used that is : a. Each cuckoo puts an egg each time, and throws the egg into a randomly selected nest; b. The best nest with high egg quality will carry over to the next generation; c. The number of existing host nest is fixed, and the eggs laid by a cuckoo are found by the bird host with $p_a \in [0,1]$ probability. In this case, the host bird can either throw away its eggs or leave its nest, and build an entirely new nest. For simplicity, this newest assumption can be approximated by the p_a fraction of the n nest which is replaced by new nest (with new random solution).
While generating new generation of $x^{(t+1)}$, a step randomization with Lévy Fights will be used which can be seen as follows:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus levy(\lambda) \tag{9}$$

Where, α > 0 is a step measurement which is associated with the level of the problem being worked on. Lévy (λ) expresses the function of position equation of Lévy Flights, which is the form of the equation:

$$levy \sim u = t^{-\lambda}, (1 < \lambda \leq 3) \tag{10}$$

The algorithm of Cuckoo Search can be seen in the following table:

Table 1: Algoritma Cuckoo Search [19]

begin
Objective function f(x), x = $(x_1,..., x_d)^T$
Generate initial population of
n host nests x_i (i = 1, 2,..., n)
while
(t < MaxGeneration) or (stop criterion)
Get a cuckoo randomly by Lévy flights
evaluate its qulity/ fitness F_i
Choose a nest among n (say, j) randomly
if ($F_i > F_j$)
replace j by the new solution;
end
A fraction (pa) of worst nests
are abandoned and new ones are built;
Keep the best solutions (or nests with quality solutions);
Rank the solutions and find the current best
end while
Postprocess results and visualization
end

4. Peak load forecasting on national holiday using FLT2-cuckoo

To apply it2fuzzy-cuckoo on peak load forecasting on national holidays then it is applied three stages that is pre-processing stage, processing stage, and post-processing stage [18].

4.1. Pre-processing

Pre-processing is the preparation stage of peak load data on national holidays to find out the Load Difference (LD), Typical Load Difference (TLD), Maximum Weekdays (Max WD), and Variation Load Difference (VLD). Load difference (LD) aims to determine the difference in load for 4 days before the national holiday which is provided by:

$$LD_{MAX}(i) = \frac{MaxSD(i) - MaxWD(i)}{MaxWD(i)} x100 \tag{11}$$

$$MaxWD_{(i)} = \frac{WD_{(i)d-4} + WD_{(i)d-3} + WD_{(i)d-2} + WD_{(i)d-1}}{4} \tag{12}$$

With, maxSD (i) is a special day peak load and maxWD is the average of maximum load 4 days before the holiday. After obtaining maxWD then the next step looks for the Typical Load Difference ($TLD_{MAX}(i)$) by averaging the $LD_{MAX}(i)$ peak load corresponding to previous years. After that, calculate Variation Load Difference ($VLD_{MAX}(i)$) that is the difference between Load Difference (LD) with Typical Load Difference ($TLD_{MAX}(i)$) which can be expressed in the following equation:

$$VLD_{max}(i) = LD_{max}(i) - TLD_{max}(i) \tag{13}$$

$$TLD_{max}(i) = \frac{LD_{max}(i-1) + LD_{max}(i-2) + LD_{max}(i-3)}{3} \tag{14}$$

4.2. Processing

The process of data processing is modelling the short-term load forecasting on national holidays by using Fuzzy Logic Type-2 which is optimized by Cuckoo Search Algorithm. The process is executed on the fuzzy operator which is performed on the Footprint of Uncertainty (FOU). FOU is a membership function that is limited by the Upper Membership Function (UMF) and Lower Membership Function (LMF).
In this method the IF-THEN fuzzy rule is used to predict the peak load on national holidays which is expressed as follows:
IF X is A_i AND Y is B_i THEN Z is C_i
The fuzzification design of X dan Y input is using Interval Type-2 Membership Function (IT2MF) editor. There are 11 membership functions that is applied, namely:

Negative Very Big (NVB)
Negative Big (NB)
Negative Medium (NM)
Negative Small (NS)
Negative Very Small (NVS)
Zero (ZE)
Positive Very Small (PVS)
Positive Small (PS)
Positive Medium (PM)
Positive Big (PB)
Positive Very Big (PVB)

The max rule which is used to select fuzzy set by taking the biggest value corresponding to the degree of membership (μ), input variables (X, Y) and output (Z). The input variables of X, Y, and Z is VLDmax from holiday data. X is VLDmax (i) of similar holiday in the year before the forecast year. Y is VLDmax (i) on the previous holiday (adjacent) in the forecast year. Z is the forecast of VLDmax (i). The LMF and UMF parameters are limited by the variable value of X, Y, and Z. The limiting values of LMF and UMF in FOU are determined by the Cuckoo Search Algorithm optimization method.

4.3. Post-processing

The final step is post-processing that is find out the difference of the forecast load difference which can be expressed as follows:

$$Forecast\ LD_{MAX}(i) = Forecast\ VLD_{MAX}(i) + TLD_{MAX}(i) \tag{15}$$

After obtaining forecasting load difference then peak load forecasting on national holidays is calculated as follows:

$$P'_{MAX}(i) = MaxWD(i) + \frac{(ForecastLD_{MAX}\,xMaxWD(i))}{100} \quad (16)$$

To measure the performance of the proposed method then it is used absolute error equation; the smaller the error obtained indicates the higher the accuracy of the proposed method. Absolute error can be expressed as follows:

$$Error = \left| \frac{P_{forecast} - P_{actual}}{P_{actual}} \right| x\,100\% \quad (17)$$

$$Error = \left| \frac{P'_{MAX}(i) - MaxSD(i)}{MaxSD(i)} \right| x\,100\% \quad (18)$$

5. Result and discussions

The data used is the peak load data on national holidays on Jawa-Bali system starting from 2009-2013 by using Fuzzy Logic Type-2 Cuckoo Search Algorithm (FLT2CSA) method. The proposed method is compared with Fuzzy Logic Type-2 (FLT2). Validation results using the FLT2-CSA method for peak load forecasting on national holidays showed excellent results with Mean Absolute Percentage Error (MAPE) was 1.741136837%. MAPE was obtained by using FLT2 was 2.04061%.
The more complete results can be seen in table 2 and figure 4. Table 2 is estimated result of peak load on national holidays. Figures 4 are plotting results.

Table 2: Results of Peak Load Forecasting on National Holidays in 2013.

No	Holidays Name	Actual (MW)	Fuzzy type 2 Forecast (MW)	Absolute Error(%)	Fuzzy-Cuckoo Forecast (MW)	Absolute Error(%)
1	Tahun Baru Masehi	15780.00	15870.823	0.57556	15827.151	0.298802
2	Proklamasi Kemerdekaan RI	17354.00	17093.66	1.5002	17131.446	1.282437
3	Idul Adha	18650.00	19071.936	2.26239	18895.612	1.316954
4	Tahun Baru Hijriyah	19477.00	19583.12	0.54485	19588.037	0.570093
5	Maulid Nabi Muhammad SAW	18307.00	17989.69	1.7333	18174.695	0.7227
6	Isra Mi'raj	19071.00	18816.812	1.3329	18853.03	1.142942
7	Idul Fitri I	13777.00	13754.865	0.1607	13755.226	0.158044
8	Idul Fitri II	14058.00	14413.331	2.52761	14389.193	2.355903
9	Wafatnya Yesus Kristus	18853.00	19123.823	1.4365	19129.859	1.468516
10	Kenaikan Yesus Kristus	19914.00	19818.335	0.4804	19901.946	0.060532
11	Natal	18782.00	18602.738	0.9544	18608.387	0.92436
12	Nyepi	18723.00	17349.985	7.3333	17358.893	7.28573
13	Tahun Baru Imlek	17875.00	17488.356	2.163	17658.714	1.20999
14	Waisak	18662.00	19700.253	5.56346	19703.137	5.578914
Mean Average Percentage Error (MAPE)				2.04061		1.741136837

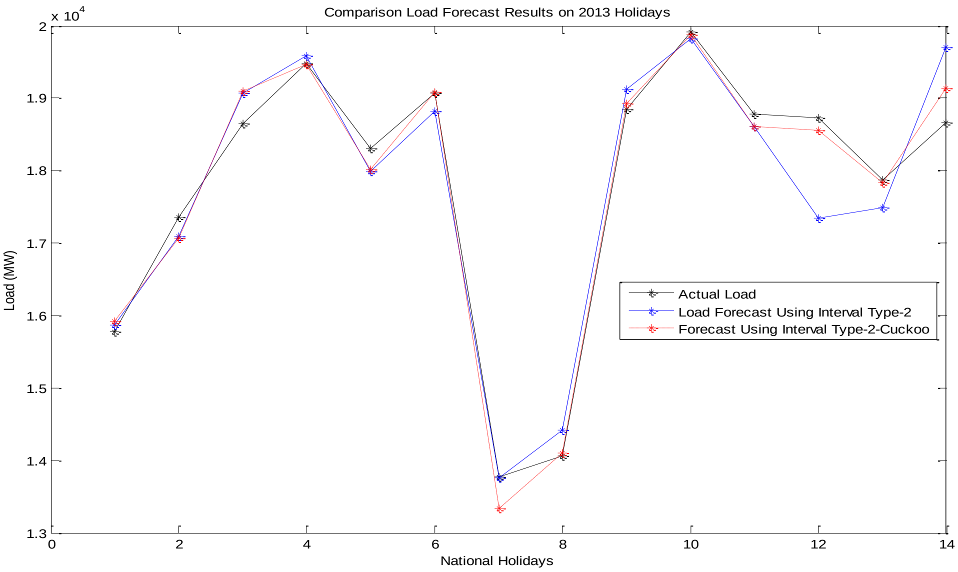

Fig. 4: Results of Load Forecast for National Holidays in 2013.

6. Conclusions

The Fuzzy Logic Type-2 method which is optimized by Cuckoo Search Algorithm is used in this research for forecasting the peak load of national holidays on the 500kV Jawa-Bali electrical system. This method shows good results, with MAPE below 2%.

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