

# Optimize Short Term load Forecasting Anomalous Based Feed Forward Backpropagation

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**Abstract.** cc This paper contains the Short-Term Load Forecasting (STLF) using artificial neural network especially feed forward backpropagation algorithm which is particularly optimized in order to getting a reduced error value result. Electrical load forecasting target is a holiday that hasn't identical pattern and different from weekday's pattern, in other words the pattern of holiday load is an anomalous. Under these conditions, the level of forecasting accuracy will be decrease. Hence we need a method that capable to reducing error value in anomalous load forecasting. Learning process of algorithm is supervised or controlled, then some parameters are arranged before performing computation process. Momentum constant value is set at 0.8 which serve as a reference because it has the greatest converge tendency. Learning rate selection is made up to 2 decimal digits. In addition, hidden layer and input component are tested in several variation of number also. The test result leads to the conclusion that the number of hidden layer impact on the forecasting accuracy and test duration determined by the number of iterations when performing input data until it reaches the maximum of a parameter value.

## 1. Introduction

Load Forecasting becomes an important instrument in the power system operation, always. Many various operation decision are determined by load forecasting, such as generator capacity regulation schedule, test analysis, and generator maintenance plan. Besides that, load forecasting accuracy is an important key to predicting electric cost. Error forecasting significantly influence benefit, stock market, and holder value of course. [1].

Short term load forecasting approach which used in literature can divided become two general categories: statistic method and artificial intelligent based method. Statistic category is consist of multiple linear regression, stochastic time series, ARIMAX and general exponential smoothing, state space model, and support vector regression (SVR), meanwhile expert system, artificial neural network and fuzzy interference are include to artificial intelligent category [2].

Artificial intelligent is very booming in this last two decades. This compute method application very interested and applied for many kind problem. Artificial intelligent gives strong and flexible



reason to decide solution of various problem that frequency unsolved by traditional and orthodox method [3]. Because forecast result proved better accuracy than traditional method.

Gradient reduce algorithm such as backpropagation (BP) or the variation in multi-layer feed-forward network has used for many application extensively. But, the most serious problem about BP is local minima. Then used algorithm modified in order to be stable result although using many hidden layers. [4].

## 2. Research Method

Researcher using holiday calendar as research data source based "Surat Keputusan Bersama Menteri Agama, Menteri Tenaga Kerja dan Transmigrasi, dan Menteri Pendayagunaan Aparatur Negara dan Reformasi Birokrasi Republik Indonesia tentang "Hari Libur Nasional dan Cuti Bersama", which determine that :

**Table 1.** National Holiday in 2008 TO 2015

2008	2009	2010	2011	2012	2013	2014	2015
1 Januari	1 Januari	1 Januari	1 Januari	1 Januari	1 Januari	1 Januari	1 Januari
10 Januari	26 Januari	14 Februari	3 Februari	23 Januari	24 Januari	14 Januari	3 Januari
7 Februari	9 Maret	26 Februari	15 Februari	5 Februari	10 Februari	31 Januari	19 Februari
7 Maret	26 Maret	16 Maret	5 Maret	23 Maret	12 Maret	31 Maret	21 Maret
20 Maret	10 April	2 April	22 April	6 April	29 Maret	18 April	3 April
21 Maret	9 Mei	13 Mei	17 Mei	6 Mei	9 Mei	1 Mei	1 Mei
1 Mei	21 Mei	28 Mei	2 Juni	17 Mei	25 Mei	15 Mei	14 Mei
20 Mei	20 Juli	10 Juli	29 Juni	17 Juni	6 Juni	27 Mei	16 Mei
30 Juli	17 Agustus	17 Agustus	17 Agustus	17 Agustus	8 Agustus	29 Mei	2 Juni
18 Agustus	21 September	10 September	30 Agustus	19 Agustus	9 Agustus	28 Juli	17 Juli
1 Oktober	22 September	11 September	31 Agustus	20 Agustus	17 Agustus	29 Juli	18 Juli
2 Oktober	27 November	17 November	6 November	26 Oktober	15 Oktober	17 Agustus	17 Agustus
8 Desember	18 Desember	7 Desember	27 November	15 November	5 November	5 Oktober	24 September
25 Desember	25 Desember	25 Desember	25 Desember	25 Desember	25 Desember	25 Oktober	14 Oktober
29 Desember						25 Desember	24 Desember
							25 Desember

**Table 2.** Furlough in 2008 to 2015

2008	2009	2010	2011	2012	2013	2014	2015
11 Januari	2 Januari	9 September	16 Mei	18 Mei	5 Agustus	30 Juli	16 Juli
29 September	18 September	13 September	3 Juni	21 Agustus	6 Agustus	31 Juli	20 Juli
30 September	23 September	24 Desember	29 Agustus	22 Agustus	7 Agustus	1 Agustus	21 Juli
3 Oktober	24 Desember		1 September	16 November	14 Oktober	26 Desember	
26 Desember			2 September	24 Desember	26 Desember		
			26 Desember	31 Desember			

Researcher need some tools to support short term load forecasting. Then, hardware that needed is PC or laptop with required Operating System Windows 7 Ultimate 64-bit (6.1, Build 7601); Processor Intel(R) Core(TM) i3-2328M CPU @ 2.20GHz (4CPUs), ~2.2GHz; Memory 2048MB RAM. Also software that needed is Matlab R2012a, Microsoft Office Excel 2007, Mendeley Desktop ver. 1.13.8.0, and Microsoft Office Visio 2007.

Feed forward backpropagation algorithm for anomalous load as follow:

- Data is selected to be weekday and holiday (anomalous load data).
- Input prefix values : hidden layer; epoch parameter; goal; learning rate; and momentum constant.

1) Training data process: backpropagation network process involve three stages that consist of input training feedforward pattern, link error backpropagation, and weight adjustment.

Feed forward backpropagation algorithm as follow :

a) Step 0: Weight insialisation (set to the random small value).

b) Step 1: When stop condition not suit, do step 2-9.

c) Step 2: For training data, do step 3-8.

Feed forward :

d) Step 3: Each input unit ( $X_i, i = 1, \dots, n$ ) receives input signal  $x_i$  and spreads to all hidden layer units.

e) Step 4: Each hidden unit ( $Z_j, j = 1, \dots, p$ ) collect input weight signal,

a)

$$z\_in_j = v_{0j} + \sum_{i=1}^n x_i v_{ij} \quad (3.1)$$

Apply its activation function to compute output signal

$$z_j = f(z\_in_j) \quad (3.2)$$

and send the signal to all ouput layer units

b) Step 5: Each output unit ( $Y_k, k = 1, \dots, m$ ) collect input weight signal

$$y\_in_k = w_{0k} + \sum_{j=1}^p z_j w_{jk} \quad (3.3)$$

and apply its activation function to compute output signal

*Error backpropagation :*

(i) Step 6: Each output unit ( $Y_k, k = 1, \dots, m$ ) receive target pattern proper as input train pattern, calculate error information with,

$$\delta_k = (t_k - y_k) f'(y\_in_k) \quad (3.4)$$

calculate weight modification with (then used to improve  $w_{jk}$ ),

$$\Delta w_{jk} = \alpha \delta_k z_j \quad (3.5)$$

and sned  $\delta_k$  to previous layer unit.

(ii) Step 7: Each hidden unit ( $Z_j, j = 1, \dots, p$ ) collect delta input (from next unit),

$$\delta\_in_j = \sum_{k=1}^m \delta_k w_{jk} \quad (3.6)$$

multiple with activation function descend to calculate error information with,

$$\delta_j = \delta\_in_j f'(z\_in_j) \quad (3.7)$$

calculate weight adjustment with (used then to improve  $v_{ij}$ ),

$$\Delta v_{ij} = \alpha \delta_j x_i \quad (3.8)$$

and calculate bias adjustment with (used then to improve  $v_{0j}$ )

$$\Delta v_{0j} = \alpha \delta_j \quad (3.9)$$

Modify weight and bias:

(iii) Step 8: Each output unit ( $Y_k$ ,  $k = 1, \dots, m$ ) improve its bias and weight ( $j=0, \dots, p$ ):

$$w_{jk}(\text{baru}) = w_{jk}(\text{lama}) + \Delta w_{jk} \quad (3.10)$$

Each hidden unit ( $Z_j$ ,  $j = 1, \dots, p$ ) improve its bias and weight ( $i=0, \dots, n$ ):

$$v_{ij}(\text{baru}) = v_{ij}(\text{lama}) + \Delta v_{ij} \quad (3.11)$$

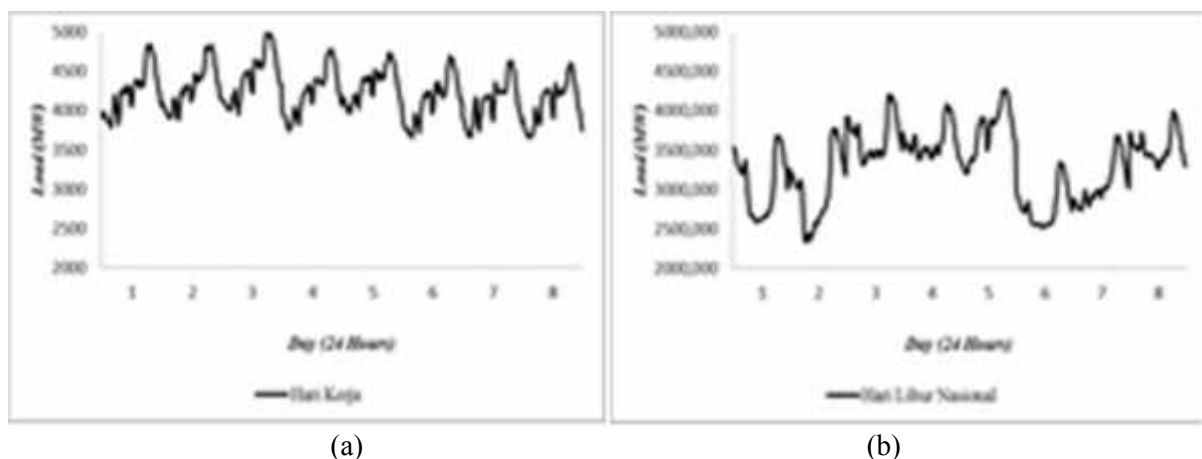
(iv) Step 9: Test stop condition. [5] [6]

- Output learning result is an forecast electric load which is needed to compute error accuracy.

Repeat data train process as many as 5 times.

### 3. Result and Analysis

Indonesia using different load electric every time. On weekday, electric load disposed stable. Weekend is different from weekday, where electric load consume can change suddenly dependent to event society. Fig. 1 below shows how the comparison between load electric consume of weekday and national weekend with take 16 days as sample.

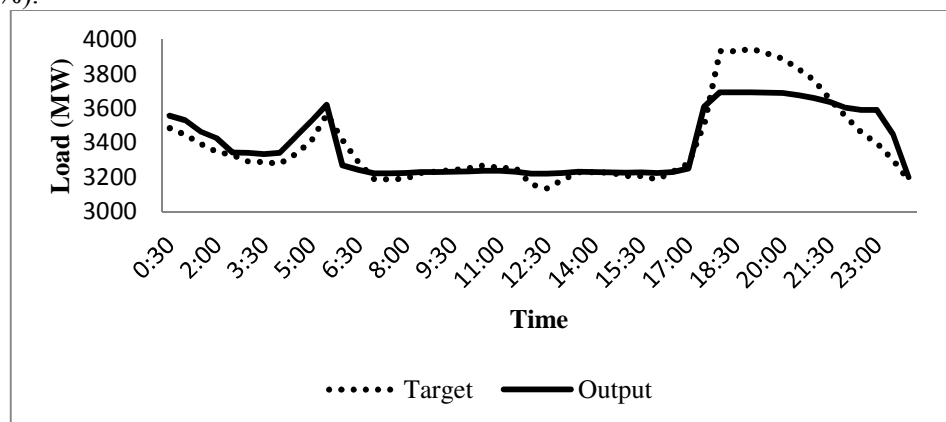


**Figure 1.** Electric Load Sample Graph of (a) Weekday and (b) National Holiday

#### 3.1. Load Forecasting using Feed Forward Backpropagation Algorithm

Feed forward backpropagation algorithm has probabilistic and random characters, thus with a same epoch value obtained different result always and derived the best average result. Optimum result will derived with ten time performs [6]. But, with time consideration, then decided to five time performs for each research. Learning of 133 inputs need 3,6 second of average time with average accuracy value

97,73%. This prefix research qualificate to good cathegory, because suit with PLN error required (maximal 5%).



**Figure 2.** Comparison Output Graph Learning Result from Target

Learning result error percentage value is 2,27% suit to used as anomalous load forecasting. However, the graph above show not careful target pattern especially on the peak load. Forecast result explain that plot keep away from 5.30 p.m to 10.30 p.m with maximum accomplishment 3694,2 MW meanwhile the peak load of target on that time accomplish 3947,58 MW.

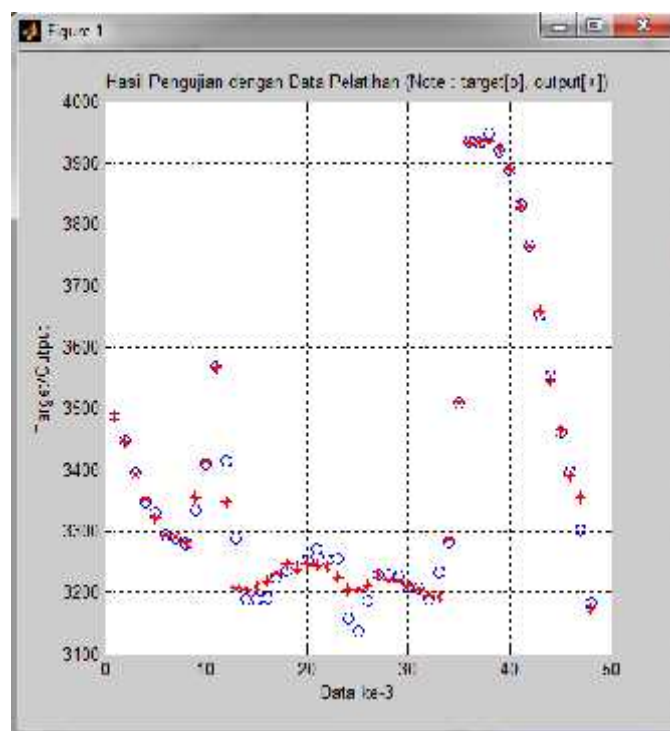
### 3.2. *Optimisation of Short Term Load Forecasting for Anomalous Load A subsubsection.*

Learning mistake reduced with optimisation. Hereafter, anomalous electric load forecasting research result turn out to be more careful and increase accuracy value. Although each trial result is different, but forecast output has expected to approaching target even if data is anomalous load. When that happen, thus accuracy value of feed forward backpropagation learning will be higher.

**Table 3.** Error Value of Input NumberOptimisation Result

Jumlah Input	Percobaan ke -					Rata-rata	Rata-Rata Waktu
	1	2	3	4	5		
10	0,55	0,56	0,53	0,51	0,53	0,54	4,4
20	0,55	0,58	0,54	0,54	0,48	0,54	2,0
30	0,54	0,54	0,53	0,52	0,53	0,53	1,2
40	0,54	0,53	0,52	0,51	0,53	0,53	2,0
50	0,50	0,54	0,52	0,50	0,53	0,52	6,4
133	0,49	0,50	0,43	0,45	0,49	0,47	4,2

Every different number of input need different time too. But, compute duration is not linear with number of input, dependent of learning trial iteration until reach an expected condition. The longest average compute time needed by 50 inputs setting because on first trial accuracy value 99,50% come down with reach maximum epoch in 18 second. The other way, the shortest average compute time achieved by 30 inputs. All trial are completed in 1 second. Nevertheless, longest and shortert trial of input number optimatation are not the least average value result.



**Figure 3.** Plot of Algorithm Optimization Result

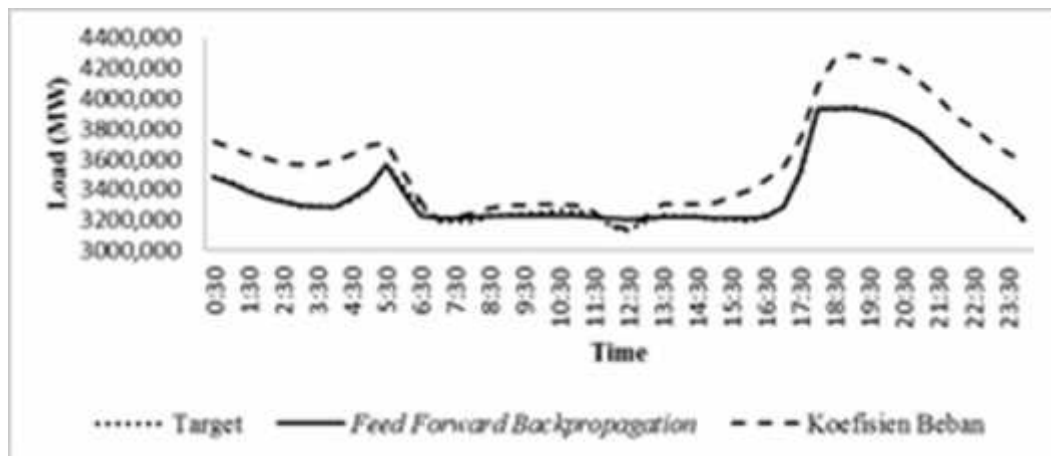
This research optimatation result is illustrated by Fig. 3. Plot figures 48 ouput (+) with target (o) positions, where the output spread approaching target. Output peak load is 3940,51 MW, 7,07 MW lower than target peak load. Meanwhile comparison of their least load as far as 70,37 MW. Value of target and output target are 3390.65 MW and 3392,09 MW.

### 3.3. Comparison Research

**Tabel 4.** Anomalous Load Forecasting Method Comparison Result.

	<b>Beban Puncak (MW)</b>	<b>Beban Minimum (MW)</b>	<b>Rata-rata Beban (MW)</b>	<b>Rata-rata Error (%)</b>
<b>Target</b>	3947,58	3135,35	3390,65	-
<b>Feed Forward Backpropagation</b>	3937,54	3203,07	3390,97	0,47
<b>Koefisien Beban</b>	4284,57	3143,47	3579,73	5,46

If each method is compared by target, then load coefficient has higher error forecast that 5,46 therefore the accuracy become 94,54%. This occasion will impact graph formation which is shown in fig 4.



**Figure 4.** Anomalous Load Forecast Result Graph.

Research toward two different methods give a conclusion that feed forward backpropagation method proved more effective than conventional method such as load coefficient to perform short term load forecasting on anomalous load case because accuracy of load coefficient cannot suit as good category yet.

#### 4. Conclusion

Load consume pattern in Indonesia's holiday is different with weekday. Historical data of PT. PLN (Persero) APB Region II West Java explain electric load consume on holiday much lower than weekday and load peak unexpected occur. Great days exclusively Idul Fitri caused anomalous load pattern formed.

Feed forward backpropagation algorithm suit to conquer STLF problem of anomalous load. This algorithm forecast accuracy established very effective within very small error accuracy. Besides that, this algorithm excellence is hidden layer generate accuracy extensively. But also this algorithm is random and probabilistic and then some trials required for each parameter.

Optimization process perform toward hidden layer and input component, resumed to epoch and learning rate parameter. The result is more odder number of hidden layer will generate accuracy significantly and each layer compute duration disposed to be same. Different of maximal epoch is not much influence toward error accuracy and duration. Each learning rate value take various duration, careful exalating from learning rate not impact to accuracy result and duration. Outfit learning rate value for feed forward backpropagation algorithm will create the best error accuracy. Number of input perform linear with its accuracy result. Compute duration reliant on number of iteration that necessary.

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