

## Effect of Real-Time Price on Short-Term Load Forecasting

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### ABSTRACT

This paper presents a short-term load forecasting model using the back-propagation neural network (BPNN) model. The proposed model is based on data on loads and factors that directly affect electricity demand, such as temperature, humidity, load over time in the past, etc., collected from the electricity market ISO New England. In addition to the common factors, the article also considers a new factor: real-time price. The data used for training and forecasting are real-time data for three years from 2019 to 2021. The paper has shown that real-time price (RTP) significantly influences forecasting. The proof is that the Mean Absolute Percentage Error (MAPE) value of the predictive model without RTP data is 2.08%, and that of the model with RTP data is 1.44%. The paper also compares the performance of the training algorithms with each other to come up with an optimal algorithm compared to the proposed model. At the same time, the model is also applied to forecast a more extensive period, such as a week or a month, and has had positive results.

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## 1. Introduction

Load forecasting has become an essential mission in developing modern power systems. Based on the time to forecast, we can divide it into forecast types as [1]: Very Short-Term Load Forecasting (VSTLF), predicting a few seconds, a few minutes, or even a few minutes in advance; Short-term load forecasting (Short-Term Load Forecasting STLF), predicting from a few hours, a few days to a few weeks; Medium-Term and Long-Term Load Forecasting (MTLF and LTLF), predicting several months to several years in advance. Long-term load forecasting is intended to aid in power system infrastructure planning. In contrast, medium and short-term load forecasting can be effectively helpful for power system operations, especially household activity. With the current demand for regular electricity, the power system will increasingly face many challenges regarding stability and meeting households' electricity supply needs. Therefore, accurate short-term power forecasting can help to limit many risks caused by problems in the power system, as mentioned.

The power system is a nonlinear system affected by many external factors. Various factors influence the consumer load's operation and the total loss in the transmission line. These elements can be classified into time, weather, economy, and unexpected problems [2]. However, real-time electricity prices also significantly influence electricity consumption habits in the outstanding development of the electricity market.

Electricity markets are increasingly encouraging clients to adjust the time of day they use electricity to help ensure energy reserves as well as ensure uninterrupted power supply, especially when the traditional power system is in place in combination with many renewable energy sources today. One of the ways to encourage consumers to change usage time in developed countries is the Time of Use Tariff (TOU), where different time frames will have different prices. Each power company will have another type of tariff, and customers can actively negotiate with electricity companies to choose the appropriate tax. The five time-varying tariff designs currently available in the electricity market are [3]:

- **Static TOU:** Prices change throughout the day, fixedly and regularly. For example, peak prices between 4 and 8 pm on weekdays and low prices at other times.
- **Dynamic TOU (DP):** The price points are fixed, but the application time varies daily. For example, there may be times of high, medium, and low prices, and the customer is notified in advance that those prices will apply.
- **Real-time pricing (RTP):** Prices change in real-time (e.g., hourly or half-hourly) depending on current wholesale electricity costs.
- **Critical peak pricing (CPP):** Prices are especially fixed, but sometimes there are price-changing for which the customer will be notified in advance.
- **Critical peak rebates (CPR) or peak time discounts:** Rates are fixed, but at selected times (with advance notification), clients are rewarded for using less electrical power from some level of agreement.

This paper mainly studies the effect of real-time changing Electricity Prices (abbreviated as RTP). As mentioned above, in addition to the primary factors, the TOU, specifically the RTP, affects the customer's electricity cost. The customer can actively arrange the time to use their electrical equipment to suit their needs.

In recent years, many short-term load forecasting studies have been proposed, such as Chujie Tian et al. proposed short-term load forecasting based on deep learning neural models. However, the data file is only the past hourly load [4]; Kunjin Chen et al. conducted a forecast of the load for the next 24 hours based on time data such as weekdays, weekends, holidays, seasons of the year, and hourly temperature and load in the past give outstanding results in terms of model accuracy and show the effect of temperature on short-term load forecasting problem [5]; Zhuofu Deng et al. also conducted a study on short-term load forecasting. However, they only used data on load in the past, days off, and time for all tests [6]; Seunghyoung Ryu et al. also made short-term load forecasting based on artificial neural networks, average daily temperature, humidity, solar radiation, cloud cover, and wind speed were used as input data [7]; Jian et al. presented a short-term load forecasting model using data taken from ISO New England, selected data including day, weekday, month, and trend for good results [8]; J.Moon et al. present a possible predictive model for each house or cluster of houses by historical loading data, work schedules, weather and event calendars using Random Forest and Multilayer Perceptron to generate corresponding results [9]; Zeng et al. have proposed a project model of a holiday load, thereby demonstrating the effect of holidays on electricity consumption, and have had good results [10]. Although the above studies have achieved many successes in terms of forecasting methods, they are still quite limited in terms of input data.

This paper uses common factors of time and weather like other studies and adds the RTP factor as training input for a back-propagation neural network to make the next 24-hour load forecast. In addition, the article also provides an assessment of the influence of electricity prices over time on short-term electricity load forecasting.

## **2. Short-term load forecasting model**

### **2.1. Input data and data normalization**

The network training data is sourced from the ISO New England electricity market, including time, holiday, temperature, humidity, past load capacity, and RTP data. The dataset is 24-hour daily data for three years from 2019 to 2021. For the training to be practical, the input raw data needs to be normalized to a suitable metric.

#### **2.1.1. Processing time data**

This section presents the processing of day/month/year data to prepare for neural network training. The date/month/year data format will cause difficulty and noise during neural network training. Therefore, it is necessary to convert the data to digital or binary to make it easier to train the network. The data processing process is shown in Figure 1.

By combining the above-normalized data and information about holidays, a binary data set represents working days and non-working days (where non-working days include Saturdays, Sundays, and public holidays shown at 0 and the working days shown at 1).

### 2.1.2. Normalize min-max data

This paper uses the min-max normalization method for load power, temperature, humidity, and RTP data [11]. Min-max normalization allows mapping existing data to other data within a set [min, max] interval. This model chooses the min and max values to be 0.2 and 0.8, respectively. The conversion function is presented as follows:

$$v' = \frac{v - A_{\min}}{A_{\max} - A_{\min}} (\max - \min) + \min \quad (1)$$

Where  $v'$  is the value after normalization,  $v$  is the initial value, and  $A_{\max}$  and  $A_{\min}$  are the maximum and minimum values in the data set of  $v$ , respectively.

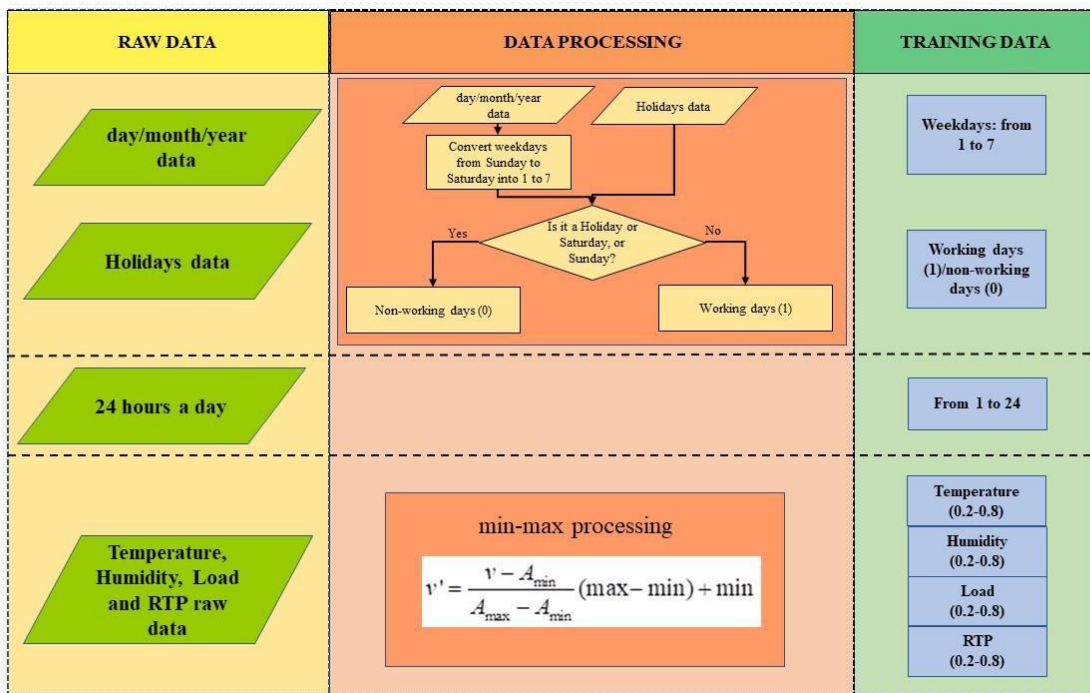


Figure 1. The block diagram shows the process of processing raw data into training data

## 2.2. Back-propagation Neural Network (BPNN)

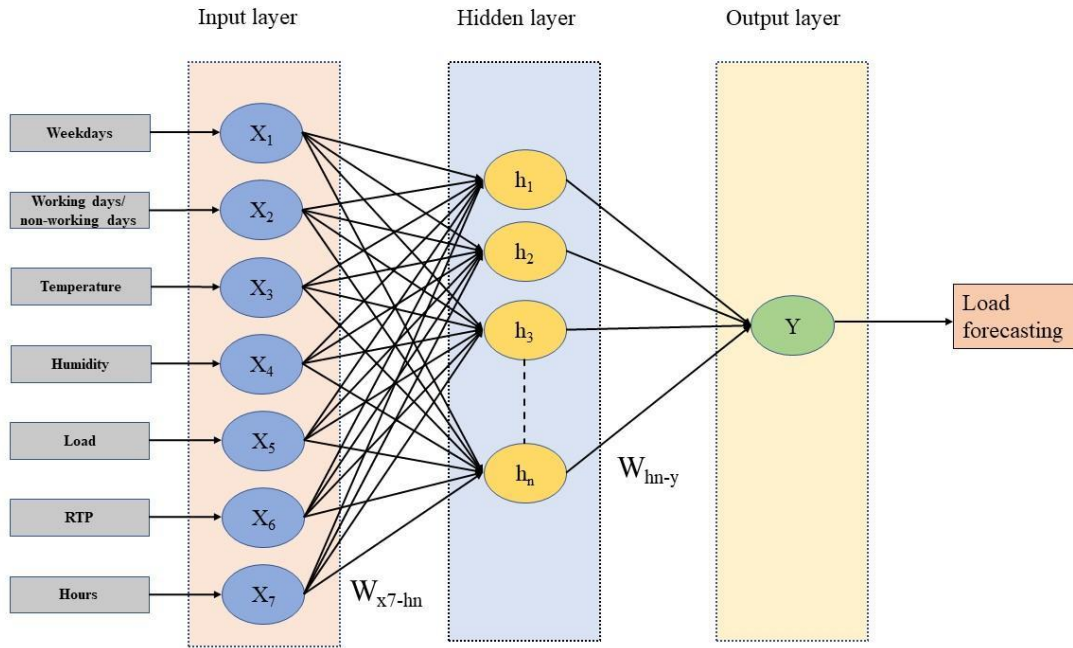
An artificial neural network is a computational model that simulates the structure and operation of a biological neural network. It consists of 3 main components: input layer, hidden layer, and output layer connected to process information. The number of neurons per layer depends on the computational model and the expert's decision.

BPNN is a multilayer feed forward network trained by false back-propagation to optimize artificial neural networks. This is a method of adjusting the weights of a neural network based on the error rate received in the prior process. Correctly tuning the weights reduces the error rate and makes the model reliable by improving its generalizability. Its learning rule is to use the method of calculating the continuous error to adjust the weight and threshold of the neural network by transmitting the error until it is impossible to minimize the square of the network. The objective function of the model is shown in equation (2):

$$J(w) = \frac{1}{2} (y_d - y)^2 \quad (2)$$

Where:  $y_d$  is the actual load power, and  $y$  is the predicted load power. The weight vector  $w$  is defined so that  $J$  is minimized.

BPNN training consists of 4 algorithms: Bayesian training algorithm (trainbr), Scaled Conjugate Gradient training algorithm (trainscg), Resilient back-propagation training algorithm (trainrp), and Levenberg - Marquardt training algorithm (trainlm) presented in the document [12].



**Figure 2.** The BPNN structure for short-term load forecasting

### 3. Simulation and results

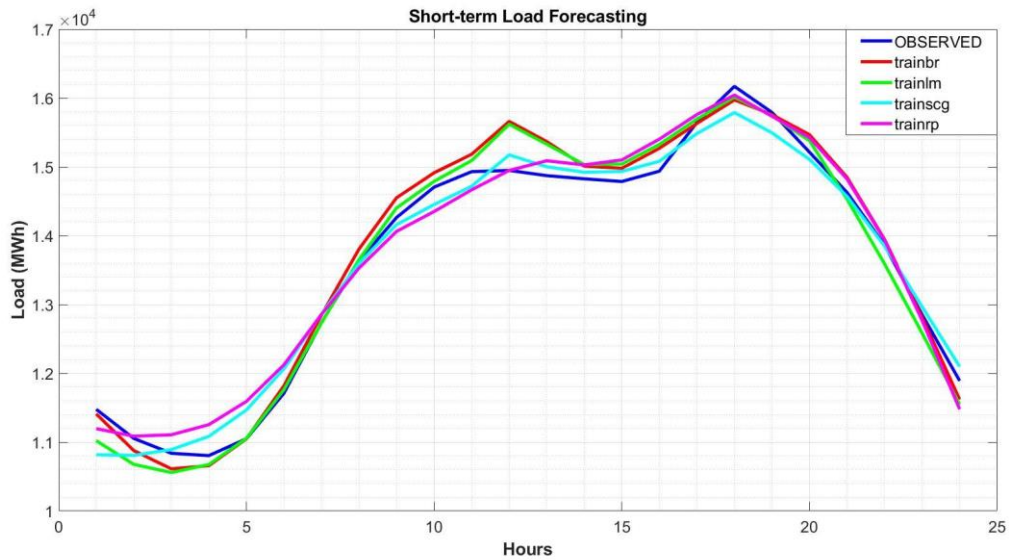
BPNN model uses seven input variables, including temperature, humidity, hour, day of the week, working days/non-working days, past load, and RTP of 26256 samples each; it uses ten neurons in the hidden layer; The output layer results in the load value in 24 hours of the day to be forecast. The structure of the back-propagation neural network in this paper is shown in Figure 2.

First, the model compares the presented training algorithms to choose the suitable algorithm for the model. Figure 3 shows the BPNN model using the algorithms mentioned in section 2.2 compared to the actual load graph. The error values of each training algorithm are presented in Table 1. It can be seen that the Bayesian algorithm has the lowest MAPE value (1.44%). Therefore, the following training models will use a Bayesian algorithm to train BPNN.

**Table 1:** Performance comparison of four training algorithms

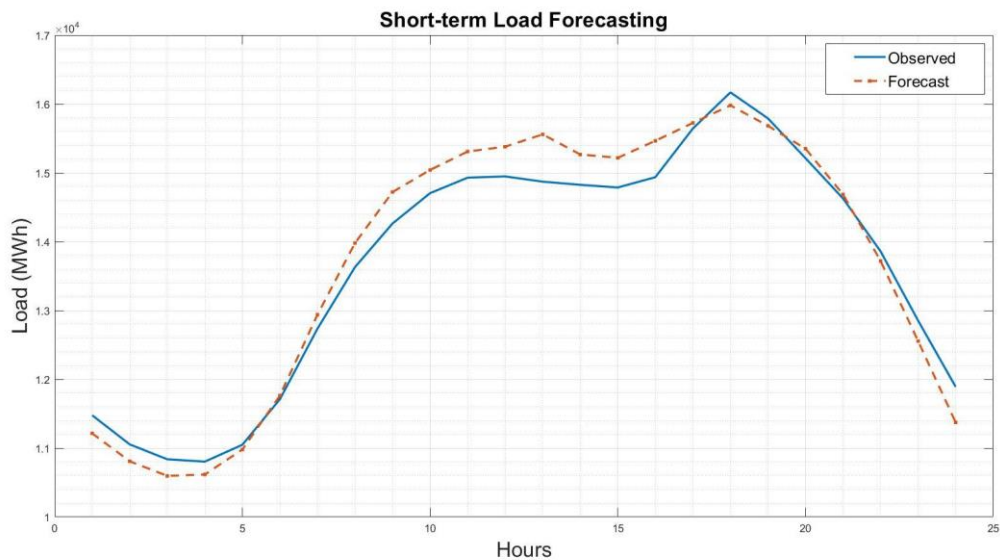
	<b>Levenberg Marquardt</b>	<b>Bayesian</b>	<b>Scaled Conjugate Gradient</b>	<b>Resilient backpropagation</b>
<b>MSE (MWh)</b>	72732.57	63354.4	60906.83	74213.34
<b>RMSE (MWh)</b>	9.37	101.97	9.39	72.47
<b>MAE (MWh)</b>	211.86	199.3	200.48	229.37
<b>MAPE (%)</b>	1.58	1.44	1.54	1.77

To consider the influence of electricity prices on short-term load forecasting, the paper presents two forecasting models between the data set with and without RTP. Conduct training and forecast multiple times for each model to get the best forecast. Then proceed to compare the error values.



**Figure 3.** Short-term load forecasting results using training algorithms

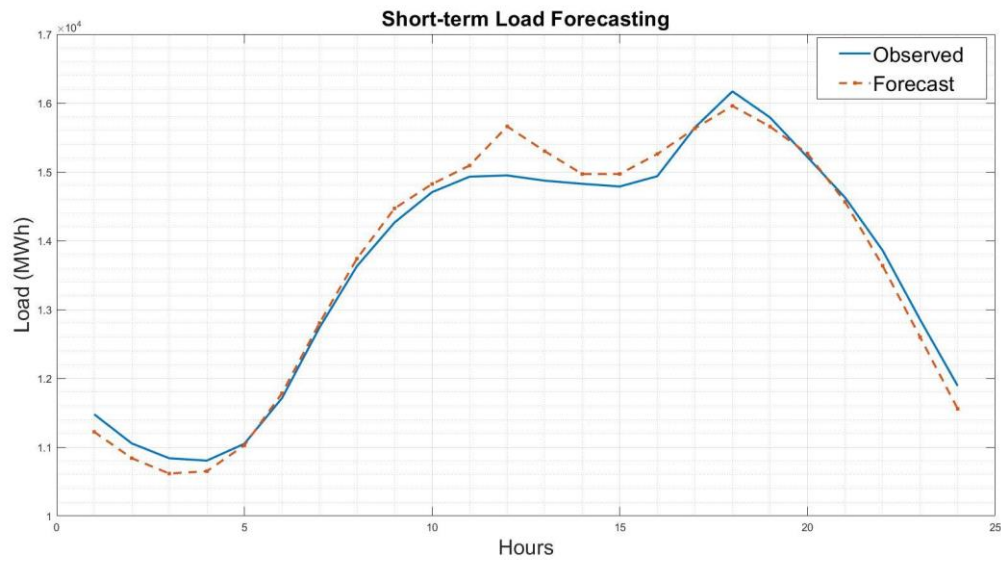
The results from Table 2, Figure 4, and Figure 5 show that in the presence of RTP data, the next-day load forecast graph is more closely aligned with the actual load graph than without RTP data. The evidence for the error values is shown in Table 1. In particular, using RTP data as the forecast input gives an error of 1.44%, while not using RTP gives an error of 2.08%. The results show that electricity prices affect short-term load forecasting.



**Figure 4.** Short-term load forecasting results without using RT

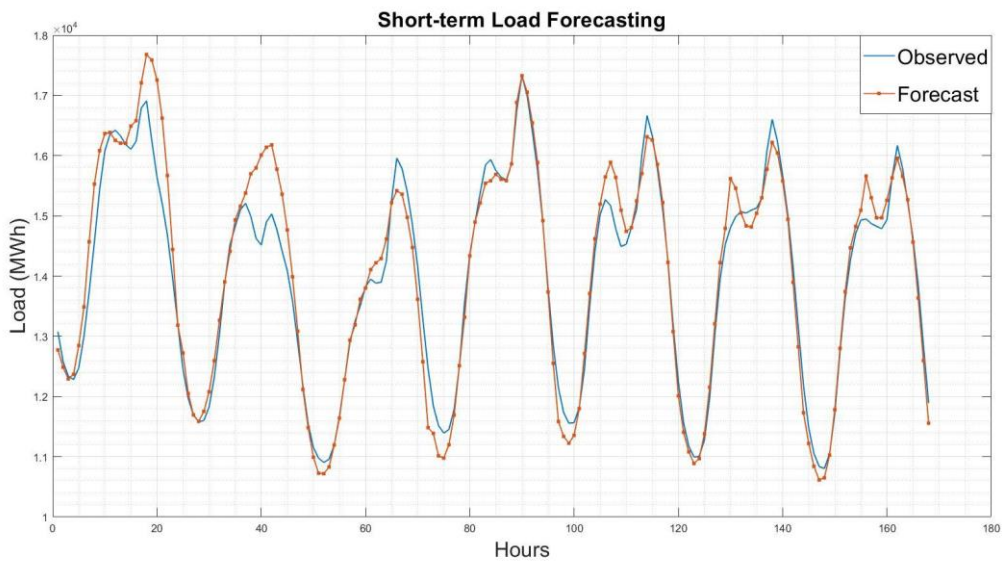
**Table 2.** Comparison of error values between the two models

	When not using RTP	When using RTP
<b>MSE (MWh)</b>	109516.12	63354.4
<b>RMSE (MWh)</b>	96.66	101.97
<b>MAE (MWh)</b>	284.65	199.3
<b>MAPE (%)</b>	2.08	1.44



**Figure 5.** Short-term load forecasting results using RTP

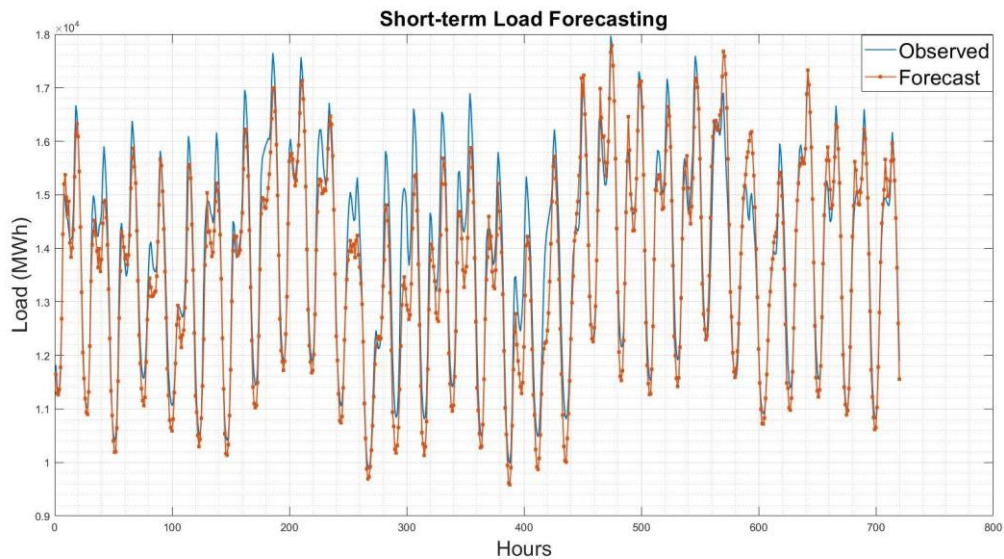
In addition to predicting the load 24 hours before the next day, the paper also uses a model with RTP to forecast the load for the next week and one month. The results obtained with error values (forecast one week gives an error of 2.1%, and forecast one month gives an error of 3.03%) are presented in detail in Table 3. The load forecast error for a month is quite significant but still acceptable.



**Figure 6.** Result of load forecast one week in advance

**Table 3.** Comparison table of error values when forecasting load in 1 week and one month

	One week	One month
<b>MSE (MWh)</b>	188908.76	307025.53
<b>RMSE (MWh)</b>	94.4	289.79
<b>MAE (MWh)</b>	296.31	423.03
<b>MAPE (%)</b>	2.1	3.03



**Figure 7.** Result of load forecast one month in advance

#### 4. Conclusions

Through the above model, the project has achieved more optimal results than the traditional models. The proof is that the MAPE value of the predictive model without RTP data is 2.08%, and that of the model with RTP data is 1.44%. It indicates that the finding of many factors that positively affect the power system combined with the development of artificial intelligence models, the short-term load forecast in the future will be more and more accurate. This paper outlines the influence of electricity price on the load forecasting model using a back-propagation neural network, which has achieved positive results. In the future, other optimization models and factors can be used to make the forecast results more accurate.

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