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Determination of Electricity Production by Fuzzy Logic Method

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Abstract

With the increase in the need for electrical energy, production amount planning is of great importance in order not to experience restrictions in terms of use, to meet the required electricity production, and to evaluate the excess production efficiently. In this study, a generation forecasting model was created with the fuzzy logic method to determine the electricity generation. The created model is aimed to determine the electrical energy that needs to be produced daily by using the previous day's production amount, temperature, and season data. Three separate sets of data were used to test the fuzzy logic model built using information from the General Directorate of Meteorology and Energy Markets Operations Inc.. Fuzzy Logic was used to predict the data and the accuracy rates were found to be high. An improvement was observed when the accuracy rates were compared with the accuracy rates obtained in the Multiple Linear Regression Model. The accuracy rates of the model were initially examined using the Fuzzy Logic approach on weekdays and weekends, followed by a seasonal analysis and an assessment of the model's performance. As a result of the analysis, it was observed that the model worked with high accuracy in the autumn season and on weekend days.

Keywords: Energy, electrical energy, fuzzy logic

1. INTRODUCTION

Electric; it has undertaken important duties in transportation, regulation of production system, operation of industry, and meeting human needs. Mechanized production processes have been used in all sectors more effectively and efficiently thanks to electricity. With the use of electricity, it has been possible to develop new techniques, and raw materials that increase added value such as wood, metal, glass, paper, and chemicals can be converted into semi-finished or finished goods. Electricity, which has come to represent progress and economic growth, has begun to replace traditional energy sources in various contexts and has permeated every aspect of our lives. Electrical energy, which has been indispensable for social, economic, and industrial life since its inception, has had great importance in our lives, especially lighting, then mechanization, transportation, and heating.

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When energy development in the world is examined; the technological transformation of the steam, engine and electrical energy for energy use has been realized. With the invention of the steam engine, the 18th century marked the first turning point for the use of energy. With this important step taken towards industrialization, renewable energy sources such as water, wood, sun, and wind, which are used as energy sources, were used. Renewable energy sources, which have been on the agenda recently, are also said to be the first energy sources used in history. In the process of the spread of coal, wood has become the primary energy source [2].

Production planning of this energy, which has an irreplaceable place in our lives, is also of great importance. Freelance generation companies, Energy Markets Operations Inc. (EMOI), companies whose operating rights have been transferred, and build-operate-transfer companies that produce electricity should also determine their production quantities using the right models to meet the demands. Accurate production estimations will guide important steps such as whether the demand can be met, how to proceed if the demand is not met, how much-installed power will be, and whether to invest in a power plant [3].

1.1. Literature Review

When the previous studies on electrical energy are examined, it is focused on electrical energy production and electrical energy production planning. In the research, it has been observed that generally focuses on electrical energy demand forecasting, and load forecasting and focuses on the electrical energy efficiency of certain devices or places. The Fuzzy logic method has been encountered in studies on electricity demand forecasting and load forecasting. Results showed that the accuracy rates were higher than other methods, especially as seen in the study of Najmi and Dalimi [4]. Particle swarm optimization [5], artificial neural networks [6], fuzzy logic [7], and adaptive network fuzzy inference systems (ANFIS) [8] were found to produce the greatest outcomes in prior studies. Fuzzy Logic method was preferred to solve our problem because it yielded high accuracy rates in studies on determining the production amount in the fuzzy logic method [9].

Karadağ Albayrak, Ö. examined the Estimation of Turkey's Renewable Energy Production with Artificial Neural Networks and ARIMA Model. The results were compared with the MAPE performance measure. An error rate of 13.1% was obtained for Artificial Neural Networks (MLP - 5-5-1) and 21.9% for ARIMA [32].

Olaru, L.M. et al. worked on electricity production and consumption modeling with fuzzy logic. It resulted in an average absolute error of 67.82 across all data sets, while the estimator based on the ARIMA model and MLP resulted in errors of 198.27 and 211.07, respectively [33].

In this study, a new model was created with the fuzzy logic method to determine electricity production and it was aimed to determine the electrical energy that should be produced daily by using the previous day's production amount, temperature and seasonal data. Estimating the production amount with high accuracy is of great importance in terms of production planning. Thanks to accurate forecasts, the producer companies will be able to produce as much electricity as necessary and plan the most efficient use of excess production, and the government will be able to allocate the necessary share to electricity production in investment plans.

2. MATERIALS AND METHODS

The Fuzzy Logic method has been preferred in solving our problem since fuzzy logic is not encountered in a model for determining the production and accuracy rates give high results in the fuzzy logic method.

In the Fuzzy Logic method, the process consists of 3 steps. These steps are fuzzification, fuzzy inference process, and defuzzification [10]. When using the method, the input data, which is precise information, is primarily blurred. The generated fuzzy inputs are calculated by going through the fuzzy inference process, taking into account the fuzzy logic rules. After this process, fuzzy outputs are obtained. Thanks to the clarification process, output data, which is precise information, is obtained. In a fuzzy system, the values of a fuzzy input execute all the rules in the knowledge pool that have the fuzzy input as part of their antecedents. This process creates a new fuzzy set representing each output or solution variable. Defuzzification creates a value for the output variable from this new fuzzy set. Fuzzy Logic Stages are shown in Figure 1.

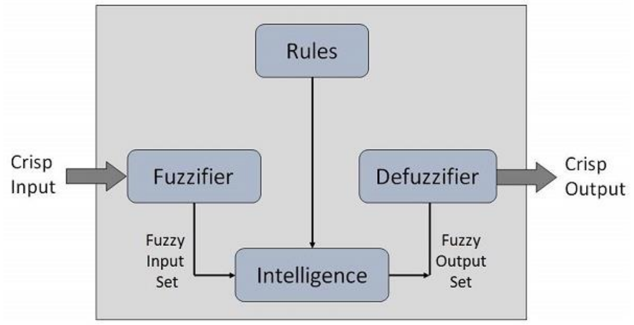

Figure 1. Fuzzy Logic Stages [11]

With the Fuzzy Logic method, a model was created in which the production amount, temperature, and seasonal inputs of the previous day and the production were determined. The generated electricity generation quantity model is shown in Figure 2. The results of the model tested with the data from EMOI and GDM were compared with the results of the Multiple Linear Regression method.

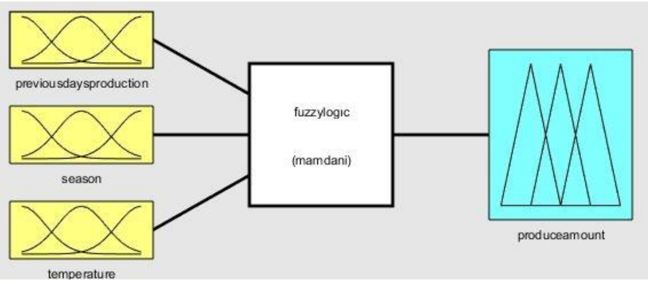

Figure 2. Fuzzy logic model of electricity production quantity

2.1. Materials

In the study, total electricity production amount obtained from natural gas, dam, lignite, river, imported coal, wind, solar, fuel oil, asphaltite coal, hard coal, biomass, naphtha, liquefied natural gas, international and waste heat from EMOI's Transparency Platform [12] used. The hourly data for 2020 and 2021 are compiled as the total daily electricity generation amount. Temperature data were compiled from GDM's Temperature Analysis [13] site by taking the average, lowest and highest values for each month in 2020 and 2021.

In February 2022, Turkey's total daily production data were obtained from EMOI's Transparency Platform. A total of 144 data were used, randomly selected from the years 2020 and 2021. The data given on the site on an hourly basis have been compiled into daily data. EMOI's total electricity production is obtained from natural gas, dam, lignite, river, imported coal, wind, solar, fuel oil, asphaltite coal, hard coal, biomass, naphtha, liquefied natural gas, international, and waste heat.

Temperature data were taken from the GDM Temperature Analysis website in February 2022. Average temperature, lowest temperature, and highest temperature data for each month in 2020 and 2021 are compiled.

Descriptive statistics for the data used are shown in Table 1.

Table 1. Descriptive statistics of independent variables

Descriptive statistics	Production Amount of the Previous Day	Average Temperature	Lowest Temperature	Highest Temperature
Average	812497,2	14,5	9,2	20,7
Median	833233,3	13,9	8,4	20,3
Standard Deviation	104116,5	7,8	6,6	8,5

2.2. Methods

Membership functions have been created for the specified input and output parameters. The previous day's production quantity parameter was created with the Gaussian membership function and includes 7 clusters as very very low-very low-low-normal-high-very high-very very high. The membership function for the previous day's production quantity parameter is shown in Figure 3. The data in the function is in MW and has been simplified to 1000.

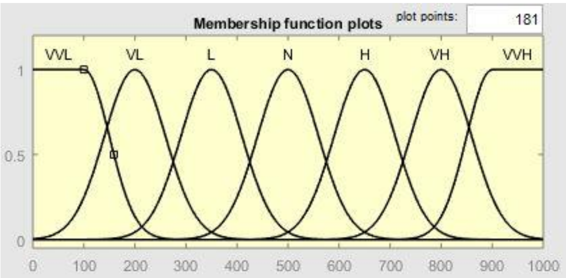

Figure 3. Membership function of production amount of the previous day

The season parameter is formed with the Gaussian membership function and includes 4 clusters winter-spring-summer-autumn. The membership function for the season parameter is shown in Figure 4. While creating the model, the month of December was considered the 1st month in the seasons.

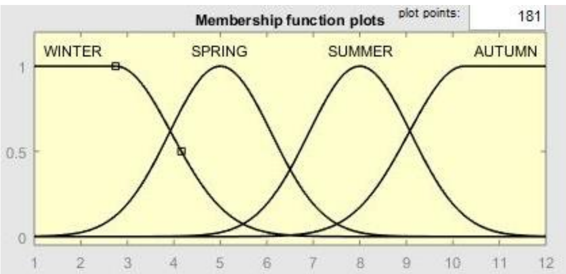

Figure 4. Membership function of the season

The temperature parameter is formed with the Gaussian membership function and includes 4 clusters as very low-low-high-very high. The membership function for the temperature parameter is shown in Figure 5.

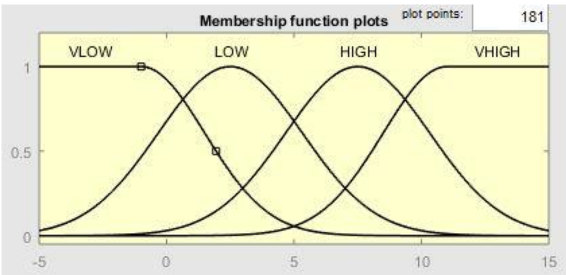

Figure 5. Membership function of temperature

The production quantity parameter is formed by triangular and trapezoidal membership functions and includes 7 clusters as very very low-very low-low-normal-high-very high-very very high. The membership function for the production quantity parameter is shown in Figure 6. The data in the function is in MW and has been simplified to 1000.

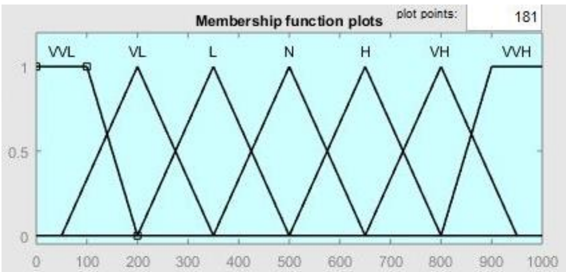

Figure 6. Membership function of production quantity

As the fuzzy inference method in the model, the Mamdani Fuzzy Inference Method, which was determined to be the most preferred in the literature studies, was used [14].

The rules in the Fuzzy Logic method were determined according to the number of clusters coming from the membership functions of the input parameters. Since there are 7 clusters in the Previous Day Production Amount parameter, 4 clusters in the seasonal parameter, and 4 clusters in the temperature parameter, 112 rules were created. The MATLAB login screen of the created rules is shown in Figure 7. After the rules were created, the model was tested in 3 different temperature categories with the previous day's production data obtained from EMOI.

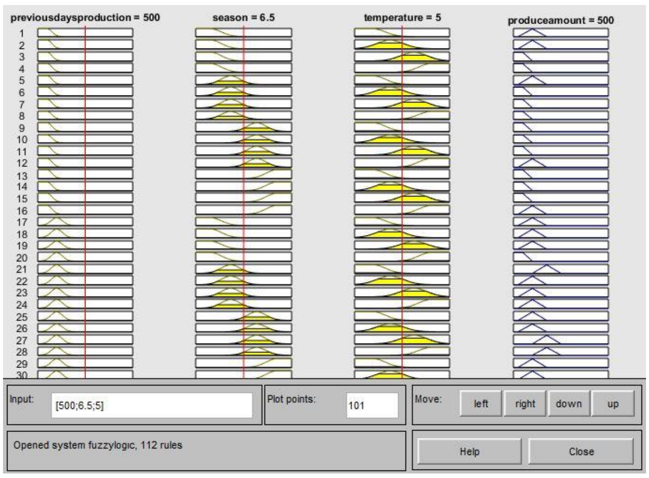

Figure 7. Rule base

Surfaces in the MATLAB Fuzzy Toolbox show the relationship between the input parameters and the output, within the framework of the determined rules. From the surfaces showing how the two input parameters affect the output parameter, the relationship of temperature and seasonal parameters with the output is in Figure 8, the relationship between the previous day's production amount and seasonal parameters with the output Figure 9, the relationship of the previous day's production amount and temperature parameters with the output shown at Figure 10. In the figures, the production amount data and the previous day's production amount are simplified to 1000 and are in MW units. The temperature data are in Celsius, the numbers in the seasonal data represent the months and the first month represents the month of December.

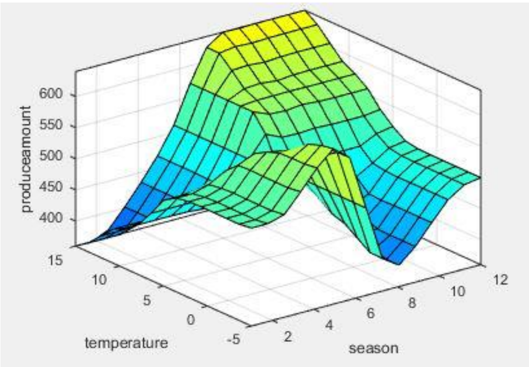

Figure 8. The effect of temperature and season on the amount of production

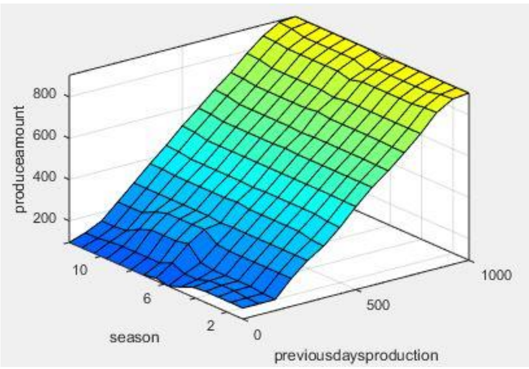

Figure 9. The effect of previous day's production and season on the amount of production

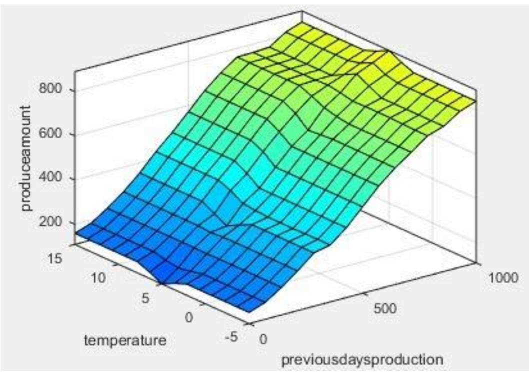

Figure 10. The effect of previous day's production and temperature on the amount of production

3. FINDING

The established model was tested with three different temperature data. The estimated data obtained and the actual production data are shown in Figure 11, Figure 12, and Figure 13.

Results were compared with Multiple Linear Regression Results. For Average Temperature data, the accuracy rate for Multiple Linear Regression was 94.62%, while for Fuzzy Logic it was 96.32%. A 1.7% increase in accuracy rate was observed with Fuzzy Logic. A decrease of 11463.74 was observed in the RMSE value. For the Lowest Temperature data, the accuracy rate was 94.34% for Multiple Linear Regression and 95.52% for Fuzzy Logic. A 0.88% increase in an accuracy was observed with Fuzzy Logic. A decrease of 2088.57 was also observed in the RMSE value.

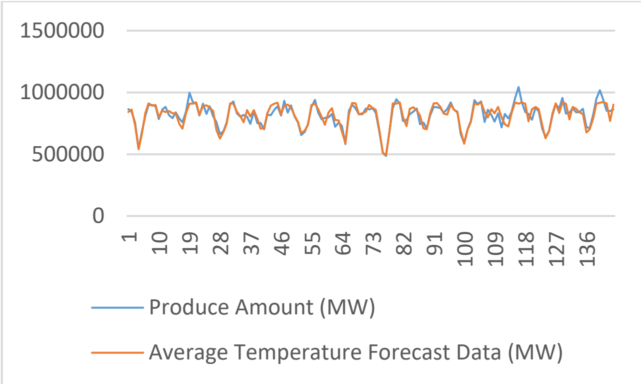

Figure 11. Forecast with average temperature data

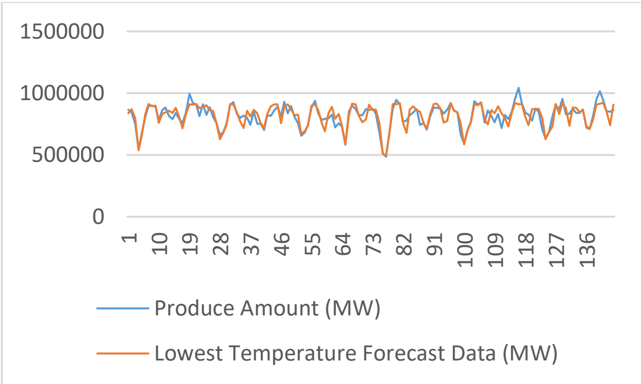

Figure 12. Forecast with lowest temperature data

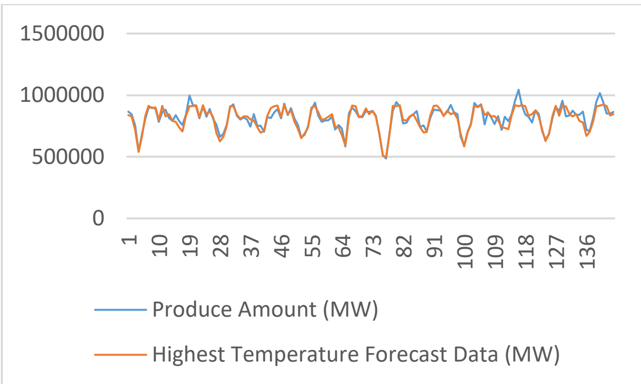

Figure 13. Forecast with highest temperature data

Peak Temperature data, the accuracy rate was 94.63% for Multiple Linear Regression and 96.78% for Fuzzy Logic. With Fuzzy Logic, an increase in accuracy rate of 2.15% was observed. A decrease of 14274.12 was also observed in the RMSE value. When evaluated in general, the Fuzzy Logic method had high accuracy for each temperature data, and the best results were obtained in the fuzzy logic method tested with the highest temperature data.

Descriptive statistics of the actual production amount and the predictions made by the fuzzy logic method are shown in Table 2.

Table 2. Descriptive statistics of fuzzy logic predictions

Descriptive statistics	Actual Production	Average Temperature	Lowest Temperature	Highest Temperature
Average	816432,4	817520,8	818375,0	811125,0
Median	830045,1	837000,0	838000,0	830500,0
Standard Deviation	92779,9	92658,4	90918,3	92655,1

Descriptive statistics of the actual production amount and the estimates made by the multiple linear regression method are shown in Table 3.

Table 3. Descriptive statistics of multiple linear regression predictions

Descriptive statistics	Actual Production	Average Temperature	Lowest Temperature	Highest Temperature
Average	816432,4	816432,2	816432,5	816432,0
Median	830045,1	803530,0	802978,3	803591,6
Standard Deviation	92779,9	77769,8	77907,4	77787,6

The results are shown in Table 4.

Table 4. Results

Accuracy Ratios (%)	Multiple Linear Regression	Fuzzy Logic	Improvement
Average Temperatures	94,62	96,32	1,70
Lowest Temperatures	94,64	95,52	0,88
Highest Temperatures	94,63	96,78	2,15
		Average	1,58

Since the Fuzzy Logic model gives less error rate, three models tested using different temperature data were examined by distinguishing between weekdays and weekends in the data used to examine its performance. It was determined that 91 weekdays and 53 weekend days were used in randomly selected day data, and the accuracy rates were calculated for the forecast results obtained using the average temperature, lowest temperature, and highest temperature data. Obtained results are shown in Table 5.

When the weekdays and weekends are differentiated by looking at the accuracy ratios in Table 5, 96.89% in the weekend data in the model tested using the highest temperature data; it is observed that it has the highest accuracy as 96.81% in weekday data. In the data tested using average temperature and lowest temperature data, the error rates were lower on weekdays than on weekend days, while the error rate was lower on weekends than on weekdays in the data tested using the highest temperature data.

Table 5. Analysis of fuzzy logic method by days

	Days	Accuracy Ratios (%)
Average Temperatures	Weekdays	96,76
	Weekend Days	95,70
Lowest Temperatures	Weekdays	96,21
	Weekend Days	94,22
Highest Temperatures	Weekdays	96,81
	Weekend Days	96,89

Since the Fuzzy Logic model gives less error rate, the data used to examine its performance are divided according to 4 seasons and 3 models tested using different temperature data are examined. Accuracy rates were calculated for the forecast results obtained using the average temperature, lowest temperature, and highest temperature data. Obtained results are shown in Table 6.

Table 6. Analysis of fuzzy logic method by seasons

	Temperature	Accuracy Ratios (%)
Winter	Average Temperatures	96,02
	Lowest Temperatures	95,35
	Highest Temperatures	96,07
Spring	Average Temperatures	96,25
	Lowest Temperatures	95,58
	Highest Temperatures	96,21
Summer	Average Temperatures	96,69
	Lowest Temperatures	96,46
	Highest Temperatures	96,70
Autumn	Average Temperatures	96,31
	Lowest Temperatures	94,71
	Highest Temperatures	97,53

Accuracy rates for Average Temperature data by season resulted in Summer > Autumn > Spring > Winter. Lowest Temperature data accuracy resulted in Summer > Spring > Winter > Autumn. Accuracy rates for Peak Temperature data resulted in Autumn > Summer = Winter > Spring. In general, the highest accuracy rate is seen in the model tested with the highest temperature data in the Autumn season.

4. DISCUSSION AND CONCLUSION

It is thought that this model, which was created with the Fuzzy Logic method, should be evaluated in terms of the accuracy rate of the analysis, the results it gives in the MAPE and RMSE criteria, and because it has better performance than the multiple linear regression analysis. With the fuzzy logic method, the accuracy rates were improved for all three-temperature data, but the highest increase was obtained in the model tested with the highest temperature data with a value of 2.15%. The model tested with the highest temperature data was examined in more detail on the basis of day and season. Although the accuracy rates on weekdays and weekends are very close to each other, it has been determined that 96.89% success is achieved on the weekend. In the seasonal analysis, the predictions obtained in the autumn season reached 97.53% accuracy. These findings reflect that our model has better predictive performance in the autumn season and on weekend days.

The results obtained have a higher accuracy rate than the results of previous studies on electricity production forecasting. Therefore, it should not be ignored that the model has high performance and can be used in electricity production planning.

The study, which is completed with the data received from EMOI and GDM, is a study on the daily production amount. The created model can be evaluated to determine the hourly production amount in EMOI. It is thought that accurate production estimations will guide important steps such as whether the demand can be met, how to follow if the demand is not met, how much the installed power will be, and the decision of whether to invest in a power plant.

Estimating the production amount with high accuracy is of great importance in terms of production planning. Thanks to accurate forecasts, the producer companies will be able to produce as much electricity as necessary and plan the most efficient use of excess production, and the government will be able to allocate the necessary share to electricity production in investment plans. It is envisaged that the model will support both power generation plants and government investment planning.

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Author contributions:
Conflict of Interest: This study was produced from the master's thesis titled "Determination and evaluation of electric energy generation strategy by fuzzy logic method", which was accepted in August 2022.

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