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Application of Neural Networks for Forecasting Energy Security Indicators

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Abstract: ***Methodological approaches to the use of neural network models for constructing short-term forecasts of energy security indicators and energy balance indicators have been developed. Experimental neural forecast models for 2 years ahead (for 24 points) have been constructed based on actual monthly data during 7 years. The best models for the indicator "Gross consumption of natural gas" showed convergence at the level of 7%, and for the indicator "Gross consumption of electricity" - 2.14%.***

Keywords: Energy security, indicators, neural network analysis, forecast

1. Introduction

The relevance of the study of the country's energy security issues is confirmed by constant challenges in connection with regional and global economic changes. Also, the situation in the country's energy sector is affected by internal risks that can have consequences in the economy if timely measures are not taken.

The need to find solutions to prevent the development of the most dangerous threats sets the tasks of a comprehensive study of the state of the energy sectors and determining the level of energy security. Indicative analysis is used for the study. Its essence consists in developing a system of indicators for analyzing an object, developing their threshold values, determining the degree of crisis of each indicator, determining the generalized final level of energy security.

2. Brief description of the study

The energy security study is carried out using a system of indicators formed taking into account the features of the country's fuel and energy complex. The indicators are distributed across 10 blocks and reflect the sectors of electricity and heat production, fuels, economic and environmental indicators related to energy. The database contains about 200 primary energy data (from 1990) and is updated annually. The state of all indicators is monitored annually and aggregate level of energy security of the country is determined.

The crisis scale is built for each indicator, which has 8 degrees of severity of the state. A software is being developed, which has several Applications (forecasts, scenarios, key indicators, graphics, short-term forecasting of indicators and energy balance, pollutants, and others). The structure is flexible and allows for the inclusion of new modules, figure 1.

Figure 1: Algorithm for the operation of a software for the analysis and monitoring of energy security indicators

2.1. List of energy security indicators

Block 1-Fuel supply: fuel consumption (gross); share of dominant fuel type; fuel consumption for the electricity and heat production; specific fuel consumption for electricity and heat; consumption in the public sector.

Block 2-Electricity and heat production: electricity and heat production; share of own sources in balance coverage; share of hydroelectric power plants, auto generation, RES in the installed capacity's structure and others.

Block 3-Electricity transmission and distribution: for the transmission network operator: ENS (Energy Not Supplied), AIT (Average Interruption Time); for the distribution network operators: SAIDI (System Average Interruption Duration Index), SAIFI (System Average Interruption Duration Index), CAIDI (Customer Average Interruption Duration Index).

Block 4-Electricity import: share of reserves in the power system, amount of electricity imports.

Block 5-Ecological: CO_2 emissions per unit of fuel burned, CO_2 emissions per capita.

Block 6-Consumers: electricity and heat consumption, share of population expenditure on the acquisition of energy resources and others.

Block 7-Economic: cost of energy resources and debt in energy and in the economy, tariffs for electricity, heat (centralized), natural gas, energy and electricity intensity.

Block 8-Investments: commissioning of electrical, heating, gas networks; volumes of investments in energy sector.

Block 9-Own energy sources: own energy resources, consumption of own energy resources for electricity and heat production, consumption in residential, institutional, commercial sectors.

Block 10-Social aspects: salary level in the energy sector, number of employers in the energy sector, number of engineers-graduates in energy specialties.

2.2. Algorithm

The algorithm includes several stages:

1) Collection of primary data (from several sources and compare values) by sectors – electricity and heat productions, installed capacity, consumed fuels and others;
2) Calculation of indicators for new year and in time series, rechecking previous values and clarifying as necessary;
3) Development of indicator threshold values, construction of crisis scales (quantitative and qualitative) for each indicator, determination of the degree of crisis and state score, visualization on the graph of the dynamics of each indicator;
4) Determination of the generalized final level of energy security based on the entire system of indicators,
5) Development of measures and recommendations for returning crisis indicators to the normal state;
6) Forecasts of indicators and analysis of their possible state to identify threats and risks;
7) Building scenarios for the implementation of the most severe threats, determining the level of energy security in this case, determining ways and measures to prevent the situation from developing towards risk;
8) Identifying the interrelations of indicators, identifying the impact of crisis indicators on other indicators, blocks, and areas of the economy, identifying the interrelations of economic and energy indicators, analyzing the impact of energy on the economy and the state of the environment.

The software allows solving the tasks of monitoring indicators, the degree of crisis of each indicator, determining the generalized final level of energy security; operational analysis carry out for the key indicators system; visualization of indicator trends build; forecasts, determine a number of other indicators related to energy (economic, environmental); scenarios of possible and most dangerous threats build, replenish the energy database for performing various types of analysis - correlation, regression, fuzzy models, neural network models.

3. Forecasting Indicator Values

Forecasting indicator values for different periods - medium-term, short-term, long-term is one of the tasks of energy security. Medium-term forecasting of indicators is carried out using nonlinear models in a special application of the computing complex [1]. Short-term forecasting is the most effective with using of neural network models due to the quality of the resulting forecast.

This method has not previously been used for forecasting energy security indicators due to the fact that the database is compiled on the basis of annual values available from statistical publications and enterprise reports.

But since 2015, data on energy resource consumption for each month has been available in national statistics, which made it possible to apply neural network analysis.

3.1 Application of neural networks to solve various problems: a brief overview and references to other literature

Neural network analysis is applied to modeling the state of indicators in various techniques fields, including energy. For example, the article of N.A. Savchenko describes the use of neural network technologies in optimizing energy systems [2]. Neural network models are applied to assessing electricity losses (article of Zaigraeva Yu.B. [3]), for environmental monitoring (Novikova S.V. [4]), to oil field data (Korovina Ya.S., Khisamutdinov M.V., Ivanov D.Ya. [5]), in geographic information systems (A.A. Pitenko [6]), neuro-modeling is described as a tool for intellectualizing energy information networks (A.S. Kamenev, S.Yu. Korolev, V.N. Sokotuschenko [7]), application in bibliometrics is described in the article Gibson E., Daim T., Garces E., Dabic M. - [8].

Issues of comprehensive analysis of energy security have been considered in studies in different countries.

Einari Kisel, Arvi Hamburg [etc al, 11] described an energy security matrix that structures energy security indicators in terms of technical resilience and vulnerability, economic dependence and political vulnerability for the electricity, heat and transport fuel sectors in Estonia.

Influencing factors and energy security index to Croatia based on 3 indicators are considered in the article of Vladimir Franki, Alfredo Viskovic [12]. Scenarios for the development of the country's energy sector are also described.

Analysis of the energy sector, installed capacities, including alternative renewable energy, energy balances for a number of years for different types of fuel, comparison with other countries is carried out in the work K.Y. Foo [13]

Scenarios for energy transition are described in the article B.Sudhakara Reddy [14]. Indicators of sustainable development (social, economic, environmental, institutional aspects), Sustainable Index are also described.

Description of energy balances, definition of 5 dimensions of energy security index is given in the article by Qodri Febrilian Erahman [etc al] [15]. Results of regression analysis of indicators are described and compared for 71 countries.

The index of energy independence and energy diversification are described in the article by Christoph Böhringer, Markus Bortolamedi [16]. The impact of energy policy on the welfare of the population is assessed when introducing subsidies for renewable energy sources, taxes on CO_2 and fossil fuels.

An integrated assessment of energy security is described and the task of transition to low-carbon energy is set in the work of J. Augutis [etc al, 17]

The need of an interdisciplinary approach to energy security, risk assessment, and the use of the same indicators for different countries for comparison purposes is noted in the article Gelengul Kocaslan [18].

With constant dynamics of economic processes, it is advisable to use simpler methods, such as linear and extrapolation trends for annual values of indicators. In the case of qualitative changes in the economy or energy sector, these methods can give erroneous results, since they do not take into account sudden changes.

For the task of analyses energy security indicators and energy balances, the use of neural network models significantly expands the capabilities of short-term forecasting, allowing making a forecast with a significantly larger number of initial points.

Constructing short-term forecasts using neural networks is a modern method with good reliability indicators for the results obtained.

***Advantages* of neural networks:**
1) Taking into account the nonlinearity of the input data of the object: allows you to reduce the forecast error;
2) Self-learning: the ability to independently determine the importance of each factor under study and assess its impact on the factor under study;
3) Adaptability: the network can be adjusted, it is flexible;
4) Good reliability indicators for the results obtained;
5) If some data is missing, the forecast deteriorates, but less than in other methods.

***Disadvantages:* complexity.**

3.2 Application of neural networks for short-term forecasts - experimental calculations for few indicators

The results calculations performed using neural network models for several few indicators are carry out below. Series of actual statistical values (by month) for the following indicators were used:
1) Gross consumption of natural gas for 2015-2019, 2020 (January-February) [10]. Neural models with a series length of 62 points and a short-term forecast for 2 years ahead (another 24 points) were constructed.
2) Gross consumption of natural gas for 2015-2022, 2023 (January-August). Neural models were constructed on a series length of 104 points and a forecast for 2 years ahead.
3) Gross electricity consumption for 2015-2022, 2023 (January-August) - 104 actual values and 24 points for forecast;
4) Electricity production for 2015-2022, 2023 (January-August) - 104 actual values and 24 points for forecast

Calculation algorithm
The calculations were performed using the program "Statistics" [9]. The calculation algorithm is described using the example of the indicator "Gross consumption of natural gas" with the length of the initial series of 62 points.

3.3 Forecasts for the indicator "Gross consumption of natural gas" for the initial series of 62 points

The graph of gross consumption of natural gas has clearly expressed seasonal fluctuations with variations for individual years. Visualization of the series of indicator values, which is step 1 of the calculation algorithms, is shown in Figure 2.

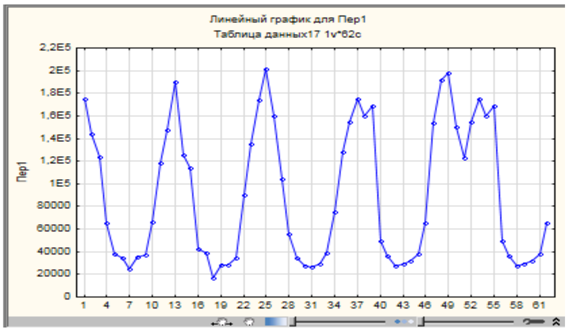

Figure 2: Gross consumption of natural gas by month for 5 years, m^3, plotted in the soft

An analysis of the graph shows that the last year in the series, 2019, for which data for all 12 months are available, has non-standard fluctuations in natural gas consumption in the summer months compared to other years. Therefore, it is not used.

Another fragment was select as the most typical for all years- 2017 (the third peak). A Fourier period gram (step 2) is constructed for it, Figure 3.

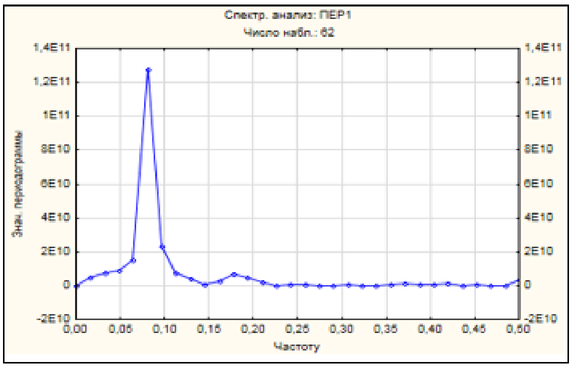

Figure 3: Fourier period gram

Then the required parameters for constructing the neural network are selected (number of perceptrons, number of hidden layers, type of output function, number of models in each cycle - step 3). A number of models are constructed using a sequential algorithm of intermediate checks of residual deviations (step 4). The next step is network training and constructing forecasts for the new 24 points (step 5).

The final stage is the analysis of the resulting models and the selection of the best model (step 6), Figure 4.

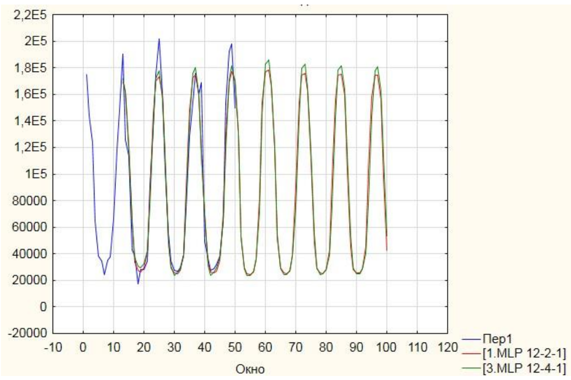

Figure 4: The obtained best calculated forecast values of indicator „Gross consumption of natural gas"

Then the discrepancy between the actual and calculated values is checked for 2017, which was chosen as the main year for the period gram. Based on the total discrepancy, a conclusion is made about the quality of the model and further actions: continuation of calculations or termination (if an accuracy of 2.5% is achieved, which is considered satisfactory).

A typical section in the initial data can be selected not only by the graph, but also analytically. It is necessary to compare the deviations of the average values with the minimum and maximum.

Table 1 shows the annual values, from which it is clear that 2017 has the greatest coincidence with the average value for gross electricity consumption. We can also consider 2020 as a possible typical year. But 2020 is a non-standard year due to the Covid epidemic, so it is rejected.

Table 1: Deviation from the mean for indicator „Gross electricity consumption"

	*Thousand kW*h*			*Deviation from the mean*		
	Auual value	*Min*	*Max*	*Gross*	*Min*	*Max*
2015	4 256 125	316 579	416 338	-84 756	4 041	-18 270
2016	4 218 985	307 241	427 359	-121 896	-5 297	-7 249
2017	4 342 208	311 976	428 417	1 327	-562	-6 190
2018	4 651 686	340 057	483 245	310 805	27 519	48 638
2019	4 356 368	327 474	420 640	15 488	14 936	-13 967
2020	4 348 876	310 335	443 306	7 996	-2 203	8 698
2021	4 211 916	274 103	422 947	-128 964	-38 435	-11 660
2022	4 343 826	328 345	411 010	2 945	15 807	-23 598
Average	4 340 881	312 538	434 608			

The construction of neural models for the indicator "Gross in particular, for this example, the total discrepancy between the actual and calculated values for 2017 was 7.1%. *Conclusion*: experiments should be continued.

3.4 Forecasts for the indicator "Electricity production"

A similar approach is applied to the second indicator "Electricity production". The initial data include 104 points for a longer period 2015-2022, 2023 (January-August), and are shown in Figure 5.

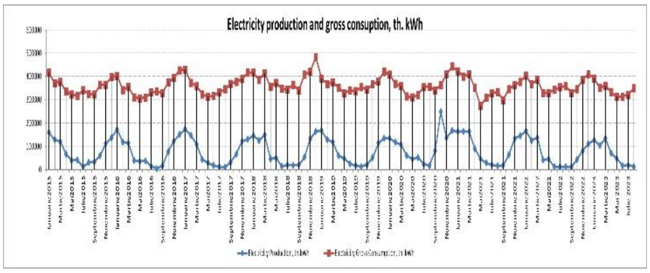

Figure 5: Month values of the indicators "Electricity production" and "Gross electricity consumption" for 2015-2023 (January-August), thousand kWh.

The described algorithm is applied - visualization of the values of the indicator "Electricity production" 104 points in soft "Statistics", the most characteristic section is selected 2017 year.

The period gram is built using Fourier spectral analysis, and a series of models (150) are built. The best convergence of the initial and forecast values for the indicator "Electricity production" is obtained at the level of 16.03%.

Conclusion: experiments should be continued to achieve a forecast accuracy of 2.5%, which is considered satisfactory.

3.5 Forecasts for the indicator "Gross electricity consumption".

A similar approach is applied to the third indicator "Gross electricity consumption". The initial data were used for the period 2015-2022, 2023 (January-August) - 104 points and are shown in Figure 5.

Electricity Consumption" is done similarly. The Fourier period gram, residual graphs, scatter plots of points around the mean value are obtained, Figure 6.

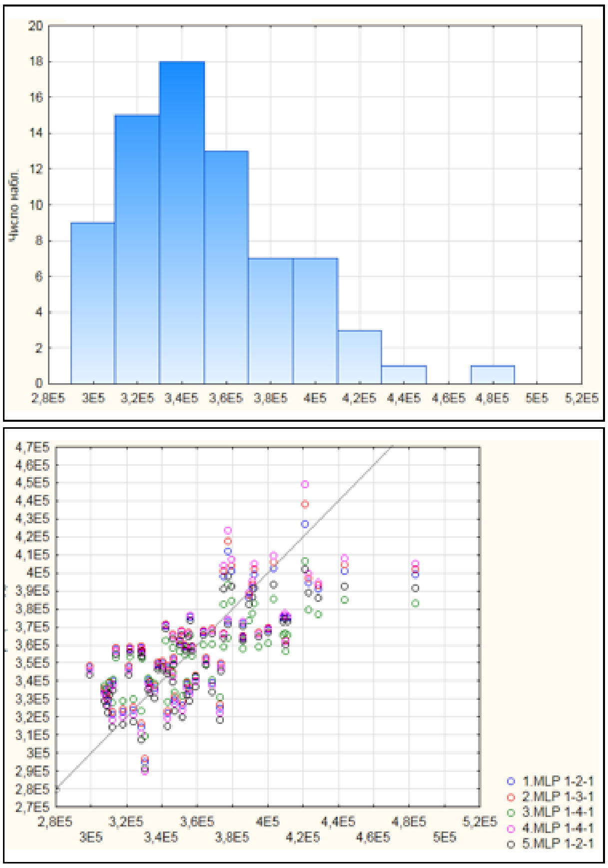

Figure 6: Residual plot and scatter plot

Based on the results of the modeling, "Projection Table" is obtained, in which the convergence of the initial and forecast values for the "Gross Electricity Consumption" indicator is calculated, the average value of which for the typical year 2017 was 2.14%.

Table 2: Comparison of initial and calculated points of the indicator "Gross electricity consumption" according to the best neural model

Month 2017	*Initial*	*Model*	*%*
January	428417,4	395023,5	7,79
February	373319,9	347898,3	6,81
March	358101,0	359137,6	0,29
April	323619,0	321557,9	0,64
May	311976,0	318680,3	2,15
June	317699,3	320227,0	0,80
July	332279,4	338709,2	1,94
August	345883,5	342509,9	0,98
September	368144,6	337493,9	8,33
October	377255,7	374046,3	0,85
November	389111,7	389264,4	0,04
December	416400,5	413026,0	0,81
Average			**2,14**

Conclusion: The network for the indicator "Gross electricity consumption" is built successfully, since the discrepancy between the actual and calculated values is small and amounted to 2.14%.

Forecasts of values for 24 points (or 2 years) can be used for further analysis of the indicator's status, identifying its degree of crisis, analyzing the relationship with other indicators in the future, developing measures to prevent threats, and so on, in accordance with energy security requirements.

3.6 Forecasts for the indicator "Gross consumption of natural gas" for the initial series of 104 points

Above, neural network models were constructed for the indicator "Gross consumption of natural gas" based on the initial series of values of -62 points. Let's perform a similar analysis, but with a longer series of -104 points. Visualization of values by month for 7 years is built in Figure 7.

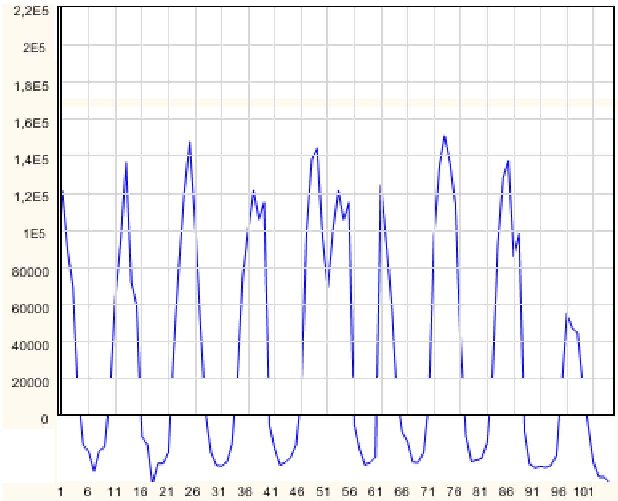

Figure 7: Gross consumption of natural gas by months 2015-2022, 2023 (January-August).

The Fourier period gram and graphical representation of the series of models is shown in Figure 8, 9.

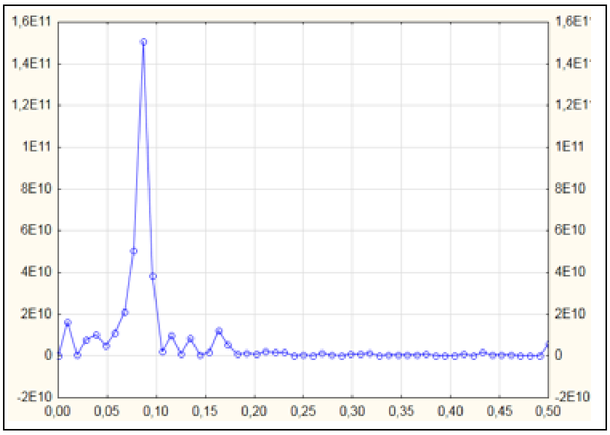

Figure 8: Fourier period gram for typical year 2017 of indicator "Gross gas consumption"

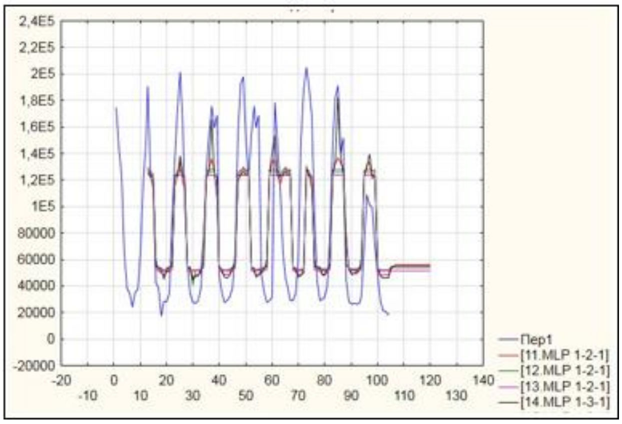

Figure 9: The series of neural models

The models were constructed for several parameter variants:
1) Number of hidden perceptrons: 2 (out of 8);
2) Type of hidden neuron functions: identity, logistic, hyperbolic;
3) Type of output function: identity, logistic, hyperbolic;

Series of models were obtained. The best model showed a convergence of actual and calculated points for a typical year of -7.13%.

This result is unsatisfactory, and the calculations were repeated with other parameters: the number of hidden perceptrons is 2 (out of 10), the type of output function is identical. Other series of models were obtained, the best of which showed a convergence of actual and calculated points of 8.19%.

Further calculations with other variations of the initial parameters did not show an improvement in the models. Experiments can be continued by selecting, for example, another typical year instead of 2017, or by continuing variations in the types of functions, the number of layers and other parameters.

As a result of the experiments, the following conclusions can be made:
1) The application of the results of such a forecast for 2 years ahead will have a possible deviation of 8-10% from the real one. For some types of subsequent analysis of the indicator from the standpoint of energy security, such a forecast may be sufficient, but the final conclusion should be made by the experimenter, based on the task at hand.
2) An increase in the number of points in the initial series of values does not necessarily lead to an improvement in the quality of the constructed models - with 62 points, the coincidence of the actual and calculated values for the best model was better and amounted to 7.1%, and with 104 points - 8.19%.

4. Conclusions

1) Modeling of forecast values was performed using neural network models for 2 indicators - "Electricity production" and "Gross electricity consumption". Experimental forecast models for 2 years ahead (for 24 points) were built based on monthly data from 2015-2023 (January-August) with a time series of 104 points. The resulting forecast models (the best of 150 network options) have the following matches of calculated points with actual ones:
   - For the indicator "Electricity production" - 16.03%;
   - For the indicator "Gross electricity consumption" - 2.14%;

2) Modeling of forecast values for the indicator "Gross consumption of natural gas» for 2 years ahead (for 24 points) were built based on monthly data for 2015-2023 (January- August) with a time series of 104 points and for comparison with a time series of -62 points (for the period 2015-2019, 2020 (January-February).

Two best (when choosing from 150 network options) forecast models were obtained for the indicator "Gross consumption of natural gas", of which they have coincidences of calculated points with actual ones at the level of 7.13% and 8.19%;
Increasing the number of points of the original series of values does not necessarily lead to an improvement in the quality of the constructed models.

The developed methodological approaches can be applied to any fuel balance line, any energy security indicator, and present great potential as a modern tool for short-term forecasting, modeling and analysis.
Experimental calculations and application of the method can be continued until the best convergence of the initial points of the calculation models is obtained.

The method can be in demand for detailed analysis and short-term forecasting of energy security indicators. The method will also be useful for comparing forecasts obtained using other methods.

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