E3S Web of Conferences **470**, 01044 (2023) https://doi.org/10.1051/e3sconf/202347001044
ESR-2023

Assessment of the energy systems resilience using artificial intelligence methods

Liudmila Massel[1*], *Aleksey* Massel[1], *Daria* Gaskova[1], and *Mirsoli* Uzbekov[2]

[1]Melentiev Energy System Institute of SB RAS, AI System Department, Irkutsk, Russia
[2]Fergana Polytechnic Institute, Energy Department, Fergana, Uzbekistan

Abstract. Recently, in Western Europe, a direction defined by the term "Resilience" has been of great interest. Issues of energy and environmental security are of great importance in resilience research. The article discusses an approach to assessing the resilience of energy systems within the framework of the concept of situational management. It is proposed to use artificial intelligence methods: semantic (cognitive) modeling and machine learning. The choice of LSTM as a machine learning model is justified. A method for qualitative and quantitative assessment of the resilience of energy systems has been developed. An example of this method application o assess the resilience of the electric power system of the Siberian Federal District (Russia) in low-water conditions at the Angara-Yenisei cascade of hydroelectric power stations is given.

1 Introduction

Recently, in Western Europe, a direction defined by the term "Resilience" has been of great interest. In Russia, research in this area is carried out mainly in the field of technical sustainability, while in Western Europe they consider this area more broadly and also include environmental, psychological, social and economic resilience. The concept of resilience does not have a unique definition, due to its widespread use in different fields with different meanings and implications. Approaches to determining "resilience" are described in detail in [1]. In the presented study, the authors adhere to the definition of "Resilience" given by Davoudi: "Resilience is the ability of a system to return to equilibrium or a stable state after a disturbance such as floods, earthquakes or other natural disasters, as well as man-made disasters such as banking crises, wars or revolutions" [2].

Issues of energy and environmental security are of great importance in resilience research. Increasing frequency of natural disasters can cause emergency situations, aggravated by the likelihood of multiple accidents, including cascading ones, in the energy sector, which, in turn, is one of the critical infrastructures that directly affects the quality of life of the population. In studies of the resilience of energy systems, it has been proposed to use an adaptation of the concept of situational management in the aspect of energy security [3]. The concept itself was proposed and developed in the 80s. 20th century by Russian scientist D.A. Pospelov.

* Corresponding author: massel@isem.irk.ru

The authors interpreted the concept of situational management for studying the resilience of energy systems [3]. This provides grounds for adaptation and application in these studies of the entire range of previously developed methods, models and tools, incl. methods of semantic modeling and machine learning.

2 Assessing the resilience of energy systems

To describe the adaptation of situational management methods, we present the basic concepts adopted in this study. $\{S_0\}$ – initial or current state of the system, i.e. state of the system before the disturbance; $\{Ei\}$ – i-th extreme situation (ExS) scenario, including factors that collectively describe the implementation of a threat to energy security (ES), i.e. a set of disturbing influences; $\{Ui\}$ is a vector of control actions for the i-th scenario of an extreme situation, and separately allocated a set of preventive, operational and liquidation measures $\{A\} = \{Aq, Ao, A_l\}$ that neutralize or mitigate the consequences of disturbing influences $\{Ei\}$; $\{Sj\}$ – state of the system after disturbances $\{Ei\}$, taking into account the implementation of a set of measures $\{Aq\}$ and/or $\{Ao\}$; $\{Sk\}$ is the new stable state of the system after the implementation of control actions [3].

It is proposed to assess the resilience of energy systems using energy security indicators, where the assessment of a particular situation includes many factors and is based on an indicative analysis and scale: “norm” (normal functioning), “pre-crisis” (critical situation), “crisis” (emergency) [4]. Each of the ES threats is realized due to a combination of a number of factors influencing the occurrence of ExS. A qualitative assessment of a number of factors influencing the occurrence of ExS was proposed as a preliminary assessment before carrying out calculations, and a formalization of the formulation of the cognitive modeling task for energy security research is presented in [5]. The indicative analysis is aimed at determining the level of energy security, and the following ratio must be met:

$$I_N \leq I_J < I_C, \qquad (1)$$

where I_N is the indicator value that determines the normal level of energy security, I_J is the current indicator value, I_C is the indicator value that determines the crisis level of security [5].

Research of the fuel and energy complex (FEC), taking into account the requirements of energy security, due to the impossibility of conducting natural experiments on operating energy systems of the FEC, are carried out using economic and mathematical models of the FEC [6]. In the current study, a complex of computer programs to support research into the directions of development of the FEC taking into account the requirements of energy security was reengineered, the new version was named program complex (PC) “INTEC-A” [7]. PC "INTEC-A" implements a model for optimizing the balances of fuel and energy resources (FER) in the regions of Russia (with the allocation of constituent entities of the Russian Federation) under conditions of possible disturbances. In a mathematical sense, it is a classical linear programming task. In a applied sense, it is based on the traditional territorial production model of FEC with power generation, heat, gas and coal supply units, as well as oil refining and fuel oil supply units. When formalizing the constraints of the specified optimization task, they are written in the form of a system of linear equations and inequalities [8].

Current research into assessing the resilience of energy systems using situational management methods and the INTEC-A software includes a description of the system state using the construction of cognitive models, and a computational experiment of a multivariate ExS scenario based on a model for optimizing fuel and energy balances, i.e. include qualitative and quantitative assessment of the resilience of energy systems. The integration of qualitative and quantitative assessment is determined, on the one hand, by the complexity of carrying out a quantitative assessment, which is usually based on the use of traditional software systems for solving such tasks. Such software systems are characterized by the length of time it takes to prepare information, the formation and adjustment of large enough models for conducting computational experiments. On the other hand, the use of cognitive models allows decision makers to select some options that require detailed justification and quantitative calculation, and not carry out calculations of all possible options. The stages of studying the sustainability of energy systems are given in the description of the resilience research method below (Section 4).

3 Application of artificial intelligence methods in research on the energy systems

Semantic modeling methods were considered by the authors in a number of publications, including [1, 3], the basic concepts of cognitive modeling are discussed in [5], so we will not dwell on them here. Let's take a closer look at the use of machine learning methods.

Machine learning methods are widely used in modeling, design and forecasting in the energy sector. Often, the tasks for machine learning in the energy sector are predictive modeling of production analysis, consumption and demand, and the choice of these methods is determined by their accuracy, efficiency and speed [10]. Article [10] highlights the main machine learning models often used in the energy sector for various tasks, including artificial neural networks, multilayer perceptron, extreme machine learning, support vector machine, wavelet neural network, adaptive network based on a fuzzy inference system, decision trees, method ensembles, and hybrid machine learning models.

In the energy industry, machine learning methods are used to solve a number of problems described, in particular, in [11-18]. The task of forecasting electricity consumption using machine learning models aims to improve energy efficiency and therefore manage energy consumption and ensure resilience.

Let us consider choosing a machine learning model for our research. In accordance with the formulation of the task (Section 5), it is required to predict time series corresponding to the parameters of the optimization model of the fuel and energy complex to analyze the state of the system and determine control actions. Artificial neural network (ANN) architecture LSTM is widely used for predicting time sequences [19-21] and belongs to a type of recurrent neural network (RNN) architecture. RNN is a type of neural network that is aimed at processing sequences [22]. RNN has short-term memory blocks to remember information from previous blocks, which makes it suitable for predicting data sequences. RNN blocks treat all inputs as useful and pass all the information to the next block, which raises the problem of learning long-term dependencies in recurrent networks. The main problem of RNN in this case is the disappearance or explosive growth of the gradient during the learning process using the back propagation method. However, this problem was circumvented using LSTM networks [23]. The main advantage of an LSTM network in comparison with an RNN is its high performance with a large data sequence length due to the ability to distinguish between long-term and short-term states using "gates" and a state vector [24]. Another advantage of an LSTM network is that it solves the long-term dependency problem of a recurrent neural network, which cannot make predictions based on long-term memory, but can produce accurate predictions based on recent information. The default LSTM network can store information for a long period of time, however, the efficiency of using an LSTM network does not improve as the amount of incoming data increases [23]. Considering the advantages of the LSTM network, it was chosen as a machine learning model to solve the task (Section 5).

4 The method for qualitative and quantitative assessment of the resilience of energy systems

Research into the resilience of energy systems is aimed at developing a variety of scenarios reflecting options for the state of energy systems and assessing the resilience of this state using indicative analysis. The proposed method was developed using an event map [9] and is aimed at integrating the qualitative and quantitative levels of research. In this case, the events are the stages of the method, the description of which is given in Table 1.

Table 1. The method stages for qualitative and quantitative assessing the resilience of energy systems.

Stage No.	The stage	Stage No.	Quality level	Stage No.	Quantitative level
1	Description of the initial (current) state of the system i.e. formation $\{S_0\}$	1.1	Construction of a cognitive model of the initial (current) state of the system, including many factors $\{C_{S_0}\}$	1.1	Construction of an economic-mathematical model of an optimization task [8]
		1.3	Clarification of factor values $\{C_{S_0}\}$ based on balance tables	1.2	Determination of fuel and energy balances
2	Description of the set of disturbing events (ES threats) $\{Ei\}$ for $\{S_0\}$	2.1	Construction of a cognitive model that includes many factors $\{C_{S_0}\}$, $\{E_i\}$ and relationships between them $\{C_E\} = \{C_{S_0}\} \cup \{E_i\}$	2.1	Formation of a multivariate scenario
		2.3	Clarifying the meanings of concepts $\{C_E\}$ based on balance tables	2.2	Performing calculations and determining fuel and energy balances
3	Assessment of system resilience after disturbances	3.1	Qualitative assessment of the system state on the "norm-pre-crisis-crisis" scale based on the concepts of indicators $\{Ij\}$	3.1	Expert assessment of the deficits presence based on relation (1)
	The transition to the next stage is due to the fact that relation (1) is not satisfied				
4	Description of the implementa-tion of control actions i.e. formation $\{S_j\}$	4.1	Construction of a cognitive model that includes many factors $\{C_E\}$, $\{U_i\}$ ($\{A_i\}$ and relationships between them $\{C_{S_j}\} = \{C_E\} \cup \{U_i\}$, $\{A_i\} \subset \{U_i\}$	4.1	Formation of a multivariate scenario
		4.3	Clarifying the meanings of concepts $\{C_{S_j}\}$ based on balance tables	4.2	Performing calculations and determining fuel and energy balances
5	Assessment of system resilience after control actions $\{S_j\}$	5.1	Qualitative assessment of the system state on the "norm-pre-crisis-crisis" scale based on the concepts of indicators $\{Ij\}$	5.1	Expert assessment of the deficits presence based on relation (1)
	The system is in a stable state when returning to $\{S_0\}$ *or transitioning to* $\{S_k\}$. *If relation (1) is not met, return to stage 4.*				

Comments on Table 1. *{S_0} is formed as an optimization model of the fuel and energy complex (FEC) for the period under study and is described by factors of the cognitive model corresponding to the variables of the optimization model of FEC {* C_{S_0} *}, including {Ij}. The set {Ei} is formed as a set of quantitative values of the variables limitations and/or inequalities of the optimization model of FEC and is described by factors of the cognitive model corresponding to disturbing influences, changes in the values of which affect the parameters of the model (constraints of variables and/or inequalities). The set {U_i} is formed as a set of quantitative values of the limitations of variables and/or inequalities of the optimization model of the fuel and energy complex and is described by factors of the cognitive model corresponding to sets of activities, changes in the values of which affect the parameters of the model (constraints of variables and/or inequalities). The sets {S_j} and {S_k} are formed as a set of results of a computational experiment of an optimization model of FEC with given parameters and are described by factors of the cognitive model corresponding to the variables of the optimization model of the FEC, disturbing influences and sets of measures, respectively.*

When conducting research of the resilience of energy systems, the initial (current) state of the studying energy system is formed for a given forecasted period of time corresponding to the considered period of time of occurrence of the disturbing influence (threat of energy security (ES)). The values of the variable constraints and inequalities used in the study are not known in advance. Such values, for example, may be the needs of a certain area for a certain amount of electricity. Currently, the values of these parameters are determined by experts, however, this is also possible using machine learning methods to predict the values of selected parameters of the system under study. Using cognitive modeling, concepts are defined that describe disturbances that affect on the of the system state. The influence of such concepts is quantitatively described in the constraints of the variables and inequalities of the optimization model of the fuel and energy complex. Next, a new version of the system state is formed and calculated. The cognitive model is supplemented with factors corresponding to a set of control actions, and quantitative values reflecting these dependencies are added to the restrictions of variables and inequalities of the optimization model of the fuel and energy complex. The system resilience is assessed based on the calculation of the corresponding ES indicator.

5 An example of the application of the proposed method for assessing the resilience of energy systems

The task has been set to assess the resilience of the electric power system of the Siberian Federal District for a period of 1.5 years (01/01/2021-07/27/2022) in conditions of low water at the Angara-Yenisei cascade of hydroelectric power stations. We use the method described above. As an indicator for this task, the indicator (Id) was selected, corresponding to the relative total shortfall of types of fuel and energy resources in the federal district for the analyzed period (electricity), formed on the basis of the list of energy supply indicators [28].

At the first stage, an economic and mathematical model of the optimization task is formed. The model includes groups of variables characterizing production, exports, imports, interregional transport and consumption of fuel and energy resources by region. The study examines the variable:

$$B \in [l_1, l_2],$$

where B is electricity consumption, l_1 is the lower limit of the variable, equal to zero; l_2 – upper limit, reflecting the specified demand for electricity. Using the INTEK-A software, a search is made for the optimal solution to the obtained version of the FEC state model. The optimal values of the variables are used to construct balance tables that display, among other things, deficits for each type of fuel and energy resources. The value of the specified demand for electricity in the Siberian Federal District, obtained using an ANN, is set as the upper limit of the corresponding variable in the model (l_2 = 214.49 billion kWh). The initial state of the electric power system of the Siberian Federal District is determined as the result of a computational experiment assessing the presence of electricity shortages in the Siberian Federal District; the calculation results are displayed in the corresponding cognitive model of the initial state of the FEC.

At the second stage, the threat of low water at the Angara-Yenisei cascade of hydroelectric power stations is described as a disturbing event; the description of the threat of ES for the cognitive model is taken from [4]. The study considers that in low-water conditions, the generation of electricity from hydroelectric power plants in the Siberian Federal District is reduced by 0.976 billion kWh per year, which is a factor *{Ei}* (disturbing impact). The optimal value of variable B reflects the predicted electricity consumption. Next, disturbing influences are applied (threat of low water), after which the system state is displayed as refined values of the cognitive model to describe the implementation of a set of disturbing influences in Figure 1.

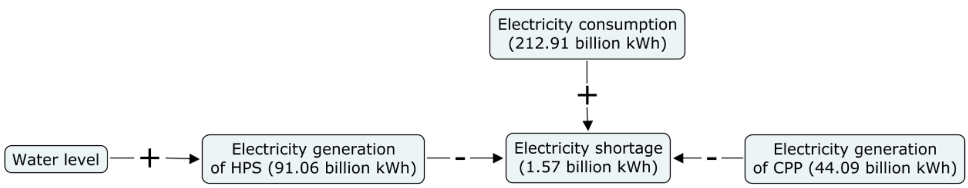

Fig. 1. Cognitive model describing the power system state in the presence of a deficit as a result of disturbing influences.

Third stage: based on assessing the presence of deficits, we will assess the resilience of the power system. Relation (1) for the I_d indicator for a given model is not satisfied at this stage since $0 < I_d$.

At the fourth stage, control actions are determined based on the results of calculating a multivariate scenario. An increase in the capacity of condensing power plants (CPP) on the territory of the Siberian Federal District was chosen as a control action, which compensates for the consequences of the threat of low water. Figure 2 shows a cognitive model for implementing control actions based on balance tables.

At the fifth stage, the equality of the specified demand and forecast consumption indicates that the FEC is capable of providing the federal district with the required amount of additional fuel and energy resources, i.e. relation (1) is satisfied for I_d due to the fact that the generation of electricity by CPP is increased by 1.57 million hours per year, which compensates for the electricity shortage. In the example under consideration, the electric power system of the Siberian Federal District is in a stable state, i.e. the system has transitioned to a new stable state.

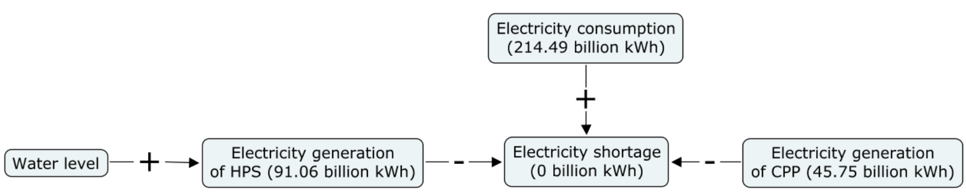

Fig. 2. Cognitive model describing the power system state with refined values after control actions.

6 Conclusion

The article discusses the use of artificial intelligence methods in research on the resilience of energy systems, namely: cognitive modeling and machine learning methods. The adaptation of the concept of situational management is described and the method for qualitative and quantitative assessment of the resilience of energy systems based on it is given. The problem of using machine learning methods to conduct such research has been formulated and an example of a computational experiment and a qualitative assessment of the situation using cognitive models is given. Further direction of work is related to application of the semantic modeling for environmental systems and conducting corresponding computational experiments using the example of assessing pollutant emissions in the Baikal region.

The research was funded by Russian Science Foundation, according to the research project No. 22-21-00841.

References

1. L.V. Massel, N. P. Komendantova, Assessment of the risks of natural and man-made threats to the resilience of energy, ecological and social systems based on intelligent information technologies, *Information and Mathematical Technologies in Science and Management*, **4** (16), pp. 31-45 (2019) (in Russian)
2. S. Davoudi, Resilience: a bridging concept or a dead end, *Planning theory and practice*, **13**(2), pp. 299-307 (2012)
3. L.V. Massel, A.G. Massel, N. P. Komendantova, An approach to research on the resilience of energy and ecological systems based on intelligent information technologies, *Proceedings of the International Scientific Conference "Sustainable Development of the Energy Industry of the Republic of Belarus: State and Prospects"* (Minsk, Republic of Belarus), Minsk: Belarus Science, pp. 33-43 (2020) (in Russian)
4. N.I. Pyatkova, et al., Energy security of Russia: problems and solutions, Ed. Voropay, N.I., Cheltsov, M.B. MESI SB RAS, Publishing House of the SB RAS: Novosibirsk, Russia, 211 p. (2011) (in Russian)
5. A.G. Massel, Cognitive modeling of threats to energy security, *Mining information and analytical bulletin (scientific and technical journal),* separate issue no. 17, M.: Publishing house “Gornaya Kniga”, pp. 194-199 (2010) (in Russian).
6. A.G. Massel, T.G. Mamedov, N.I. Pyatkova, Technology of computational experiment in studies of the work of energy industries in the implementation of threats to energy security, *Information and mathematical technologies in science and management*, **3**(23), pp. 62-73. (2021) (in Russian).
7. A.G. Massel, T.G. Mamedov, Adaptation of methods for reengineering legacy software systems, *Information and mathematical technologies in science and management*, **4** (24), pp. 88-99 (2021) (in Russian).
8. S.M. Senderov, S.V. Vorobyov, N.I. Pyatkova, Analysis of promising opportunities to meet the demand for boiler and furnace fuel in conditions of sudden cold snaps in the territories of federal districts, *Izvestiya RAS. Energy*, **6**, pp. 3-11 (2017) (in Russian).
9. A.G. Massel, V.O. Tyuryumin, Integration of semantic models in studies of energy security problems, *News of Tomsk Polytechnic University*, **324**, no. 5, pp. 70-78 (2014) (in Russian).

10. A. Mosavi, M. Salimi, S.F. Ardabili, T. Rabczuk, S. Shamshirband, A. Varkonyi-Koczy, State of the art of machine learning models in energy systems, a systematic review, *Energies*, **12**(7), 1301 (2019).
11. D.A. Boyarkin, D.S. Krupenev, D.V. Yakubovsky, Using machine learning methods in assessing the reliability of electric power systems using the Monte Carlo method, *Bulletin of the South Ural State University. Series: Mathematical Modeling and Programming,* **11**, no. 4, pp. 146-153 (2018) (in Russian).
12. V.A. Kryukov, A.A. Gorlov, Forecasting the development of wind energy in the North Sea basin based on learning curves, *Forecasting Problems,* no. 2 (173), pp. 93-103 (2019) (in Russian).
13. A.V. Zhukov, D.N. Sidorov, Modification of the random forest algorithm for classification of non-stationary streaming data, *Bulletin of the South Ural State University. Series: Mathematical modeling and programming*, **9**, no. 4, pp. 86-95 (2016) (in Russian).
14. N.V. Tomin, V.N. Kornilov, V.G. Kurbatsky, Increasing the efficiency of hourly forecasting of electricity consumption using machine learning models using the example of the Irkutsk energy system, part 1, *Electricity. Transmission and distribution,* **6** (69), pp. 44-53 (2021) (in Russian).
15. N.V. Tomin, V.N. Kornilov, V.G. Kurbatsky, Increasing the efficiency of hourly forecasting of electricity consumption using machine learning models using the example of the Irkutsk energy system, part 2, *Electricity. Transmission and distribution*, **1** (70), pp. 36-42 (2022) (in Russian).
16. N.V. Tomin, V.G. Kurbatsky, A.V. Domyshev, Development of an intelligent decision support system "Artificial dispatcher" based on deep machine learning technology with reinforcement, *Methodological issues in studying the reliability of large energy systems,* book 2, no. 70, pp. 305-314 (2019) (in Russian).
17. N. Tomin, N. Voropai, V. Kurbatsky, C. Rehtanz, Management of voltage flexibility from inverter-based distributed generation using multi-agent reinforcement learning, *Energies*, **14**, no. 24 (2021).
18. V. Kornilov, V.G. Kurbatsky, N.V. Tomin, Improving the principles of short-term electric load forecasting of the Irkutsk region, *E3S Web of conferences,* **25**, 03006 (2017).
19. K. Ito, H. Iima, Y. Kitamura, LSTM forecasting foreign ex-change rates using limit order book, *Finance research letters,* **47**, part 1, 102517 (2021).
20. L. Han, R. Zhang, X. Wang, A. Bao, H. Jing, Multi-step wind power forecast based on VMD-LSTM. IET renewable power generation, **13**, Is. 10, pp. 1690-1700 (2019)
21. C.W. Wu, L. Ji, K. He, G. Tso, Forecasting tourist daily arrivals with a hybrid sarima–lstm approach. *Journal of hospitality & tourism research,* **45**, Is. 1, pp. 52-67, (2020) DOI: 10.1177/1096348020934046.
22. O. I. Abiodun, A. Jantan, A.E. Omolara, K.V. Dada, N.A. Mohamed, H. Arshad, State-of-the-art in artificial neural network applications: A survey, *Heliyon*, **4** (11), e00938 (2018)
23. S. Hochreiter, J. Schmidhuber, Long short-term memory, *Neural computation,* **9**, no. 8, pp. 1735-1780, (1997)
24. W. Wei, P. Li, Multi-channel LSTM with different time scales for foreign exchange rate prediction, *Proceedings of the International conference on advanced information science and system*, no. 28, pp. 1-7 (2019).

25. V.M. Nikitin, N.V. Abasov, T.V. Berezhnykh, E.N. Osipchuk, Angara-Yenisei cascade of hydroelectric power stations in a changing climate, *Energy Policy*, no. 4, pp. 62-71 (2017) (in Russian).
26. V.M. Nikitin, V.A. Savelyev, T.V. Berezhnykh, N.V. Abasov. Hydropower problems of Lake Baikal: past and present, *Region: economics and sociology*, **3**(87), pp. 273-295 (2015) (in Russian)
27. Indicators of UES operation. Generation and consumption in the IPS of Siberia (days). System operator of the UES, URL: https://www.so-ups.ru/functioning/ees/oes-siberia/oes-siberia-indicators/oes-siberia-gen-consump-day/ (date of access: 08/30/2023). (in Russian)
28. S.M. Senderov, V.I. Rabchuk, Indicators for assessing the Russian energy security doctrine for the reliability of fuel and energy supply, *Energy Policy*, **3**(141), pp. 86-95 (2019) (in Russian)