https://doi.org/10.26160/2474-5901-2019-14-118-123

# CURRENT STATE OF PREDICTIVE ANALYTICS SYSTEMS DEVELOPMENT IN THE ENERGY SECTOR

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**Keywords**: predictive analytics system, energy, neural networks, big data, industry 4.0.
**Abstract.** The review of models, methods and algorithms used in modern systems of predictive analytics for power equipment is carried out.

# СОВРЕМЕННОЕ СОСТОЯНИЕ ПРОБЛЕМЫ РАЗРАБОТКИ СИСТЕМ ПРЕДИКТИВНОЙ АНАЛИТИКИ В ЭНЕРГЕТИКЕ

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**Ключевые слова**: система предиктивной аналитики, энергетика, нейронные сети, большие данные, Индустрия 4.0.
**Аннотация.** Проведен обзор моделей, методов и алгоритмов, применяемых в современных системах предиктивной аналитики для энергетического оборудования.

Obtaining an accurate prediction of equipment failure will allow planning activities and resources (financial, human, materials and machines) to bring a particular piece of equipment into proper technical condition. For forecasting the characteristics based on expert knowledge and the assumption that dynamics of change of a number of parameters testifies to failure of the equipment (with a certain confidence through some interval of time) are used. Such systems are called predictive or predictive. Predictive analytics systems (PAS) are increasingly used in various fields due to the increasing capabilities of computer technology for the software implementation of mathematical methods for processing large amounts of data. Big data is heterogeneous. Therefore, the methods of their treatment and SPA are inseparable and are part of the technological basis of the new industrial revolution or Industry 4.0 [1].

Let us agree that the Big Data in the framework of this study will be understood as unstructured telemetry information tied to real-time counts and coming from the systems of the AMR and SCADA level, as well as accounting systems, MES, ERP, EAM. Big Data and its processing capabilities should provide the energy sector with a qualitative leap forward in the near future.

When implementing PAS and Big Data methods in the energy sector, a very important aspect is the technical side of this issue, reflecting the complexity of the implementation of algorithms and their applicability to specific types of data, as well as obtaining forecasts of faults and failures [2]. KNIFE [3] uses k-means algorithm and autoregressive model for predicting parameter values for data clustering. Two drawbacks should be noted, namely that it is necessary to know in advance the number of clusters and that this algorithm is extremely sensitive to the choice of the initial cluster centers. Autoregressive models are sensitive to the choice of order, which in turn affects the time (the speed of calculations decreases with increasing the order of the regression model) to obtain the forecast.

One of the most frequently used methods of predicting the technical condition of equipment, including in power engineering, is modeling using time series. In fact, the analysis of time series of parameters that characterize the technical condition of the equipment. The time series itself is the sum of two components (trend and error functions) [4]. Machine learning systems based on artificial neural networks (ANN) can be used for the purposes of forecasting based on retrospective data [5].

As part of the IDARTS methodology, solutions based on knowledge and rules used for decision-making, troubleshooting, potential deviations and other critical events for the operation of equipment are used [6]. The practical implementation of IDARTS is a multi-agent system, where there is a number of agents who are responsible for monitoring equipment, monitoring subsystems that combine several units of equipment, etc.

Methods of Deep Learning [7] can be used to solve prediction problems, for example, multilayer ANN. These technologies are used to monitor operating conditions, identify emerging defects, diagnose root causes of failures [8], diagnose and classify equipment faults [9]. The [7] also refers to the need to develop an intelligent maintenance strategy that will determine the current state of the equipment during its operation to predict maintenance activities. It is noted, that general recurrent ANN can be used to predict the propagation of defects and estimate the remaining life of elements.

In [10], data-based diagnostic methods are divided into signal processing, intelligent, and pattern recognition methods. As forecasting methods for establishing various kinds of functional dependencies in the energy sector are used: regression models, for example, linear regression to predict the speed of the power turbine depending on the reduced speed of the high-pressure compressor, multiple linear regression, nonlinear regression to predict the reliability and reliability of energy equipment [11]; ANN to diagnose the state and fault location equipment [12]; fuzzy set theory and fuzzy logic for solving problems of energy consumption forecasting [13].

Advantages and disadvantages of classical methods of forecasting models construction (without ANN and fuzzy systems) on the basis of data and time series are described in [11]. Regression models of a special type [14] allow to obtain adaptive predictive models. These methods operate only with statistical data of large volume and allow not to study deeply the physics of the processes. But at the same time, the successful implementation of these models and methods requires large amounts of samples and computing resources, which often leads to the need for multi-computer and cloud computing.

The classical methods of forecasting can also include mathematical models that use Markov chains, when the future state of the object does not depend on the trajectory of the object to the current state. Markov processes can be used to obtain normative values of reliability indicators in the design of equipment of energy enterprises [11]. There is also a class of methods, called classification and regression trees (CART models) or sometimes called decision trees. In power engineering CART is used for various purposes [15]: assessment of the production safety, transport and distribution of energy, for example, the transition to a potentially hazardous mode of operation; preventive and corrective control, ensuring the operation of the equipment in modes close to the limit, but not allowing the transition to an unacceptable state; emergency protection system ensuring the disconnection of the equipment before the occurrence of adverse events, and failure; forecasting and identification of energy equipment conditions; equipment fault diagnosis.

Monitoring of the object state and early detection of instability of its functioning can be carried out using Hotelling maps, when the exit from the control border on the map is an indicator of early detection of a violation in the operation of the equipment [16]. Various modifications of the Bayesian approach can be used to predict the occurrence of accidents and failures in the energy sector. In work [17] the dynamic Bayesian network of trust which realization allows to predict values of probability of failures and to carry out search of defects and malfunctions in the corresponding systems of decision support is offered. Decision support systems (DSS) are a separate subclass of energy equipment maintenance systems in good technical condition [18]. In the development and implementation of such systems, much attention is paid to the organization of human-machine interaction.

Another very important task is to determine the mechanisms of models integration describing the production or energy system with models of forecasting and analytical data processing. For example, the work [19] uses the expertise of process engineers and specialists in the field of data processing, forming a certain set of metamodels of the subject area. And forecasting is carried out using the ANN. There are systems that predict the period of trouble-free operation and allocate dangerous modes of operation of the equipment ("PRANA" system) [20]. The PRANA system uses empirical models based on statistics, which requires conversion of coefficients and involves significant computational difficulties.

The critical analysis of literature sources in the field of processing of big data and time series for the purposes of assessing the state of the equipment and predicting its reliability leads to the conclusion that it is advisable to develop an original approach to creating a PAS for energy companies.

## References

1. Lu Y. Industry 4.0: A survey on technologies, applications and open research issues // Journal of Industrial Information Integration. Vol. 6. 2017. - P. 1-10.
2. Kozjek D., Vrabic R., Kralj D., Butala P. A Data-Driven Holistic Approach to Fault Prognostics in a Cyclic Manufacturing Process // Proc. in The 50th CIRP Conference on Manufacturing Systems. 2017. Vol. 63. - P. 664-669.
3. Silipo R., Winters P. Big Data, Smart Energy, and Predictive Analytics Time Series Prediction of Smart Energy Data. 2013. URL: https://files. knime.com/sites/default/files/inlineimages/knime_bigdata_energy_timeseries_ whitepaper.pdf.

4. Shevtsov Yu.D. et al. Forecasting of parameters of technical condition of engines of power plants // Polythematic network electronic scientific journal of Kuban State Agrarian University. 2017. № 132. - P. 508-517.
5. Shin S.J., Meilanitasari P. Developing a big data analytics platform for manufacturing systems: architecture, method, and implementation // Int. Journal of Advanced Manufacturing Technology. 2018. - P.1-42.
6. Peres R.S. et al. IDARTS - Towards Intelligent Data Analysis and Real-Time Supervision for Industry 4.0 // Computers in Industry. 2018. - P. 1-12.
7. Wang J., Ma Y., Zhang L., Gao R.X., Wu D. Deep learning for smart manufacturing: Methods and applications // Journal of Manufacturing Systems. 2018. Vol. 48. - P. 144-156.
8. Park J.K. et al. Machine learning-based imaging system for surface defect inspection. International Journal of Precision Engineering and Manufacturing-Green Technologies. 2016. Vol. 3. No. 3. - P. 303-310.
9. Zhao R., Yan R., Chen Z., Chen Z., Mao K., Wang P., et al. Deep learning and its applications to machine health monitoring: a survey. 2016. URL: https://arxiv. org/pdf/1612.07640.pdf.
10. Wu D. et al. A fog computing-based framework for process monitoring and prognosis in cyber-manufacturing // Journal of Manufacturing Systems. 2017. Vol. 43. - P. 25-34.
11. Rybalko V. V. Mathematical models of energy facilities reliability control. Monograph. - SSTURP. SPb., 2010. - 151 p.
12. El-Sharkawi M.A. et al. Localization of Winding Shorts Using Fuzzified Neural Networks. Proceedings of IEEE Transactions on Energy Conversion. 1995. Vol. 10. № 1. - P. 147-155.
13. Iranmanesh H., Abdollahzade M., Miranian A. Forecasting energy consumption using fuzzy transform and local linear neuro fuzzy models // International Journal on Soft Computing. 2011. Vol. 2. No. 4. - P. 11-24.
14. Bhinge R. et al. An Intelligent Machine Monitoring System for Energy Prediction Using a Gaussian Process Regression // Proc. in IEEE International Conference on Big Data (Big Data). 2014.
15. Liu C., Rather Z.H., Chen Z., Bak C.L. An overview of decision tree applied to power systems // International Journal of Smart Grid and Clean Energy. 2013. Vol. 2. No. 3. - P. 413-419.
16. Klyachkin V.N. Evaluation of the effectiveness of the diagnosis of the state of the object by the presence of non-random structures on the Hotelling map // Automation of management processes. 2015. № 1(39). - P. 50-56.
17. Vichuzhanin V.V., Shibaeva N.O. Informatization of risk prediction of structurally complex technical systems using models of Bayesian networks // Computer science and mathematical methods in modeling. 2016. Vol. 6. №. 3. - P. 205-214.
18. Shin S.J. et al. Developing a decision support system for improving sustainability performance of manufacturing processes // Journal of Intelligent Manufacturing. 2017. Vol. 28. Iss. 6. - P. 1421-1440.

19. Lechevalier D. et al. An Intelligent Machine Monitoring System for Energy Prediction Using a Gaussian Process Regression. Proc. in IEEE International Conference on Big Data (Big Data). 2014.
20. Lipatov M. Russia's first complex of predictive Analytics for power and industrial equipment // Jekspozicija. Neft'. Gaz. 2016. № 3 (49). - P. 82-83.

**Список литературы**

1. Lu Y. Industry 4.0: A survey on technologies, applications and open research issues // Journal of Industrial Information Integration. Vol. 6. 2017. - P. 1-10.
2. Kozjek D., Vrabic R., Kralj D., Butala P. A Data-Driven Holistic Approach to Fault Prognostics in a Cyclic Manufacturing Process. Proc. in The 50th CIRP Conference on Manufacturing Systems. 2017. Vol. 63. - P. 664-669.
3. Silipo R., Winters P. Big Data, Smart Energy, and Predictive Analytics Time Series Prediction of Smart Energy Data. 2013. [Электронный ресурс]. - Режим доступа: https://files.knime.com/sites/default/files/inline-images/knime_bigdata_energy_timeseries_whitepaper.pdf.
4. Шевцов Ю.Д. и др. Прогнозирование параметров технического состояния двигателей энергетических установок // Политематический сетевой электронный научный журнал Кубанского государственного аграрного университета. 2017. № 132. - С. 508-517.
5. Shin S.J., Meilanitasari P. Developing a big data analytics platform for manufacturing systems: architecture, method, and implementation // Int. Journal of Advanced Manufacturing Technology. 2018. - P.1-42.
6. Peres R.S. et al. IDARTS - Towards Intelligent Data Analysis and Real-Time Supervision for Industry 4.0 // Computers in Industry. 2018. - P. 1-12.
7. Wang J., Ma Y., Zhang L., Gao R.X., Wu D. Deep learning for smart manufacturing: Methods and applications // Journal of Manufacturing Systems. 2018. Vol. 48. - P. 144-156.
8. Park J.K. et al. Machine learning-based imaging system for surface defect inspection. International Journal of Precision Engineering and Manufacturing-Green Technologies. 2016. Vol. 3. No. 3. - P. 303-310.
9. Zhao R., Yan R., Chen Z., Chen Z., Mao K., Wang P., et al. Deep learning and its applications to machine health monitoring: a survey. 2016. [Электронный ресурс] Режим доступа: https://arxiv. org/pdf/1612.07640.pdf.
10. Wu D. et al. A fog computing-based framework for process monitoring and prognosis in cyber-manufacturing // Journal of Manufacturing Systems. 2017. Vol. 43. - P. 25-34.
11. Рыбалко В.В. Математические модели контроля надёжности объектов энергетики. Монография. - ГОУВПО СПбГТУРП. СПб., 2010. - 151 с.
12. El-Sharkawi M.A. et al. Localization of Winding Shorts Using Fuzzified Neural Networks. Proceedings of IEEE Transactions on Energy Conversion. 1995. Vol. 10. № 1. - P.147-155.

13. Iranmanesh H., Abdollahzade M., Miranian A. Forecasting energy consumption using fuzzy transform and local linear neuro fuzzy models // International Journal on Soft Computing. 2011. Vol. 2. No. 4. - P. 11-24.
14. Bhinge R. et al. An Intelligent Machine Monitoring System for Energy Prediction Using a Gaussian Process Regression. Proc. in IEEE International Conference on Big Data (Big Data). 2014.
15. Liu C., Rather Z.H., Chen Z., Bak C.L. An overview of decision tree applied to power systems // International Journal of Smart Grid and Clean Energy. 2013. Vol. 2. No. 3. - P. 413-419.
16. Клячкин В.Н. и др. Оценка эффективности диагностики состояния объекта по наличию неслучайных структур на карте Хотеллинга // Автоматизация процессов управления. 2015. № 1 (39). - С. 50-56.
17. Вычужанин В.В., Шибаева Н.О. Информатизация прогнозирования риска структурно сложных технических систем с помощью моделей байесовских сетей доверия // Информатика и математические методы в моделировании. 2016. Том. 6. №. 3. - С. 205-214.
18. Shin S.J. et al. Developing a decision support system for improving sustainability performance of manufacturing processes // Journal of Intelligent Manufacturing. 2017. Vol. 28. Iss. 6. - P. 1421-1440.
19. Lechevalier D. Bhinge R. et al. An Intelligent Machine Monitoring System for Energy Prediction Using a Gaussian Process Regression. Proc. in IEEE International Conference on Big Data (Big Data). 2014.
20. Липатов М. Первый в России комплекс предиктивной аналитики для энергетического и промышленного оборудования // Экспозиция. Нефть. Газ. 2016. № 3 (49). - С. 82-83.

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*Received 04.04.2019*