E3S Web of Conferences 458, 01014 (2023) https://doi.org/10.1051/e3sconf/202345801014
EMMFT-2023

Application of data models in power grids for loss reduction and disaster anticipation

Fariza Nusipova[1] and *Amandyk* Kartbayev[1*]

[1]Kazakh-British technical university, Almaty, Kazakhstan

Abstract. This paper addresses the critical objective of optimizing power flow within a region, particularly focusing on the Mangystau region, amidst evolving energy demands and the integration of renewable resources. The escalating challenges associated with maintaining both system stability and economic viability underscore the significance of this research, as suboptimal power flow conditions can exacerbate climate change. To expedite the solution to the optimal power flow problem, machine learning algorithms are explored. Initially, load data from the region is analyzed, and various supervised learning algorithms are tested using simulation data to predict power flow patterns. The primary concern in the Mangystau region lies in the aging infrastructure of oil companies, which operates under suboptimal conditions. This study employs neural networks in Matlab to simulate the electrical system's parameters, unveiling the intricate relationship between optimal system parameters and those of the examined system. Comparing these results with analytical grid modeling, the study reveals that system optimization aligns with target values, particularly concerning optimal receiver replacement schemes. Keywords: power distortion, data analysis, neural networks, power grids, reactive power, disaster anticipation.

1 Introduction

Kazakhstan, known for its diverse energy resources and significant global energy contributions, faces multifaceted challenges and opportunities within its energy landscape. The Mangystau region, nestled within this energy-rich nation, is a notable energy generator, primarily reliant on its gas resources. Additionally, it once housed Kazakhstan's sole nuclear power plant, in Aktau, featuring a 350MW fast neutron reactor, which was operational from 1973 to 1999. However, the nation has since steered away from nuclear energy as part of its energy mix.

This article seeks to shed light on the intricate electricity supply issues encountered within the oil fields of Mangystau Oblast, offering insights into the complex web of energy distribution, losses, and optimization strategies. Traditionally, the equivalent method of resistance has been the go-to approach for estimating energy losses in power grids, offering a simplified means of assessing losses across the network [1]. However, this method's

* Corresponding author: a.kartbayev@gmail.com

accuracy diminishes when applied to modern enterprise electrical networks grappling with dynamic loads that impact the industrial processes.

In response to these challenges, the realm of computational digital technology and artificial intelligence has ushered in a plethora of advanced tools and techniques. Among these, neural networks stand out as a progressive and highly precise method for addressing the complexities of energy distribution and optimization [2].

To delve into the intricacies of energy forecasting and optimization, a neural network with error reversal has been developed, consisting of seven neurons and leveraging the Levenberg-Marquardt back propagation algorithm. Utilizing the Simulink package within the MATLAB software system, this model simulates the operation of a power grid while factoring in active and reactive overloading of consumers, driven by stochastic processes with normal distributions and exponential-cosine correlative functions [3].

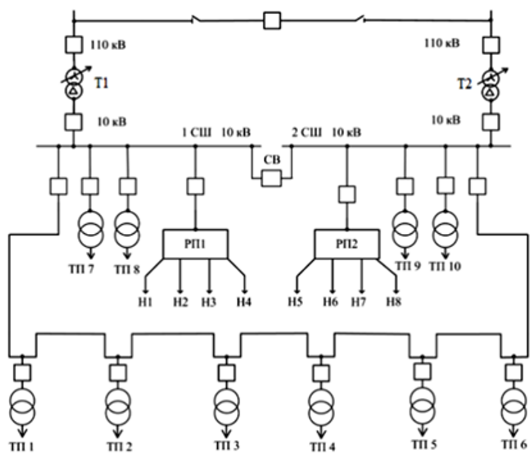

Fig. 1. The example of the site of the power grid

Despite their inherent complexity, neural networks excel in capturing intricate dependencies, outperforming conventional prediction methods [4]. This potential holds promise for refining energy forecasts and optimization. Optimizing the reactive power mode relies on compensating devices guided by reactive load forecasts. Gradient optimization methods, utilizing iterative algorithms, drive the search for optimal solutions..

2 Problem statement

This section delves into the application of neural networks to tackle the challenge of calculating and mitigating losses in a complex power grid, exemplified in Figure 1. The examined power grid comprises radial branches and a ring section, housing six substations drawing power from 10 kV main lowering substations—a configuration typical of industrial power grids. Figure 2 provides a detailed model of this power grid.

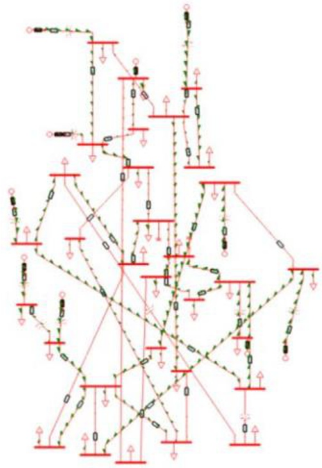

Fig. 2. IEEE 39 Bus Model

Power supply systems in oil complex enterprises, including those in the Mangystau region, feature substantial capacity, diverse electric receiver loads, and extensive geographical dispersion. Meanwhile, socially important facilities pose unique challenges related to power quality, characterized by load asymmetry, concentrated locations, and heightened sensitivity to electric energy quality.

The research scope encompasses electric complexes of both oil industry enterprises and socially significant facilities, serving as representative examples of diverse enterprises. For electrical complexes of socially important objects, characteristics include shorter power lines, a higher non-linearity coefficient, and relatively smaller installed capacity.

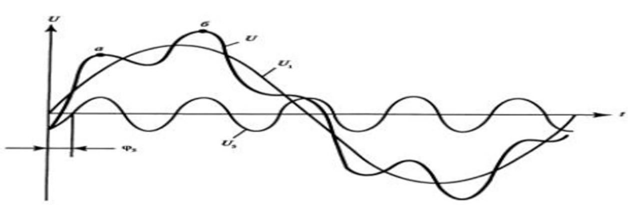

Fig. 3. Decomposition of the non-sinusoidal curve into sinusoidal components

It is evident that different enterprises will be impacted differently by varying indicators of electric energy quality, making it essential to analyze the key quality indicators that influence energy losses within an enterprise's electrical supply system. The primary quality indicators that exert a significant influence on energy losses are non-sinusoidal current and load power factor.

Non-sinusoidal curves result from loads with nonlinear volt-ampere characteristics. These loads introduce non-sinusoidal currents into the mains, which are characterized by the presence of higher harmonic components. This distortion subsequently affects the mains voltage curve. Figure 3 illustrates the presence of harmonic distortions in the voltage curve, which can be disentangled into its main (first harmonic) and fifth harmonic components using the Fourier transform [5]. This results in the formation of a zero sequence, especially in the presence of symmetrical loads, as depicted in Figure 4.

Non-sinusoidal characteristics pose adverse effects on consumers and electrical energy quality control devices. For instance, capacitors in the network may fail due to higher harmonic currents, as capacitor resistance is inversely related to the harmonic component's order.

Consequently, the non-sinusoidal nature of the current curve directly influences active power loss. While non-sinusoidal voltage doesn't directly impact active power loss, it can distort the current curve's sinusoidality. The relationship between losses and current distortions is quantified [6].

Bus Number	Base kV	Voltage (pu)	Angle (deg)	Normal Vmax (pu)	Normal Vmin (pu)	Emergency Vmax (pu)	Emergency Vmin (pu)
1	1.0	1.0789	-8.13	1.1000	0.9000	1.1000	0.9000
2	1.0	1.0968	-5.92	1.1000	0.9000	1.1000	0.9000
3	1.0	1.0809	-8.47	1.1000	0.9000	1.1000	0.9000
4	1.0	1.0630	-9.13	1.1000	0.9000	1.1000	0.9000
5	1.0	1.0635	-8.02	1.1000	0.9000	1.1000	0.9000
6	1.0	1.0614	-7.36	1.1000	0.9000	1.1000	0.9000
7	1.0	1.0500	-9.35	1.1000	0.9000	1.1000	0.9000
8	1.0	1.0488	-9.81	1.1000	0.9000	1.1000	0.9000
9	1.0	1.0622	-9.67	1.1000	0.9000	1.1000	0.9000
10	1.0	1.0666	-5.20	1.1000	0.9000	1.1000	0.9000

Fig. 4. Dependence of inductance resistance on the order of harmonic components at different resistances on the main harmonic

Reactive power (reactive energy) is detailed in [7], and it doesn't perform useful work as it cannot convert to thermal or mechanical energy. The power factor represents the proportion of total power that becomes active power. It's crucial to distinguish it from the reactive power factor, which considers the nature of reactive power (inductive or capacitive) and is more precise. Moreover, the power factor remains relevant even with higher harmonic voltage or current distortions in the network.

3 Results

Short-term electric load forecasting currently relies on several factors, including historical load patterns, weather forecasts, and data from the previous year. However, these methods often require the construction of complex load models[8]. To address this limitation, neural network forecasting technology has emerged as a promising alternative, comprising two key stages: the selection of neural network architecture and the determination of weights through training.

Optimizing electrical energy loss is crucial and neural network optimization proves rational due to its simplicity and ability to provide multiple solutions. It identifies the minimum set of corrective devices with maximum impact on power quality. Distortion levels depend on factors such as load composition, receiver power, operation modes, spatial distribution of consumers, and orientation to the energy source. Assessing consumer impact on active power losses considers active power and power factor, with assumptions in place for investigation. The optimal solution is chosen based on rationality and efficiency criteria.

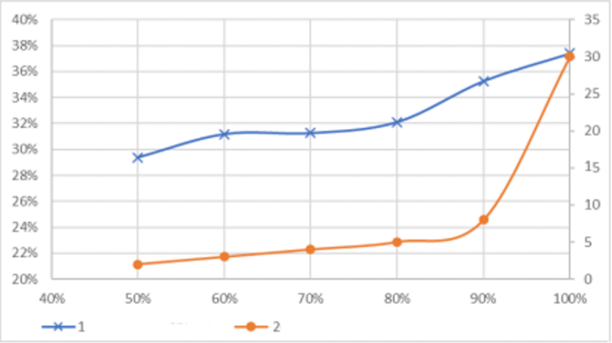

Fig. 5. Dependence of total power loss

The analysis of Figure 5 charts reveals promising insights into compensation strategies' potential benefits. Specifically, compensating for distortions created by 80% of consumers can lead to a remarkable 32% reduction in electric energy losses. Expanding this compensation to encompass all consumers results in a slightly higher reduction of 37.4%. Notably, the cost associated with implementing compensation devices for 80% compensation is considerably lower compared to compensating for all distortions, underscoring the economic feasibility of targeted compensation strategies.

Classical mathematical methods face challenges due to the numerous factors influencing electric load and the nonlinear nature of these dependencies[9]. Traditional statistical approaches often fall short in providing accurate forecasts in modern conditions, making neural network-based methods increasingly attractive. Comparative analyses of forecasting techniques have highlighted limitations in some methods, leading to significant estimation errors, while others, due to their complex mathematical nature, struggle to find practical utility in the power industry. Therefore, there is an ongoing need for the development of improved load forecasting methods[10].

In addition to conventional approaches, a novel method that combines fuzzy logic and neural networks is gaining popularity. Neural networks excel at various tasks like approximation, classification, prediction, and estimation without requiring the construction of detailed object models, making them resilient to incomplete input data[11]. However, they have drawbacks such as slow training and challenges in post-analysis. These limitations can be mitigated by integrating fuzzy logic systems. Given the inherent randomness in power system load fluctuations, which lack strict periodicity due to natural growth, variable factors, and random influences, traditional load prediction methods face substantial challenges.

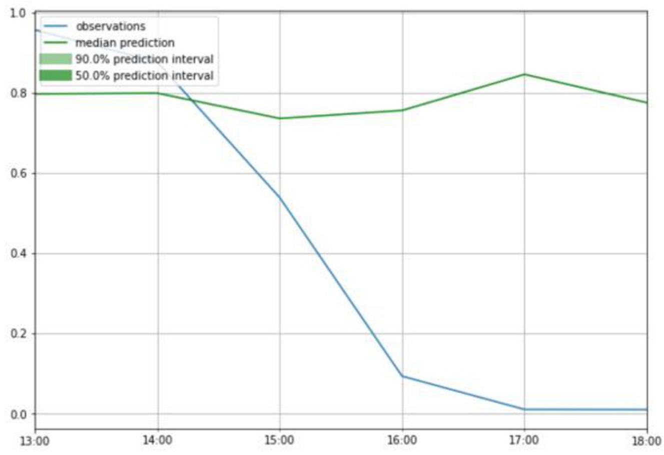

Fig. 6. Forecasting peak loads

This has opened the door for the adoption of neural networks and fuzzy neural networks, with the proposed fuzzy neural network method demonstrating superior forecasting accuracy[12]. On average, it exhibits a forecast error of 2.5% for working days and 1.5% for weekends. In comparison, regression analysis yields the highest forecast error, with errors of 3.5% for working days and 3.0% for weekends, while neural networks show an average forecast error of 2.9% for working days and 2.1% for weekends. Consequently, forward propagation neural networks (multilayer perceptrons) and fuzzy neural networks emerge as the optimal tools for accurate electrical load forecasting.

4 Conclusion

The analysis encompassed various distribution network modes within an enterprise, each characterized by distinct technological processes, network topology, and load profiles, leading to the identification of deviations in electric energy quality indicators from the desired levels. Subsequently, an effective multidimensional optimization method was selected for application in optimizing the distribution network modes of the enterprise, targeting minimum power losses, even in the presence of voltage and current distortions.

The development of methodological support for solving the problem of enhancing the efficiency of compensating device utilization, considering diverse functional relationships between power losses and electric energy quality indicators, was a crucial aspect of this study. Additionally, a computer program was designed to determine the connection points and parameters of compensating devices using the established methodology. The simulation model, aligned with the analytical findings, validated the correctness of the derived expressions and results, providing a comprehensive framework for optimizing distribution network modes and improving energy efficiency.

References

1. E. Gracheva, M. Toshkhodzhaeva, O. Rakhimov, A. Vohidov, I. Ismoilov. Experience in Reactive Power Compensation in the Power Supply System of Industrial Facilities. In: Sustainable Energy Systems: Innovative Perspectives, pp.110-118. (2021)
2. M. Amin, The electric power grid: Today and tomorrow, MRS bulletin 33, 04, pp.399-407 (2008)

3. F. Kiessling. Overhead power lines: planning, design, construction, Springer, 321. (2014)
4. A. Kartbayev. Refining Kazakh Word Alignment Using Simulation Modeling Methods for Statistical Machine Translation. Lecture Notes in Computer Science, Springer, vol. **9362**, pp. 421-427. (2015)
5. A. Kartbayev, U. Tukeyev, S. Sheryemetieva, A. Kalizhanova, B.K. Uuly. Experimental study of neural network-based Word alignment selection model trained with Fourier descriptors. Journal of Theoretical and Applied Information Technology **13(96)**, pp.4103-4113 (2018)
6. A.V. Varganova. On methods of optimizing the operating modes of electric power sys-tems and networks. Bulletin of the South Ural State University, Series: energy **17**, 3 (2017)
7. Y.S. Zhelezko. Loss of electricity. Reactive power. Electric power quality: Manual for practical calculations. ENAS, Moscow (2009)
8. T.T. Omorov, B.K. Takyrbashev. To the problem of the asymmetric operation modes optimization of the distribution networks. Devices and systems. Management, control, diagnostics, Issue 9, pp.11-15 (2016)
9. T.A. Sadykbek, R.E. Matov. Methods and Technical Tools of Improving the Electric Power Quality. Bulletin of the Kazakh Academy of Transport and Communications named after M. Tynyshpaev, Issue **6 (91),** 149-154. (2014)
10. D. Srinivasan, Evolving artificial neural networks for short term load forecasting. Neuro Computing, Elsevier, Issue **23**, 265–276 (1998)
11. A. Kartbayev. An initial study of quality assurance techniques for automated water level control systems, in International Scientific Siberian Transport Forum - TransSiberia, Novosibirsk, E3S Web of Conferences, Volume **402**, pp. pp. 363–369. (2023)
12. Wenna Wang, Defu Cai, Haiguang Liu, Chu Zhou, Kan Cao, Kunpeng Zhou, and Chang Liu. Theoretical Analysis of Power Loss Reduction for Typical Power Grid. In Proceedings of the 2020 International Conference on Aviation Safety and Information Technology, NY, pp.383–387. (2020)