УПРАВЛІННЯ В ТЕХНІЧНИХ СИСТЕМАХ

CONTROL IN TECHNICAL SYSTEMS

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APPLICATION OF BAYESIAN REGULARIZATION FOR IMPROVING THE QUALITY OF ELECTRICAL ENERGY IN THE ELECTRICAL SUPPLY SYSTEM

The possibility of using neural networks in the field of the energy coefficients correction of a power supply system with uneven load in phases is being studied. This need is justified by the fact, that the calculation of the necessary parameters of the symmetry-compensating device was previously based on the Nelder – Mead search optimization method. Search optimization performing is computationally expensive, takes long computation times, and may calculate anomalous values. The article develops the idea of using technology for predicting the parameters of a symmetry-compensating device, based on neural network modeling using Bayesian regularization. For a given set of initial data, the best selected configuration turned out to be a neural network of two layers, implemented in the MATLAB package using the machine learning tool Neural Network Toolbox. The network input parameters are a set of tuples, consisting of load values in each of the three phases of the power supply system, which are resistive-inductive in nature. There are six input quantities in total (load resistance and inductance values in each of the three phases) and all their values are different, which causes current asymmetry in the network and reactive power. The target matrix is formed from tuples, consisting of three values, which are the parameters of the symmetrical compensating device, calculated by the optimization method, in such a way as to compensate reactive power and to balance currents in the network. The number of data tuples, required to train a neural network was determined empirically. During the experiments, the optimal number of neurons in the neural network was also revealed. The use of the generated neural network to calculate the parameters of the symmetry-compensating device determined approximate solutions is comparable in accuracy to the values, found by optimization methods. With the help of the generated neural system, adequate quasi-solutions for calculating the parameters of the symmetry-compensating device were determined, which, in case of calculation, using the optimization method, led to anomalous values, that didn't optimize the energy coefficients of the power supply system to the required extent. Also, such neuropredictions protect the system from receiving excessive high parameters of symmetry compensating device, which can be obtained with an optimization approach.

Keywords: neural network, Bayesian regularization learning algorithm, input matrix, target matrix, set of taples, search optimization methods, power supply system.

Introduction. Issues of improving the quality of electrical energy are key to the development of the Ukrainian economy and require the implementation of modern intellectual tools to improve energy performance. The unbalanced load of consumers in the phases of a three-phase power supply system leads to such phenomena, as an increase in current values in the network, their asymmetry and an increase in reactive power. High values of these indicators have a negative impact both on the equipment, used by consumers themselves, and on the power supply system as a whole. One way to solve this problem is to use special symmetry-compensating devices connected to a section of the power supply system, the parameters of which are calculated in such a way as to balance the currents in the power supply system and reduce reactive power to zero.

Optimization methods make it possible to calculate the parameters of symmetry-compensating devices with high accuracy [1, 2], however, this approach has a number of disadvantages. It takes quite a long time, since the number of iterations on average reaches 200–300. In addition, depending on the setting of the initial conditions, alternative cases may arise, when, using optimization methods, where the values of symmetry-compensating devices determined are by an order of magnitude greater than those, used in practice [3]. Situations arise, when calculations lead to anomalous values, that do not actually balance currents in the network and do not reduce reactive power.

The application of neural networks is a powerful tool for quickly determining the parameters of symmetry-compensating devices and monitoring their adequacy of the solution [4–10], so the issue of their use in the field of improving electrical energy coefficient is actual.

Purpose of the study. The purpose of the article is to study the possibility of using a neural network with Bayesian regularization learning algorithm to calculate the parameters of a symmetry-compensating device, that increases the energy coefficients of the power supply system.

Main part. The power supply system, considered in the study, consists of voltage sources, resistance of power line wires, characterized by active and inductive elements, designated accordingly in each phase za, zb, zc, La, Lb, Lc, load currents, consisting of active resistances Ra, Rb, Rc and inductances La, Lb, Lc. Compensation of reactive power, reduction of current values and their balancing in the network is carried out by a symmetry compensating device, which consists of three balancing capacitors, each of which is connected between two phases of the supply system, respectively Cab, Cbc, Cac. An uneven load in each phase of the power supply system creates current asymmetry (fig. 1) and contributes to an increase in reactive power in the power supply.

To balance currents in the network and minimize reactive power, it is necessary to calculate the corresponding values of compensating capacitors. Such values can be determined with high accuracy using the Nelder – Mead optimization method or the deformed polyhedron method. In this study, this method was used to compile a training set of experimental data for further training of the neural network.

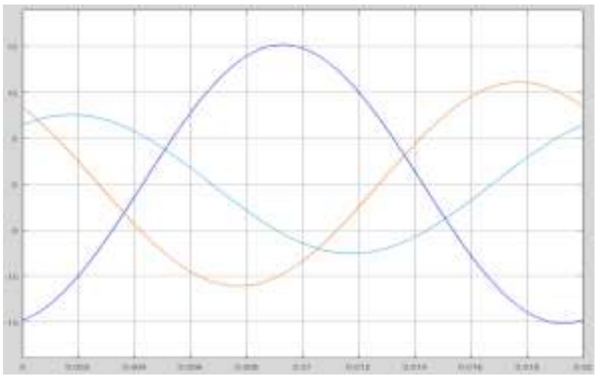


Fig. 1. Oscillograms of power network currents in asymmetric load mode

The research itself was carried out in MATLAB using the machine learning tool Neural Network Toolbox. To train the neural network, the Bayesian regularization algorithm was chosen, which is based on a probabilistic approach. This kind of approach to training a neural network has a number of advantages: it allows to carry out fairly accurate data predictions, does not require iterative training procedures, and is cost-effective from a computational point of view [11–13]. The architecture of the selected neural network is shown in fig. 2. During the experiments carried out, it was found, that the most acceptable network training occurs with a number of neurons equal to 28.

Initial training of the neural network was completed on data set, that consisted of 70 tuples. Here, the training data sets were compiled in such a way, that the load value in one of the phases (for example, in phase C) significantly exceeded the load values in the other phases. To do this, the load in phase C gradually increased in the following ranges Rc = [1–10] Om, Lc = [0.005–0.08] H in the tuples, and the parameter values in other phases changed within the following limits of their values – in phase A: Ra = [0.09–0.1] Om, La = [0.001–0.02] H; in phase B: Rb = [0.9–3] Om, Lb = [0.01–0.12] H. At the same time, two variants of the target matrix were considered for training the neural network. In the first version, the matrix consisted of both positive and negative values of the symmetry-compensating device (as it was determined directly during optimization); fig. 3, *a–c*.

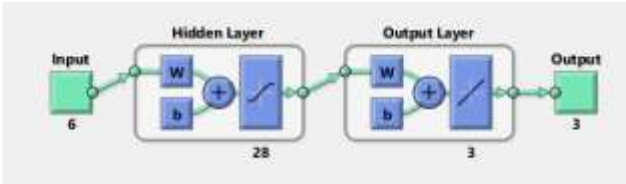


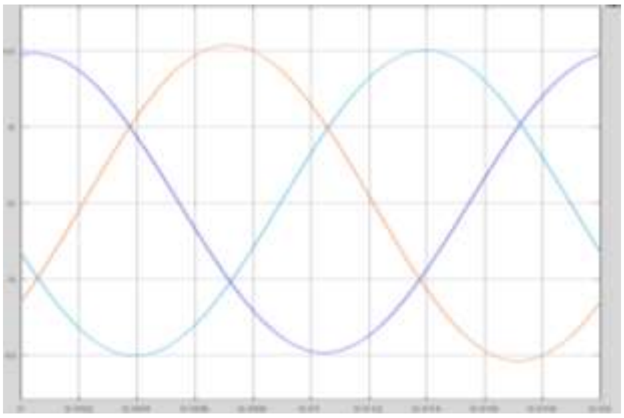
Fig. 2. Architecture of the selected neural network

In the second option, all negative values were replaced with positive equivalents (fig. 4, *a–c*), since in fact values that are substituted into the symmetry-compensating device, are previously converted to positive values and are multiplied by 10^{-6}. Using a neural network, in which only positive values are specified in the target matrix gives a more accurate result (fig. 3, *a*) than a neural network in which the target matrix was used with both positive and negative values (fig. 4, *a*). Therefore, in future researches, a target matrix is used, which consists only of positive values.

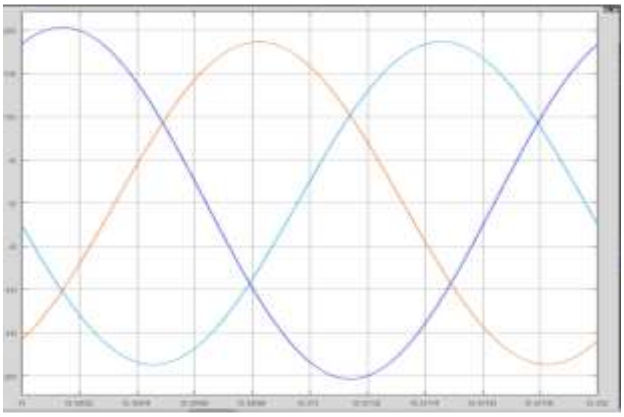
The calculation results showed, that the data used, in which the load value in phase C exceeds the load values in the other phases, made it possible to train a neural network that determines the parameters of the control system with sufficient accuracy, setting the load in the phases within the appropriate limits. However, for example, when the load in phase B sufficiently increased, the neural network calculated values that do not balance the load currents in the network and do not compensate reactive power (fig. 5, fig. 6). So, we have to expand the data set.

To improve the accuracy of the calculations, the dataset for training the neural network was increased three times by adding new data sets of tuples. First additional data set was generated by swapping position of the parameters of phases of power supply system A with B, that are parameters of the input matrix and in the target matrix. Second additional data set has been received by swapping tuples position of the input matrix and of the target matrix of phases A with C. Such a way we reached an opportunity to expand the training capabilities of a neural network. Thus, the trained neural network made ability to conduct a number of experiments that made it possible to find adequate values for the parameters of symmetry-compensating devices (fig.7).

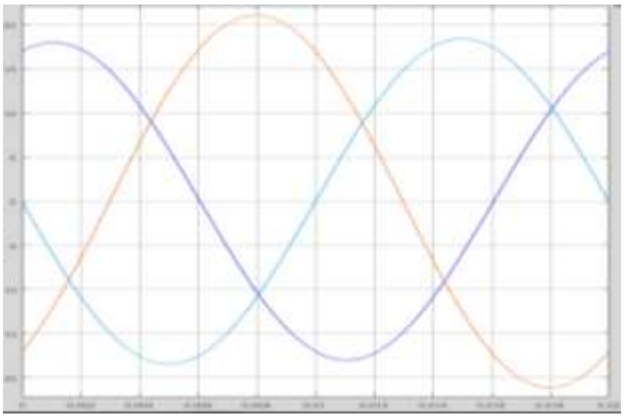
However, in some cases, current balancing may not be performed to the required extent (fig. 8). In such a case, the neural network was retrained, which led to a positive result (fig. 9).



a

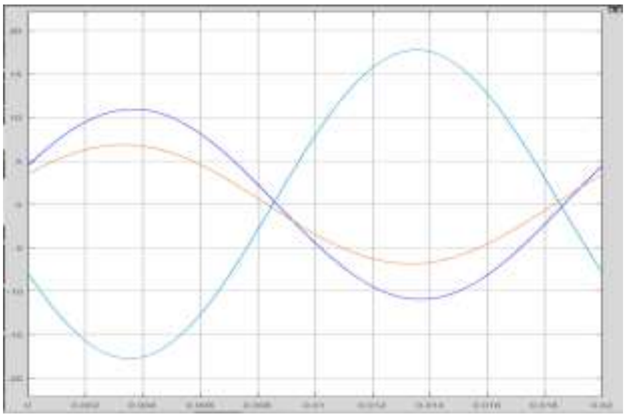


b



c

Fig. 3. Oscillogram of currents in supply line with parameters of SCD calculated by a neural network with a target matrix having only positive values: *a* – with parameters Ra = 0.1, La = 0.003, Rb = 1.2, Lb = 0.1, Rc = 2.5, Lc = 0.04 and capacities of compensating capacitors Cab = 220.6514, Cbc = 90.8858, Cac = 316.5833; *b* – with parameters Ra = 0.7, La = 0.005, Rb = 1, Lb = 0.01, Rc = 2.5, Lc = 0.08 and capacities of compensating capacitors Cab = 759.2736, Cbc = 317.1794, Cac = 152.9549; *c* – with parameters Ra = 0.6, La = 0.005, Rb = 1, Lb = 0.01, Rc = 2, Lc = 0.08 and capacities of compensating capacitors Cab = 711.8675, Cbc = –281.2767, Cac = 116.2679



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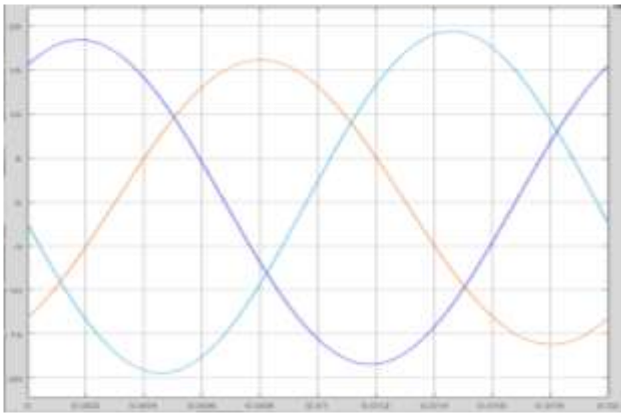

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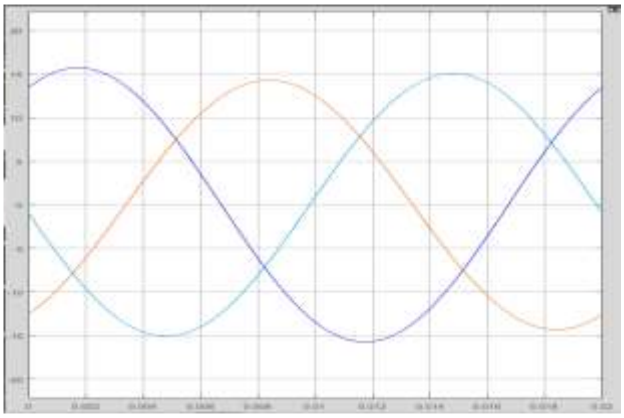

c

Fig. 4 Oscillogram of currents in supply line with parameters of SCD calculated by a neural network with a target matrix specified by positive and negative values: *a* - with parameters Ra = 0.1, La = 0.003, Rb = 1.2, Lb = 0.1, Rc = 2.5, Lc = 0.04 and capacities of compensating capacitors Cab = 17.1714, Cbc = –148.2129, Cac = 413.4182; *b* - with parameters Ra = 0.7, La = 0.005, Rb = 1, Lb = 0.01, Rc = 2.5, Lc = 0.08 and capacities of compensating capacitors Cab = 707.7111, Cbc = –331.1599, Cac = 150.9918; *c* - with parameters Ra = 0.6, La = 0.005, Rb = 1, Lb = 0.01, Rc = 2, Lc = 0.08 and capacities of compensating capacitors Cab = 711.8675, Cbc = –281.2767, Cac = 116.2679

Using the developed neural network, the parameters of the control system were determined in operating modes in which anomalous values were obtained during search optimization that did not balance the currents in the network. These data are shown in table 1.

To reduce the number of iterations when using optimization methods, non-zero initial conditions are set. However, with this approach, the resulting solution can be characterized by fairly large values of energy coefficients. For example, with the parameters of the supply network Ra = 0.7, La = 0.005, Rb = 1, Lb = 0.01, Rc = 2, Lc = 0.04

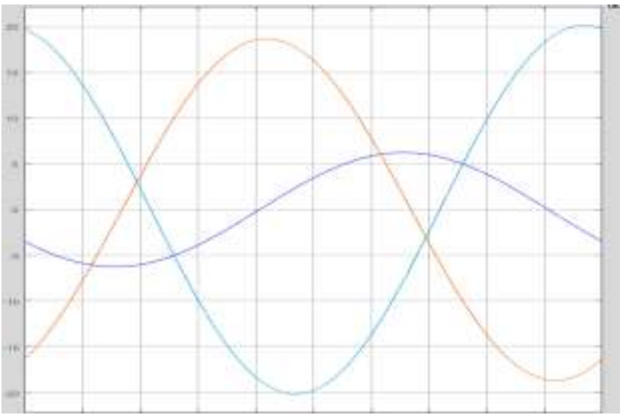

Fig 5. Oscillograms of currents of network with parameters Ra = 1, La = 0.01, Rb = 2, Lb = 0.04, Rc = 0.3, Lc = 0.003 and capacities of compensating capacitors Cab = –346.0767, Cbc = –205.0130, Cac = 393.6867 calculated by a neural network trained on 70 sets of tuples

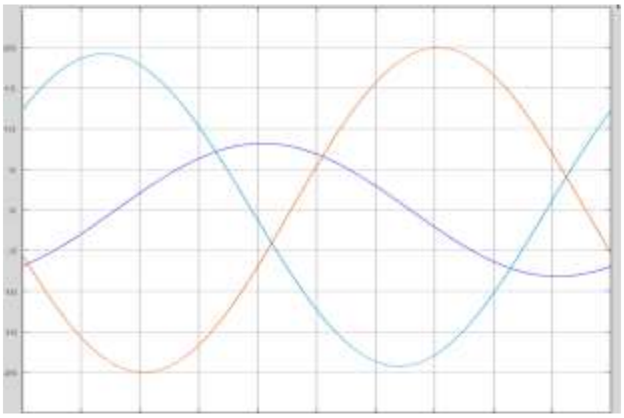

Fig. 6. Oscillograms of currents of network with parameters Ra = 2, La = 0.04, Rb = 0.3, Lb = 0.003, Rc = 1, Lc = 0.01 and capacities of compensating capacitors Cab = 45.8234, Cbc = 382.2415, Cac = –26.90376, calculated by a neural network trained on 70 sets of tuples

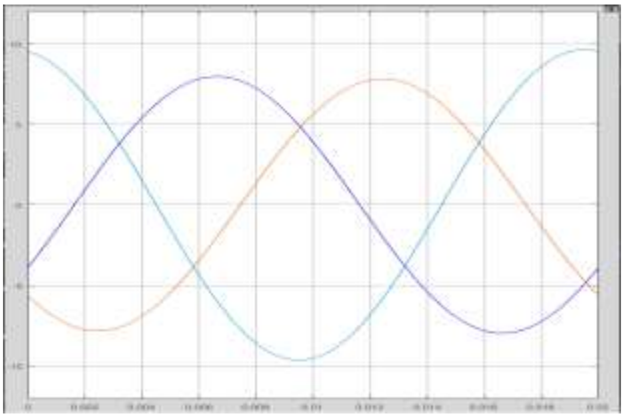

Fig. 7. Oscillograms of currents of network with parameters Ra= 1, La = 0.01, Rb = 2, Lb = 0.04, Rc = 0.3, Lc = 0.003 and capacities of compensating capacitors Cab = 137.8644, Cbc = 45.4429, Cac = 621.1652 calculated by a neural network trained on 210 sets of tuples

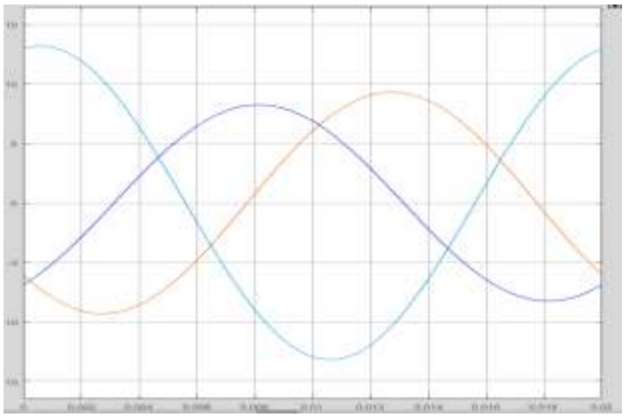

Fig. 8. Oscillograms of currents of network with parameters Ra = 2, La = 0.04, Rb = 0.3, Lb = 0.003, Rc = 1, Lc = 0.01 and capacities of compensating capacitors Cab = 46.1874, Cbc = 631.5026, Cac = 26.9037 calculated by a neural network trained on 210 sets of tuples

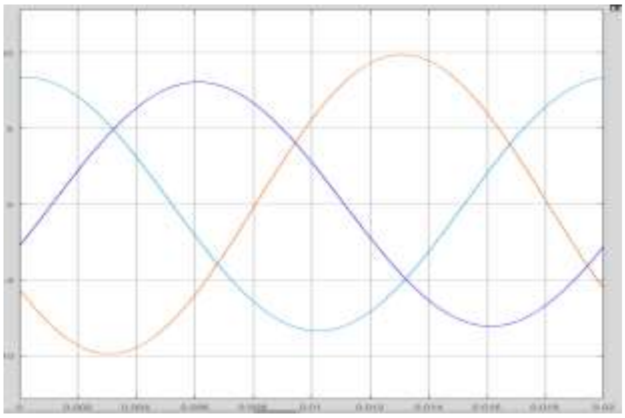

Fig. 9. Oscillograms of currents of network with parameters Ra = 2, La = 0.04, Rb = 0.3, Lb = 0.003, Rc = 1, Lc = 0.01 and capacities of compensating capacitors Cab = 35.7603, Cbc = 613.3234, Cac = 128.8183 calculated by a neural network trained on 210 sets of tuples after retraining

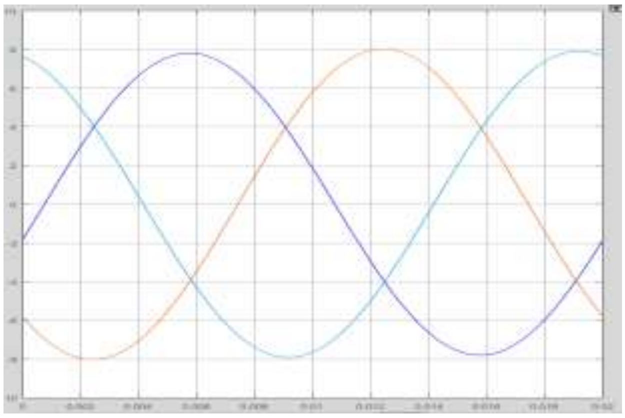

Fig. 10. Oscillograms of currents of network with parameters Ra = 0.7, La = 0.005, Rb = 1, Lb = 0.01, Rc = 2, Lc = 0.04 and capacities of compensating capacitors Cab = 543.8627, Cbc = 159.7113. Cac = 12.7429

Table 1 – Parameters of symmetry-compensating device with anomalous values

Electrical network parameters Ra, La, Rb, Lb, Rc, Lc	Anomalous values received by optimization Cab, Cbc, Cac	Capacitor values calculated using a neural network Cab, Cbc, Cac
0.3; 0.0061; 1; 0.04; 1.9; 0.06	135.4102; –0.0000; –0.4816	194.4882; 11.6204; 109.8851
0.3; 0.0061; 1; 0.04; 1.91; 0.06	135.4781; 0.0000; –0.4822	194.5336; 11.6506; 109.9143
0.3; 0.0061; 1; 0.04; 2.5; 0.06	139.3876; –0.0000; –0.4576	200.2118; 7.5557; 105.3951
0.3; 0.006; 1; 0.04; 2; 0.06	135.9989; 0.0000; 0.8182	196.3479; 11.9890; 110.6901
0.3; 0.001; 1; 0.04; 2; 0.06	176.9020; –0.0001; –0.5585	270.6922; 25.1454; 156.7750

and the initial conditions Cab = Cbc = Cac = 4000, the capacitance values of the compensating capacitors reached high values Cab = 3935.3, Cbc = 3555.5, Cac = 3407.7. Such values actually compensate reactive power and balance currents in the phases, however, the values of network currents reach more than 800 A, which is extremely dangerous for the wires of the power supply system and unacceptable for use. When calculating the parameters of a symmetry-compensating device using the generated neural network, the values Cab = 543.8627, Cbc = 159.7113, Cac = 12.7429 were obtained. They balance the currents and reduce their values sufficiently (fig. 10), and can be used in practice. It should also be noted, that the results obtained are quite close to the exact values obtained from calculations using the optimization method with initial conditions Cab = Cbc = Cac = 0, where final result is Cab = 562.2, Cbc = 182.3, Cac = 34.4.

Conclusions

1. During the experiments, the parameters of the neural network and the number of training data sets were determined, which calculate the parameters of the symmetry-compensating device that optimizes the operation of the power supply system. This significantly reduces the time required for balancing network currents and reactive power compensation in the power supply system.

2. The generated neural network, trained using Bayesian regularization algorithm, makes it possible to determine adequate parameters for symmetry-compensating device, which, when calculated using optimization methods, did not increase the energy coefficients in the power supply system and were not anomalous parameters,

3. When receiving data that does not sufficiently improve the energy coefficients of the power supply system, it is possible to correct the symmetry-compensating device data sets by retraining the neural network using the Bayesian regularization algorithm.

References

1. Ягуп Е. В. Расчет параметров устройства компенсации реактивной мощности с использованием модели и поисковой оптимизации. *Збірник наукових праць Української державної академії залізничного транспорту.* 2014. № 150. С. 115–120.
2. Ягуп Е. В. Моделирование несимметричной системы электроснабжения с использованием оптимизации для определения параметров симметрирующего устройства. *Збірник наукових праць Українського державного університету залізничного транспорту*. 2016. №161. С. 130–138.
3. Ягуп Е. В., Ягуп В. Г. Исследование режимов полной компенсации реактивной мощности в трехфазной системе электроснабжения. *Електротехніка і електромеханіка*. 2019. №2. С. 61–65.
4. Hu W., Liu B., Gomes J. *Strategies for Pre-training Graph Neural Networks.* URL: https://arxiv.org/abs/1905.12265 (access date: 01.11.2023).
5. Dahl G., Jaitly N., Salakhutdinov R. *Multi-task neural networks for QSAR predictions*. URL: https://arxiv.org/abs/1406.1231 (access date: 01.11.2023).
6. Graves A., Wayne G., Danihelka I. *Neural Turing machines*. URL: https://arxiv.org/abs/1410.5401 (access date: 01.11.2023).
7. Хайкин С. *Нейронные сети.* Полный курс. Москва: Вильямс, 2006. 1104 с.
8. Haykin S. *Neural networks. A comprehensive foundations.* McMillan College Publ.Co. N.Y., 1994. 696 p.
9. Люгер Ф. *Искусственный интелект: стратегии и методы решения сложных проблем*. Москва: Вильямс, 2003. 864 с.
10. Xianjun Ni Research of Data Mining Based on Neural Networks. *World Academy of Science, Engineering and Technology*. 2008. Vol. 39. P. 381–384.
11. Wyner A. J., Olson M., Bleich J., Mease D. Explaining the success of adaboost and random forests as interpolating classifiers. *The Journal of Machine Learning Research.* 2017. Vol. 18, no. 1. P. 1558–1590.
12. Opper M.,. Archambeau C. The variational gaussian approximation revisited. *Neural Computation*. 2009. Vol. 21 (3). P. 786–792.

References (transliterated)

1. Yagup E. V. Raschet parametrov ustroystva kompensatsii reaktivnoy moschnosti s ispolzovaniem modeli i poiskovoy optimizatsii [Calculation of parameters of a reactive power compensation device using a model and search optimization]. *Zbirnyk naukovykh prats Ukrainskoi derzhavnoi akademii zaliznychnoho transportu* [Collection of scientific works of the Ukrainian State Academy of Railway Transport]. 2014, no. 150, pp. 115 –120.
2. Yagup E. V. Modelirovanie nesimmetrichnoy sistemyi elektrosnabzheniya s ispolzovaniem optimizatsii dlya opredeleniya parametrov simmetriruyuschego ustroystva [Modeling of an unbalanced power supply system using optimization to determine the parameters of a balun]. *Zbirnyk naukovykh prats Ukrainskoi derzhavnoi akademii zaliznychnoho transportu* [Collection of scientific works of the Ukrainian State Academy of Railway Transport]. 2016, no. 161, pp. 130–138.
3. Yagup E. V., Yagup V. G. Issledovanie rezhimov polnoy kompensatsii reaktivnoy moschnosti v trehfaznoy sisteme elektrosnabzheniya. [Research of full reactive power compensation modes in a three-phase power supply system]. *Elektrotekhnika i elektromekhanika* [Electrical engineering and electromechanics]. 2019, no. 2, pp. 61–65.
4. Hu W., Liu B., Gomes J. *Strategies for Pre-training Graph Neural Networks.* URL: https://arxiv.org/abs/1905.12265 (access date: 01.11.2023).
5. Dahl G., Jaitly N., Salakhutdinov R. *Multi-task neural networks for QSAR predictions*. URL: https://arxiv.org/abs/1406.1231 (access date: 01.11.2023).
6. Graves A., Wayne G., Danihelka I. *Neural Turing machines*. URL: https://arxiv.org/abs/1410.5401 (access date: 01.11.2023).
7. Haykin S. *Neyronnyie seti. Polnyiy kurs.* [Neural networks. A comprehensive foundations]. Moscow, Vilyams Publ., 2006. 1104 p.
8. Haykin S. *Neural networks. A comprehensive foundations.* McMillan College Publ.Co. N.Y. 1994. 696 p.
9. Lyuger F. *Iskusstvennyiy intelekt: strategii i metodyi resheniya slozhnyih problem* [Artificial Intelligence: Strategies and Methods for Solving Complex Problems]. Moscow: Vilyams Publ., 2003. 864 p.

10. Xianjun Ni Research of Data Mining Based on Neural Networks. *World Academy of Science, Engineering and Technology*. 2008, vol. 39, pp. 381–384.
11. Wyner A. J., Olson M., Bleich J., Mease D. Explaining the success of adaboost and random forests as interpolating classifiers. *The Journal of Machine Learning Research.* 2017, vol. 18, no.. 1, pp. 1558–1590.
12. Opper M., Archambeau C. The variational gaussian approximation revisited. *Neural Computation*. 2009, vol 21 (3), pp. 786–792.

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ЗАСТОСУВАННЯ БАЙЄСІВСЬКОЇ РЕГУЛЯРИЗАЦІЇ ДЛЯ ПІДВИЩЕННЯ ЯКОСТІ ЕЛЕКТРИЧНОЇ ЕНЕРГІЇ В СИСТЕМІ ЕЛЕКТРОПОСТАЧАННЯ

Досліджується можливість використання нейронних мереж у сфері підвищення енергетичних показників системи електропостачання з нерівномірним навантаженням у фазах. Така необхідність обґрунтована тим, що розрахунок необхідних параметрів симетро-компенсувального пристрою раніше ґрунтувався на методі пошукової оптимізації Нелдера – Міда. Виконання пошукової оптимізації вимагає значних обчислювальних витрат, займає тривалий час обчислення і може розраховувати аномальні значення. У статті розвивається ідея використання технології прогнозування параметрів симетро-компенсувального пристрою на основі нейромережевого моделювання із застосуванням байєсівської регуляризації. Для заданого набору вихідних даних найкращою підібраною конфігурацією виявилася нейронна мережа двох шарів реалізована в пакеті MATLAB засобами інструменту машинного навчання Neural Network Toolbox. Вхідні параметри мережі являють собою набір кортежів, що складаються з величин навантажень у кожній із трьох фаз системи електропостачання, що мають резистивно-індуктивний характер. Усього вхідних величин шість (значення опору та індуктивності навантаження в кожній із трьох фаз) і всі їх значення відрізняються, що і створює несиметрію струмів у мережі та реактивну потужність. Матриця цілей сформована з кортежів, що складаються з трьох величин, що є розраховані методом оптимізації параметри симетро-компенсувального пристрою, таким чином, щоб компенсувати реактивну потужність і відсиметрувати струми в мережі. Досвідченим шляхом визначено кількість кортежів даних, необхідні навчання нейронної мережі. Під час проведення експериментів також виявлено оптимальну кількість нейронів нейронної мережі. Застосування сформованої нейромережі для розрахунку параметрів симетро-компенсувального пристрою визначило наближені рішення, які можна порівняти за точністю зі значеннями, знайденими оптимізаційними методами. За допомогою сформованої нейронної системи визначено адекватні квазірішення розрахунку параметрів симетро-компенсувального пристрою, які при розрахунках оптимізаційним методом призводили до аномальних значень, які не виконували оптимізацію енергетичних показників системи електропостачання у необхідній мірі. Також такі нейропередбачення захищають систему від отримання надмірно завищених параметрів симетро-компенсувального пристрою, які можуть бути отримані при оптимізаційному підході та аномальних значень,

Ключові слова: нейронна мережа, навчання за алгоритмом Байєсівської регуляризації, вхідна матриця, матриця цілей, набір кортежей, методи пошукової оптимізації, система живлення.

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