Non-Iterative Neural-Like Predictor for Solar Energy in Libya

Roman Tkachenko[1[0000-0002-9802-6799]] Hakan Kutucu[2[0000-0001-7144-7246]]

Ivan Izonin[1[0000-0002-9761-0096]] Anastasiya Doroshenko[1[0000-0002-7214-5108]]

Yurii Tsymbal[1[0000-0001-9119-6771]]

[1] Lviv Polytechnic National University, Lviv, S. Bandera, 12, 79013, Ukraine
{roman.tkachenko, ivanizonin, anastasia.doroshenko, yurij.tsymbal}@gmail.com
[2] Karabuk University, Department of Computer Engineering, 78050, Karabuk, Turkey
hakankutucu@karabuk.edu.tr

Abstract. In this paper, a new method for predicting the solar radiation potential in Libya was developed. It is constructed on the basis of the combined use of RBF and non-iterative paradigm of the artificial neural networks construction - the Successive Geometric Transformations Model. This method has the advantages of both approaches - the high prediction accuracy from RBF characteristics and fast non-iterative learning provided by the Successive Geometric Transformations Model. A series of practical experiments were conducted. The training model contained 1440 vectors of the monthly solar radiation, which recorded in 25 Libya's cities from 2010 to 2015. The test model contained 360 data's vectors. Comparison of the proposed method with existing ones is presented. The proposed method showed the best prediction results (MAPE, RMSE) compared to SVM, Linear Regression, the linear Neural-like structure of the Successive Geometric Transformation Model (SGTM), and the RBF based on the NLS SGTM. The proposed approach can be used in different areas, such as e-commerce, material science, images processing and others, especially in Big Data cases.

Keywords: Renewable Energy, Neural-Like Structure, Solar-Radiation Potential, Successive Geometric Transformations Model.

1 Introduction

The reserves of renewable energy on Earth are enough to meet all human needs today and in the distant future. Renewable energy sources, the presence of which is due to traditional physical processes on the Earth's surface and at some depth of the earth's crust, accompanied people at all times in its history, and they were the first sources of energy that people began to use meaningfully. Here you can name sails, water and wind mills, wave energy converters, and so on.

The potential of renewable energy sources in the world is substantially higher than the amount of all currently consumed fuel and energy resources [1]. Its rational use will solve a number of problems associated with environmentally hazardous processes for the carbon fuel processing and its savings. In the modern world, energy is the basis for the national economic base industries development, which determines the social production progress [2]. Taking all this into consideration, the use of the power generation alternative sources, in particular, solar energy, is an additional incentive for industrial development, employment and people's living standards, and, ultimately, strengthening and stimulating the economy [3]. All this prompts the intensification of the solar energy use since it can effectively transform into heat and electricity and be used for different consumer needs. The construction of such systems requires, among other things, accurate predicted data on the solar radiation level in a given region [3]. Such information will provide the opportunity to optimize the spent resources for the construction of alternative terrestrial energy [4]. The geographic location of Libya (Fig. 1) (relative humidity, temperature, sunshine duration), as well as meteorological parameters (month, longitude and latitude) (Table 1), suggest that there is sufficient amount of solar radiation in this area [5].

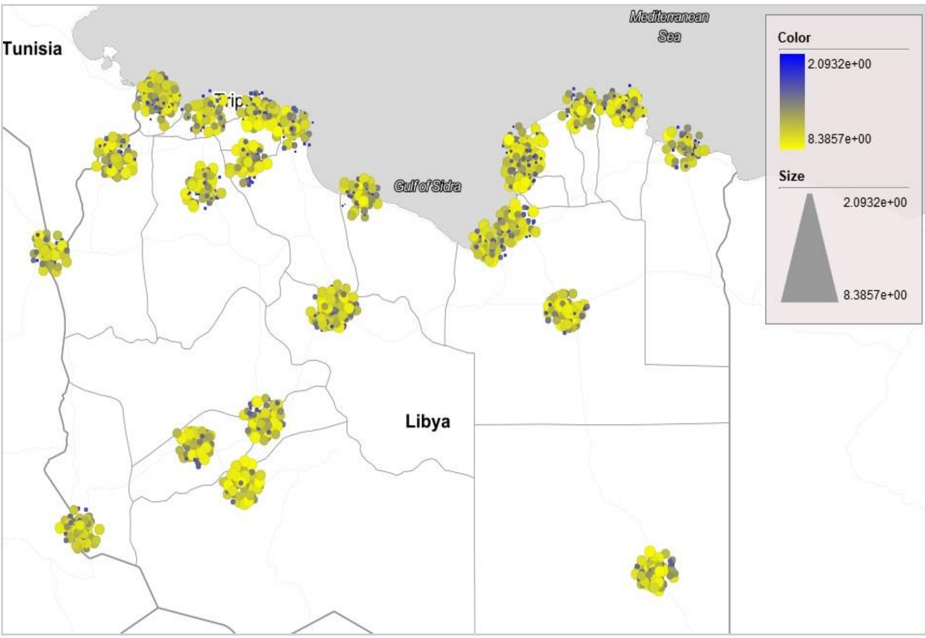


Fig. 1. The map of Libya cities used for prediction (based on Orange Software version 3.8.0).

Collected statistical data [5] in 25 cities of Libya in the period from 2010 to 2015 shows the level of solar radiation, ranging from 2.09 to 8.39 kWh / m2 / day, with average temperature variations in the region of 7 to 35 Celsius.

Table 1. Solar radiation statistical indicators for the period 2010-2015 at 25 cities in Libya.

Indicators							
Month	Latitude	Longitude	Elevation	Mean Temperature	Relative Humidity	Mean sunshine duration	Daily solar radiation

The aim of this work is to describe the developed solar radiation prediction method, which would provide the best results (based on Mean Absolute Percent Error - MAPE, Root Mean Square Error – RMSE, Mean Absolute Error - MAE [3, 6, 7].

2 Predictors Based on the Known Methods

The use of modern computational intelligence tools provides good results, but training models of such systems require a large sample of data [8, 9]. In addition, iterative algorithms for their training are quite slow [10, 11]. The developed linear methods of the solar energy predicting on the basis of SVM [12-16] are characterized by a number of shortcomings. In particular, such methods are sensitive to noise and data standardization. In addition, they are slowly training. Prediction methods based on linear regression [17-19] show satisfactory results only for short-term prediction with stable data. But with a sharp change, they give too many errors. Using such methods may result in an incorrect prediction, which may cause significant damage.

In this paper, we conducted an experimental evaluation of the above methods performance (according to RMSE, MAPE, MAE). The training sample from [5] was used for the experiment. It contains a collection of 1800 data's vectors about the state of solar radiation in 25 cities of Libya for 6 years. The attributes of each vector are given in Table 1. The sample was randomly divided into halves - on the training (80%) and the test (20%) data. It should be noted that the same data was used to solve the problem by the proposed method.

The results of the solar radiation potential prediction in Libya using the SVM-based method and Linear Regression are shown in Fig. 2. We use the Orange software (version 3.8.0) for obtaining these results.

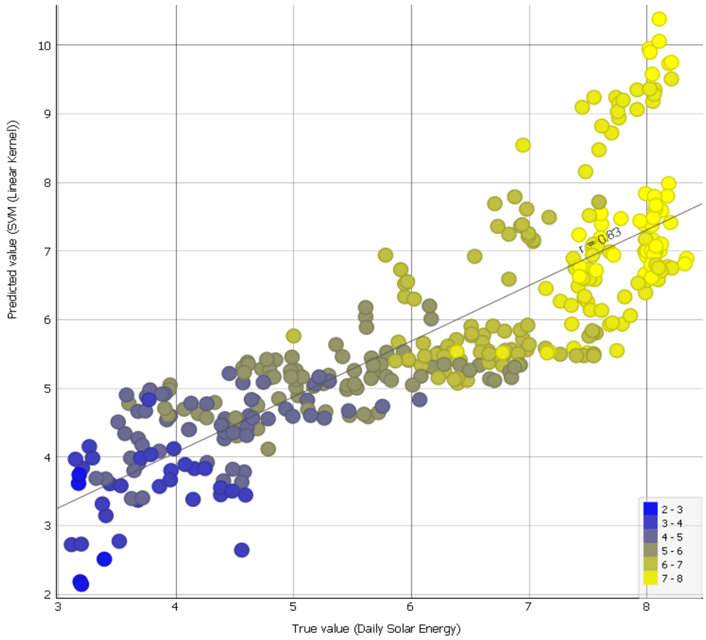
Table 2 presents the results and parameters of both methods comparison using.

Table 2. The comparison of the predicted results by the known methods (obtained by using Orange software).

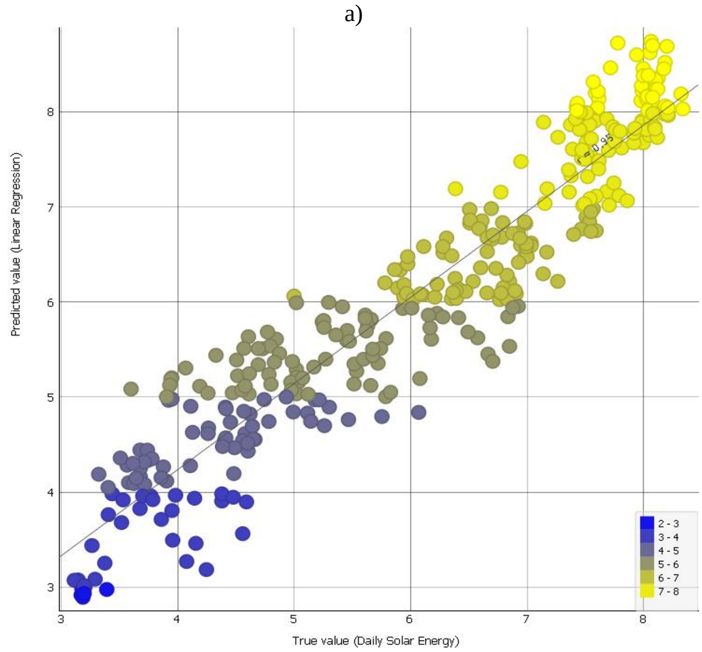
Method	Parameters	RMSE	MAE	MAPE, %
SVM	Linear kernel; Cost: 1.0; Epsilon: 0,10; Numerical tolerance: 0,0010.	0.961497	0.963701	16.4687
Linear Regression	The horizon is equal to 1	0.503864	0.410635	7.3649463

As shown in Table 2, the prediction method based on SVM shows significantly worse results. This is also evident from Fig. 2.

Despite the best results of the linear regression method, its practical application at RMSE = 0.5 and MAPE=7.4 is also ineffective.



a)



b)

Fig. 2. Visualizations of the predicted results by known methods: a) SVM; b) Linear regression.

3 Short-Term Predictors Based on the Neural-Like Structure of Successive Geometric Transformations Model

Modern neural paradigms that are used to solve various different tasks are based on the use of the iterative learning procedures [20]. This causes both a number of advantages and disadvantages. The disadvantages include the impossibility of solution reproducing in connection with the random initialization of the initial parameters of one or another ANN. This imposes a number of limitations (especially in case of need to ensure repetition of the solution) on the use of such tools for solving a number of practical tasks. We propose a new non-iterative paradigm (without the random initialization of the initial parameters) for constructing ANN - the Successive Geometric Transformations Model (SGTM) [20, 21], in particular for solving the prediction task.

The architecture of the linear-type Neural-like Structure of a Successive Geometric Transformations Model (NLS SGTM) used to solve the solar radiation prediction task in Libya is shown in Fig. 3. In this scheme, x_i is the i^{th} input characteristic in the input vector, where $i = 1, ..., n$ and y is the output. The ordered lateral connections between the hidden layer neurons reflect the dependence of each subsequent step of successive geometric transformations from the previous one.

The general training procedure for NLS SGTM is performed by means of step-by-step geometric transformations in (n + 1) -dimensional implementation space, where n is the number of input attributes [20]. The main steps of the training procedure are [20]:

- to determine the longest axis of the ellipsoid of the inputs scattering, the direction along which will coincide with the first coordinate of the intermediate coordinate system, which is formed during the training process;
- to determine the ellipsoid axis dimension (the second input coordinate), and to approximate the remainder of the previous approximation step, etc.

In this algorithm, the principle of greedy learning is used, that is, the consistent calculation of the principal components that meet the requirements that are put forward to them. Based on this, the speed of the method is increasing and practical limitations on the task dimensionality are removes, for example, in comparison to the PCA method.

In general, the training results are the parameters of the intermediate coordinate system, and for the supervised mode training, the parameters of the elementary approximation surfaces for each step of the transformation.

The neural-like structure's training time is determined by known in advance the number of transformation steps and depends only on the hardware. A detailed description of the application of this computing intelligence tool in supervised and unsupervised modes is given in [20].

In [22-25], satisfactory results of both short-term and long-term of solar energy prediction using RBF network are presented. The main drawbacks of these methods are the "curse of dimensionality" that is typical for RBF networks as well as a large number of iterations that provide a poor performance. In [26], a new approach - RBF based on NLS SGTM for another task is presented. Its architecture is shown in Fig. 4.

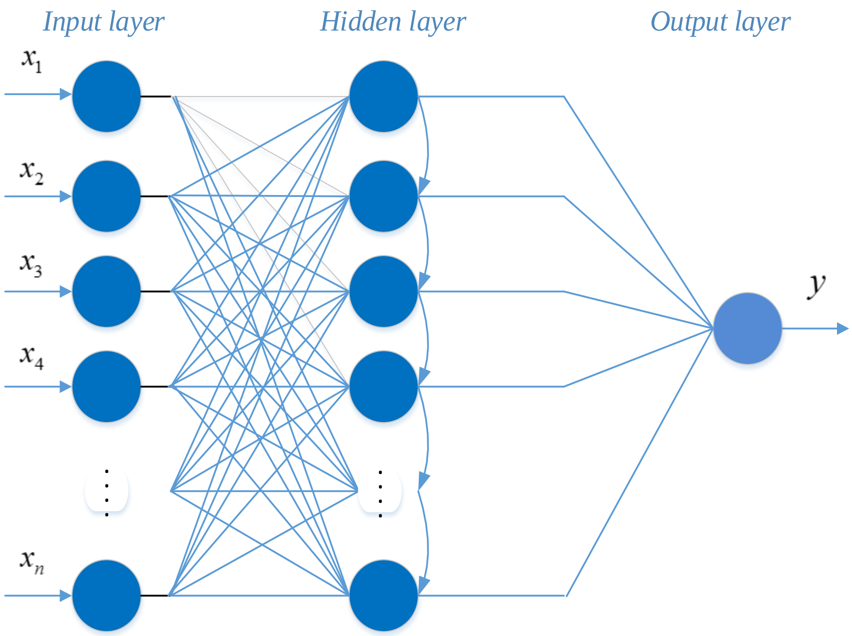


Fig. 3. The topology of the Neural-like structure of SGTM.

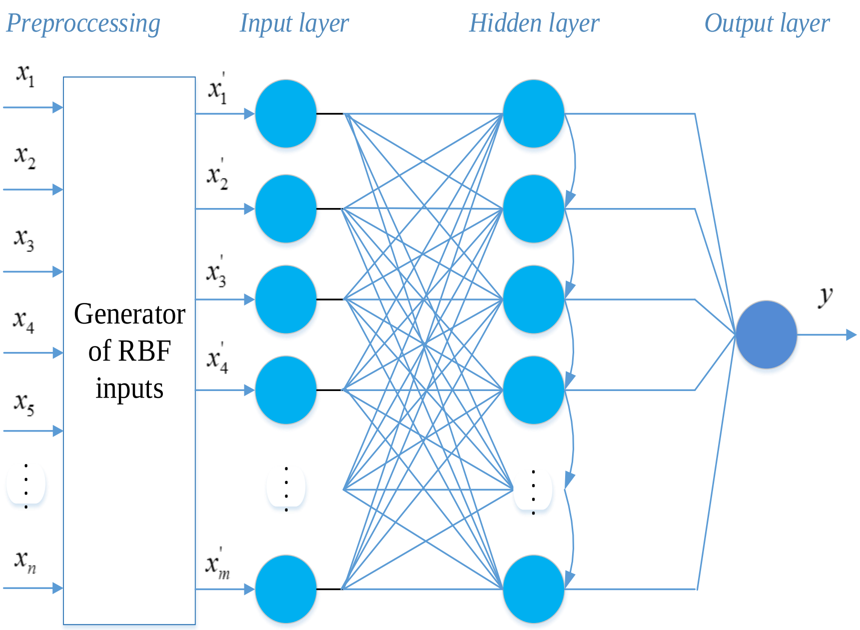


Fig. 4. The topology of the RBF based on the NLS SGTM.

RBF based on the NLS SGTM involves inputs signals transformation in the RBF inputs by the equation:

$$x_j^{'} = \exp\left(-\frac{D_j^2}{2\sigma^2}\right) \tag{1}$$

where [27]: σ is the tilt function parameter; D_j is a Euclidean distance between current vector point x_i, where $i = 1,...,n$ and j^{th} base, where $j = 1,...,m$ and m is dimensional of the RBF centers (user elects); $x_j^{'}$ is the magnitude of the signal appropriate to the RBF input.

The neural-like structure outputs are formed according to the classical representation of RBF-method in the form of a linear combination of the formed radial inputs.

Further training and use procedures of this ANN type correspond to the training and use procedures of the NLS SGTM [20, 27].

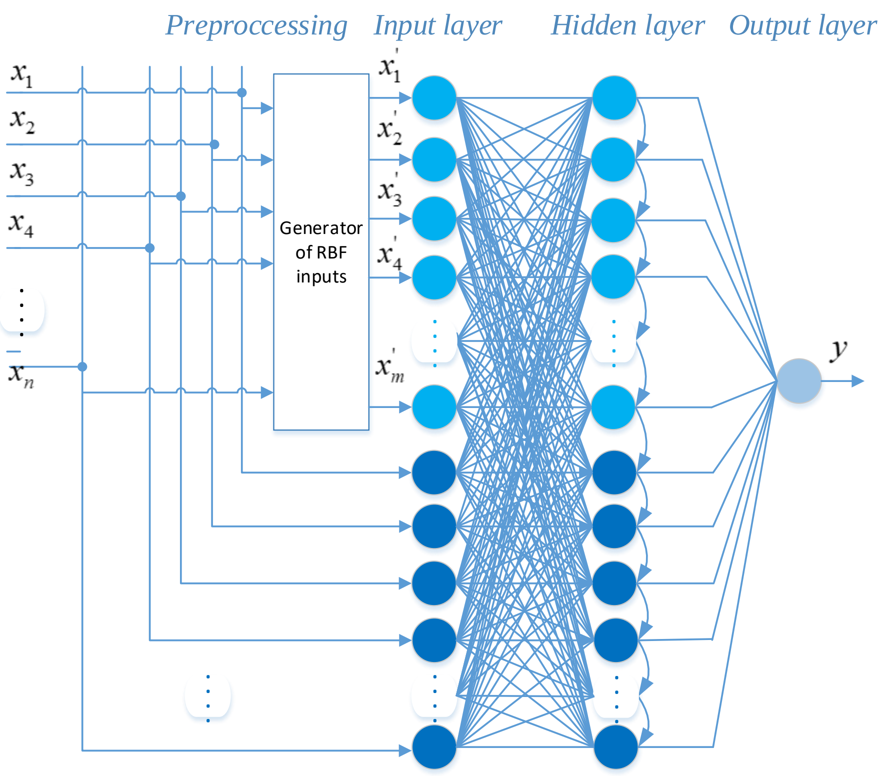


Fig. 5. The topology of the Combined RBF+SGTM neural-like structure.

In this paper, we propose the Combined RBF + SGTM architecture in the supervised mode for solving the prediction task. It is shown in Fig. 5**.**

Characteristics of such neural network combine the advantages of both used approaches - high accuracy, as well as non-iterative learning, which in turn greatly increases its speed. The peculiarity of the proposed Combined RBF+SGTM neural-like structure is that it solves the essential problem of the almost degenerate tasks, which often occurs when the method of radial functions is implemented.

4 Results and Discussions

The solar radiation prediction results (MAPE and RMSE) using NLS SGTM, RBF based on the NLS SGTM and the Combined RBF + SGTM are shown in Table 3. The best prediction results were obtained using the proposed method - Combined RBF + SGTM. Visualization of the method results is shown in Fig. 6.

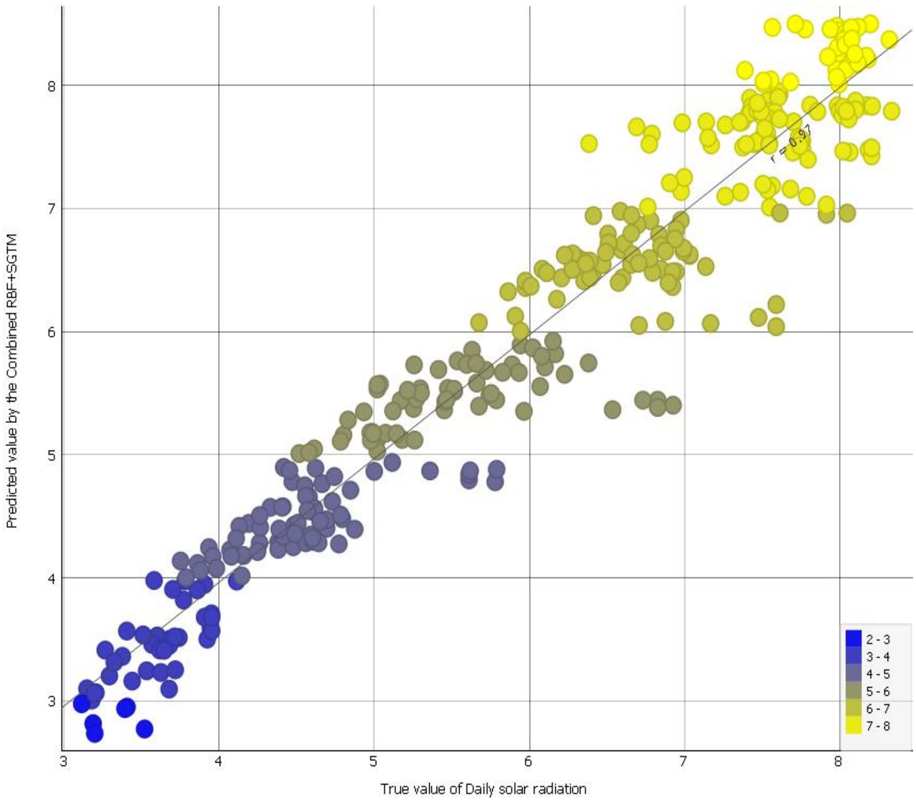


Fig. 6. Visualization of the prediction results by the proposed method.

The accuracy of all described methods in the paper is given in Fig. 7. As it can be seen, the lowest error (MAPE = 5.22) for solving the task of the solar radiation predicting in Libya provides the proposed method.

Further studies of the proposed approaches will be conducted in the direction of

Table 3. The comparison of the predicted results by non-iterative methods and proposed ones.

Method	Parameters	MAPE, %	RMSE	MAE
Linear NLS SGTM	7 inputs, 7 neurons in the hidden layer, 1 output	8.1694	0.5576	0.4310
RBF based on the NLS SGTM	100 inputs, 100 neurons in the hidden layer, 1 output	6.3519	0.6374	0.4064
Combined RBF+SGTM	107 inputs, 107 neurons in the hidden layer, 1 output	**5.2231**	**0.4105**	**0.3114**

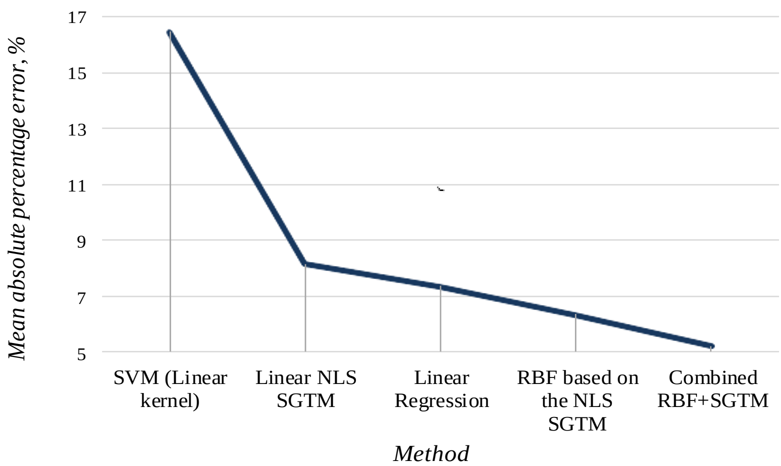


Fig. 7. Prediction accuracy comparison based on MAPE by all methods.

investigating the topologies and parameters of neural-like structures for solving prediction task, in particular, for determining the durability of the wheel pairs of rail transport [28] and high-pressure gas pipelines [29]. This will allow not only to save material resources but also to prevent possible man-made disasters.

5 Conclusion

In the article, the solution of the solar radiation prediction problem in Libya is described. The learning prediction model was based on seven geographical and meteorological indicators derived from 25 different Libya's cities over a period of 6 years. The training and test samples contained 14400 and 360 vectors respectively.

The disadvantages of SVM and Linear Regression prediction methods are described. An experimental analysis of their work was made.

In order to solve the prediction task, a method of computational intelligence on the basis of the combined use of RBF and the new paradigm of constructing artificial neural networks - the Successive Geometric Transformations Model was developed. The training process of such method (Combined RBF + SGTM) occurs in a supervised mode. Its main advantages are as follows: non-iterative training procedure; the similarity of training and using procedures; the high speed of work; high prediction accuracy.

An experimental comparison (based on MAPE and RMSE) of all methods described in the work is carried out. The smallest MAPE and RMSE was obtained by applying the proposed method.

References

1. Bodyanskiy Y., Vynokurova O., Pliss I., Peleshko D.: Hybrid Adaptive Systems of Computational Intelligence and Their On-line Learning for Green IT in Energy Management Tasks. In: Kharchenko V., Kondratenko Y., Kacprzyk J. (eds) Green IT Engineering: Concepts, Models, Complex Systems Architectures. Studies in Systems, Decision and Control, vol 74. Springer, Cham (2017) doi.org/10.1007/978-3-319-44162-7_12
2. Medykovskyy, M., Tsmots, I., Tsymbal, Y., Doroshenko A.: Development of a regional energy efficiency control system on the basis of intelligent components. In: 2016 XIth International Scientific and Technical Conference Computer Sciences and Information Technologies (CSIT), pp. 18-20, Lviv (2016).
3. Mutaz, T., Ahmad, A.: Solar Radiation Prediction Using Radial Basis Function Models. In: 2015 Int. Conf. on Developments of E-Systems Engineering, pp. 77-82. Duai (2015)
4. Bodyanskiy, Y., Setlak, G., Peleshko D., Vynokurova, O.: Hybrid generalized additive neuro-fuzzy system and its adaptive learning algorithms. In: IEEE 8th Int. Conf. on Intelligent Data Acquisition and Advanced Computing Systems, pp. 328-333. Warsaw (2015)
5. Kutucu, H., Almryad, A.: Modeling of solar energy potential in Libya using an artificial neural network model. In: 2016 IEEE First International Conference on Data Stream Mining & Processing (DSMP), pp. 356-359, Lviv (2016). doi: 10.1109/DSMP.2016.7583575
6. Dronyuk, I., Fedevych, O., Poplavska, Z.: The generalized shift operator and non-harmonic signal analysis. In: 2017 14th International Conference The Experience of Designing and Application of CAD Systems in Microelectronics (CADSM), pp. 89-91. Lviv (2017)
7. Rashkevych, Y. M., Peleshko, D. D., Kovalchuk, A. M., Kupchak, M. I., Figura, R.: Time series partitional clustering. In: Perspective Technologies and Methods in MEMS Design, pp. 170-171. Polyana (2011).
8. Bodyanskiy, Y., Vynokurova, O., Pliss, I., Setlak, G., Mulesa, P.: Fast learning algorithm for deep evolving GMDH-SVM neural network in data stream mining tasks. In: 2016 IEEE First Intern. Conf. on Data Stream Mining & Processing (DSMP), pp. 257-262. Lviv (2016)
9. Bodyanskiy, Ye., Vynokurova, O., Setlak, et al.: Adaptive multivariate hybrid neuro-fuzzy system and its on-board fast learning. Neurocomputing, 230, 409-416. (2016)
10. Kazarian, A., Teslyuk, V., Tsmots, I., Mashevska, M.:Units and structure of automated "smart" house control system using machine learning algorithms. In: 2017 14th Intern. Conf. The Experience of Designing and Application of CAD Systems in Microelectronics (CADSM), pp. 364-366. Lviv (2017) doi: 10.1109/CADSM.2017.7916151
11. Perova, I., Pliss, I.: Deep Hybrid System of Computational Intelligence with Architecture Adaptation for Medical Fuzzy Diagnostics. International Journal of Intelligent Systems and Applications (IJISA), 9(7), 12-21, (2017).
12. Abuella, M., Chowdhury, B.: Solar Power Forecasting Using Support Vector Regression. In: Proc. of the American Society for Engineering Management Intern. Ann. Conf., (2016).

13. Zeng, J., Qiao, W.: Short-term solar power prediction using a support vector machine. Renewable Energy, 52, 118-127 (2013) doi.org/10.1016/j.renene.2012.10.009
14. Yang, X., Jiang, F., Liu, H.: Short-term solar radiation prediction based on SVM with similar data. In: 2nd IET Renewable Power Generation Conference, pp. 1-4. Beijing (2013)
15. Kazem, H. A., Yousif, J. H., Chaichan, M. T.: Modelling of Daily Solar Energy System Prediction using Support Vector Machine for Oman. International Journal of Applied Engineering Research, 11(20), 10166-10172 (2016)
16. Bakhashwain, J. M.: Prediction of global solar radiation using support vector machines. International Journal of Green Energy, 13(14), 1467-1472 (2016)
17. Ibrahim, S., Daut, I., Irwan, Y. M., Irwanto, M., et al.: Linear Regression Model in Estimating Solar Radiation in Perlis. Energy Procedia, 18, 1402-1412 (2012)
18. Dedgaonkar, S., Patil, V., Rathod, N., Hakare, G., Bhosale, J.: Solar Energy Prediction using Least Square Linear Regression Method. International Journal of Current Engineering and Technology, 6(5), 1549-1552 (2016)
19. Abuella, M., Chowdhury, B.: Solar power probabilistic forecasting by using multiple linear regression analysis. In: SoutheastCon 2015, pp. 1-5. Fort Lauderdale, FL (2015)
20. Tkachenko, R., Izonin, I.: Model and Principles for the Implementation of Neural-Like Structures based on Geometric Data Transformations. In: Hu, Z.B., Petoukhov, S., (eds) Advances in Computer Science for Engineering and Education. ICCSEEA2018. Advances in Intelligent Systems and Computing. Springer, Cham, vol. 754, pp. 578-587, (2019) https://doi.org/10.1007/978-3-319-91008-6_58
21. Tsmots, I., Teslyuk, V., Teslyuk, T., Ihnatyev, I.: Basic Components of Neuronetworks with Parallel Vertical Group Data Real-Time Processing. In: Shakhovska N., Stepashko V. (eds) Advances in Intelligent Systems and Computing II. CSIT 2017. Advances in Intelligent Systems and Computing, vol 689. Springer, Cham (2018)
22. Mutaz, T., Ahmad, A.: Solar Radiation Prediction Using Radial Basis Function Models. In: 2015 Intern. Conf. on Developments of E-Systems Engineering, pp. 77-82. Duai (2015)
23. Zeng, J., Qiao, W.: Short-term solar power prediction using an RBF neural network. In: 2011 IEEE Power and Energy Society General Meeting, pp. 1-8. San Diego, CA (2011)
24. Mutaz, T., Ahmad, A.: Solar Radiation Prediction Using Radial Basis Function Models. In: 2015 Intern. Conf. on Developments of E-Systems Engineering, pp. 77-82. Duai (2015)
25. Zeng, J., Qiao, W.: Short-term solar power prediction using an RBF neural network. In: 2011 IEEE Power and Energy Society General Meeting, pp. 1-8. San Diego, CA (2011)
26. Tsymbal, Y., Tkachenko R.: A digital watermarking scheme based on autoassociative neural networks of the geometric transformations model. In: 2016 IEEE First International Conference on Data Stream Mining & Processing (DSMP), pp. 231-234. Lviv (2016).
27. Tkachenko, R., Doroshenko, A., Izonin, I., Tsymbal Y., Havrysh, B.: Imbalance Data Classification via Neural-like Structures of Geometric Transformations Model: Local and Global Approaches In: Hu, Z.B., Petoukhov, S., (eds) Advances in Computer Science for Engineering and Education. ICCSEEA2018. Advances in Intelligent Systems and Computing. Springer, Cham, vol. 754, pp. 112-122, (2019) https://doi.org/10.1007/978-3-319-91008-6_12
28. Ivanytskyj Y.L., Lenkovskiy T.M., Molkov Y.V., et al. Influence of 65G steel microstructure on crack faces friction factor under mode II fatigue fracture. International Scientific Journal Achives of Material Science and Engineering, 82(2), 49-56, (2016).
29. Kharchenko, L.E., Kunta, O.E., Zvirko, O.I. et al. Diagnostics of Hydrogen Macrodelamination in the Wall of a Bent Pipe in the System of Gas Mains. In Mater Sci 51(530). (2016) doi.org/10.1007/s11003-016-9872-x