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THE INTENSITY OF SOLAR RADIATION FORECASTING BASED ON ARTIFICIAL NEURAL NETWORKS

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Artificial neural networks, as a tool for modelling and forecasting, are widely accepted as an alternative way of solving complex and undetermined problems.

The modelling technique with using artificial neural network offers a solution for developing a more generalized model for predicting large arrays of various experimental data, for instance, using climatic and meteorological parameters.

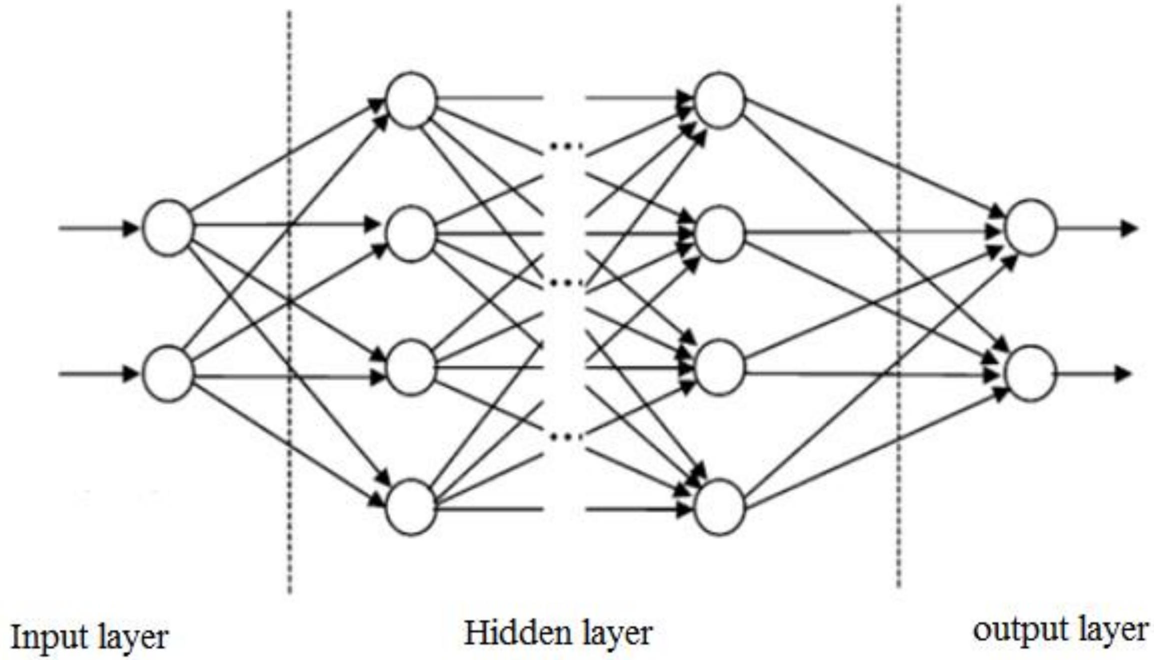


Fig.1. Artificial neural network model.

Table 1. Solar intensity prediction. Publication.

Author	Journal	Year	The ANN architecture	Performance	Location
F.Rodríguez, A.Fleetwood, A.Galarza, L.Fontan.	Renewable Energy	2018	One hidden layer (144-10-1)	RMSE 14,67..73,00 Вт/м^2	Spain
E. F. Alsina et al.	Energy Convers. Manage.	2016	One hidden layer (7-4-1)	MAPE (%) 1.67	Italy
F.S. Tymvios et al.	Solar Energy	2005	Two hidden layers (3-46-23-1)	MBE (%) 0.12 RMSE (%) 5,67	Cyprus, Athen
M.A. Behrang et al.	Solar Energy	2010	Two hidden layers (5-3-3-1)	MAPE (%) 5,21 R^2 (%) 99,57	Iran
J.Waewsak et al.	Energy Procedia	2014	One hidden layer (6-9-1)	RMSE: 0.0031 to 0.0035 MBE: -0.0003 to 0.0011	Thailand

Table2. INDICATORS USED IN THE UNDERLYING STUDIED WORKS [1]

Performance indicator	**Formula**
correlation coefficient	$\frac{\sum_i^n \left(o_i - \left(\frac{1}{n}\sum_i^n(o_i)\right)\right)\left(t_i - \left(\frac{1}{n}\sum_i^n(t_i)\right)\right)}{\sqrt{\sum_i^n \left(o_i - \frac{1}{n}\sum_i^n(o_i)\right)^2 \sum_i^n \left(t_i - \frac{1}{n}\sum_i^n(t_i)\right)^2}}$
coefficient of determination	$1 - \left(\frac{\sum_i^n(t_i - o_i)^2}{\sum_i^n(o_i)^2}\right)$
RMSE (root mean square error)	$\sqrt{\frac{1}{n}\sum_i^n(o_i - t_i)^2}$
MAPE (mean absolute percentage error)	$\frac{1}{n}\sum_i^n \left\lvert\frac{o_i - t_i}{t_i}\right\rvert \times 100$
MBE (mean bias error)	$\sqrt{\frac{1}{n}\sum_i^n(o_i - t_i)}$
RMBE (relative mean bias error)	$\frac{\sum_i^n(o_i - t_i)}{\frac{1}{n}\sum_i^n(o_i)} \times 100$
MAE (mean absolute error)	$\frac{\sum_i^n\lvert o_i - t_i\rvert}{n}$
MRV (mean relative variance)	$\frac{\sum_i^n(t_i - o_i)^2}{\left(t_i - \left(\frac{1}{n}\sum_i^n(t_i)\right)\right)^2}$
DA (degree of agreement)	$1 - \frac{\sum_i^n(o_i - t_i)^2}{\sum_i^n \left(\left\lvert o_i - \frac{1}{n}\sum_i^n(t_i)\right\rvert - \left\lvert t_i - \frac{1}{n}\sum_i^n(t_i)\right\rvert\right)^2}$

[1] M. Marzouq, H. El Fadili, Z. Lakhliai and K. Zenkouar, "A review of solar radiation prediction using artificial neural networks," *2017 International Conference on Wireless Technologies, Embedded and Intelligent Systems* , 2017, pp. 1-6,doi: .1109/WITS.2017.793465

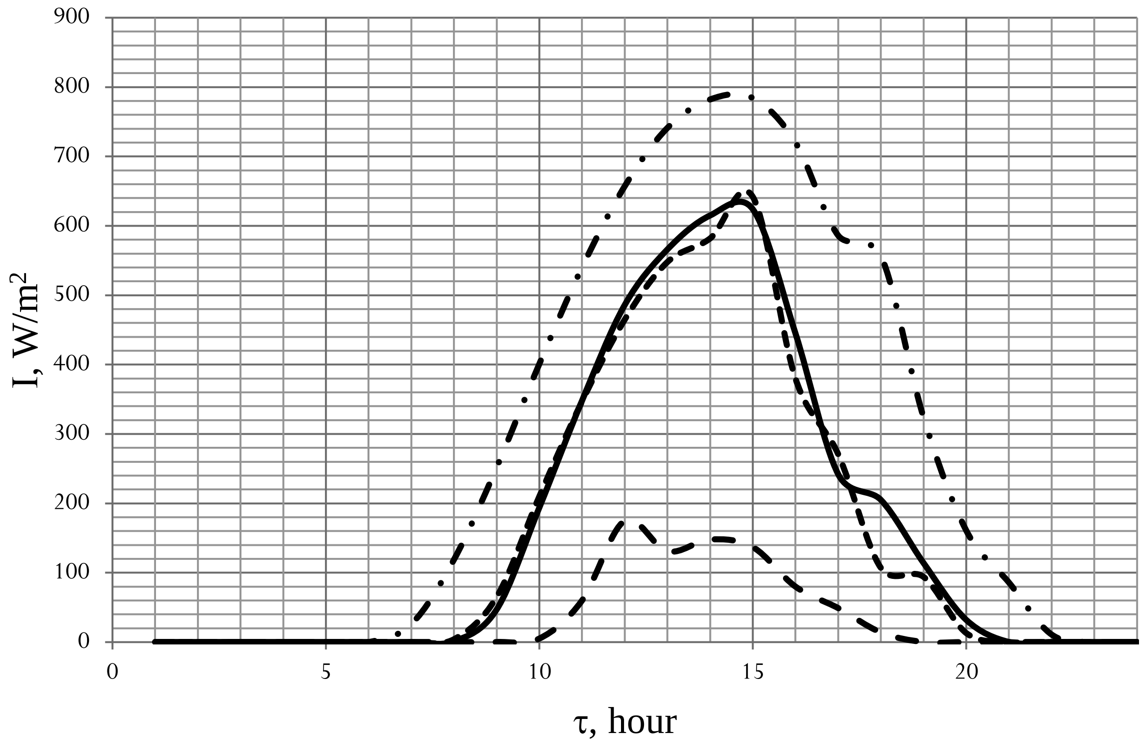


Fig.2. Dependence of the intensity of solar radiation on time.

———— – 20 March, — - — - — – 20 June,

- - - - - – 22 September, — — – – 21 December.

Data of the ground meteorological station installed on the roof of Odessa National Polytechnic University [2].

[2] Kravchenko, V.P., et al., 2018. Instrumental determination of insolation for city Odessa Power engineering: economics, technique, ecology. 2016. № 1 (43). p. 20–27. (Ukr)

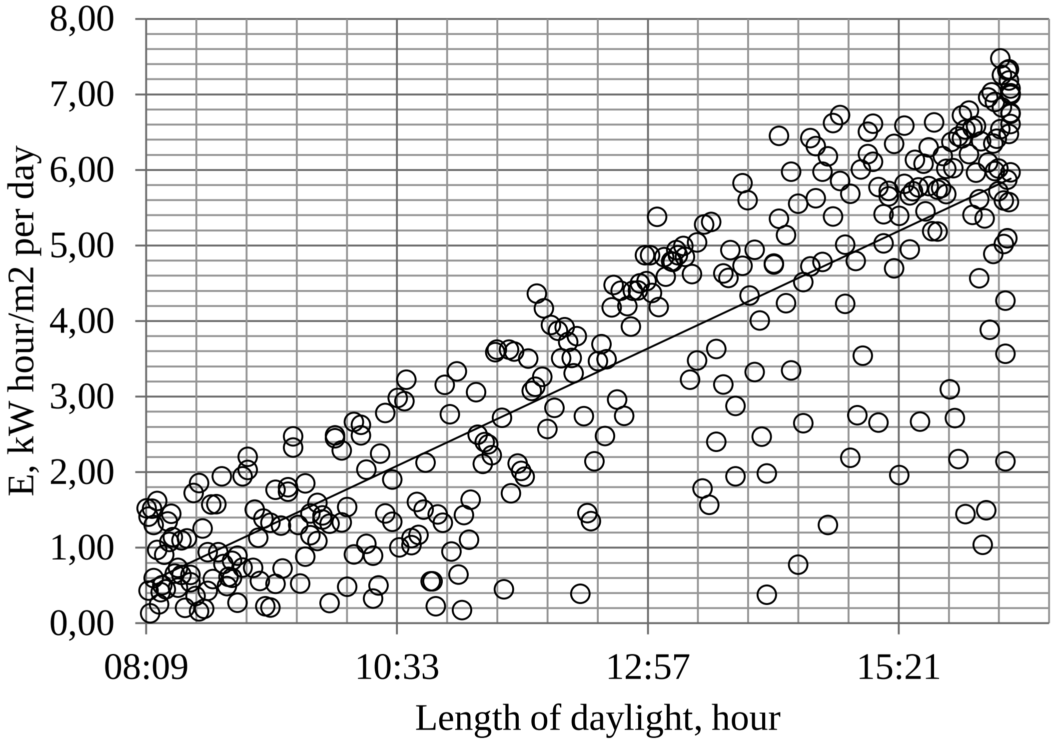


Fig. 3 Correlation between insolation during the day and length of daylight.

1. Season : (1) – winter; (2) – spring; (3) – summer; (4) – autemn;
2 . (1) - night, from 0 to 6 (2) - morning, from 6 to 12, (3) - day, from 12 to 18, (4) - evening, from 18 to 23.
3-26 . data of the intensity of solar radiation taken from the previous day normalized to the maximum value of the intensity of solar radiation per season I_{i-1}/I_{max}

The Levenberg-Markwatt model.

One hidden layer and 10 neurons were present in the model.

The array of analysed data was divided into proportions of 70%, 15%, 15% for neural network training, validation and testing, respectively

$$\sqrt{\frac{1}{n}\sum_{i}^{n}(o_i - t_i)^2}$$

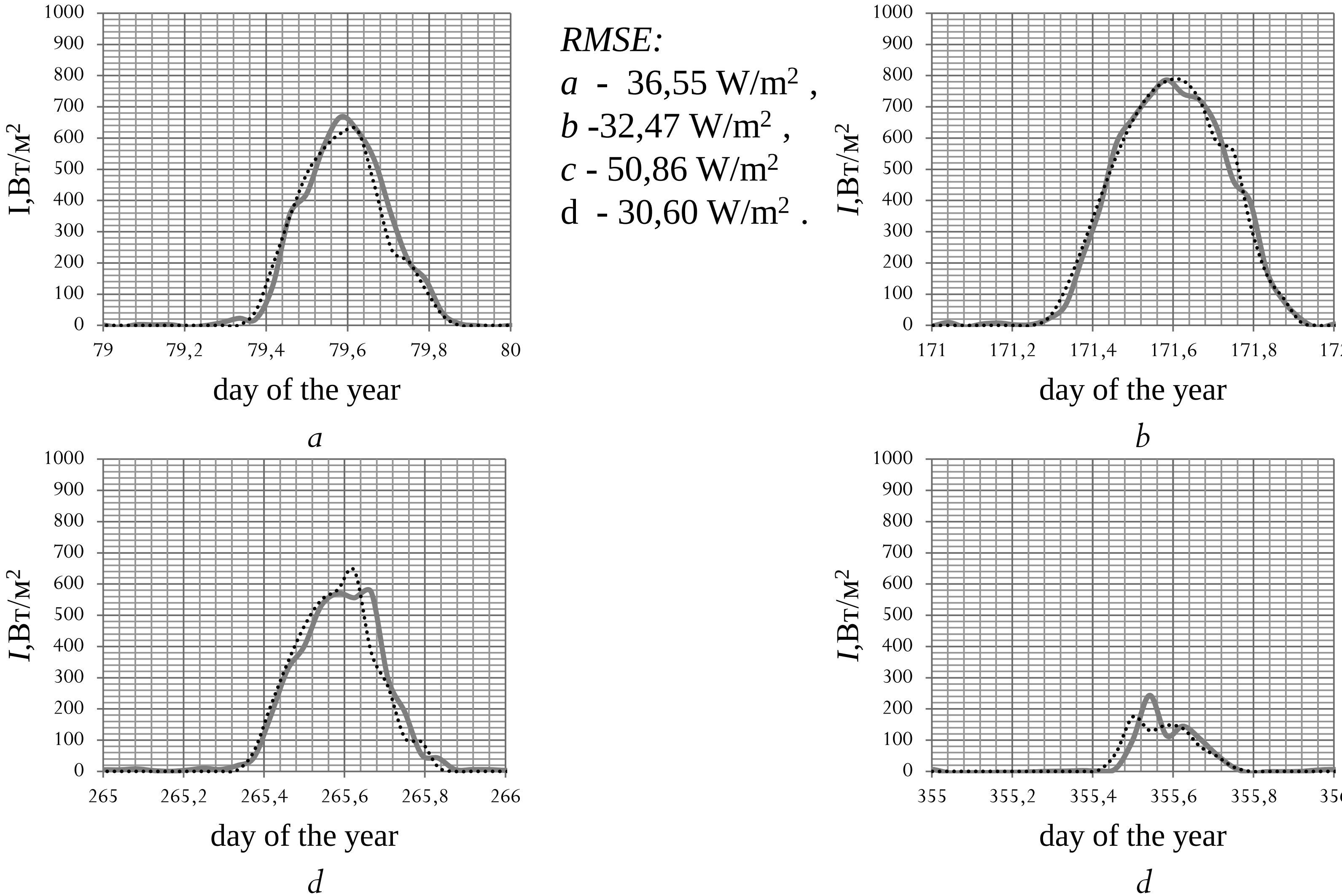
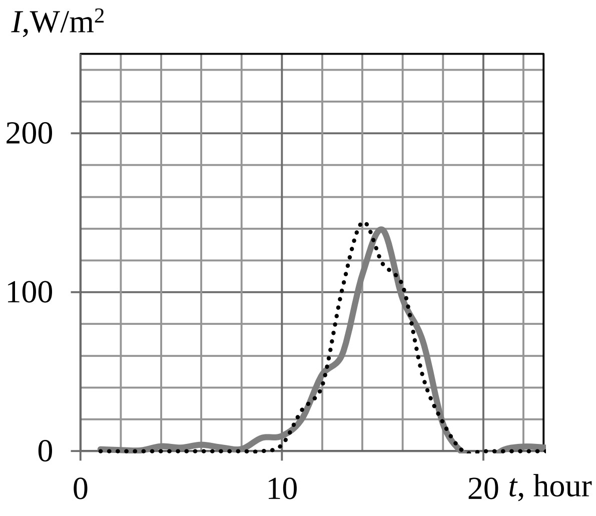


Fig. 4. Forecasting the intensity of solar radiation in the city of Odessa with the help of artificial neural networks *a* - 20 of March; *b* – 20 of June ; *c* - 22 September; *d* - 21 December

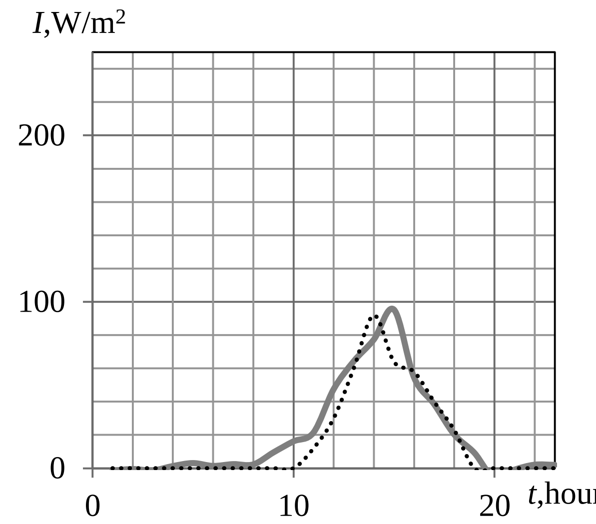
_ _ _ _ _ - data of the ground meteorological station installed on the roof of Odessa National Polytechnic University (Kravchenko, V.P., et al., 2018);

————— - forecasting with the help of an artificial neural network.

$RMSE$ = 13,03 W/m^2 and 9,44 W/m^2.



a



b

Fig. 5. Forecasting the intensity of solar radiation in the city of Odessa with the help of artificial neural networks *а* - December 26,2016, *б* - December 27, 2016 _ _ _ _ _ - data of the ground meteorological station installed on the roof of Odessa National Polytechnic University (Kravchenko, V.P., et al., 2018); ———— - forecasting with the help of an artificial neural network.

Conclusions. Artificial neural networks can be successfully used for forecasting renewable energy problems. In particular, forecasting the volume of electricity generation for the following hour is important for sustainable operation of the unified energy system of Ukraine.

Data representing the description of a real system are required for forecasting the parameters based on artificial neural networks. In the formulation of this problem, these are annual meteorological data, which are obtained daily with high accuracy and measurement frequency, for example, one measurement of each parameter every hour, or even more often.

Evaluation of the perfection of the artificial neural network has shown its effectiveness in predicting the intensity of solar radiation, the discrepancy between the forecast and real data for the end of December (the period with the lowest insolation) did not exceed 10%.

Thanks for your attention!