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SOLAR IRRADIANCE FORECASTING BASED ON LONG-WAVE ATMOSPHERIC RADIATION

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Abstract

This work contains information concerning long-wave atmospheric radiation. Artificial neural networks were developed to forecast total mean hourly irradiance based on long-wave atmospheric radiation as cloudiness indicator. It was proved that using this variable in models for forecasting irradiance is wellgrounded. The proof was based on the neural networks sensitivity analysis. It was proved that neural network model is capable to utilize information carried by long wave atmospheric radiation only when the air temperature is provided as additional explanatory variable.

Nomenclature

The following variables were used for the purpose of the this research:

– Itot-2 – mean global irradiance registered two hours prior to the current time [W/m^2]

– Itot-1 – mean global irradiance registered one hour prior to the current time [W/m^2]

– Itot – mean, hourly, current total irradiance at the current time [W/m^2]

– Itot+1 – mean global irradiance registered at the hour following the current time [W/m^2]

– IR – mean hourly long-wave atmospheric radiation registered at the current time [W/m^2]

– Temperature – mean hourly temperature at the current time [^{o}C]

– RH – relative humidity at the current time[%]

– Pressure – mean atmospheric pressure at the current time [hPa]

– Time – current time [hours]

– No of day – number of the day of the year (Julian calendar day), variable that assumes values from 1 to 366.

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Introduction

Development of distributed power energy based on renewable resources of energy has recently enjoyed popularity not only among scientists and researchers but also politicians and various business circles. Multi-faceted development of related technologies can be observed. One of them is the need to predict future states of electrical power production in order to balance both the electrical power system and „off grid" systems. This knowledge allows both to optimize the cost of energy consumption and to maintain normal work of the system, and, given the development of renewable resources of energy, including solar energy, will assume growing importance. Forecasting radiation is, therefore, an important issue. However, there is a significant difficulty connected with the development of models related to in changes in radiation caused by cloudiness. Although this is a complicated and chaotic process, factors that have an impact on it are known. It is a difficult task to model these relations using classical computational methods, and new methods need to be sought to solve these problems such as computational intelligence, which seems promising. Particular attention ought to be focused on artificial neural networks which can „learn" relations between variables and generate correct results, with no need to possess knowledge related to said relations. In this work, authors propose artificial neural networks for forecasting total mean hourly radiation using long-wave atmospheric radiation as cloudiness indicator. It was proved that using this variable in models for forecasting total radiation is wellgrounded.

Long-wave atmospheric radiation

Long-wave atmospheric radiation (infrared, IR) is an object of interest to researchers who study atmospheric phenomena. Infrared IR radiation has an impact on plant growth by influencing the process of water evaporation. There exist mathematical models that allow to forecast IR index for clear sky and take cloudiness into account. Steam and, to a lesser degree, carbon dioxide, ozone, methane, aerosols, nitrogen oxides are responsible for the emission of infrared radiation to the atmosphere (KJAERSGAARD et al. 2007). It is thermal (heat) radiation related to air temperature. Therefore, models that estimate IR in clear sky conditions are based on air temperature as the main parameter, sometimes partial pressure of steam is additionally used (KJAERSGAARD et al. 2007). Presence of clouds causes increase in long-wave atmospheric radiation (LHOMME et al. 2007). The change depends on cloud density and composition, and, due to the decrease of temperature connected with the altitude of clouds, this parameter is also significant (KJAERSGAARD et al. 2007). Based on the above description of the phenomenon, it can be supposed that IR may introduce information concerning the amount and type of clouds for the neural model. An example course of long-wave atmospheric radiation in successive hours of April is shown in Figure 1.

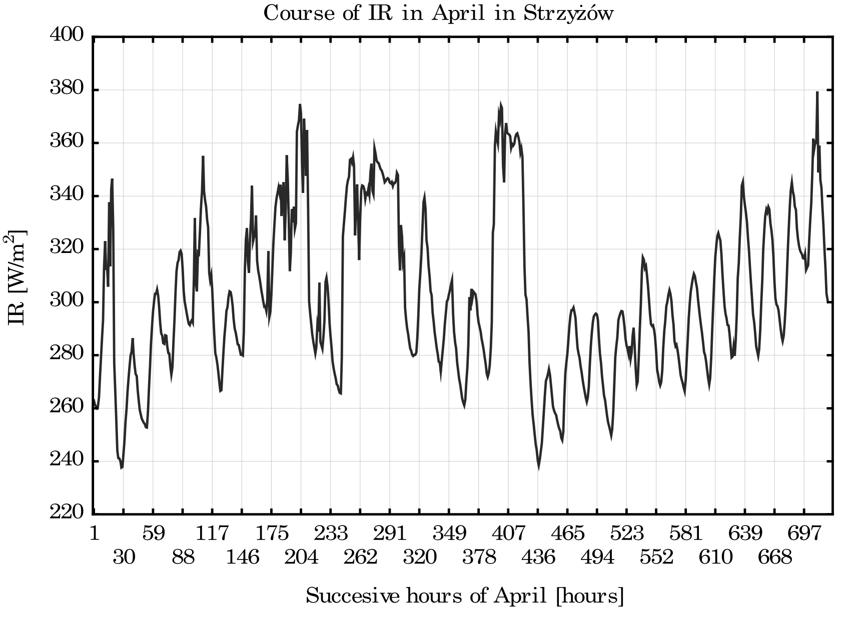

Fig. 1. An example course of long-term atmospheric radiation in Strzyżów

Material and methods

Data come from a radiation transfer SolarAOT research station operated by Krzysztof Markowicz. The station belongs to the Warsaw University Institute of Geophysics. The station is located in Strzyżów (49.8786°N, 21.8613°E). The data set contains measurements from march 2009 to august 2013, which were collected with one minute basic time interval. The metrological data were collected using Ulitmeter 2100 electronic metrological station, global solar irradiation was measured using Eppley Black and White 8-48 pyranometer and long wave atmospheric radiation was collected by Eppley PIR pyrgeometer.

Artificial neural networks with the structure as in Figure 2 were used.

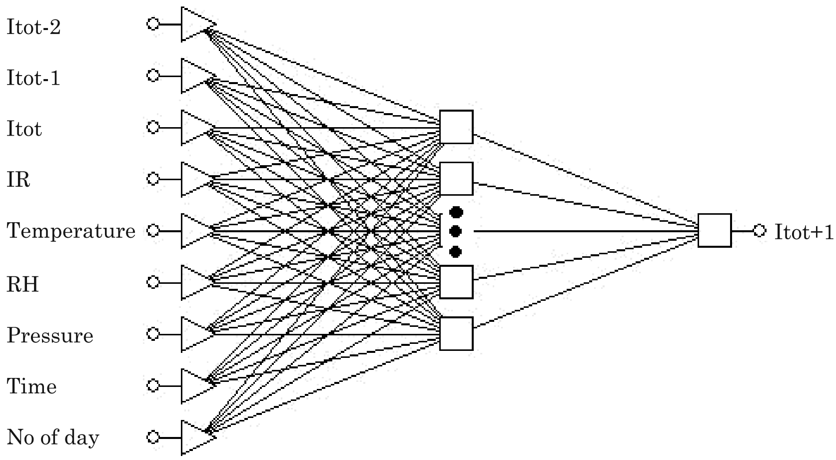

Fig. 2. Structure of neural networks for forecasting solar radiation

Usefulness of variables was assessed based on sensitivity analysis, calculated as a quotient of the error that network generates, when no data is given instead of the value of the examined variable, and the error calculated when all variables are available. As a result of the performed analyses using different sets of input variables, it was proved that using temperature and number of the day of the year is indispensible in order to „sensitize" the model to variable IR. Otherwise, the network generated forecasts based on the radiation values for previous hours. Based on these variables, EM algorithm (modified algorithm k – mean described in detail in (WITTEN, FRANK 2000)), was used to perform cluster analysis. In all these combinations pressure sensitivity was equal 1, and, therefore, was omitted in further examinations.

Discussion and research results

The cluster analysis proved two similar phenomena that occurred. It was observed that these phenomena can be identified based on the number of the day of the year. Cluster 1 was called a warm period, and included summer months, most days in spring and autumn months, and cluster 2 was called a cold period as it included winter months mostly. While developing models for the clusters obtained as a result of analyses performed for other combinations of data it was proved that clusters identified based on IR, temperature and the number of the day of the year, were the best cognitive formulae for neural models. Figure 3 shows the results of cluster analysis. Selection of input variables was based on sensitivity analysis.

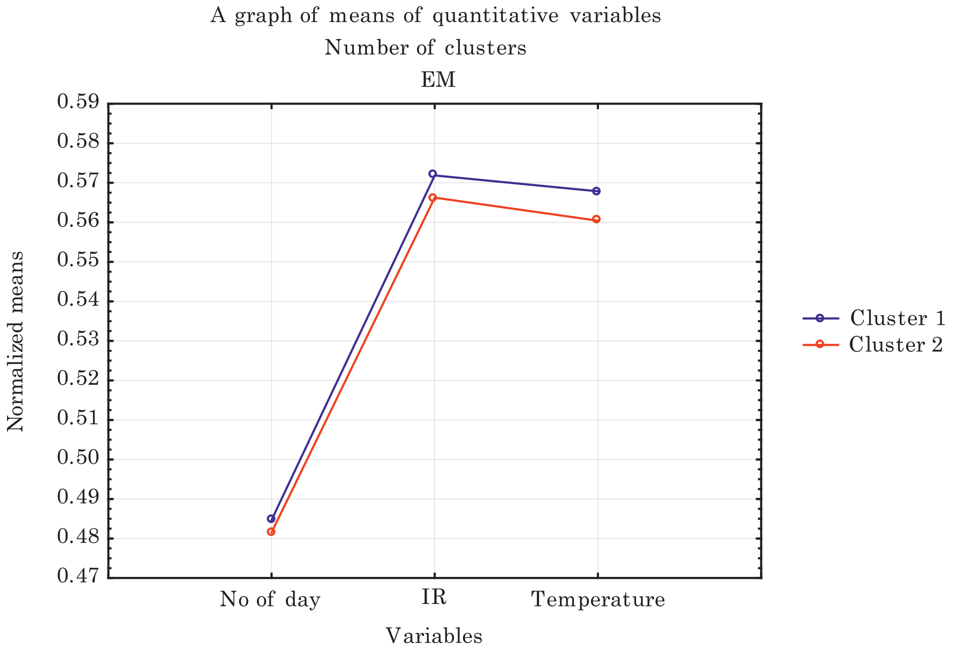

Fig. 3. Results of cluster analysis using EM method

Forecast for the warm period

Table 1

Data of a neural network that forecasts radiation in the warm period

Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Activation (hidden)	Activation (output)
MLP 8-10-1	0.935	0.935	0.942	BFGS 98	Exponential	Linear

Table 2

Sensitivity of the network that forecasts radiation in the warm period

Predictor	Itot [W/m^2]	Time [hours]	Temperature [°C]	IR [W/m^2]	No of the day of the year	Itot-2 [W/m^2]	RH [%]	Itot-1 [W/m^2]
Error quotient	4.414	3.174	2.186	1.817	1.269	1.110	1.099	1.081

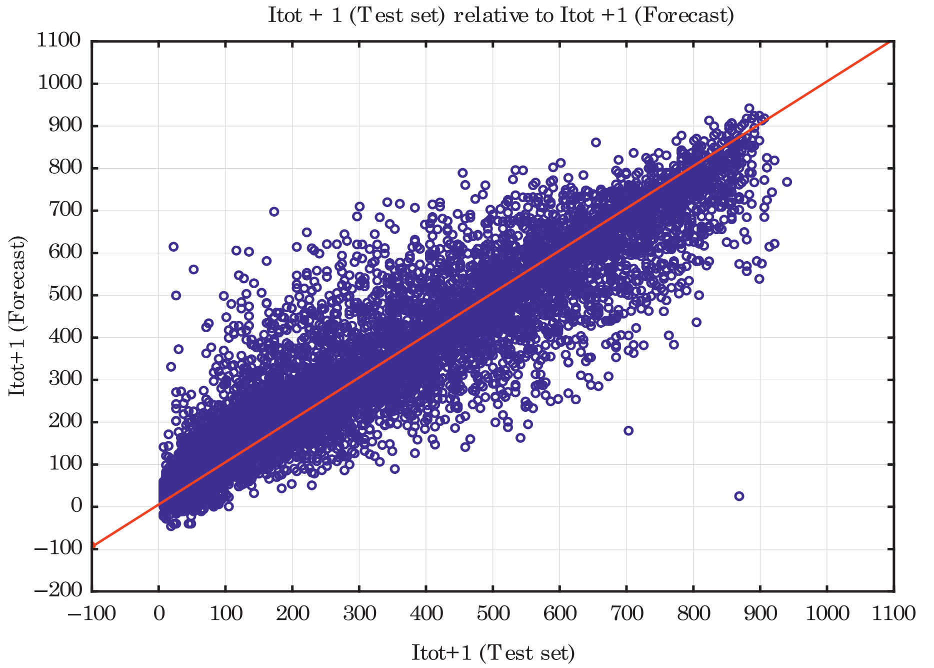

Fig. 4. Scatter of measurements from the test set relative to the forecast values

Forecast for the cold period

Table 3

Data of a neural network that forecasts radiation in the cold period

Network name	Quality (learning)	Quality (testing)	Quality (validation)	Learning algorithm	Activation (hidden)	Activation (output)
MLP 8-13-1	0.969	0.967	0.968	BFGS 138	Logistic	Hyperbolic Tangent

Table 4

Sensitivity of the network that forecasts radiation in the cold period

Predictor	Itot [W/m^2]	Time [hours]	No of the day of the year	IR [W/m^2]	Temperature [°C]	Itot-1 [W/m^2]	Itot-2 [W/m^2]	RH [%]
Error quotient	8.869	3.618	2.792	1.737	1.649	1.252	1.104	1.020

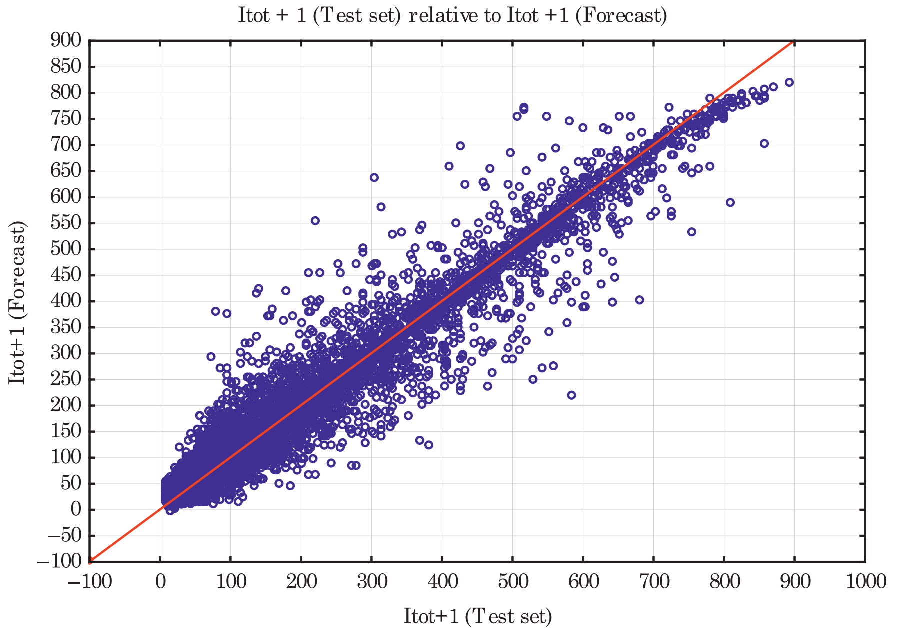

Fig. 5. Scatter of measurements from the test set relative to the forecast values

Table 5

Assessment of developed forecast models

Name	δ [%]	RMSE	NRMSE
All year	20.798	72.041	0.280
Warm period	21.798	86.274	0.278
Cold period	17.665	45.293	0.252

The results suggest that models, which did not use long-wave atmospheric radiation, and, in which data about cloudiness were introduced to the network in the form of octants, exhibited larger error in the winter period in European conditions, where the degree of cloudiness is much higher than in the summer period (TRAJER, KOZŁOWSKI 2005). Models developed by the authors do not possess this feature. However, they exhibit larger errors in the summer period when the degree of cloudiness is subject to more dynamic changes, which makes them more difficult to predict. Simultaneously, cloudiness in the summer period has a smaller influence on atmosphere transparency in the winter period. Nevertheless, networks that use IR generate better forecasts than in the cold period. Hence, it can be assumed that long-wave atmospheric radiation is an indicator of cloudiness.

For the model that forecasts total radiation for the whole year, graphs showing how the forecast depends on the predictors were generated. Figure 6 presents the relationship between the solar radiation intensity and the temperature during a year. It should be noted that temperatures below +5 degrees Celsius for days numbered 150–210 (summer) as well as temperatures above +20 degrees Celsius for days numbered 0–60 and 300–360 (winter) have no physical sense. This should also be considered while interpreting the graph. Although the model can generate forecasts for the above values, they should be omitted while analysing the graph. Figure 7 shows changes in IR influence on solar radiation during the year. The higher temperature and smaller IR, the higher total radiation intensity.

Together with the increase in IR, solar radiation intensity decreases. It is caused by greater opacity or cloudiness. Additionally, increase in opacity or cloudiness results in the horizon temperature rise, and consequently, long-wave radiation increase.

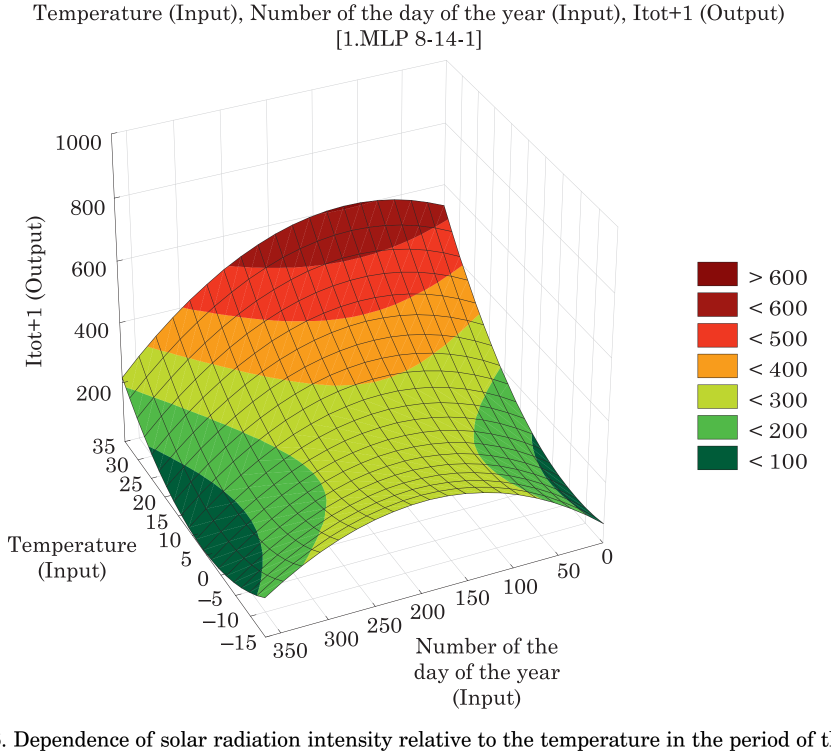

Fig. 6. Dependence of solar radiation intensity relative to the temperature in the period of the year

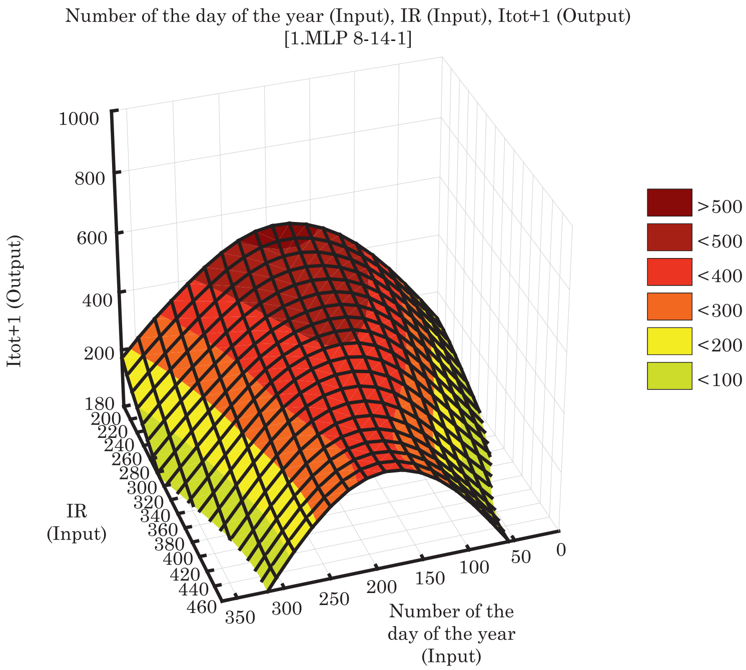

Fig. 7. Dependence of solar intensity radiation relative to long-wave radiation IR in the period of the year

Conclusions

Based on the performed examinations, the following conclusions were formulated:

1. Application of cluster analysis allowed to develop models for two periods (summer and winter), for which the quality of forecasts is better than for the whole year.

2. MLP neural networks are an appropriate tool to forecast mean hourly total solar radiation, and these networks should be applied in this field to a greater extent.

3. The examinations confirm that long-wave atmospheric radiation may be cloudiness indicator, which high quality of forecasts confirms.

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