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Digital Energy Path for Planning and Operation of the sustainable grid, products and society – project objectives and selected preliminary results in Polish conditions

***Abstract**. This paper presents the objectives and selected preliminary results of the international research project entitled Digital Energy Path for Planning and Operation of sustainable grid, products and society (DIEGO), planned for years 2022 – 2024. The article presents selected results of the analysis of the electric power system of the considered industrial plant, where the demonstration installation will be built, in terms of electric power and energy demand and generation. A statistical analysis of measurement data from the industrial plant was carried out. The article also presents the results of forecasts of demand and generation of electric power and energy using various methods and prediction models. The paper ends with a summary and indication of directions for further research planned to be carried out as part of the DIEGO project.*

***Streszczenie.** W niniejszym artykule przedstawiono cele i wybrane wstępne wyniki międzynarodowego projektu badawczego pt. Cyfrowa Ścieżka dla Planowania i Eksploatacji Zrównoważonych Sieci Elektroenergetycznych, Produktów i Społeczności (DIEGO), zaplanowanego do realizacji w latach 2022 – 2024. W artykule przedstawiono wybrane wyniki analizy układu elektroenergetycznego rozważanego zakładu przemysłowego, na terenie którego zbudowana zostanie instalacja demonstracyjna, w zakresie zapotrzebowania i wytwarzania mocy i energii elektrycznej. Przeprowadzona została analiza statystyczna danych pomiarowych z zakładu przemysłowego. W artykule zaprezentowano również wyniki prognoz zapotrzebowania i generacji mocy i energii elektrycznej z zastosowaniem różnych metod i modeli predykcyjnych. Artykuł zakończony został podsumowaniem oraz wskazaniem kierunków dalszych badań zaplanowanych do realizacji w ramach projektu DIEGO.* **(Cyfrowa Ścieżka Energii dla Planowania i Eksploatacji zrównoważonej sieci, produktów i społeczeństwa – cele projektu i wybrane wstępne wyniki w warunkach polskich**)

Keywords: planning and operation of digital solutions, sustainable power grid, electricity forecasting, statistical analysis of data.
Słowa kluczowe: planowanie i funkcjonowanie rozwiązań cyfrowych, zrównoważona sieć elektroenergetyczna, prognozowanie mocy i energii elektrycznej, analiza statystyczna danych.

Introduction

International research project entitled "Digital Energy Path for Planning and Operation of sustainable grid, products, and society" (acronym DIEGO) is realized under the "Digital Transformation for Green Energy Transition" (EnerDigit) initiative, funded by the European Union's Horizon 2020 research and innovation programme [1]. It is expected that digital transformation will have an essential impact on energy system design in the future. Digitalization can bring many various, positive effects in the domain of energy systems. Therefore, EnerDigit promotes applied research and development, piloting, and demonstration in the field of digitalisation of energy systems and networks. It calls for the development of scalable, adaptable, and replicable solutions, applicable from local through interregional and up to global levels, making effective use of the opportunities offered by digitalization to drive the energy transformation [1].

In the initial phase of the project, research concerning analysis of the considered industrial plant's electric power system was carried out. The structure of the existing internal electrical grid and installation was analysed and preparation of a project for its modernization aimed at installing appropriate measuring devices was done. The collected measurement data were used to determine the profiles of the industrial plant's demand for power and electricity, the operating logic of the energy storage facility and the energy generation profile in the photovoltaic system installed at the plant. The description of the electrical grid and installation's structure in industrial plant and the analysis of measurement data allowed to determine limits of input data's usability for the algorithms controlling the demonstration installation, which are to be developed in the subsequent phases of the project.

The structure of the paper is as follows.
First project objectives are defined, and then demonstration installation in Poland has been characterized along with the analysis of the existing electrical grid and installation of the industrial plant. Next selected results of statistical analysis of measurement data and forecasting of demand and generation of electric power were presented. At the end of the paper summary and final conclusions have been placed.

Project objectives

The main objective of the DIEGO project is the development and testing of consistent methods and applications for a digital integrated energy system and components crosslinking of processes and infrastructures to provide reliable multigrid and sustainable industrial products. With DIEGO project planning and operation digital energy solutions, an optimized local energy symbiosis and an increase in system resiliency, reliability, and maintenance management should be guaranteed [2].

To ensure a reliable, continuous and safe supply of electricity in the future, the development of new sustainable and clean energy sources is gaining importance [2]. The use of information and communications technology (ICT) and digital applications enable to monitor, control and protect power systems. It also enables services offering that will be significant in grids with a large share of renewable sources and thus smooth the transition from conventional to sustainable smart grids. The ICT will increase the complexity of such integrated systems and necessitate new methods and tools for planning, operation and optimal integration of advanced digital solutions in energy systems domain. The DIEGO project aims to develop and test methods, solutions and tools for planning and operating components and local energy systems in the environments of manufacturing enterprises, industrial parks, public campuses, and living test laboratories.

The DIEGO digital solutions, consisting of concepts of data models, interfaces, and pilot applications, will be implemented and operated in 5 demonstration installations in different locations (one location each in Austria, Israel, and Poland as two locations in Germany) to test several use cases and scenarios of digital energy path for planning and operation of the sustainable grid, products, and society. In Poland the real test environment will be the coupling of energy (RES generation, load, storage) and electrical components in the AC grid of industrial enterprise for sustainable and energy-efficient manufacturing [2].

Demonstration installation in Poland

A short description of the electric power arrangement of the demonstration installation concerning an industrial enterprise located in Poland is presented below.

The considered factory (see Fig. 1) is supplied from existing overhead line of 15 kV via MV/LV substation located on its premises. In the mentioned substation a transformer with a rated power of 630 kVA is installed. This transformer supplies the main LV switchgear with five LV circuits going out from it. Four bays are used to power the main switchgears in particular buildings of the enterprise, and one bay is a connection to the switchgear of a photovoltaic installation (PV system) located on the factory premises.

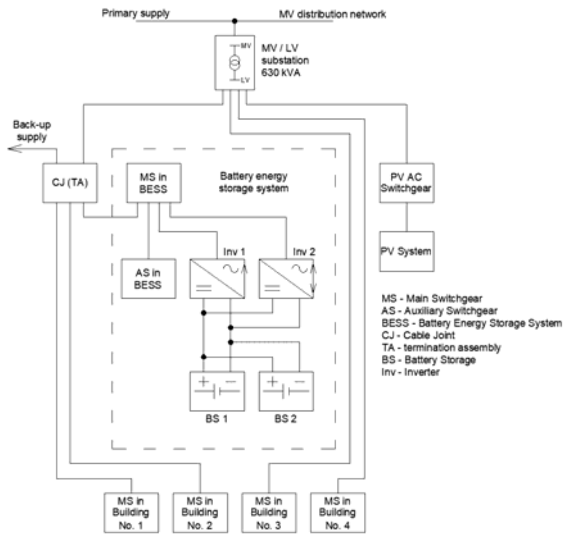

Fig. 1. The connection diagram concerning an internal electric power grid in the considered industrial enterprise.

An electricity storage facility is also located on the premises of the industrial enterprise. The storage system includes two inverter systems and two lithium-ion batteries. One of the inverters together with the batteries serves as an electricity storage system, and the second one together with the batteries creates an UPS system for needs of the industrial enterprise.

The production specialties of the considered industrial enterprise are listed below:

- production of the steel car accessories,
- laser processing of metal elements,
- production of home and garden accessories and advertising gadgets.

The production of door sills, rear bumper protectors and other car accessories made of steel and dedicated to particular kinds of cars is a main goal in the first above production category. In turn, laser cutting of the flat metal sheets, pipes, and various profiles is a subject of the second-mentioned category.

Different types of electricity loads are located in 4 buildings of the factory. These are:

- mainly lighting and plug-in sockets circuits supplying typical administrative and office equipment in Building no. 1;
- industrial loads in Building no. 2 with the highest power demand in the factory. These are four teams of laser cutters and circuits supplying additional loads of lasers. Fiber lasers of 6 kW, 10 kW, and 3 kW rated powers are applied. The maximum power demand of the largest unit is equal to 54 kVA;
- circuits of electrical installation in Building no. 3 which serves as a warehouse;
- circuits of electrical installation in Building no. 4. Rooms subleased to various tenants are located in the building. Besides lighting and plug-in socket circuits supplying typical office equipment, there are also electric heaters.

Computerized numerical control (CNC) machines work 24 hours a day and night and 7 days a week in Building no. 2 in the factory.

Internal electric power system analysis

As part of the DIEGO project, analyses of the power system located on the premises of the industrial plant will be carried out, in particular:

- analysis of electric power arrangement existing in the enterprise and technological processes realized there,
- exploration of an accessed measurement data on received power and electrical energy consumption as well as generation of power and electrical energy in the factory,
- modeling of selected electrical energy loads and technological processes realized in the factory in the scope of electric power demand,
- development of the real-time electrical energy balancing method on the level of the considered factory as well as the method which allows for setting proper operation regimes of electrical energy source, electrical energy storage system, and controllable electric power loads existing in the factory,
- development of preventive measures and methods concerning for example reducing the peak loads at the level of the analyzed factory as well as improvement of the energy efficiency of selected technological processes realized in the factory in the scope of electrical energy.

As it was mentioned, one of the tasks expected to be realized in the scope of the DIEGO project is the development of practicable preventive measures (methods) for reducing peak electric loads at the level of the considered factory.

For reducing peak electric loads, it is theoretically possible to apply the following preventive measures (methods):

- reduction of the total demand for electric power and energy at the level of the considered factory by limitation of the level of power and energy received by power loads exploited in the factory;
- reduction of the total demand for electric power and energy at the level of the considered factory by shifting the power consumption periods during the day by power loads exploited in the factory;
- increase of level of electric power and energy produced by a generation source located on the premises of the factory;
- applying appropriate operating regimes of the electric energy storage system for reducing peak electric loads at the level of the considered factory.

Were all the mentioned preventive measures used, the peak electric loads would decrease. Taking into account existing operating conditions and technological processes in the factory, applying appropriate operating regimes (charging, discharging) of the existing electric energy storage system will be a subject of analysis in the further part of the paper.

Fig. 2, 3, and 4 show daily characteristics of an active energy generated in PV installation (black line) and daily profiles of residual active energy (grey line) in 15-minute intervals in the considered factory for three selected days on April 2023: Wednesday, Saturday, and Sunday. Also, relevant characteristics of the mentioned energies on the days preceding the mentioned days have been shown, in order to show the periods of both days during which it would be possible to charge and discharge the energy storage system. A residual active energy is defined as a difference between an active energy generated by the PV installation and the total hypothetical consumption of an active energy in the considered factory. A negative sign of the residual active energy means that the active energy generated by the PV installation is lower than the total hypothetical consumption of an active energy at the level of the factory.

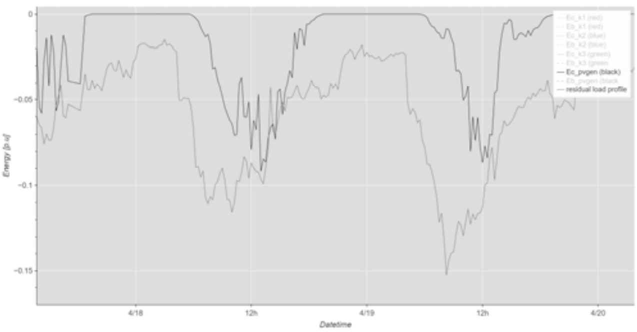

Fig. 2. Daily characteristics of an active energy generated in PV installation and a daily profile of residual active energy in 15-minute intervals in the considered factory on selected working day - Wednesday

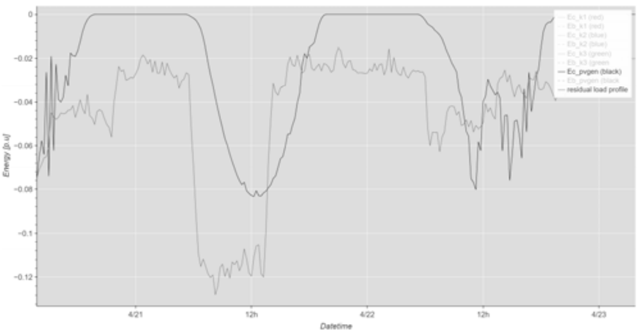

Fig. 3. Daily characteristics of an active energy generated in PV installation and a daily profile of residual active energy in 15-minute intervals in the considered factory on selected Saturday

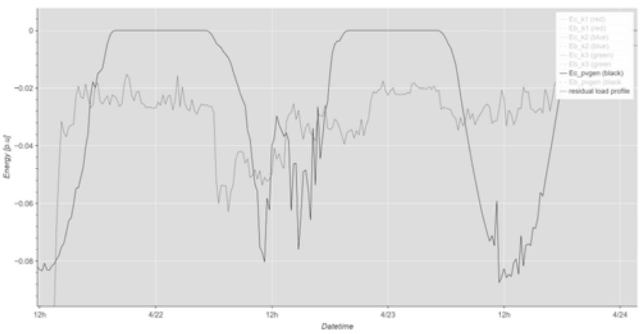

Fig. 4. Daily characteristics of active energy generated in PV installation and a daily profile of residual active energy in 15-minute intervals in the considered factory on selected Sunday

Analyzing the characteristics (15-minute averages) shown in Fig. 2, 3, and 4, the following observations can be made:

- in the evening hours on April 18th and at night on April 19th, it would be possible to charge the electrical energy storage system with active energy received from the DSO grid. This would slightly increase the absolute value of the residual active energy in the mentioned hours and, in consequence, it would also slightly increase the total hypothetical consumption of active energy at the level of the considered factory during these hours. Simultaneously, this would allow to discharge of the energy storage system during the peak period of the absolute value of the residual active energy on April 19th (between 7 a.m. and 12 p.m.). This, in turn, would decrease the peak absolute value of the residual active energy and, in consequence, it would limit the peak consumption of the active energy at the level of the factory on April 19th;
- on April 22nd (Saturday) and on April 23rd (Sunday) too high absolute values of the residual active energy and, consequently, very high consumption of the active energy at the level of the considered factory were not observed. Periods, in which the absolute value of the active energy generated by the PV installation was greater than the absolute value of the residual active energy could be used to charge the energy storage system. This would slightly increase the absolute value of the residual active energy in these periods and, in consequence, also increase the total hypothetical consumption at the level of the factory. The active energy accumulated in this way could be utilized in the process of discharging the energy storage system during the period of the peak consumption of the active energy on the next day, i.e. April 24th.

As shown, for each of these days it is possible to define the appropriate period for charging and discharging the electric energy storage system. In this way, the energy storage system can be used to limit the peak daily demand for active energy at the level of the factory in the considered 15-minute intervals.

The choice of relevant parameters of an electric energy storage system is an important issue in this context. Information from literature sources (e.g. [3]), shows that these parameters are closely related to the function that the energy storage system is to perform.

From the consumers point of view, the most important issues regarding the possible utilization of energy storage systems are the possibility of shifting electrical power and energy during the day (flattening the peak load – decreasing the peak power, reducing the costs of charges for power), the possibility of using them as emergency supply sources, and the possibility of using electric vehicles as mobile energy storage systems in the aspect of local and global balancing of electric power grids.

In turn, regarding the possible use of energy storage systems by RES owners, the most important question here is the possibility of shifting electrical power and energy during the day, i.e. the possibility of storing surplus energy generated in RES and utilization of the energy in periods of its shortage, i.e. usually during peak load times.

Each of the above-mentioned functionalities will require appropriate dimensioning of an electrical energy storage system. This issue has been described e.g. in [3 - 6].

Statistical analysis of data

For statistical analysis two types of data are available: demand for power/electricity in an industrial plant and generation of power/electricity in a PV system. Due to the lack of an appropriate amount of historical data from the PV installation located on the premises of the plant PV located nearby the industrial plant was used.

During the initial research, data preprocessing, statistical analysis of data from the PV system, and preliminary selection of explanatory variables for predictive models were conducted. Data resolution is 1 minute but it was converted to 15 minute values for forecasting purposes. Preprocessing of "raw" data was executed as the first step: identification and correction of incorrect or missing data and time change problems. The data were normalized for anonymization to relative units (1 relative unit is equal to the maximum value from time series). Pearson linear autocorrelation coefficients for analysed time series were calculated – choice of the most important lagged values of the explained variable. Figure 5 shows results of linear Pearson autocorrelation up to 2 days backward. All correlation coefficients are statistically significant (5% level of significance). The analysis revealed a very strong daily periodicity and high repeatability of the examined process. The values of the linear Pearson correlation coefficient for a lag of exactly 1 day (96 lags) are 0.770, which is greater than the correlation coefficient from lag 6 (lag 6 has a correlation coefficient of 0.788, while lag 7 has a value of 0.7526). For lags that are multiples of 96, the correlation coefficient decreases very slowly, and for a lag of exactly 10 days, it is 0.672. Using the last 6 lagged values and several lags that are multiples of 96 (exactly the same periods in previous days) as potential input data for predictive models is justified based on the correlation magnitude.

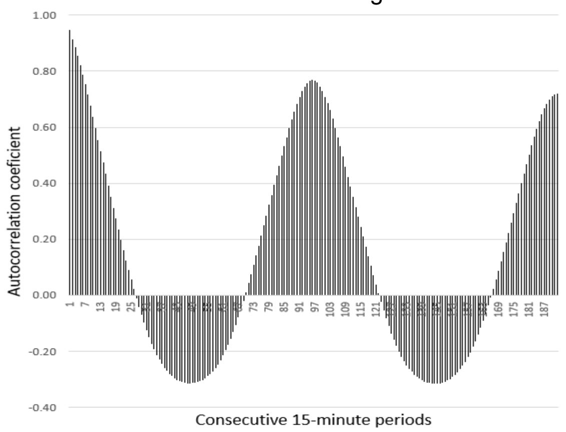

Fig. 5. Autocorrelation function (ACF) of the analysed time series (192 lagged 15-minute values).

Verification of daily periodicity and seasonality in available electricity generation time series was executed as the next task. The aim of the task was to determine additional explanatory variables for forecasting models (daily periodicity and seasonality markers). An example of similar research is described in the article [7,8]. Figure 6 shows the seasonality of electricity generation in the PV system (the sum of energy generation in each month of 2022). The sum of energy generation in June 2022 was almost 44 times higher than in the month of December 2022. The proposed input data includes the marker of daily variability (hour) and the marker of seasonality (month). Additionally, a marker for the time of day was suggested (value +1 until noon, and value -1 after noon) to sensitize the model to the direction (trend) of changes in generation values (increasing/decreasing).

Statistical analysis of electricity generation time series in order to find the most valuable explanatory variables for linear and non-linear prediction models was executed as the next task. Applied methods include analyses of Pearson linear correlation coefficients and explanatory variables cross-correlation matrix. Additionally, a weighted averaging of the time series of electricity generation values was performed. This activity should reduce the random component of this time series. The selected past values of such transformed time series may be a valuable set of input data. A full set of proposed input data is as follows: month, hour, rising solar irradiance marker, declining solar irradiance marker, smoothed generation in period T-1, generation and solar irradiance in periods: T-1, T-2, T-3, T-4, T-5, T-6, T-96 and T-192, air temperature in periods: T-1, T-2 and wind speed in period T-1.

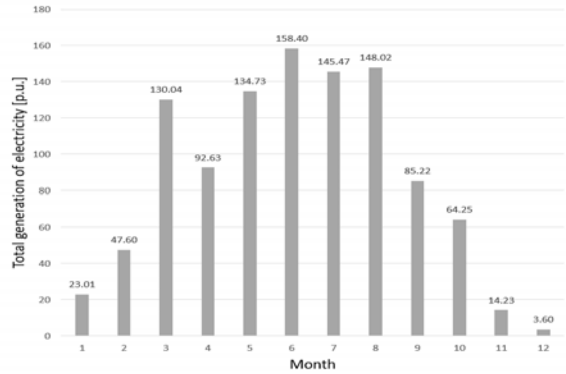

Fig. 6. Seasonality of electricity generation in the PV system (total generation).

Figure 7 shows a scatter plot between electricity generation in period T (output data) and solar irradiance in period T-1. For both dispersion diagrams the data in the XY coordinate system is fitted with a curve using a weighted least squares smoothing procedure with distance (the influence of points decreases with their horizontal distance from a given point on the curve). In this case, the shape of the fitting curve indicates a slight degree of nonlinearity between the output data and input data. Especially for the largest values, the fitting curve exhibits a slightly nonlinear form.

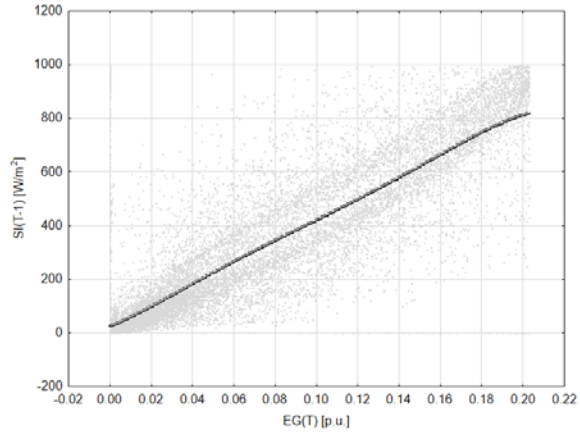

Fig. 7. Relationship between electricity generation in period T and solar irradiance in period T-1.

Fig. 8 shows the scatter plot of the generation of electrical energy values and the values of solar air temperature. The data in the XY coordinate system is fitted with a curve using a weighted least squares smoothing procedure with distance (the influence of points decreases with their horizontal distance from a given point on the curve). A slight nonlinearity is observed on the fitting curve for the highest values of electricity generation (the growth dynamics of generation decrease with increase in air temperature). This effect is likely due to the phenomenon of decreased efficiency of photovoltaic panels under very high air temperatures. An interesting observation is the dynamic increase in the magnitude of generation (lowest values) evident on the fitting curve as the temperature rises from approximately 7 degrees Celsius to around 15 degrees Celsius.

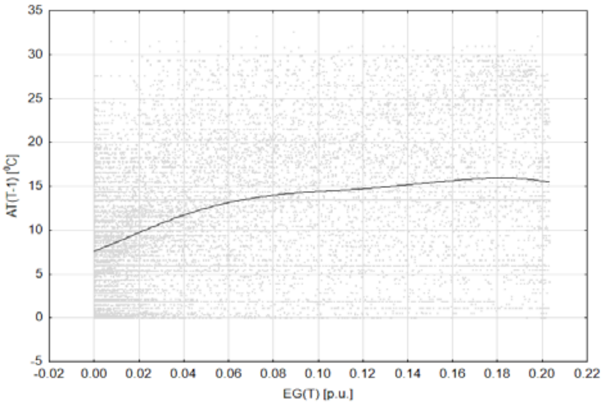

Fig. 8. The scatter plot of the generation of electrical energy values and the values of air temperature.

Sensitivity analyses/importance rating by Multi-Layer Perceptron (MLP) artificial neural network, random forest, gradient-boosted decision trees, and backward stepwise regression was executed. Based on the conducted tests of input data importance, a ranking of importance was developed, incorporating results from all methods. Based on the balancing ranking of input data importance, it can be concluded that the most important input data are electricity generation and solar irradiance from the last few 15-minute periods preceding the forecast period. Additionally, smoothed generation in period T-1 is also among the most important input data. On the other hand, the least valuable input data are wind speed and the seasonality marker (month).

Forecasting of energy generation and electric energy demand

The next point of project research will be the selection and development of forecasting models for power and electricity demand. During the initial electricity generation forecasting energy generation of a photovoltaic farm with a 15-minute forecast horizon, different methods were checked. The forecasts were generated using data from the year 2022. From original time series, covering full days, samples between sunrise and sunset were extracted and treated as valid data. The purpose of this transformation was to simplify the problem for predictive models (results from the period between sunset and sunrise have no practical application, and typically forecast values are zeroed as part of post-processing). In order to divide the dataset into training and validations subsets, full dataset was divided into 4 climatic seasons. Spring lasted from 2022-03-01 01 to 2022-06-01 00, summer from 2022-06-01 01 to 2022-09-01 00, fall from 2022-09-01 01 to 2022-12-01 00, and the rest of the year 2022 was treated as winter. One last week of each season was labelled as test data, while the rest of the data constituted a combined training/validation dataset. For this combined dataset one last week of each season was taken as validation data. In total data was divided into training/validation and test with 83.35-16.65% proportion, where validation data constituted 20.67% samples in training/validation dataset. In order to have a broader view of the quality of individual forecasting models, four evaluation criteria are used, including nRMSE, nAPE, nAPEmax and nMBE. The nRMSE error was adopted as the most important measure due to the greater sensitivity to large partial errors. Sets of input data selected for forecasting methods are following:

- SET1(24 inputs) - all available/created input data including: endogenous variables, exogenous variables, seasonality markers, daily variability markers, and process trend markers (increasing/decreasing),
- SET2(12 inputs) - 12 highest ranked input data (from 24 input data) based on the final balancing ranking of the importance of input data,
- SET3(13 inputs) - only endogenous variables and seasonality markers, daily variability markers, and process trend markers (increasing/decreasing),
- SET4(9 inputs) - only endogenous variables without markers,
- SET5(1 input) – generation in period T-1.

The following Machine Learning (ML) techniques were applied: Long Short-Term Memory (LSTM) neural network, Multi-Layer Perceptron (MLP) neural network, Random Forest (RF), and Gradient Boosted Decision Trees (XGBoost type). Methods from these categories are described in articles [9, 10, 11]. For each ML technique, the search for the best hyperparameters was conducted in 5 variants (using 5 different sets of input data).

Table 1 presents the forecasting results using different ML models for the test range. The best results for each error metric have been highlighted in bold in the table. The number of tested models to find the right hyperparameters (criterion - minimum nRMSE error on the validation set) was as follows for each machine learning technique: 498 (MLP), 240 (LSTM), 500 (XGBoost), and 192 (RF).

The best RF model has following structure and hyperparameters: the available number of input data: 24 (SET3), the number of randomly chosen input data for each decision tree individually is 19 (80%), the number of decision trees used for generating forecasts (determined based on the observation of quality changes, i.e., prediction errors) is 300, the minimum number of samples in a node subject to splitting is 100, the maximum number of levels in the decision trees is 10, the maximum number of nodes in the decision tree is 100 and minimum samples per leaf - the number of samples in a node after a split is 10. The best RF model achieved an nRMSE error that was 10.56% lower compared to the reference model (naive model) (see Table 1). The nMBE error was also lower than in the naive model. Among the 4 sets of input data, SET1 is the best for the best RF model. Therefore, RF model differs from other machine learning techniques, where SET3 is the best set of input data. The utilization of markers (SET3) for RF model compared to the variant with the same input data but without markers (SET4) improved the result by 0.94%, indicating that the application of markers is fully justified. The number of randomly chosen input data for each decision tree individually even 80% is always better than 60% for RF models.

Figure 9 depicts the relationship between the best RF model residuals and the magnitude of energy generation. The data in the XY coordinate system is fitted with a curve using a weighted least squares smoothing procedure with distance. A slight nonlinearity is observed on the fitting curve. A slight tendency for underestimations (forecast values are lower than actual values) is clearly visible for high energy generation values, and there is also a tendency for overestimations (forecast values are higher than actual values) for low energy generation values. Fig. 10 shows actual electricity generation values and forecasts by the best RF model for three consecutive days in the spring month of 2022 (May 19, 20, and 21).

Table 1. Summary of prediction results for different ML models and the naive model.

Forecasting model	Input data variant	nRMSE (p.u.)	nMAE (p.u.)	nAPEmax (%)	nMBE (p.u.)
RF	SET1	**0.021232**	0.010263	18.7999	-0.00071
RF	SET3	0.021315	0.010145	19.8930	-0.00044
XGBoost	SET3	0.021361	**0.009863**	19.7055	-0.00052
RF	SET2	0.021468	0.010438	20.0389	-0.00065
MLP	SET3	0.021495	0.009953	19.3563	-0.00060
RF	SET4	0.021519	0.010399	19.9537	-0.00065
LSTM	SET3	0.021538	0.010164	**18.5626**	-0.00044
MLP	SET1	0.021601	0.010069	18.5677	-0.001095
XGBoost	SET1	0.021642	0.010895	18.2109	-0.00146
XGBoost	SET4	0.021712	0.010279	19.7528	-0.00063
LSTM	SET4	0.021953	0.010080	19.6159	-0.00011
XGBoost	SET2	0.021958	0.010451	19.4267	-0.00090
MLP	SET2	0.021996	0.010277	19.8986	-0.000335
MLP	SET4	0.022059	0.009930	20.0266	-0.00026
MLP	SET5	0.022682	0.010810	20.0872	-0.00047
XGBoost	SET5	0.022682	0.011475	19.8671	-0.00138
LSTM	SET2	0.022912	0.011803	18.7428	0.00115
LSTM	SET5	0.023042	0.010852	20.0897	**-0.00005**
LSTM	SET1	0.023591	0.013196	20.2756	-0.00253
Naive	SET5	0.023739	0.009884	20.2918	0.00035

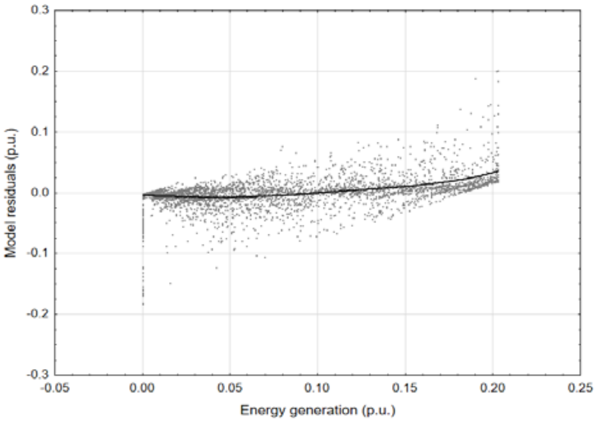

Figure 9. The relationship between the best RF model residuals and the magnitude of energy generation (test range)

Among the analyzed ML models, the most advantageous one turned out to be the RF model (ranked 1st on input data SET1, 2nd on input data SET3). The second-best ML model in the ranking is XGBoost. The least favorable is the LSTM model, although the differences in nRMSE error values between the best RF model and the best LSTM model are negligible. The best RF model (SET1) has an nRMSE error that is 1.4% lower than the best LSTM model (SET3).

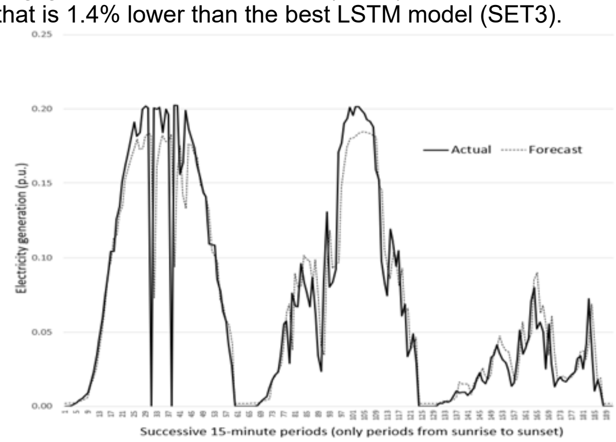

Figure 10. Actual electricity generation values and forecasts by the best RF model for three consecutive days in the spring month of 2022 (May 19, 20, and 21).

In the subsequent stages of the project, proprietary ensemble and hybrid models will be proposed, potentially further reducing the nRMSE error in forecasting energy generation in the photovoltaic system. Within the project, ML single models as well as hybrid and ensemble models will also be developed for forecasting electricity demand in the industrial facility.

Summary and conclusions

The results from the research conducted so far and presented in this article will be used to develop (in the industrial plant being under consideration):

- countermeasures for limiting electrical load peaks and limiting starting currents of selected power loads,
- predictive models determining the expected efficiency of selected technological processes,
- real-time electricity balancing method and algorithm,
- methods and algorithm for determining appropriate operating regimes of sources, storage facilities and controllable loads of electrical power.

The developed methods and algorithms will be integrated with the SCADA system used to monitor and manage the demonstration installation.

The implementation of DIEGO international research project will contribute to increasing the energy efficiency of the electrical installation of the industrial plant under consideration and will increase the degree of integration and cooperation of renewable energy sources, energy storage units and selected electricity loads. The methods and algorithms developed during the project may significantly contribute to reducing the carbon footprint of the company, where the demonstration installation will be established, which in the era of rising energy prices is one of priority areas of interest of the European Union authorities.

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