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Key Technical Performance Indicators for Power Plants

Simona Vasilica Oprea and Adela Bâra

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Abstract

In this chapter, we will underline the importance of the key performance indicators (KPIs) computation for power plants' management. The main scope of the KPIs is to continuously monitor and improve the business and technological processes. Such indicators show the efficiency of a process or a system in relation with norms, targets or plans. They usually provide investors and stakeholders a better image regarding location, equipment technology, layout and design, solar and wind exposure in case of renewable energy sources and maintenance strategies. We will present the most important KPIs such as energy performance index, compensated performance ratio, power performance index, yield, and performance, and we will compare these KPIs in terms of relevance and propose a set of new KPIs relevant for maintenance activities. We will also present a case study of a business intelligence (BI) dashboard developed for renewable power plant operation in order to analyze the KPIs. The BI solution contains a data level for data management, an analytical model with KPI framework and forecasting methods based on artificial neural networks (ANN) for estimating the generated energy from renewable energy sources and an interactive dashboard for advanced analytics and decision support.

Keywords: Power plants, key performance indicators, renewables, business intelligence, forecasting models

1. Introduction

The main objective of key performance indicators (KPIs) evaluation and monitoring consists in detecting low performance in power plant operation, investigating issues and setting up maintenance plans in order to minimize the operational costs. Another objective is to point out the commissioning and inspection of power plants after major repairs so that the results recorded during a period of at least 6 months will be compared with the expected results from

the climatic conditions, design and exposure point of view, etc. The objective entails identifying errors related to layout in case of renewables (especially photovoltaic power plants), incorrect installation, equipment failure, damage, premature aging, etc.

In order to provide a real time and complete analysis of KPIs, it is necessary to develop informatics systems that monitor and report the operational activity of the power plant and offers decision support for stakeholders. Various informatics solutions and applications are currently proposed and used, especially for renewable power plants' management: decision support systems (DSS) for wind power plants with (GIS) Geographic Information Systems capabilities [1], DSS for off-shore wind power plants [2] or GIS DSS for photovoltaic power plants [3]. Also, there are well-known software solutions for power plants' complete management provided by Siemens or Emerson that can be set up and customized depending on the equipment's configuration, location and size.

In this chapter, we will present the main key performance indicators for wind and photovoltaic power plants, identify new indicators for maintenance activities and propose an informatics solution that monitors and analyzes these KPIs through an interactive dashboard developed as a business intelligence portal accessed as a cloud computing service. The proposed solution is developed as part of the research project—intelligent system for predicting, analyzing and monitoring performance indicators and business processes in the field of renewable energies (SIPAMER), funded by National Authority for Scientific Research and Innovation, Romania, during 2014–2017.

2. Key performance indicators for power plant operation

The main objectives of assessing the technical performance of power plants based on renewable sources are

- Monitoring the operation of generating units or groups, identifying decline in their performance and also the need to perform maintenance/repairs on the affected groups. In this case, we recommend the use of energy performance index (EPI) and compensated performance ratio (CPR);

- Commissioning, recommissioning or evaluation after repairs, benchmarks for measuring and comparing further performance. We recommend using energy performance index (EPI) and power performance index (PPI);

- Calculating specific parameters such as yield, performance ratio (PR) to enable comparisons between power plants operation in different geographical areas and assisting decisions regarding investment in new groups or extending existing ones. In some cases, depending on the objectives, it is recommended to use several indicators (yield, PR, CPR, and/or EPI, depending on the level of effort and the level of uncertainty), so that the comparison to be more efficient.

Technical performance indicators allow the following comparisons:

- Operation of the power plant or a group compared with expectations at some different points in its runtime period;

- Operation of the power plant for a period of assessment compared to other power plant operation under similar climatic conditions;

- Standard power plant operation on short and long term in comparison with power plant operation under certain conditions (design, location, exposure, etc.);

- Power plant operation in consecutive time, the current performance being compared to past performance.

The main objective of the technical performance evaluation consists in detecting the decrease of power plant performance, investigating issues and completion of the maintenance operations, so that the involved costs are minimal.

In this section, we will present a series of key performance indicators for monitoring the operation of the wind power plants (WPP) and photovoltaic power plants (PPP). For a better analysis, we grouped KPIs in four categories: operational KPIs, indicators for photovoltaic power plants, indicators for wind power plants, and maintenance KPIs.

2.1. Performance indicator techniques based on operational data

1. The average power (P_{avg}) is the ratio between the produced energy (W) and power plant's runtime (t), depending on the yearly power plant operational time. According to [4], we may consider t as follows:

   - onshore WPP, t = 1900 hours/year;

   - offshore WPP, t = 3500 hours/year;

   - solar, t = 1100 hours/year.

$$P_{avg} = \frac{W}{t} \ [kW] \tag{1}$$

The average power calculated at different time intervals is necessary to determine the installed power load factor. P_{avg} allows comparisons between monthly/quarterly or annual results of the same power plant, or it can be used to compare the generating units' performance within the same power plant.

2. Installed power load factor (K_u) is calculated as the ratio of average power (P_{avg}) and installed power (P_i):

$$K_u = \frac{P_{avg}}{P_i} \tag{2}$$

This coefficient can be calculated on monthly, quarterly or annually basis and indicates the availability of renewable resource and production capacity of the power plant. Also, it can indicate the degree of generating units or equipment's aging but must be correlated with meteorological factors that influence the production. For example, for wind power plants, the installed power load factor can range between 0.15 and 0.39.

3. Installed power load duration (T_i) is determined based on installed power load factor (K_u) multiply by power plant's runtime (t):

$$T_i = K_u \times t \ [h] \tag{3}$$

For photovoltaic power plants, the number of operating hours can be accordingly reduced, considering only those daytime hours when the PPP is operating. We may consider [4] for reference to operational time.

4. Maximum power load duration (T_{max}) is calculated as ratio between generated energy (W_a) and maximum power plant output (P_{max}):

$$T_{max} = \frac{W_a}{P_{max}} \ [h] \tag{4}$$

P_{max} can be calculated on monthly, quarterly or annual basis, and it can be used to compare results between different periods of time and identify the influence factors.

5. Power factor ($\cos\varphi$) can be determined based on active energy (W_a) and reactive energy (W_r):

$$\cos\varphi = \frac{1}{\sqrt{1 + \left(\frac{W_r}{W_a}\right)^2}} \tag{5}$$

Power factor is monitored for energy quality assurance.

6.   Performance index (PI) is the ratio between the generated power/energy and forecasted power/energy:

$$PI = \frac{W}{W_f} \tag{6}$$

As described in [5], unlike performance ratio, index performance should be very close to 1 for the proper functioning of the PPP, and it should not vary from season to season due to temperature variations. There are several definitions of formal performance index:

- Energy performance index (EPI)—measures the energy (kWh) for a specific time period;

- Power performance index (PPI)—measures the effective power of the power plant (kW).

Energy or power forecast can be determined using different prediction models (regression model using historical data operation or system advisor model (SAM) which uses current climate data as input), thus the accuracy of performance index depends on the accuracy of the used forecast

model. In Section 3, we will present a forecasting model based on artificial neural networks (ANN) for estimating the generated energy for photovoltaic and wind power plant.

2.2. Key performance indicators for photovoltaic power plants

Several technical performance indicators for PPP were defined by different organizations, for example, National Renewable Energy Laboratory (NREL) [6], the International Electrotechnical Commission (IEC) [7], associations and companies in the industry. Some of them are described in the following sections:

1. Performance ratio (*PR*) is defined according to IEC 61724 standard [7], as follows:

$$PR = \frac{Y_f}{Y_r} = \frac{\frac{kWh_{AC}}{kW_{DC\,STC}}}{\frac{kWh_{Sun}}{1kW}} \tag{7}$$

Where:

- Y_f represents the ratio between annual active energy and rated power;

- Y_r is the ratio between insolation (kWh/m^2) and reference solar irradiance (1000 W/m^2). Irradiation is an instant size of solar power in a given area, and insolation measures energy gained for a certain area for a certain period of time.

Performance ratio can be evaluated on different time intervals (hourly, monthly, quarterly and annually). The main disadvantage of this indicator is that it is sensitive to temperature variations, and when plotted in a typical year, the index values are lower in warm periods and higher in cold periods.

It can be calculated on annual basis to make comparisons between photovoltaic power plants having similar climatic conditions but is not suitable for short periods of time or for comparing PPP efficiency under different climatic conditions.

2. Compensated performance ratio (CPR)

As reflected in the performance ratio formula, it is directly influenced by the energy produced by the photovoltaic power plant, which is directly influenced by solar irradiation and indirectly by the cell temperature. Therefore, it appears that PR decreases with increasing temperature.

According to [5, 8], offsetting factors such as cell temperature (K_{temp}) can be applied to the performance ratio to adjust the rated power under standard test conditions (STC).

$$PR_{TempComp} = \frac{\frac{kWh_{AC}}{kW_{DC\,STC} \times K_{Temp}}}{\frac{kWh_{Sun}}{1kW}} \tag{8}$$

Where

- $K_{Temp} = T_{Cell} - T_{STC}$

- $T_{STC} = 25^{\circ}C$

This indicator is suitable for daytime values due to the fact that during night, the PPP production, irradiation and insolation are zero.

3. The yield is the ratio between the PPP's produced energy (kWh) during the operation time (t) and peak load power (kWp or kW peak) of the PPP or rated power on standard test conditions (STC), and it varies yearly depending on climate conditions.

The yield is determined annually based on the formula:

$$Yield = \frac{\sum_{i=1}^{t} kWh_{AC}}{kW_{DC\,STC}} \tag{9}$$

Due to the fact that the yield increases with the number of hours of operation and insolation etc., a high yield due to favorable climatic conditions can mask problems of premature aging of the equipment and vice versa.

When comparing the performance for two power plants or the yield for the same PPP in different periods of time, then the number of hours, insolation and cell temperature must be equivalent to achieve a fair comparison. Also, the power plant output (measured annually or at smaller intervals) can be compared with PPP's output from previous years. In this case, it must be taken into consideration the climate influence and correct the differences with a correction coefficient, to avoid masking problems of degradation of solar panels.

4. Normalized efficiency is another KPI for measuring the performance ratio [8]:

$$\eta_N = \frac{\frac{P}{P_n}}{\frac{E_{POA}}{E_{ref}}} \tag{10}$$

Where:

- P is the measured power;

- P_n is the rated power;

- E_{POA} is the plane-of-array irradiance;

- E_{ref} is the reference irradiation (1000 W/m²).

Exposure to irradiation measures the total available solar exposure, and it is based on location exposure and direction of modules. It is calculated at the module level and average at central level. In order to maximize exposure to irradiation, modules are oriented towards the equator, the tilt modules depending on geographical latitude of the location. Optimal orientation in terms of space restrictions may not coincide with the orientation that maximizes exposure (due to the fact that a lower slope leads to more modules in a project).

One drawback of the performance index is that the normalized efficiency is sensitive to temperature variations, as any change in temperature leads to changes in efficiency, power and consequently in the produced energy.

Changing efficiency or power for a photovoltaic module can be quantified using the temperature coefficient of power γ, which allows the module power (or efficiency) to be modelled to a

certain temperature. For silicon crystals, γ is between $-0.3\%/°C$ (for newer technologies) and $-0.5\%/°C$ (for older technologies).

Power for a certain temperature for a photovoltaic cell is determined by:

$$P(T) = P_{STC}\left(1 + \gamma(T_{cell} - T_{STC})\right) = P_{STC}(1 + \gamma\Delta T_{STC}) \tag{11}$$

Where

- T_{STC} is 25°C;

- T_{cell} is the temperature of the photovoltaic cell.

The temperature—corrected power (P^*) can be determined as in [9]:

$$P^* = \frac{P(T)}{1 + \gamma\Delta T_{STC}} \tag{12}$$

Thus, the temperature-corrected normalized efficiency can be expressed as:

$$\eta_N{}^* = \frac{\frac{P^*}{P_n}}{\frac{E_{POA}}{E_{ref}}} \tag{13}$$

This indicator shows the performance of the photovoltaic module as if it operates at standard temperature (T_{STC}). In this way, the technical performance of the PPP can be attributed to other factors, such as the irradiance spectrum or inverter efficiency at lower irradiances [9].

2.3. Key performance indicators for wind power plants

1. Specific energy production (SPE) measured in kWh/m^2 for a wind turbine is defined in [10] as the ratio between total energy production during nominal period (W) and swept rotor area (S_{SR}):

$$SPE = \frac{W}{S_{SR}} \tag{14}$$

The nominal period is the period covered by the report, usually considered as 1 year. SPE is also called as energy yield or energy productivity [11], and it depends on the turbines' rated power.

2. Capacity (load) factor (CF %) defined in [11] is the ratio between total energy production during the nominal period (W) and the potential energy production during the reported period (W_p):

$$CF = \frac{W}{W_p} \tag{15}$$

Usually, the capacity factor varies depending on the turbines specifications and climate conditions between 18 and 40% for onshore turbines and 30–40% for offshore turbines.

3. Equivalent full load hours (E_h) can be defined as the annual energy production (W) divided by the rated power (S_n), and it represents the number of hours as if turbines generate at rated power:

$$E_h = \frac{W}{S_n} \qquad (16)$$

4. Availability factor (%) represents an important indicator especially for WPP due to the wind influence that affects the turbines' generation and can be calculated as ratio between total hours of operation during the reported period (T_{op}) and total hours of reported period (T_p):

$$AF = \frac{T_{op}}{T_p} \qquad (17)$$

2.4. KPIs for maintenance operations

Several maintenance strategies have been developed as described in [12, 13] with the main objective to preserve the efficiency of power plants' components. Each of these methodologies has its own characteristics, but mainly they focus on internal characteristics of the power plants' components. The industry has adopted for a long period of time maintenance that focuses on corrective actions. But, in recent years, the maintenance plans focus on predictive maintenance where monitoring or inspection activities are performed to determine the best time to start the maintenance in order to minimize the efforts compared to corrective maintenance.

Preventive maintenance activity has a direct impact on the reliability of the equipment or components by improving their technical condition and prolonging their life. All maintenance procedures involve both costs and benefits. Maintenance operations are profitable when the costs are lower than associated potential cost of a failure, which these operations are trying to prevent. Most of the maintenance plans on short and medium term do not take into account the operation conditions in which the components operated throughout their runtime but rather are scheduled based on the occurrence of defects and previous repairs. But, in recent years, several applications for continuous monitoring of current operation led to the development of a variety of diagnostic techniques. According to [14], these techniques verify certain parameters and then analyze whether certain components are defective at the moment and can make an estimate of their evolution.

The main purpose of the maintenance plan is to minimize production costs per unit of energy generated. In general, this is achieved by minimizing operational and maintenance costs, improving turbine/photovoltaic panels' performance and efficiency and lowering insurance policy and equipment's protection. Thus, we proposed two KPIs for determine the loss due to preventive (planned) maintenance or to corrective (unplanned) maintenance.

1. Preventive loss indicator (PLI_{plan}) is the ratio between estimated energy loss caused by planned interruptions and the maximum energy that can be produced during the reported period (usually 1 year).

$$PLI_{plan} = \frac{W_{lossplan}}{W_{max\_prod}} \times 100\% \qquad (18)$$

Where:

- $W_{lossplan}$ represents the energy loss caused by the planned interruptions;

- W_{max_prod} is the maximum energy that can be produced during the reported period.

2. Corrective loss indicator (PLI_{unplan}) is the ratio between estimated energy loss caused by unplanned interruptions and the maximum energy that can be produced during the reported period.

$$PLI_{unplan} = \frac{W_{lossunplan}}{W_{max\_prod}} \times 100\% \qquad (19)$$

Where:
- $W_{lossunplan}$ represents the energy loss caused by the unplanned interruptions;

- W_{max_prod} is the maximum energy that can be produced during the reported period.

Depending on these indicators, the maintenance policy can be schedule in order to minimize the production losses.

3. Informatics solutions for monitoring and analyzing the power plants' KPIs

In order to analyze and monitor the key performance indicators, the executives of the power plants require an advanced decision support system (DSS). Our proposal consists in developing an informatics solution based on three levels architecture that involves models for data management, analytical models and interfaces (**Figure 1**):
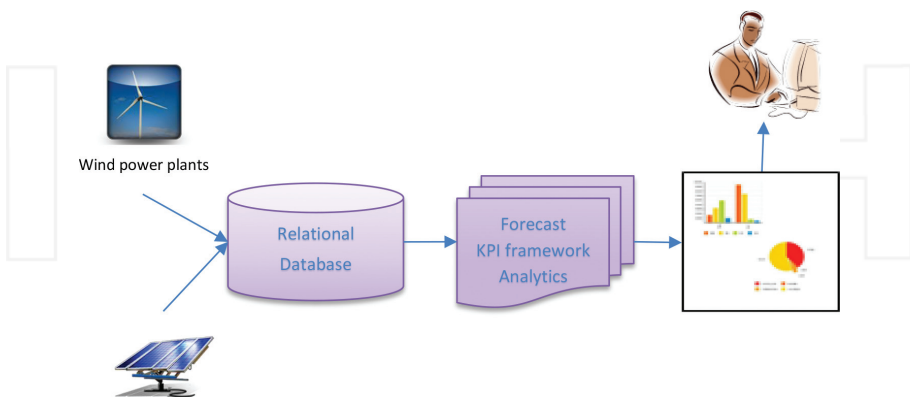
The architecture components are as follows:

Figure 1. SIPAMER's architecture.

3.1. Level 1—data management

All data sources gathered from wind/photovoltaic power plants are extracted, transformed and loaded into a central relational database running Oracle Database 12c Edition in order to enable user access through cloud computing. The sources are heterogeneous: measuring devices for climate conditions (wind speed, direction, temperature, atmospheric pressure, and humidity), sensors for photovoltaic cells and wind turbines, SCADA API for measuring real-time parameters regarding power plant output. These sources are mapped into a relational data stage; then, the extract, transform and load (ETL) process is applied, and data are finally loaded into a relational data mart that organizes objects as dimensions and facts. This approach makes it easier the development of the analytical model with KPIs framework and enables an advanced roll-up/drill-down interfaces.

Based on the executives' requirements regarding the KPIs, we designed the main structural entities (objects) that will enable multidimensional data exploration. They will be organized as dimensions (subject entities) with descriptive attributes structured on hierarchies with multiple levels to enable typical OLAP operations: roll-up/drill-down, slicing and dicing. The data mart contains the following dimensions: DIM_STAKEHOLDER, DIM_POWERPLANT, DIM_REGION, DIM_TURBINE, DIM_PV and DIM_TIME.
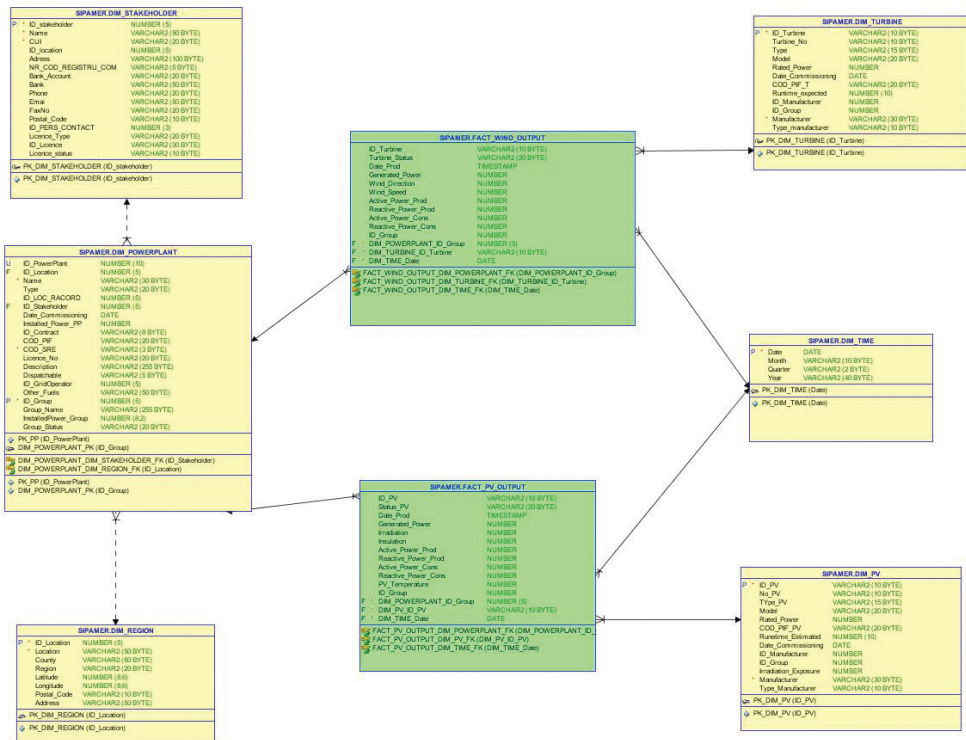

Figure 2. Snowflake schema for the KPIs data mart.

Facts tables are objects that contain attributes like measures (metrics) and foreign keys to the dimension tables. Facts are usually numerical data that can be aggregated and analyzed by dimensions' levels. The model contains the following facts: FACT_PV_OUTPUT and FACT_WIND_OUTPUT. The objects are organized in a snowflake schema as shown in **Figure 2**.

The data mart allows us to design the KPIs framework in a subject-oriented and multidimensional view.

3.2. Level 2—models

This level contains models for forecasting the power plant output on short term (hourly, up to 3 days) and the KPIs analytical framework.

Forecasting models are build distinct for each type of renewable power plant, WPP and PPP due to the different influence factors that affect the power plant' operation and generation. The aim of the model is to improve predictions made and transmitted currently by the producer on short-time intervals. The deviations between forecasting and recorded production are currently about 30–35% for wind power plants and 15–20% for photovoltaic power plants [15, 16]. Minimizing these deviations will lead to lower costs for stakeholders due to the fact that imbalances are paid. The model consists in a set of experimental methods based on data mining algorithms, developed, validated and tested on WPP and PPP data sets. We developed three algorithms based on artificial neural networks (ANN): Levenberg-Marquardt algorithm (LM), Bayesian regularization algorithm (BR), and scaled conjugate gradient algorithm (SCG).

3.2.1. Forecasting the photovoltaic power plants' output

We identified the input parameters (irradiance, temperature, wind speed & direction, tilt, exposure) and the output (power), and for the training and validation, we used a data set that consist of 50,631 samples from every 10 minutes direct measurements in a PPP located in Romania, Giurgiu County, during January 1, 2014—December 31, 2014. Within this photovoltaic power plant are installed two types of ABB—PSV800 invertors, with 600 kW and 760 kW, 30,888 solar panels and the solar module has a rated power of 245 W with a 20-kV connection. The configuration is widely used in other PPP; therefore, the developed ANN can be easily implemented in other power plants with similar configuration.

Since solar energy presents seasonal variations related to the various climate conditions of the year, we designed the neural networks adaptable to irregular seasonal variations by changing the settings on the number of neurons in hidden layers and developed two types of ANN.

First, we designed one neural network for each of the three algorithms (LM, BR and SCG) based on the whole year data. The results were good, with an average mean squared error (MSE) of 0.19, and average for correlation coefficient, R = 0.95, with 0.9573 for LM.

Then, we consider the second option, to take into account the seasonal variations for solar energy, and we designed neural networks based on LM, BR and SCG for each month. So, we obtained 36 neural networks with a much better results than the previous case (yearly ANNs). Comparing results from the monthly data, we found that the prediction accuracy is excellent in
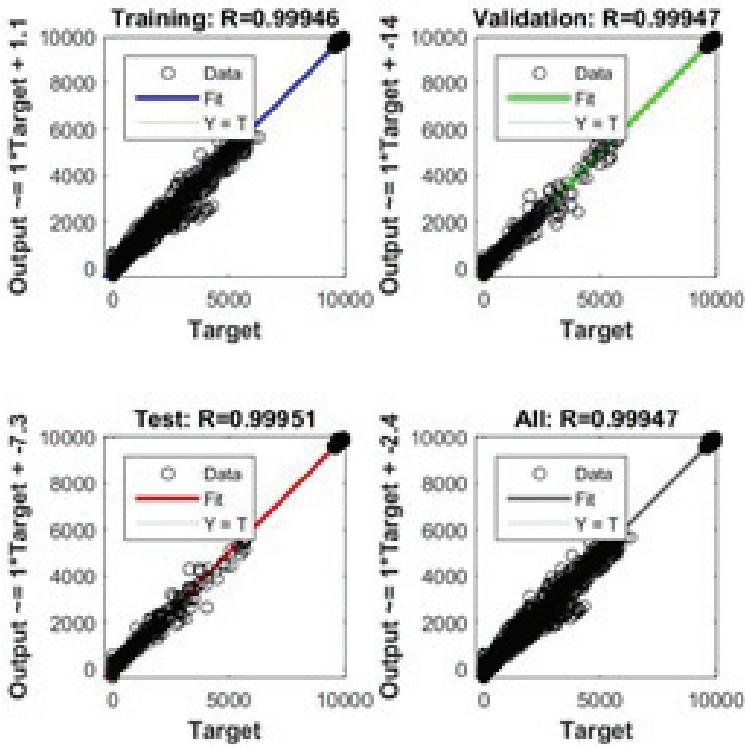
Figure 3. Regression between target values and the output values of the neural network *SfebruaryLM*.

all months, and monthly performance indicators have comparable values. The MSE is between 0.03 and 0.1, and coefficient R is between 0.997 and 0.999. For example, **Figure 3** shows the correlation coefficient for the neural network *SFebruaryLM* developed on Levenberg-Marquardt algorithm.

By comparing the forecasting results through the development of neural networks based on the three algorithms, we found that in 69% of cases, neural networks developed with Bayesian regularization produced a better generalization than networks developed with Levenberg-Marquardt and SCG algorithms. But, in 31% of cases, the forecasting results with the highest level of accuracy have been obtained in the case of Levenberg-Marquardt algorithm.

If, in order to improve the accuracy of the forecasting model, new elements are added as input data, the LM algorithm will offer the advantage of a higher training rate compared with the BR algorithm but would have the disadvantage of an increased memory consumption. When new inputs are added and we want to obtain a high speed and performance, then the best solution is to develop the ANN based on SCG algorithm as it is faster than the other two algorithms (LM and BR) requiring low memory consumption, with the drawback that it provides a lower level of prediction accuracy.

3.2.2. Forecasting the wind power plants' output

We identified the input parameters (temperature, wind speed & direction at 50 m, 55 m, 75 m, 90 m, humidity, atmospheric pressure, turbine height, soil orography, slipstream effect) and the output (power). For ANN training and validation, we used a data set of 17,491 samples from hourly measurements in a WPP located in Romania, Tulcea, for 2 years (January 1, 2013– December 31, 2014). In this WPP, there are two types of wind turbines: V90 2MW/3MW IEC IA/IIA, with a height of 90 meters. These types of wind turbines are commonly used, so we can consider the data set suitable for training a generalized neural network, as described in [17].

Since wind energy presents seasonal variations over 1 year period, we design two sets of ANN based of three algorithms: Levenberg-Marquardt algorithm (LM), Bayesian regularization algorithm (BR) and scaled conjugate gradient algorithm (SCG).

First, we designed the neural network based on data set covering 2 years records for each algorithm (LM, BR and SCG). For the second solution, we take into account seasonal variations that affect wind energy and designed neural networks for each season, dividing the data into 4 sets corresponding to 4 seasons specific to Romania region. The results between the ANN trained for the whole year and the ANN trained for corresponding season are compared in **Table 1**.

The best approach is to develop and train the neural networks adjusted with seasonal data, due to the fact that the prediction accuracy is excellent in all seasons, and performance indicators have comparable values. Comparing the results for each algorithm (LM, BR, SCG), in most cases, neural networks based on Bayesian regularization produced a better generalization than Levenberg-Marquardt or SCG algorithms, but LM performed faster and with minimum memory consumption.

KPIs analytical framework provides methods for calculating the key performance indicators used by executives to monitor the power plants in terms of technological and business processes. For technological processes, we build the KPIs presented in Section 2 based on formulas (1) to (19). For business processes, we included commonly used KPIs as income, cost, profit/ loss, etc. The KPIs are developed directly into the facts tables, as derived measures and accessible into the interface level.

Period	MSE			R			Errors interval		
	LM	BR	SCG	LM	BR	SCG	LM	BR	SCG
Year	0.06090	0.05789	0.06640	0.92922	0.93306	0.92739	−0.9651; 0.8758	−1.001; 0.8677	−0.7543; 0.7062
Spring	0.04817	0.03608	0.05079	0.96238	0.95877	0.94980	−0.3296; 0.2347	−0.3811; 0.1868	−0.2089; 0.3043
Summer	0.06692	0.05970	0.05985	0.95232	0.95695	0.93996	−0.2564; 0.1772	−0.2558; 0.1779	−0.3218; 0.28
Autumn	0.07313	0.06837	0.11224	0.92163	0.93524	0.93134	−0.6642; 0.5724	−0.2466; 0.2653	−0.4059; 0.261
Winter	0.05927	0.05591	0.06317	0.95109	0.95147	0.94960	−0.3932; 0.5173	−0.3445; 0.4948	−0.3835; 0.5423

Table 1. Comparison between ANN developed for one year and ANN with seasonal adjustments.

3.3. Level 3—interface

The forecasting and analytical models are integrated into an online dashboard developed in Java with application development framework (ADF). The dashboard is built as a business intelligence (BI) portal with a very friendly interface and interactive charts, reports, pivot tables, maps and narrative elements that allows executives and stakeholders to easily analyze the KPIs. The dashboard contains three sections:

- Production management—it contains reports for power plant current operations and maintenance plans, it displays the generation groups' configuration and location, real time data gathered from measuring devices, SCADA and generation groups or the entire power plant;

- Forecasting—it contains access to the forecasting models and offers reports and charts to display the estimations versus actual values for different periods of time, selected by the user. For example, **Figure 4** shows a chart that displays for one day interval, on hourly
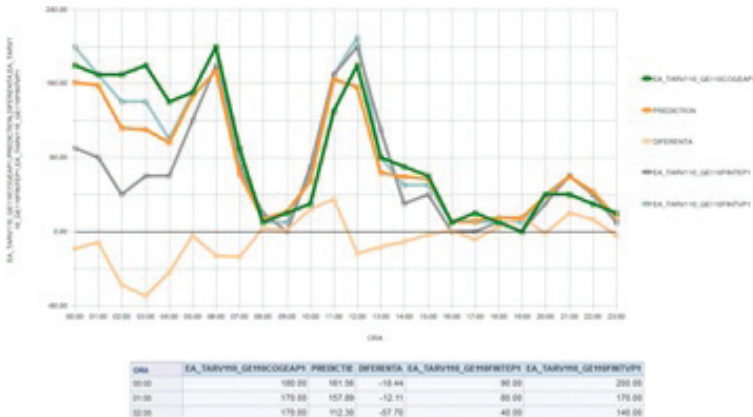

Figure 4. Forecast versus actual energy for WPP groups.

basis, the forecasted energy (orange line) versus actual produced energy (green line) for a WPP group. The chart displays also other 2 generation groups (grey and light blue lines) situated in the same region with the green marked group and the difference between estimated and actual values (light orange line).

- KPIs Analytics—contains analytical Business Intelligence elements (interactive charts, gauges, reports, maps, pivot tables) that enable KPI advanced analysis through dimensions' hierarchies that allows executives to compare indicators over different periods of time, regions and locations, aggregate/detailed KPIs over power plants' groups or module/turbines. For example, **Figure 5** shows the average power, installed power load factor, installed power load duration and maximum power load duration for a wind power plant with two groups of 5 and 10 MW.

Figure 5. KPIs dashboard.

The dashboard is developed in a cloud computing architecture, and it is accessible as a service, customized and configured depending on stakeholders' interest.

4. Conclusions

In this study, we proposed a framework for calculating the most relevant key performance indicators for wind power plants and photovoltaic power plants that offer a realistic perspective on technical aspects of the operational and maintenance activities. Also, it is proposed an informatics solution for KPIs analysis that can support decision process and integrates models for data management, analytical models and interactive interfaces.

Through the business intelligence dashboard that integrates the key performance indicators, the stakeholders can monitor the current operation of power plant and identify the decline in performance and the need to set up the maintenance strategy. Also, the KPI framework is useful for commissioning, recommissioning or evaluation after major repairs, establish benchmarks for measuring and comparing further performance.

The proposed solution integrates two major components: the forecasting model that provides estimations regarding the wind power plants' or photovoltaic power plants' output with a good accuracy for short-term interval (intraday and up to 3 days); the KPIs analytical model that allows a very interactive analysis of power plant management regarding past operation, detecting possible issues, offering smart analyses of KPIs, setting thresholds for metrics and present them in a user friendly and interactive dashboard.

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