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MODEL ASSUMPTIONS FOR EFFICIENCY OF WIND POWER PLANTS' OPERATION

Abstract. *While the exploitation of the renewable resources takes more ground, especially internationally, also in Romania we can identify some major projects in the field of renewable energy, considered of great interest nowadays. As we talk of an environment with low predictability, stimulating investors can be achieved by using decision support systems with a powerfully predictions simulator.*
The architecture of the proposed informatics solution and the model of data integration are briefly mentioned, as they were already exposed in our other works. Instead, this paper focuses on forecasting and predictive models of renewable energy and also on financial simulations performed in order to determine the profitability of investments.
Keywords: *Renewable energy, Databases, Decision Support Systems, Forecasting, Naïve Bayes, Decision Trees, Support Vector Machines, Financial models.*

JEL Classification: C01, C53, L86, O13, Q42, Q43, Q47, Q48

1. Introduction

In the Energy Strategy of Romania for 2007–2020 (HG no.1069/2007), one of the priorities of Romanian sector development is the promotion of energy production based on renewable resources, so that these resources share in total electricity consumption to be 35 % in 2015 and 38 % in 2020. According to Transelectrica' studies (Transelectrica, 2008-2013), currently, in Romania, there are a significant number of producers of energy from renewable sources, which receive green certificates whose installed capacity is about 2500 MW to April 1, 2013, of which 2095 MW in wind power plants (207 undispatchable and 1888 MW dispatchable), 94 MW photovoltaic power plants, 365 MW in small hydro power plants and 40 MW installed in biomass plants.

Investments in this area have increased rapidly from 2009, where the total energy capacity was approximately 100 MW, to more than 2500 MW today. Currently, new connection requests are registered in wind energy, covering over 20 000 MW, in phase of contracting and technical connection approval, mainly in Dobrogea, Moldova and Banat. In Romania, the main types of renewable energy sources connected to NPS are: wind farms, photovoltaic power plants, small hydro plants (SHP) and biomass and biogas plants. The largest share consists of wind farms, followed by photoelectric power plants. *But, integration into the National Power System (NPS) of renewable resources is highly complex and involves technical, economic and legal aspects, environmental issues, and issues related to information flows and decision-making processes.*

From the technical point of view, the production of renewable energy is determined by a number of characteristics, depending on type of resources involved. So, wind farms characteristics bring together the following issues, (Landberg, 2003):

- Dependence on weather conditions for wind power generation, leads, even when the wind blows at a more limited production conditioned by many meteorological factors: velocity, direction and duration of wind. Due to the random nature of wind, an accurate weather prediction (with errors less than 10 %) can be achieved only through stochastic methods. Existing forecasting systems can produce significant errors which may generate grid outages, what's more, being recorded many cases both on national and in European level,
- Power fluctuations caused by wind generation requires tertiary reserves that can be used in two distinct situations: when the wind increases production, reserves must be disconnected and when production decreases, reserves must be engaged to cover the consumption of the power system. As estimates of electricity produced from wind sources become more accurate, the need for tertiary reserves in the system is reduced. The role of good estimation of the wind generation is particularly important, because it reduces the costs of operating safety of the system, costs which could cause significant increases in electricity prices as a result of using of these reserves. Assuming a forecast with an error of 10 %, wind power fluctuations being about 300 MW per hour, it means that the power reserve needed is about 330 MW per hour. However, if the fluctuations is 600 MW per hour, then the reserve requirements doubles, doubling the availability and costs of power reserve dial. In reality when operating, power fluctuations generated in an hour of wind power is 300 MW, but reserving a power of 600 MW lead to higher costs without requiring using the reserves.

From an economic point of view, this field can be very profitable because of the support scheme and promotion of renewable resources based on green certificates

(GC). Depending on resource type, renewable energy producers receive a number of green certificates for electricity produced and delivered to the system. The green certificates are traded on a dedicated market where the demand is represented by energy suppliers who must purchase a number of GC in percentage to the consumption covered by that energy producer. GCs' price varies between a minimum price, according with the laws, meant to protect producers so that they can recoup the investment, and a maximum price, designed to protect the end consumers whose final price of electricity covers entirely the green certificates. The higher will be the number of producers and production is more widespread, the price will be oriented to the minimum value. Besides, the large number of producers reflected in high installed power does no guarantees of full integration into the network, being possible that the Transmission and System Operator (TSO) – Transelectrica SA to limit their operation taking into account the safety principle. Thus, an integrated simulation and analysis system of the power plants operation based on renewable resources will increase the system security and will optimize the resources involved.

To support investments in this field, the potential investors need advice and active support, both technically on grid connection solutions, but also financially for making a business plan efficiently as much as can be done.

From information point of view, renewable energy producers use now, for the management of current activities, various heterogeneous systems developed in house or purchased from IT solutions vendors. This approach involves additional investments in infrastructure, products and IT services, resulting heterogeneity of information provided by these systems. Thus, monitoring and activities analysis by production units are not performed consistently, which produces differences, sometimes major, regarding information provided to Regulatory Authority (ANRE) and Transmission and System Operator (TSO). For instance, hourly production estimations for renewable generation within 1-3 days record significant errors, depending on the forecasting system or service used locally. Under the Commercial Code (ANRE, 2004) of the energy market in Romania, the production companies are required to notify the hourly production, as these must to comply the estimation transmitted to the Romanian Gas and Electricity Market Operator (OPCOM) and the National Dispatching Centre (NDC). If there are fluctuations in comparison with the estimations then imbalances are paid. The Code provides for the existence of Balancing Responsible Party (BRP), consisting of one or more production companies which aim to avoid imbalances. For instance, such an association can be formed by wind farms, hydro power plants and photovoltaic power stations. An incorrect notification made by the wind farms can have adverse consequences for hydro power plants and photovoltaic power stations. In the event that notification of BRP is not met, the TSO (Transelectrica) must dispatch electricity production units to ensure permanently the balance between production and consumption which is reflected in the operation frequency of the system. A good estimate of production, from BRP side, would mean an additional cost reduction caused by

imbalances, and nationally, can optimize the resources allocated in the system and the balance production/consumption would be more predictable.
In this context, based on team experience in decision making systems, we believe that the research motivation in proposing an analytical and support system for decision making process, in a dynamic field with a significant impact on economic and social environment is entirely justified. *Accordingly, we propose a prototype to forecast and analyze investments in renewable energy field with application in wind power plants*. The relevance of this model follows from benefits of both producers and investors in renewable energy.

2. System's architecture

The proposed prototype is designed for renewable investors in wind power plants (WPP) and will offer advice and active support by providing simulation services and achievement of the business plan on which to base their investment decision making. The components of the prototype are:

- An integration model, where sources derived from current activities are stored in on a cloud computing infrastructure. This approach will allow the design of a unified forecasting and analytical model for wind energy production.
- A predictive model of energy produced from wind sources by which we aim to improve the estimates given by the producers on hourly and daily averages in order to decrease costs related to differences between notices and real production and to increase operation safety.
- An advanced analysis, simulation and strategic planning model, based on sets of performance indicators, which can be used by managers to analyze in real time the activities of their renewable power plants and in a most efficient way, by means of customizable and interactive reports.

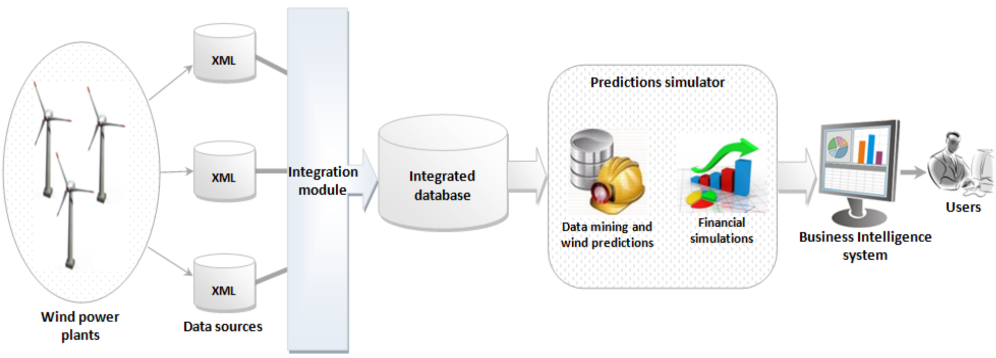

Figure 1 – The architecture of the proposed prototype

3. The integration model

The data sources received regularly from wind farms will be integrated into a central database via an integration framework. Data will be received in XML format and will be stored in a relational database.

The locations of wind farms and also the areas that record energy consumption and production will be stored in the database in the form of spatial data in order to represent them on geographic maps for activity monitoring.

An effective way to facilitate data integration involves specifying a standard structure, consistent with the template of data that will be received from operators of wind turbines. Based on such standard structures, defined through XML Schemas, the following database tables will be created: *date_meteo_t*, *consum_t, productie_t*. These XML Schemas were also used to validate data received in various formats from various external sources.

For example, the following is the XML Schema corresponding to the structure of XML documents relating to the consumption in MW registered at the connection points. Subsequently, the XML Schema was transformed in a database table, through a mapping algorithm.

```
<?xml version="1.0" encoding="ISO-8859-1" ?>
<xs:schema xmlns:xs="http://www.w3.org/2001/XMLSchema">
<!-- defining a complex element, whose components will be
mapped to attributes of the consum_t table -->
<xs:element name="consum_eol">
 <xs:complexType>
  <!-- indicating the use of a sequence that will group the
sub-elements-->
  <xs:sequence>
    <!-- defining simple datatype elements, which will be
mapped to attributes of the consum_t table -->
    <xs:element name="data">
       <xs:simpleType>
       <xs:restriction base="xs:date">
       </xs:restriction>
       </xs:simpleType>
    </xs:element>
    <xs:element name="consum">
       <xs:simpleType>
       <xs:restriction base="xs:decimal">
       </xs:restriction>
       </xs:simpleType>
    </xs:element>
   <!-- defining a simple type attribute that is mandatory to
be completed and that will be mapped to a primary key
attribute in the database table consum_t -->
  </xs:sequence>
..<xs:attribute name="id_statie_racord" type="xs:integer"
use="required"/>
```

```
 </xs:complexType>
</xs:element>
</xs:schema>
```

In order to implement the defined model in a database, XML Schema is transformed according to the algorithm proposed in (Botha, 2012), resulting specific elements of the database. This gives, in fact, the source code for data definition statements (DDL commands belonging to Data Definition Language)

```
CREATE TABLE consum_t
(id_statie_racord NUMBER PRIMARY KEY,
data TIMESTAMP,
consum NUMBER);
```

These database tables are obtained from the transformation of XML Schemas related to documents to be received from the wind farm operators. XML documents in question are automatically generated at the connection points (data related to energy consumption), by the anemometers placed in the area of each wind farm (data on weather conditions) and by the wind turbines (data related to energy production). Once these documents are generated, the operators will load them in the system, in order to check their consistency again by using XML Schemas (see the data component from the system's architecture).

4. The predictive model

At this moment, renewable power plants, based mainly on wind resources, have not been able to establish effective solutions for estimating and forecasting the production, errors of 10-15% are common. The most important problem, which production, profitability of investments in wind power and sizing of energy reserves in the system depends on, is the component that builds their operation, namely the wind. Wind energy production is conditioned also by other factors such as: slipstream effect, soil orography, power characteristics, losses up to the connection point of etc. These factors are identified and detailed in the fundamental work (Ackerman, 2005), (Burton, 2001), (Landberg, 2003). For knowledge based management, it is necessary to be able to make an accurate prediction with minimum errors. Studies carried out nationally (studies realized by SC ISPE SA, Tractebel Engineering SA, ICEMENERG) revealed that these errors propagated in the national energy system can lead, in periods of maximum consumption, to a failure of the produced power in specific regions. In Europe, some forecasting systems are used, built in Germany, France, Denmark, Spain, for example CrossGrid systems - Weather Forecasting Application, Zephyr - Prediktor - Anemo (DMI, 2013), AWPPS (ARMINES Wind Power Prediction System 2013) developed at Ecole des Mines de Paris (AWPPS, 2013), ALADIN project (Adaptation Dynamique Développement international Aire limits) initiated in 1990 by Meteo -France, but errors recorded are still high, with an accuracy of 85-90 %, which may lead to over- dimensioning of resources or systems crashes (Bossanyi, 1985), (Fukuda, 2001). In addition to the recorded errors, appears also the extremely high costs issue, related to the computing power for servers, which leads to the impossibility of their application widely in Romania.

As specified in (Lungu, 2012), (Bara, 2010), depending on measured meteorological factors, investments can be made in wind generators whose power features best fit the potential of the respective emplacement. Power characteristics can be very different. For example, for an average wind speed of 6-7 m/s it will be chosen a generator to produce at rated power at lower wind speeds. The primary energy used to drive the wind turbine blades is determined by the movement of air masses under the action of temperature differences on the surface of the globe According to (Heir, 2006) and (Oprea, 2009) the P_{WA} theoretical power that can be obtained is:

$$P_{WA} = \frac{1}{4} \cdot A \cdot \rho \cdot (v_1^2 - v_2^2) \cdot (v_1 + v_2) = \frac{A \cdot \rho \cdot v_1^3}{4} \cdot \left(1 - \frac{v_2^2}{v_1^2}\right) \cdot \left(1 + \frac{v_2}{v_1}\right) \tag{1}$$

where:

t - time

V - the volume of air mass;

ρ - the air density (ρ_{air} = 1,2 kg/m^3);

m - air mass;

v1/v2 - wind speed in front/rear of the blades of the wind generator.

The above expression reveals a variation of the P_{WA} theoretical power depending on the *v2/v1* ratio. It notes that the appropriate choice of the *v2/v1* ratio can lead to maximizing the power taken from the energy of the air masses.

$$\frac{d}{d(v_2 / v_1)} P_{WA} = 0 = \frac{A \cdot \rho \cdot v_1^3}{4} \cdot \left[1 - 2 \cdot \frac{v_2}{v_1} - 3 \cdot \frac{v_2^2}{v_1^2}\right]$$

$$(v_2 / v_1)_{opt} = 1/3 \tag{2}$$

Therefore, the maximum power that can be taken from the energy of air masses, with current technology, is:

$$P_{WA,\max} = \frac{8}{27} \cdot A \cdot \rho \cdot v_1^3 \tag{3}$$

where:

A – scanned area by the wind generator group paddles;

ρ – air density (ρ_{air} = 1,2 kg/m^3);

v – wind speed.

In conclusion the available power of a WPP is proportional to the air density, wind speed to third power and with scanned area by the generator paddles.

According to (Heir, 2006) and (Oprea, 2009), it results that the maximum power is only part of this:

$$P_{WA,\max} = \frac{8}{27} \cdot A \cdot \rho \cdot v_1^3 = \frac{1}{2} \cdot A \cdot \rho \cdot v_1^3 \cdot 0{,}59 = P_{vant} \cdot C_P \tag{4}$$

where C_P is the power coefficient or power factor.

According to (Bara, 2010-2013), power factor can be calculated individually for each WPP. It is determined as the ratio between produced power and installed power. This factor depends heavily on weather conditions of each emplacement. Typically, the power factor lies in the range 0.25 (low wind speeds) and 0.4 (high wind speeds). From the above it follows that determining the electricity produced by wind sources is extremely important both in the investment stage, in order to choose the type of wind generator and the field emplacement of each production unit and in the exploitation phase in order to achieve production forecasts.

The predictive model for the produced energy is based on a set of data mining algorithms that can determine to what degree the produced energy is influenced by factors such as direction and velocity of wind at different altitudes, atmospheric pressure, temperature, luminosity, soil orography, placement of turbines, slipstream effect, power characteristics, loses up to the connection point.

Mainly a general feature for the wind turbines, the optimal range of wind speed in which they produce energy is between 3 and 25 m/s. If the wind speed drops below this limit or it exceeds 27 m/s the turbines stop. From previous analysis in (Bara, 2010) it is revealed that the main natural factor, wind speed, records significant fluctuations even within a few hours (Figure 2).

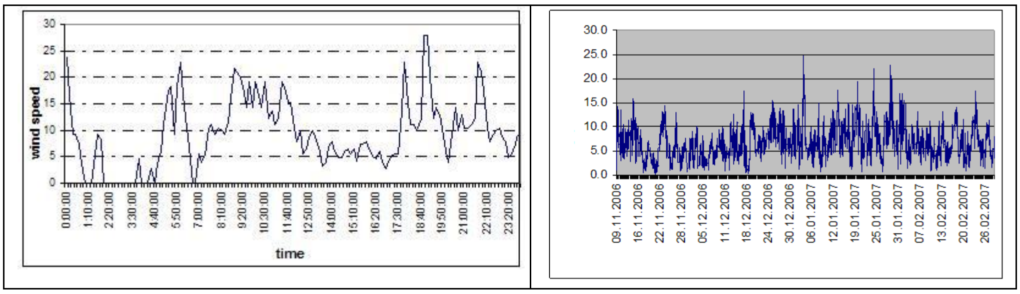

Figure 2 - Fluctuations of wind velocity within day/months

Hence, the importance of making the best possible forecasts for each park. Forecasts are realized also based on historical data recorded by the devices from the park, devices installed on to the pole so: three anemometers at a height of 52 m, 50 m, 30 m that measure wind speed, two wind vanes at 50 m and 30 m that measure wind direction, a barometric pressure sensor and a temperature sensor. Measurement performed with the anemometer mounted at 52 m it is not disturbed by the presence of the pole.

The algorithms are developed and tested based on three-site measurement data recorded from 10 to 10 minutes between 14 November 2011, 23h and 4 September 2012, 11h in 29 WPPs. The records from the measurements devices are processed and loaded into the central database as described in Section 2. The total of values recorded for the height of 50 m is 16037. The minimum value recorded in this time interval is 0 m/s, the maximum is 24.8 m/s, and the average is 6.9 m/s

From the set consisting of 16037 records of wind speed at a height of 50 m, about 2500 were lower or equal to 3.5 m/s - the start speed of a wind generator group (WGG). In approximately 1100 cases the wind speed exceeded 12 m/s. Approximately 8,800 of the measured values were lower than the average speed, and about 7200 were over the average wind speed (6.9 m/s).

Thus the records in the source table in which the measured values have been imported are divided into three sets for each stage that will be covered:

- the learning stage which consists in applying the algorithm built on the data set from the *wind_build* table and building the analysis model;
- the testing step, in which the pattern constructed in the previous step is tested on the set of data from the *wind_test* table;
- the validation phase, in which is applied the built model on the *wind_apply* dataset to verify the results obtained from applying the algorithm.

Attributes used in the algorithm are:

S1 – wind speed at a height of 52 m;
S2 – wind speed at a height of 50 m;
S3 – wind speed at a height of 30 m;
D1 and *D2* – vector components of the wind direction;
H1 – humidity;
T1 – temperature;
B1 – atmospheric pressure;
R1 – the amount of precipitation;
E – produced energy;

The output of the data mining model is the produced energy. We developed two sets of algorithms: the first set is used to determine with a high degree of accuracy whether the energy is produced or not (*E01* values) and the second set is used to determine the actual value of the produced energy (*E*). In both cases we have started the research from the existing specialty studies, like (Costea , 2009), (Ecer, 2013), (Agapie, 2009) and (Pazienza, 2011).

First set – predicting the target attribute for *E01* where 0 – no energy will be produced caused by the wind speed less then 3.5m/s or above 25 m/s, 1 – energy will be produced due to the wind speed between 3.5-25m/s.

We applied two types of data mining algorithms that allow us to predict with a high accuracy the yes/no values:

- ***Naïve Bayes –*** we obtained an average of 94% accuracy;
- ***Decision Tree -*** the accuracy is 99%, better then the Naïve Bayes.

In conclusion by using the decision tree algorithm we can obtain an excellent accuracy that can be considered very reliable.

The second set – predicting discrete values for the produced energy.

In order to scale properly the influence factors we applied the ***Attribute Importance*** algorithm and identified first attributes that have the greatest influence on the produced energy. These attributes are wind speed and direction at 52 and 50 m, temperature and air pressure.
Than we build the ***Regression with Support Vector Machines*** algorithm to predict the actual energy that can be obtained using these attributes. The accuracy of the model is about 58% which is a low accuracy and cannot be used for forecasting. The residual plot indicates that the errors are significant and the differences between the actual energy and the predicted energy can be of ± 800 kW. Supposing that the actual energy is 100 kW, the model will predict around 900 kW or in a negative scenario that the WPP will not produce.
Therefore, given the high degree of scattering of the data, the regression model should be applied to an attribute with values in certain intervals depending on wind speed and temperature. Thus, we introduced the attribute E_THRESHOLD grouping values of produced power by intervals depending on variation of wind velocity of 0.5 m/s. For example, we have found that at wind speeds between 0 and 3.5 m/s power output is 0 kW, at speeds of 3.5-4 m/s power output is of 43 kW, etc. These thresholds are defined according to the power characteristic of a WGG.
After building the regression model there can be noticed significant increase in prediction accuracy from 57.68% to 93.72% (Figure 3). The errors are between ± 20 kW, so if the recorded energy is 100 kW, the model will provide estimation within 80 kW and 120 kW.

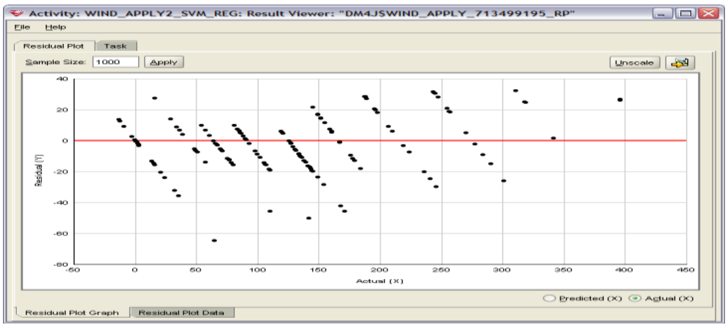

Figure 3 - Residual plot data results of the regression with thresholds values for 24h

In the following table we compared the results from the regression models with the actual energy. The regression with E_THRESHOLD has a better accuracy.

Table 1. Comparison between predictions and recorded energy within 2 hours

Date/Time	E recorded	E predicted	E_THRESHOLD recorded	E_THRESHOLD predicted
25-02-2010 00:00:00	357.91	779.1	343	341.1
25-02-2010 00:10:00	250.05	694.7	216	245.7
25-02-2010 00:20:00	140.61	617.5	125	170.4
25-02-2010 00:30:00	140.61	620	125	170.7
25-02-2010 00:40:00	110.59	612.7	91	141.2
25-02-2010 00:50:00	54.87	651.1	43	56.9
25-02-2010 01:00:00	0	506.4	0	15.5
25-02-2010 01:10:00	0	695.4	0	34.5
25-02-2010 01:20:00	0	771.3	0	20.4
25-02-2010 01:30:00	79.51	618.4	64	109.5
25-02-2010 01:40:00	140.61	627.9	125	167.2
25-02-2010 01:50:00	125	622.3	125	153.3
25-02-2010 02:00:00	0	695.7	0	23.6

Figure 4 represents a comparison between the recorded energy (*E*) and the predicted energy by the regression algorithm (Predicted E Threshold) and it can be observed that the curves of E and Predicted E Threshold are almost similar.

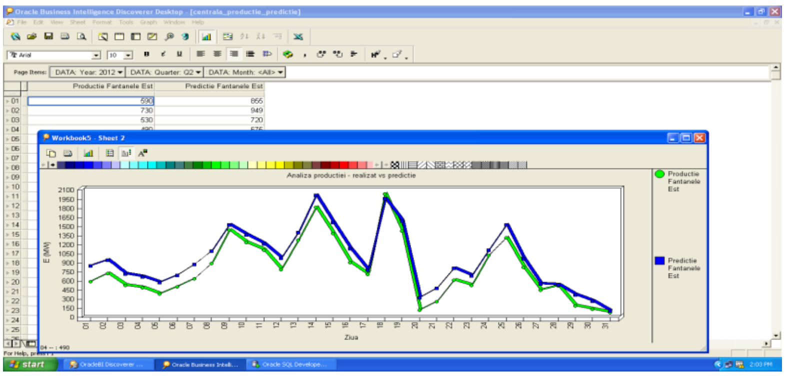

Figure 4 – Comparative results: Predicted *E_Threshold* vs. *Produced E*

By applying the data mining algorithms for predicting power produced by WPP there have been obtained good results in particular by establishing some thresholds of power. With their help, the data mining algorithm was able to learn and better establish the dependency between variables, the forecast being much closer to the values measured in reality.

5. The advanced analysis, simulation and strategic planning model

The model will be developed as a simulator that relies on a financial model based on parameters such as capacity factor, nameplate capacity, percentage of time the plant will be operating, capital expenditures regarding the amount of euro per installed kilowatt, the inflation rate per period, operating and maintenance costs, the lifetime of the plant, balancing costs and revenue. The simulator will allow the investors to fundament their decisions.

The presented analysis is based on the fictive company Wind Park S.R.L. that has a nameplate capacity of 50MW, powered by 20 turbines, each with a capacity of 2.5 MW. The plant is on-line 25% of the year. The energy production of the plant will be the product of the nameplate capacity and the number of hours when the power plant is online. Four different cases that would underline the efficiency of the simulator presented in this paper will be further presented.

In order to discount future cash expenses and cash revenues, the weighted average cost of capital is used:

$$WACC = \frac{E}{E+D} \cdot r_e + \frac{D}{E+D} \cdot (1-t) \cdot r_d \qquad (5)$$

where $r_e = r_f + ß \times (r_m - r_f)$;
r_f - the risk-free rate;
$ß$ - predicted equity beta (levered);
$(r_m - r_f)$ - the market risk premium;
r_d - the debt .

The capital structure of the company is 50% private equity and 50% borrowed capital. The tax which we take into account is the income tax in Romania, 16%. The chosen risk-free rate is 0.048, and the market risk premium for Romania is 0.081, according to the analysis of (Fernandez, 2014). The beta estimate for wind projects varies between 1.25 (Carson, 2013) and 1.87 (Konrad, 2009). An alternative to compute the beta estimate for a wind park project is based on the performance of other renewable energy companies that operate in the same business. For the present analysis, a beta estimate of 1.518 is used.

When introducing the values in the *WACC* formula, the result becomes a value of 0.1149. This value is in EIA's discount rate used for renewable energy projects, which varies between 8% and 13% (EWEA, 2009).

Wind power investments are constituted out of two main costs types: the net present value of total capital costs (TKC_{pv}) and operations and maintenance costs ($O\&M_{pv}$).

The total capital costs comprise the costs of the feasibility studies, consultancy, land, foundation, the turbines, ex works transportation, electric installation, grid-connection and road construction, if they were to happen in one day. However, the construction of a wind park usually takes around 3 years. The cash flow expenses need to be discounted to present with the following discount rate:

$$R = \frac{(1+i)}{(1+r)} \qquad (6)$$

where i= 3% and r=$WACC$=11,49%. Thus, R= 0.9238

Depreciation, operation and maintenance are deductible costs that reduce taxable income. This way, these costs are reduced by the amount recovered from the income taxation. The total capital costs of WP also take into account the depreciation tax shield (Formula 7). The depreciation tax shield is taken into consideration after the project has been finalized and the assets have been put in function. In the present case, these will run starting with the 3rd year.

$$DTS_{pv} = x \sum_{n=t}^{t+z} \frac{D_n}{(1+r)^n} \qquad (7)$$

where DTS_{pv} - present value of the depreciation tax shield;

x – tax rate;

D_n – depreciation in period n;

t – the number of periods for construction;

z – the economic life of the asset;

r – the nominal discount rate.

Depreciation is always discounted with the nominal discount rate. The discount rate R used for depreciation will be 1/(1+r). The formula for the NPV of total capital costs becomes:

$$TCK_{pv} = \left[\frac{OK}{t} \cdot \frac{1-R^t}{1-R}\right] - x \sum_{n=t}^{t+z} \frac{D_n}{(1+r)^n} = \left[\frac{O_k}{t} \cdot \frac{1-R^t}{1-R}\right] - x\left[\frac{D}{L} \cdot R^t \cdot \frac{1-R^L}{1-R}\right] \qquad (8)$$

$$TCK_{pv} = \left[\frac{OK}{t} \cdot \frac{1-R^t}{1-R}\right] - x\left[\frac{D}{L} \cdot R^t \cdot \frac{1-R^L}{1-R}\right] \qquad (9)$$

According to the estimations of (EWEA, 2009) in 2006, the capital costs in Europe can vary between 1000-1350 EUR per installed kW. The structure of capital costs includes turbines with ex works transport, foundation, electric installation, grid-connection, consultancy and land. For our simulation, we will use a cost of 1100 EUR/kW. The used depreciation method will be accelerated, with 50% of the total capital costs being depreciated in the first year of production, and 50% depreciated in equal amounts during the remaining 29 years.

The operation and maintenance costs used for the analysis are 20EUR/installed kW/year. Operation and maintenance costs will only start after the project lead time is over and the power plant is functional. No operational expenses will be approved in the last year before the plant decommissioning.

$$O\&M_{pv} = (1-x) \cdot [OM_0 \cdot R^t \cdot \frac{1-R^p}{1-R}] \tag{10}$$

The revenues of the company are generated from the price of electricity and green certificates. The price of the electricity varies from hour to hour. Based on the average electricity price on the regulated market in January 2014, an average price of 45EUR/MWh will be used in our analysis. The average price for green certificates in 2013 also averages around 45 EUR/MWh. Thus, the revenues of the company will be the product of the electricity output and the prices per MWh and per green certificate.

The energy producer may sign a regulated or unregulated contract with an energy provider that must comply with the commercial code for the energy market. The producer thereby engages to provide a certain energy production, for a market based price for each hour of the day. The energy producer may also participate to the day-ahead market, registering an offer with a maximum of 25 quantity-price pairs. Each pair of the selling offer defines the minimum price at which the producer is willing to sell an energy quantity that doesn't exceed the one mentioned in the quantity-price pair. All licensed energy providers are obliged to participate to the balancing market, where they must register offers for power increase and power reduction. Based on these offers, the market deficit and excess prices are calculated (ANRE, 2004).

The chosen market closure price for the present analysis is 45 EUR/MWh. The energetic deficit price is 63.9 EUR/MWh (the average deficit price in January), and the energetic excess price is 8.05 EUR/MWh (the average excess price in January).

The prediction of the energy production consequently gains a major importance in maximizing the producer's profits. Creating a deficit on the market by announcing a higher production on the market than the later real production, triggers an equilibration cost that the company must pay. Also, when exceeding the planned production, one would receive revenue based on excess prices, instead of the market closing price, losing possible revenue based on a wrong prediction.

The usual estimation errors of energy players recorded by the actual forecasting systems have an average between 15% and 30%. The tests of the presented solution have shown an average estimation error of 5%.

Four different cases will be further presented, with estimation errors of 20%, respectively 5%, as follows:

- Scenario I: an error of 20%, with actual production higher than the planned production (P_p<P_a); the planned production was of 95,812.5 MWh. The actual production was 114,975 MWh, 20% over the estimation;

- Scenario II: an error of 20%, with actual production lower than the planned production ($P_p>P_a$); the planned production was 109,500MWh. The actual production was 91,250 MWh, 20% below the estimation;
- Scenario III: an error of 5%, with actual production higher than the planned production ($P_p<P_a$); the planned production was of 109,500 MWh. The actual production was 114,975 MWh, 5% over the estimation;
- Scenario IV: an error of 5%, with actual production lower than the planned production ($P_p>P_a$); the planned production was 95,812.5 MWh. The actual production was 91,250 MWh, 5% below the estimation.

The revenues for the four cases are based on the below calculations:

- Scenarios I & III ($P_p<P_a$): $P_p*MCP+P_p*P_{cert}+(P_a-P_p)*P_e$
- Scenarios II & IV ($P_p>P_a$): $P_a*MCP+P_a*P_{cert}+(P_a-P_p)*P_d$,

where MCP is the market closing price and P_{cert} is the price per green certificate
The four models are extrapolations of cases where a wind energy provider continuously overestimates or underestimates the energy production, for analysis purposes.
The overnight capital costs for the power plant amount to 55Mil EUR. The annual *O&M* costs add up to 1Mil EUR. The depreciation method is accelerated, with 50% of the capital costs being depreciated in the first year of operation; the remaining amount is split into equal amounts during the 29 years left. Depreciation will lower capital costs with 4.4 Mil current Euro in the first year and a further amount of 151,724 current Euro annually, in the remaining 29 years. Operation and maintenance costs will also generate a cost cut of 160,000 EUR annually through deductibility. All costs will be discounted with $R = (1+i)/(1+r) = 0.9238$, while depreciation is discounted using a nominal discount rate $1/(1+r) = 0.8969$.
The implementation of the presented prediction model had different results depending on the prediction error type. When comparing the prediction errors of actual production being lower with 20%, respectively 5%, the difference between the two *NPV*s (net present value) and *IRR*s (internal rate of return) are smaller than the difference occurring between prediction errors of actual production being higher than predicted. In all four scenarios, the *IRR* is higher than the hurdle rate of 11,49%. However, Scenario II, with a prediction error of 20% and an actual production lower than the planned production, is only 0,5% higher than the hurdle rate. The overview of the four models can be analysed in Table 2.

Table 2. Prediction error models

	Scenario I ($P_p<P_a$)	Scenario II ($P_p>P_a$)	Scenario III ($P_p<P_a$)	Scenario IV ($P_p>P_a$)
Prediction error	20%	20%	5%	5%
IRR	15.56%	12.01%	17.78%	13.82%
NPV	27786437	11528004	38322658	19743231

DPP (years)	9.75	15.75	8.00	12.00
PP (years)	5.50	7.00	4.50	6.25

Legend: *IRR* – internal rate of return, *NPV* – net present value, *DPP* – discounted payback period, *PP* – payback period

The third scenario ($P_p<P_a$), with a prediction error of 5%, had a *NPV* with 10,536,221.4577 EUR more than the first scenario ($P_p<P_a$), with a prediction error of 20%. The discounted payback period of the third scenario is almost two years shorter than that of the first model. Given that both models have the same actual production, the error variable when underestimating the production has a considerable impact on the financial outcome. For and output of 114,975 EUR, 5% higher than the planned production, the revenue loss of the company is determined by the energy output that could have been sold for the closing price of the day ahead market, but was instead sold for the market excess price. In this case, the product of 5,475 MWh and the difference between the day ahead market closing price and the price of the excess market (45 EUR - 8,044 EUR), with a result of 202,328 EUR per year. The revenue loss of scenario I is 708,150 EUR per year, 3.5 times higher than in scenario III.

When analysing scenarios II and IV, the difference between the two prediction models is decisive when determining whether to invest in the power park. While scenario II has an *IRR* barely higher than the hurdle rate, scenario IV has an *IRR* with 1.8 percentage units higher, a *NPV* higher with 8,215,227.396 EUR than scenario II, and a 3.75 years shorter discounted payback period. The equilibration cost of scenario II is 1,166,201 EUR annually, while the equilibration cost of scenario IV is 291,550 EUR per year.

It is well known that prediction errors vary for each day and each hour, and the comparison of companies using the two prediction models for a specific time frame would be most defining for the financial impact of the proposed model in the given time frame. However, for analysis purposes, the extrapolation used has shown that the difference of the two models may strongly influence the investment decision.

6. Conclusions

The field of renewable energy represents one of the key development areas for our country in the near future, being also one of the main interest points in the European Union's Energy Strategy until 2020.

Considering the importance of this particular type of energy and the current interest surrounding it we present in this paper a proposal for a prototype for an analytical and support system for the decision making process, which will forecast and analyze investments in renewable energy field, with application in wind power plants.

The proposed prototype supports investments in the researched field through two models. The first one is a predictive model that helps potential investors to give an accurate estimation of their energy production to the TSO after integration in the NPS, therefore cutting operating costs and increasing efficiency. For this model we used data recorded in the span of 10 months and consisting of more than 16000 observations. We used data mining techniques, we built a regression model and we obtained an estimation accuracy of approximately 95%. This means an estimation error of 5%, which is 3 to 6 times better than existing forecasting systems where the usual estimation errors have an average between 15 and 30%.

The second model of the prototype is an advanced analysis, simulation and strategic planning model, developed as a simulator that relies on a financial model, which will allow investors to fundament their decision based on solid data regarding the costs and revenue from operating a WPP.

We consider that the implementation of such a system on a national scale can support the growth of investments in the area at a faster pace and help achieve the European Union's 2020 climate change/energy targets of 20% of energy coming from renewables.

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