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Short Term Wind Speed Forecast Using Recurrent Neural Networks for Wind/Battery Energy Management

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Abstract: As the enhanced energy crisis, wind power generated through wind turbines, widely known as a bright renewable energy source, is being mostly utilized. As a result, wind energy forecasting, notably wind speed forecasting is crucial for power energy management and production-consummation balance. Nevertheless, wind speed prediction is deeply challenging due to its non-stationary and nonlinear character. The main research aim to develop an effective paradigm for wind speed estimation based on recurrent neural network. Three topologies are proposed namely the modified Elman neural network, the Jordan neural network and the hybrid model that combines the latest cited networks. The mentioned forecasting models are evaluated through various statistical metrics mainly the normalized root mean squared error, the mean absolute percentage error and the correlation factor. The experimental results show that the predictors performed satisfactory forecasts. While, the efficiency index is slightly finer using the hybrid algorithm with an R-ratio equal to 99%. The estimated wind power is derived through the forecasted wind speed via a mathematical model. The derived generated power is utilized for Wind/Battery energy management in isolated area. The proposed supervision algorithm raises the wind power use to 92%.

Keywords: *wind power, forecasting, recurrent neural network, management*

1. Introduction

The energy consummation is widening all over the word. Sources of energy based on Fossils threat the environment with their huge gas emission. Thus, renewable energies are the green solution to generate a clean and durable energy. One of the most prospective sustainable energy is the wind power [1]. However, the most inherent problem of the wind power is the wind speed fluctuation. Hence, wind power forecasting through wind speed is the most considering issue to exploit this clean energy [2]. As the generated wind power is proportional to the cubic of the wind speed, a small variation of the speed can affect the produced power. Thus, its prediction should be based on effective tools that offers excellent forecast with a minor error. Recently, many researches are steering on renewables energies production forecast. The forecasters can be partitioned on three classes: physical, statistical and deep learning. Physical models requisite meteorological data such us shadow, pressure, solar irradiation, ambient temperature and density. They demand enormous computing sources and their efficiency is not guaranteed [3]. Statistical topologies utilize the linear relationship hypothesis and the historical data. Their utilization for wind speed estimation is painful owing its nonlinear character [4]. One of the statistical model the autoregressive moving average (ARMA) and the autoregressive integrated moving average (ARIMA) [5]. Artificial intelligence models are significantly used on prediction by dint of its applicability for time series presenting a nonlinear form [6]. They can be divided into two categories. The first type is the feed forward neural network such us the multilayer perceptron network [7], the radial basis neural network [8] and the generalized neural network [9]. The second type is the recurrent network. It presents both forward and backup path. It offers the ability to get information from the previous sate and utilizes it on the future. This advantage improves the wind speed prediction accuracy.

The main research presents a comparative study between three recurrent networks namely the modified Elman neural network (M-ENN), the Jordan neural network (JNN) and the hybrid model that combines the latest topologies (MEJNN). Their performance is evaluated through metric evaluators. The forecasted wind speed is deployed for deriving the wind power. The generated energy is employed for isolated area electrification with the use of batteries as storage system. The management algorithm aims to boost the use of the sustainable source of energy. The study plan is summarized on the organogram in figure 1.

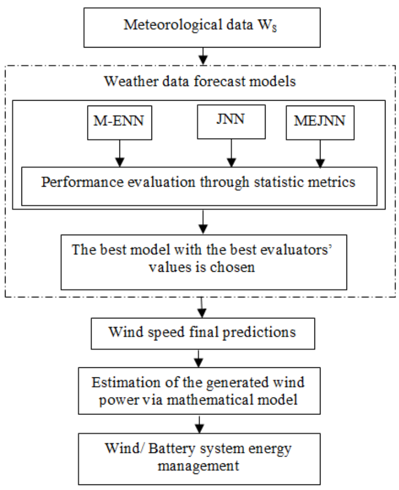

Fig. 1. Prediction and management organogram

The remaining paper is organized as follow: section 2 presents the various recurrent predictors and the statistic metric. Section 3 describes the mathematical model of the wind turbine and the battery. Section 4 shows the simulation results. Section 5 outlines

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the conclusion.

2. Methodologies description

Recurrent neural networks (RNN) present an internal feedback loop to stockpile information for later use. This information improves the prediction accuracy. Three RNN have been utilized: the M-ENN, JNN and MEJNN. Their description is cited below. The accuracy of each predictor can be evaluated through various statistic metrics.

2.1. Modified Elman Neural Network

The main difference between the old version and this one appears on the pure delay time. The structure of the M-ENN is presented in figure 2. The context units are derived from the hidden units [10].

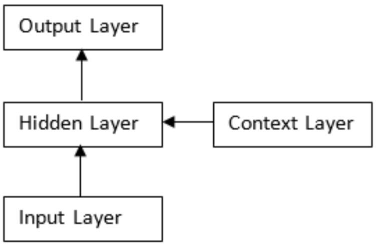

Fig. 2. MENN structure

The input vector and the output of the MENN are described, respectively, in (1) and (2).

$$X = x_1, x_2, x_3, \ldots\ldots, x_m, x_{m+1}, x_{m+2}, \ldots\ldots, x_{m+1+n} \quad (1)$$

$$Y_k = f_{yk}\left(\sum_{j=1}^{n+1} w_{jk} f_{zj}\left(\sum_{i=1}^{m+1+n} w_{ij} x_i\right)\right) \quad (2)$$

Where

$$(x_{m+2}, \ldots, x_{m+1+n}) = \left(z_1(t-1), \ldots, z_j(t-1)\right) \quad (3)$$

X is the input vector, $(x_1, x_2, x_3, \ldots\ldots, x_m, x_{m+1})$ are the input neurons, $(x_{m+2}, \ldots\ldots, x_{m+1+n})$ are the hidden context neurons, y is the actual output vector, z is the hidden vector, w_{ij} is the weight values between the ith input neuron and the jth hidden neuron, and 'w_{jk} ' is the weight values between the jth hidden layer and the kth output layer.

2.2. Jordan Neural Network

The structure of the JNN is displayed in figure 3. In this topology, the context units are involved from the output units [10].

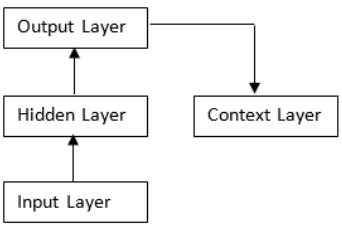

Fig. 3. JNN structure

The input vector and the output of the JNN are mentioned, respectively in (4) and (5).

$$X = x_1, x_2, x_3, \ldots\ldots, x_m, x_{m+1}, x_{m+2}, \ldots\ldots, x_{m+1+o} \quad (4)$$

$$Y_k = f_{yk}\left(\sum_{j=1}^{n+1} w_{jk} f_{zj}\left(\sum_{i=1}^{m+1+o} w_{ij} x_i\right)\right) \quad (5)$$

Where

$$(x_{m+2}, \ldots, x_{m+1+o}) = \left(y_1(t-1), \ldots, y_k(t-1)\right) \quad (6)$$

$(x_1, x_2, x_3, \ldots\ldots, x_m, x_{m+1})$ are the input neurons, $(x_{m+2}, \ldots\ldots, x_{m+1+o})$ are the output context neurons.

2.3. Modified Elman Jordan Neural Network

The MEJNN is the combination of the MENN and the JNN. In this topology, the context units are displayed from both the hidden and the output units as shown in figure 4 [11].

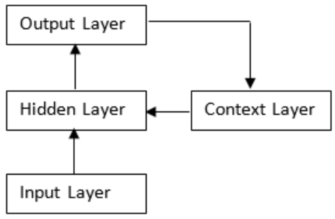

Fig. 4. MEJNN structure

The input vector and the output of the MEJNN are outlined in (7) and (8).

$$X = x_1, \ldots, x_m, x_{m+1}, x_{m+2}, \ldots, x_{m+1+n}, x_{m+2}, \ldots, x_{m+1+o} \quad (7)$$

$$Y_k = f_{yk}\left(\sum_{j=1}^{n+1} w_{jk} f_{zj}\left(\sum_{i=1}^{m+1+n+o} w_{ij} x_i\right)\right) \quad (8)$$

Where

$$(x_{m+2}, \ldots., x_{m+1+n}, x_{m+2}, \ldots., x_{m+1+o}) = \begin{pmatrix} z_1(t-1), \ldots\ldots, z_j(t-1) \\ y_1(t-1), \ldots\ldots, y_k(t-1) \end{pmatrix} \quad (9)$$

2.4. Statistic metrics

Four metrics are designed for RNN performance accuracy namely: the Mean Squared Error (MSE), the Normalized Root Mean Squared Error (NRMSE), the correlation Factor (R value) and the Mean Absolute Percentage Error (MAPE). Their expressions are depicted below [12-13].

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_{Ri} - \widehat{y_{Pi}})^2 \quad (10)$$

$$\text{NRMSE} = \frac{\sqrt{MSE}}{\frac{1}{N}\sum_{i=1}^{N} y_{Ri}} \quad (11)$$

$$\text{R}_{\text{value}} = 100\,\frac{\sum_{i=1}^{N}\left((\widehat{y_{Pi}} - \overline{y_P})(y_{Ri} - \overline{y_R})\right)}{\left[(\sum_{i=1}^{N}(y_{Ri} - \overline{y_R})^2)(\sum_{i=1}^{N}(y_{Pi} - \overline{y_P})^2)\right]^{\frac{1}{2}}} \quad (12)$$

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y_{Ri} - \widehat{y_{Pi}}}{y_{Ri}}\right| \quad (13)$$

Where y_{Ri} is the real value, $\widehat{y_{Pi}}$ is the predicted value and N is the number of observations.

3. Wind turbine and battery model description

The derived wind power was investigated to develop an optimal management algorithm in isolated area. The studied system encloses wind turbine and batteries. Their mathematical models and the management approach area described below.

3.1. Wind turbine model

The forecasted wind speed was utilized to estimate the generated wind power based on the mathematical model depicted in (14) [14].

$$P_W(t) = \begin{cases} 0\,; W_S(t) \le W_{Si} \ or \ W_S(t) \ge W_{So} \\ P_{WN}\frac{W_S{}^3(t) - W_{Si}{}^3}{W_{SN}{}^3 - W_{Si}{}^3}; \qquad W_{Si} < W_S(t) < W_{SN} \\ P_{WN}; \qquad W_{SN} \le W_S(t) \le W_{So} \end{cases} \qquad (14)$$

Where: $W_S(t)$ is the wind speed at time t, W_{Si} is the cut-in value, W_{So} is the cut- out value, W_{SN} is the nominal wind speed and P_{WN} is the nominal wind energy.

3.2. Battery model

The batteries are introduced to compensate the energy in case of lack and to store the excess of energy. The battery mathematical model can be expressed using the expressions cited below [15].

$$C_{R_{(t)}} = C_{R_{(t-1)}} + \frac{\partial t}{3600} I_{bat}^{k_p} \qquad (15)$$

$$dod_t = 100 - soc_{(t)} \qquad (16)$$

$$soc_{(t)} = \frac{C_{R(t)}}{C_P} \qquad (17)$$

Where, C_R is the battery charge, ∂t is the time difference between t and (t-1), I_{bat} is the battery current, k_p is the Peukert coefficient, dod_t is the depth of discharge, soc is the state of charge, C_P is the Peukert capacity.

3.3. Wind/ Battery management approach

The derived wind power was investigated to develop an optimal management algorithm in isolated area. The main system introduces batteries as storage system. The main criteria of the supervision approach intents to feed the load via the wind energy. In case of lack, the load requirements can be covered through the sustainable sources and the batteries. In case of excess energy, it can be stored on the batteries depending on their capacities. Another important criterion is batteries protection from excess charging and discharging by maintaining the state of charge between 20% and 80%. The flowchart of the management algorithm is presented in figure 5.

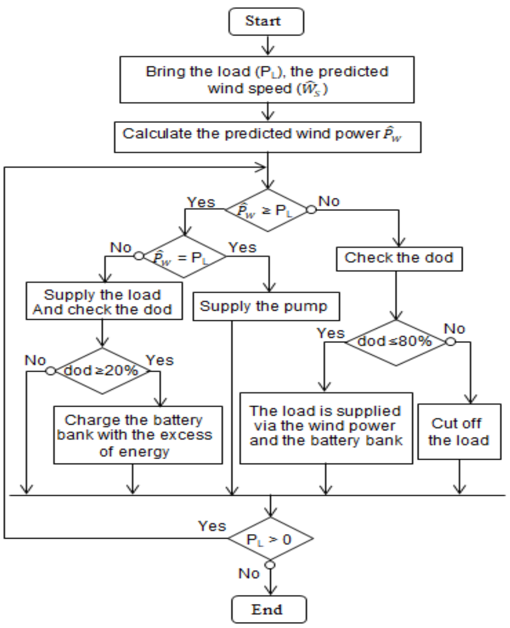

Fig. 5. Flowchart of the Wind/Battery management

4. Simulation and results

Wind speed prediction results and the management approach application were done using Matlab-mfile. The wind speed data are collected from the Research Center and Energy Technologies in Borj Cédria, Tunisia. They are presented by 5min step. The main database is stated from 4 November 2017 to 12 November 2017. Below the simulation results was defined.

4.1. Wind speed forecasts

The available data were divided into training and testing. The wind speed data from 4 November to 9 November are utilized for training and validation of the designed recurrent networks. The rest of data is stacked for testing their performances.

The predictors' topologies incorporate two neurons in the input and the hidden layers. For the output layer one neuron is defined. The main difference appears on the context layers, the number of neurons for the M-ENN, JNN and the MEJNN is equal to 2, 1 and 3 neurons, respectively.

The cited matrix below describes the input and the output layer data for the testing process.

$$Input = \begin{pmatrix} W_{S,t-2,12\,Nov} \\ W_{S,t-1,12\,Nov} \end{pmatrix} \qquad (18)$$

$$Output = \left(W_{S,t,12\,Nov}\right) \qquad (19)$$

Figure 6 displays the forecasted wind speed in comparison with the testing records using the recurrent predictors. As is apparent, the designed models have a high degree of accuracy, as their forecasts are very close to real values.

Based on the statistical evaluators presented in table 1, the hybrid MEJNN achieve the most reliable predictions with a MAPE and a correlation factor equal to 8.72% and 99.21%. MEJNN efficiency can be defined as it collects more informations from the contexts layers related to the hidden and the output layers.

Table 2. Metric evaluators

	M-ENN	JNN	MEJNN
MSE (m/s)	0.11	0.12	0.06
NRMSE (m/s)	0.08	0.08	0.06
R-Value (%)	98.64	98.55	99.21
MAPE (%)	9.75	11.45	8.72

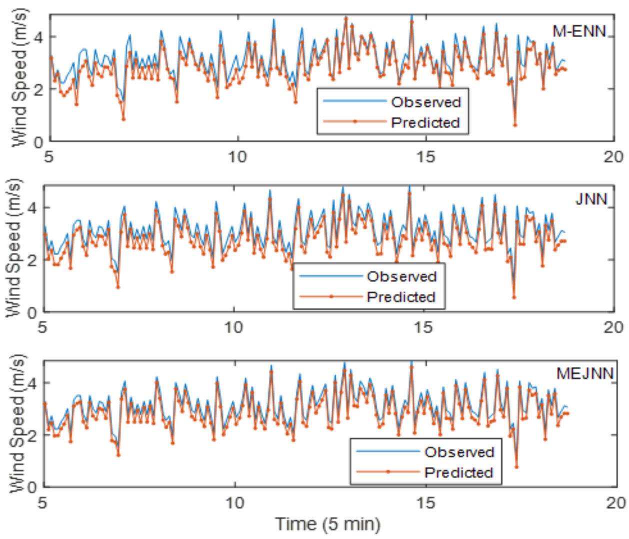

Fig. 6. Wind speed forecasts

4.2. Wind/Battery management algorithm

The studied system consist of a wind turbine, a multistring inverter and batteries as presented in figure 7. The main system aim to cover the load on an isolated area

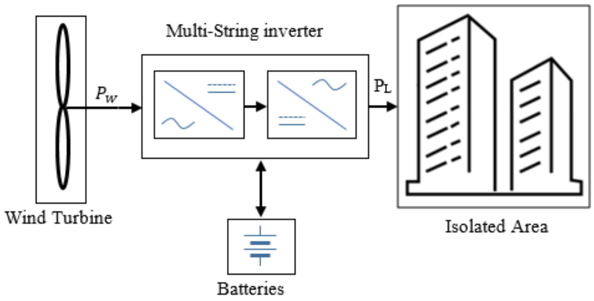

Fig. 7. Wind /Battery system

The estimated wind power can be deduced through the wind speed data forecasted using the MEJNN and the mathematical model cited previously.

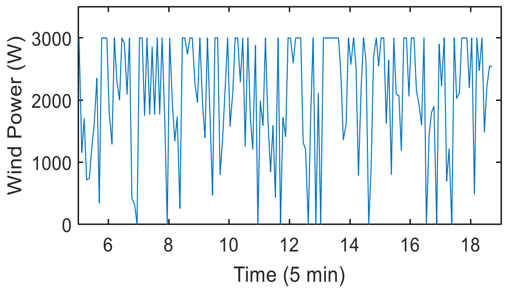

Fig. 8. Estimated wind power

The simulation results of the management algorithm are displayed in figure 9. It's clear that the supervision approach has ensured the load requirements (P_L) correctly based on the wind turbine and the batteries.

P_{WL} presents the utilized wind power to feed the load. In case of lack, the batteries intervenes to compensate the deficit. P_{BL} is the storage system discharged power. The excess of energy designed with (P_{CB}) was stored on the battery bank.

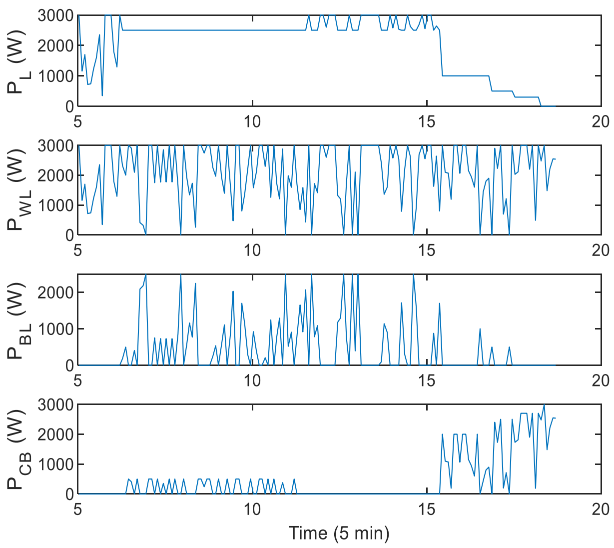

Fig. 9. Management algorithm simulation results

An excellent contribution of the wind turbine on feeding the load is equal to 92%.Only 8% were covered through the batteries as shown in figure 10.

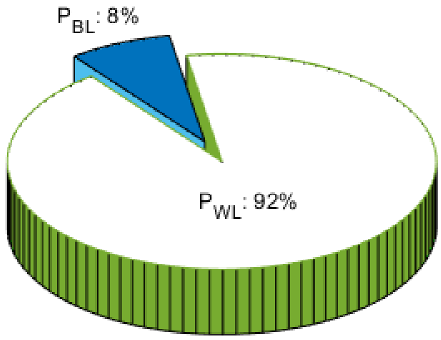

Fig. 10. Batteries/Wind turbine contribution

5. Conclusion

The main research presents a comparative study between three recurrent neural networks. Impressive forecast were derived using the hybrid model witch combines both the modified Elman neural network and the Jordan network with a correlation factor in the range of 99.21%. The predicted wind speed was exploited for deducing the estimated wind power. In order to ensure a load supply continuity for isolated area, a management algorithm of a wind/battery system, was developed. The supervision approach deal with the designed load with an effective contribution of the sustainable source equal to 92%.

Author contributions

Ben Ammar Rim: Conceptualization, Methodology, Software, Field study, Writing-Original **Ben Ammar Mohsen:** Data creation, draft preparation, Software, Validation, Field study **Oualha Abdelmajid:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] Z. Maheshwari, K. Kengne and O. Bhat, "A comprehensive review on wind turbine emulators," Renewable and Sustainable Energy Reviews, Vol. 180, p. 113297, Jul. 2023, doi: 10.1016/j.rser.2023.113297.

[2] W. Yang, M. Hao and Y. Hao , "Innovative ensemble system based on mixed frequency modeling for wind speed point and interval forecasting," Information Sciences, Vol. 622, pp. 560-586, doi: 10.1016/j.ins.2022.11.145.

[3] S. M. Valdivia-Bautista, J. A. Domínguez-Navarro, M. Pérez-Cisneros, C. J. Vega-Gómez and B. Castillo-Téllez, "Artificial intelligence in wind speed forecasting: A review," Energies, vol. 16(5), p. 2457, March 2024, doi: 10.3390/en16052457.

[4] Y. M. Zhang and H. Wang, "Multi-head attention-based probabilistic CNN-BiLSTM for day-ahead wind speed forecasting," Energy, Vol. 278, p. 127865, Sept 2023, doi: 10.1016/j.energy.2023.127865.

[5] S. Sheoran and S. Pasari, S, "Efficacy and application of the window-sliding ARIMA for daily and weekly wind speed forecasting," Journal of Renewable and Sustainable

Energy, Vol. 14(5), p. 053305, Oct 2022, doi: 10.1063/5.0108847.

[6] L. P. Joseph, R. C. Deo, R. Prasad, S. Salcedo-Sanz, N. Raj and J. Soar, “Near real-time wind speed forecast model with bidirectional LSTM networks,” Renewable Energy, Vol. 204, pp. 39-58, Jan 2023, doi: 10.1016/j.renene.2022.12.123.

[7] Y. Amellas, O. El Bakkali, A. Djebli and A. Echchelh, “Short-term wind speed prediction based on MLP and NARX networks models,” Indonesian Journal of Electrical Engineering and Computer Science, Vol. 18(1), pp. 150-157, Apr 2020, doi: 10.11591/ijeecs.v18.i1.

[8] M. Madhiarasan, “Accurate prediction of different forecast horizons wind speed using a recursive radial basis function neural network,” Protection and Control of Modern Power Systems, Vol. 5(3), pp. 1-9, Oct 2020, doi: 10.1186/s41601-020-00166-8.

[9] J. Ding, G. Chen, Y. Huang, Z. Zhu, K. Yuan and H. Xu, “Short-term wind speed prediction based on CEEMDAN-SE-improved PIO-GRNN model,” Measurement and Control, Vol. 54(1-2), pp. 73-87, Nov 2021, doi: 10.1177/0020294020981400.

[10] M. Motahari-Nezhad, “Elman and Jordan neural networks for prediction of transient thermal contact for engine exhaust valve,” Automotive Science and Engineering, Vol. 13(1), pp. 4051-4061, March 2023, doi: 10.22068/ase.2023.633.

[11] E. Fedorov, O. Nechyporenko and T. Neskorodieva, “Method for Creating a Computer Agent Based on the Jordan-Elman Neural Network for Supply Chains,” In 4th International Workshop on Intelligent Information Technologies and Systems of Information Security, Vol. 3373, pp. 34-47, March 2023.

[12] D. Bujak, S. Ilic, H. Miličević and D. Carević, , “Wave Runup Prediction and Alongshore Variability on a Pocket Gravel Beach under Fetch-Limited Wave Conditions,” Journal of marine science and engineering, Vol. 11(3), p. 614, March 2023, doi: 10.3390/jmse11030614.

[13] S. Chen, W .Feng, L. He, W. Xiao, H .Feng, Q. Yu, Q. and J. He, “Parameterization of the Ångström–Prescott formula based on machine learning benefit estimation of reference crop evapotranspiration with missing solar radiation data,” Hydrological Processes, Vol. 38(2), p. 15091, Feb 2024, doi: 10.1002/hyp.15091

[14] A. Petrović and Z. Đurišić, “Genetic algorithm based optimized model for the selection of wind turbine for any site-specific wind conditions,” Energy, Vol. 236, p. 121476, Dec 2021, doi: 10.1016/j.energy.2021.121476.

[15] I. Ouachani, A. Rabhi, I. Yahyaoui, B. Tidhaf, T. F. Tadeo, “Renewable energy management algorithm for a water pumping system,” Energy Procedia, Vol. 111, pp. 1030-1039, Mar 2017, doi: 10.1016/j.egypro.2017.03.266.