MRABET BELLAAJ Najiba [(1), (2)], BOUZIDI Lotfi [(1)], ELLEUCH Mohamed [(1)]

Regular paper

Development of a Neural Model for Wind Power Integration into the Dispatching Process¶

In the recent years, the increased production of the wind power raised a major problem of wind farm connection to electrical network. Thus, it needs more investigations to allow the integration of the intermittent wind energy to the dispatching process. In this work, we have profited from the performances of the artificial neural network to model the economy and security of the dispatching task in order to integrate the wind farm into it. The study of the actual dispatching database is helpful to extract the most relevant factors on which the Tunisian Operator of Electricity and Gaz is based to dispatch the power plants. Several learning procedures are necessary to define the optimal neural network structure to model the dispatching. An important contribution is proposed to integrate the wind energy into the electrical network.

Key words : Wind power integration, economy and security of dispatching, modelling, neural networks.

1. Introduction

Based on the evaluations of the wind energy potential in Tunisia, the strategic study on renewable energies reveals that, according to a conservative scenario of wind energy development, the capacities installed (less than 50 MW today) should reach 310 MW in 2010; 1130 MW in 2020; and 1840 MW in 2030. Until nowadays, the Tunisian Operator of Electricity and Gas had not integrated the wind power in its control system (dispatching). It is required to develop a strategy to integrate this strongly intermittent energy in the Tunisian electrical network. Several international studies and projects were made on the large-scale integration of the wind power [1,2,3]. These studies showed that this integration generates several technical and economic problems. In the study of the electrical networks, the control of the power plants production and their availability instantaneously is required. When the daily consumption is predicted, it is necessary to distribute this energy on the various power plants (Figure 1) to ensure the safety and economy components leading to the optimal function of the dispatching.

The economic problem of the dispatching is an optimized multi-objective problem with several constraints (economic, environmental…) [4]. The linear and nonlinear methods remain limited [5]; some ones use statistical methods [6] which are sometimes efficient, but the intelligent techniques have proved better performances in this field. Indeed, fuzzy logic, the genetic algorithms and the neural networks are used more and more in this field due to their powerful search ability to reach the global optimum and they are extremely robust versus to the complexity of the problem [7,8,9].

Najiba.bellaaj@isi.rnu.tn, lotfi.enit@yahoo.fr, mohamed.elleuch@enit.rnu.tn
(1) LSE-ENIT, B.P. 37 le Belvédère 1002 Tunis-Tunisia
(2) Institut Supérieur d'Informatique, 2 Rue Abou Raihane Bayrouni 2080 Ariana, Tunisia

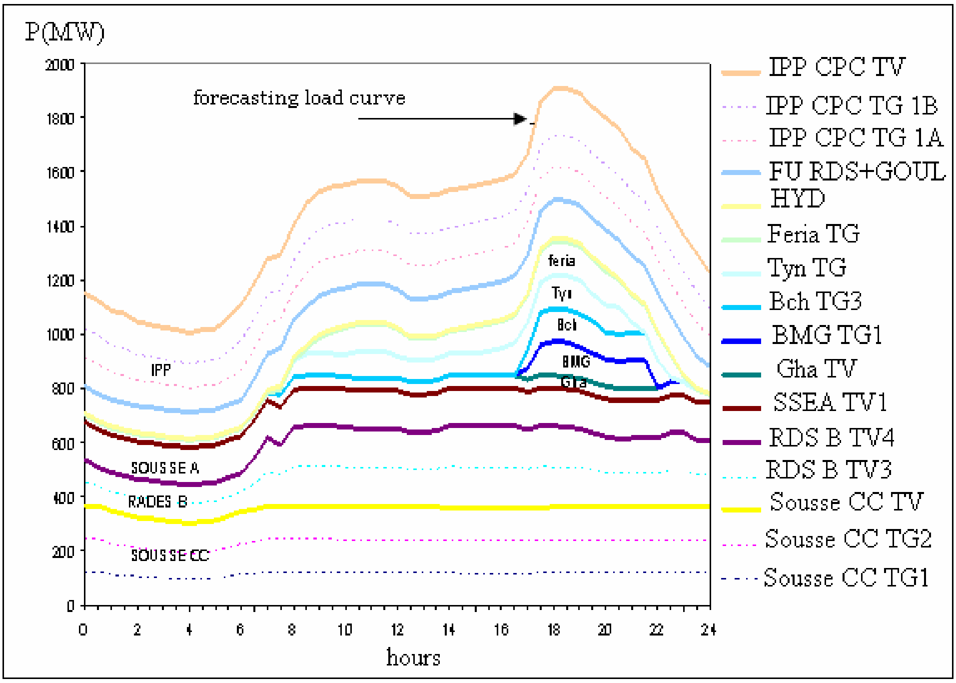


Figure 1: Distribution of the consumption for an ordinary day
(T: turbine, V: steam, G: gas, CC: Combined Cycle)

Until now, the wind farm has not yet been considered by the dispatching of the Tunisian electrical network operator. In fact, the present power wind generation is marginal (less than 1%) and really it seems difficult to take into account the wind farm for dispatching purposes. This is not the case for the future when the installed wind power reaches several hundred MWs. We present in this paper an attempt to integrate the wind energy into the dispatching modeled by an Artificial Neural Network (ANN) and, control the effects resulting from the re-dispatching (new distribution of load power to the active power plants). firstly, we present the choice of the ANN structure used to model the operation of the dispatching process by studying the most relevant influential factors; afterwards the capacity of generalization of the ANN model is tested, and finally a methodology of wind power integration is then presented.

Neural Network Technique

ANNs offer an alternative way to tackle complex and ill-defined problems. Their advantages over standard computing are that they can both "learn" from experiences and "guess" or interpolate results, even when their inputs are incomplete. They are fault tolerant in the sense that they are able to handle noisy and complex data. They are able to deal with nonlinear problems and, once trained, they can perform predictions and generalizations at high speed [10-11]. The ANN model has been criticized as a "black box": If care is not taken, all intuition for the relationship between the forecasts and what is being forecast may be lost [12]. The structure of the biological neural network is not well understood, and therefore, many ANN models have been proposed in [13]. The most popular ANN is the Multilayer Perceptron (MLP) architecture. Back Propagation (BP) algorithm is the most frequently used training method for this multilayer feed forward ANN.

The MLP model represented in Figure 2 consists of a set of source nodes that constitute the input layer, one or more layers of hidden neurons depending on the complexity of the problem and one output layer. The model of each neuron in the MLP network includes differentiable nonlinearity at the output end. A commonly used form of nonlinearity that satisfies this requirement is sigmoidal nonlinearity defined by a logistic function [14]. The network exhibits a high degree of connectivity determined by the weights of the network. A change in the connectivity of the network requires a change in the population of network weights.

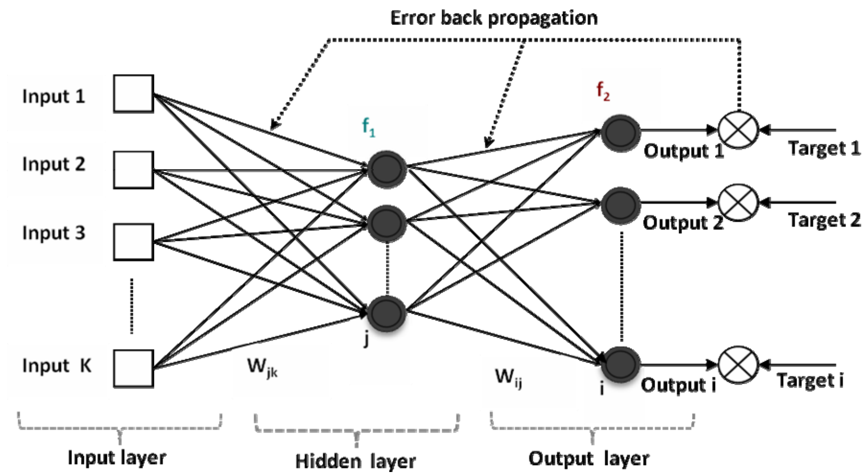


Figure 2: Schematic diagram of a multilayer feed forward ANN

The standard back-propagation learning rule is employed to train the ANN. The weights of the network (connection between neurons) are then found from training, to minimize the objective function mean square error (MSE) by gradient descent methods with or without adaptive step size learning rate. These weights are randomly (depending on application) selected initially in the range [-1,1]. Fast and improved versions of back propagation algorithms have been proposed in the literature, but the Levenberg Marquardt algorithm, applied in this work, is widely used because of its fast convergence [17].

Dispatching Model

The NN structure choice

In order to model the operation of the economic dispatching in safety conditions, a BP-ANN is used. The choice of the ANN inputs is not systematic, but it is especially dependent on the database richness and the influences of each component on the dispatching whereas the ANN outputs are set as the several power plants productions. By analyzing all the available load diagrams and their distribution according to different plants, we tried to find the most influential inputs on this distribution. According to Figure 1, which represents an example of a daily dispatching operation, we note that several plants have priorities. The technical maximum and the technical minimum of power production relative to each power plant must be taken into account. It is worth noting that the management of the different wind plants is carried out partly by software and especially by human expertise so it will be taken into account by training, based on the database. By integration of the inputs one by one, and by elimination of those which do not improve the training and test performances, we fixed 15 input ANN structures, which are:

$Pch(t)$: forecast load at the instant (t),
$Pch(t-1)$: forecast load at the instant (t-1),
$Pch(t+1)$: forecast load at the instant (t+1),
$Pch(t-2)$: forecast load at the instant (t-2),
Pch_{max} : maximum of the daily forecast load,
Pch_{min} : minimum of the daily forecast load,
Pch_{md} : maximum of the predicted load during the midday period,
Day (type of day):

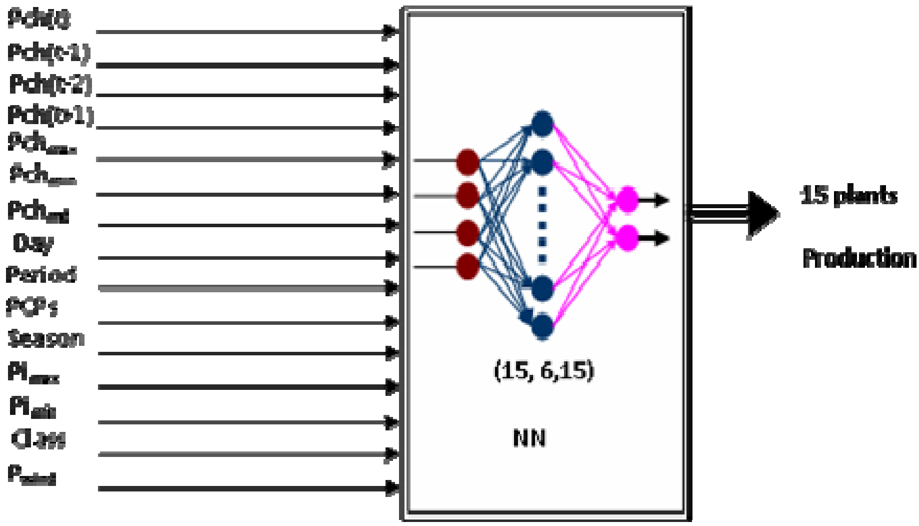
- ordinary working day,
- holiday (national),
- feast day (religious),
- special day (when an international event existing),

Season : 2 seasons (a heat season and a cold season),
Period :

- 1 st period of the day: 00h → 12h (minimum load period)
- 2nd period of the day: 12h → 24h (peak load period)

PCPs : Production Cost of the Power station. It is an economic priority depending on the specific consumption of each power plant,
Pi_{max} : maximum power of each power plant,
Pi_{min} : minimum power of each power plant,
Class : input containing the various power plants classified according to the power production level,
P_{wind} : the wind energy production is considered like a null power produced during all the phase modeling of the dispatching because the wind production is not considered in the considered database.
The season, the period and the PCPs are represented by some codes chosen judiciously, then they are integrated one by one in order to improve the ANN performances.

In BP-ANN, the number of hidden neurons determines how well a problem can be learned. If too many are used, the network will tend to try to memorize the problem, and thus not generalize well later. If too few are used, the network will generalize well but may not have enough 'power' to learn the patterns well. The choice of right number of hidden layer and neuron number in each layer is the most vital task in constructing the ANN, since there is no knowledge of it [11]-[15,16]. This number depends on the number of inputs, outputs and training patterns [16]. In our case, the number of hidden layers and its nodes are those given



the least Learning Means Square Error (LMSE) and the least Test Mean Square Error (TMSE). The complexity of selected ANN structure is a compromise between minimization of LMSE and TMSE. After much trainings and tests, we have chosen the (15-6-15) structure corresponding to 15 inputs, 1 hidden layer with 6 nodes and 15 outputs. This ANN structure is represented in Figure 3.
Figure 3: ANN Structure for the dispatching model

It is shown in [17], that the ANN performances are also improved by a coherent data base which is generally divided in two sequences:

- *Training Sequence* : which is composed of :
  - ✓ 52 working days
  - ✓ 30 holidays
  - ✓ 2 feast days (religious holiday with minimal consumption)
- *Test Sequence* : which is composed of :
  - ✓ 1 special day (international event during which any major disturbance is not permitted)
  - ✓ 1 peak load (maximum consumption)
  - ✓ 1 feast days (*Aid El Fitr*)

In all the work, every day is divided in two independent periods; the first corresponds to the peak period and the second to the minimum load period. We designed one ANN for each period to decrease the degree's non linearity of the studied system.

Validation of the structure

After training the ANN, we tested it with the test sequence data. Figures 4 and 5 represent respectively the real and estimated power production and the relative errors for each special daily period. These two figures show that the used approach gave good results. Indeed the estimated number of functional power plants is correct, the relative error of the total production does not exceed 3 to 4 % and the relative error of each power plant reaches in worst case (during the starting of some plants) from 10 to 15 %.

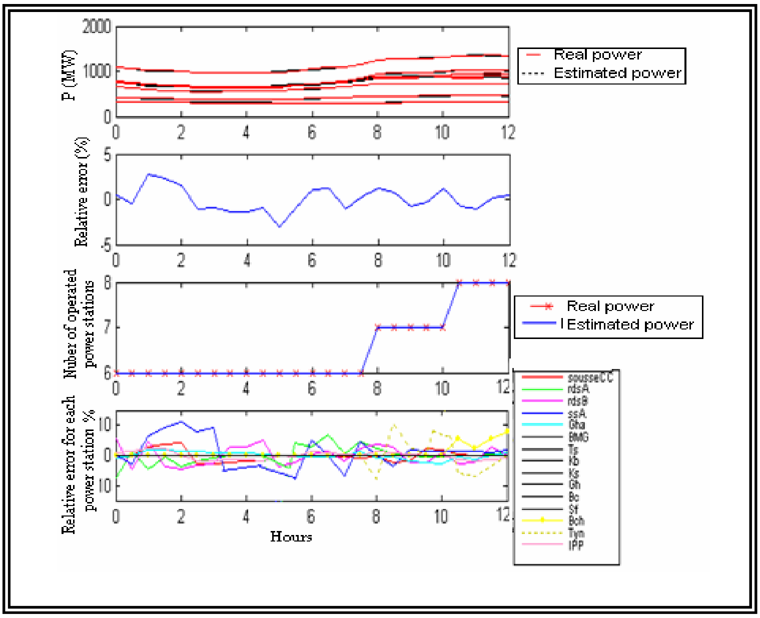


Figure 4: Illustrative results for the 1rst period of a special day

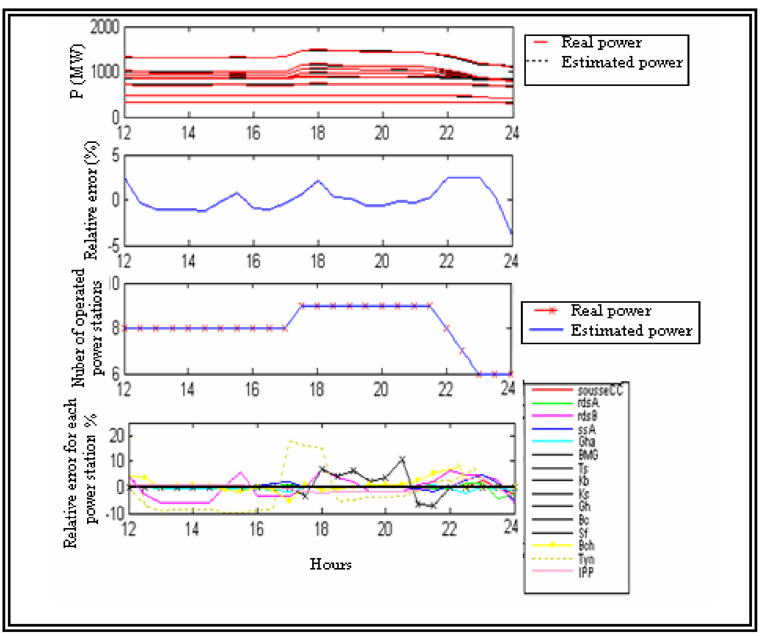


Figure 5: Illustrative results for the 2nd period of a special day

Wind Energy Integration into the dispatching

Due to the neglected amount of wind power production, the latter is not yet integrated in the dispatching and consequently it is not learned by the ANN (P_{wind} =0 during both learning and test phases). In this section we will present how the ANN model can take into account this intermittent component of power. We will present two cases; the first one shows a simple and unrealistic case which assumes that the wind power is constant. The second one shows a general case containing an intermittent wind profile.

Case 1: Constant wind energy

Considering that wind production is constant is an unrealistic case, just used to test the ability of the ANN dispatching model to deal with such perturbation for different states of load. This power (P_{wind}= 150MW) is supposed to be consumed at 100% and the control system will consider only the 15 traditional power stations. This power component will be considered as a negative load that means that it will be decreased from the total power consumption (curve load). The obtained results are satisfactory because the estimated production for each functional power plant always evolves between the maximum and minimum values of production (respect of an economic and secure operation). In Figure 6, we present the real and estimated total production (sum of the real and estimated power production of all power plants after integration of wind energy). The relative error between the real and estimated total power production increased and reached in the worst case 12% of the total power produced in the minimum load zone. This error depends on the type of the power plant. In fact, in Figure 7, we show the evolution of the real and estimated production of some power plants compared to the technical and daily maximum and minimum of the production of each power plant. In the case of an integration of a wind farm with such significant power, we find an over-estimation or under-estimation and even equality between the real power and that estimated of each power plant. In all cases, the economic secure dispatching is surely obtained since the production of each power plant varies always between the technical boundaries.

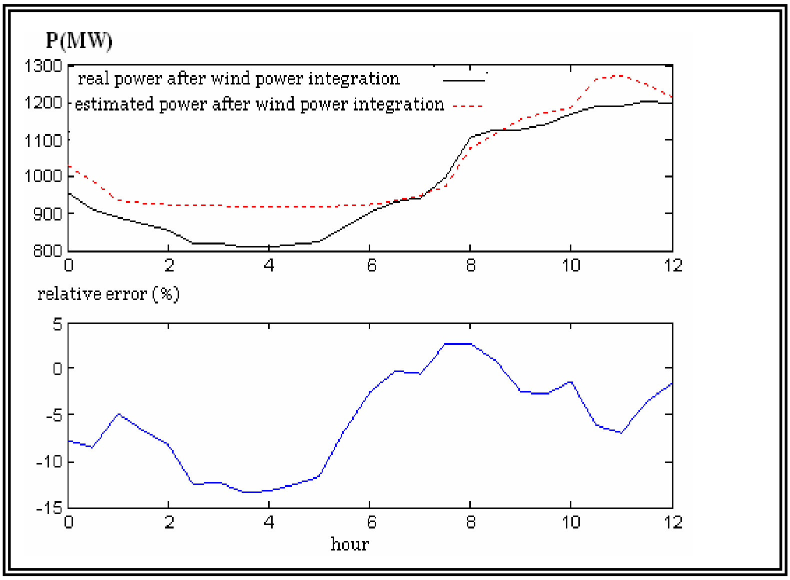


Figure 6: Comparison between real and estimated power after wind power integration

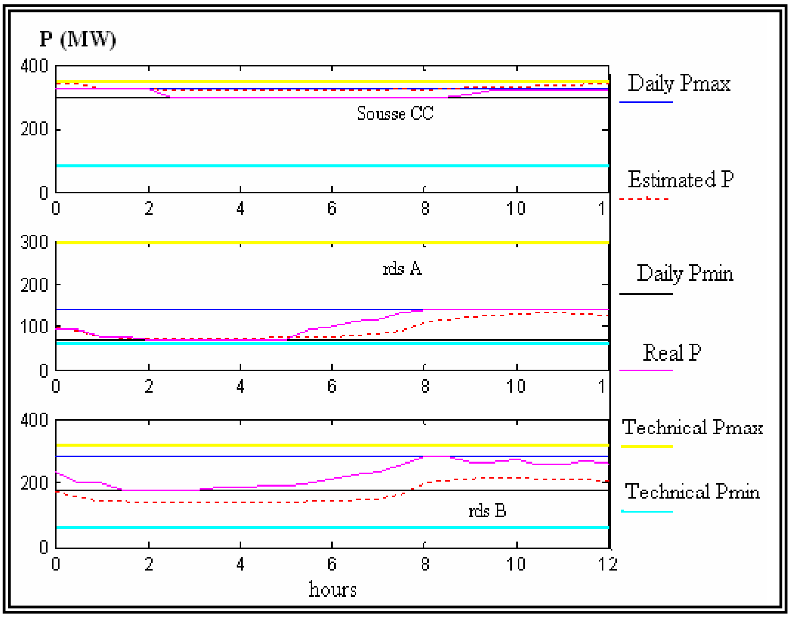


Figure 7: Power produced by (sousseCC, rdsA, rdsB) before and after wind power integration

In this paragraph, we have neglected the considerable intermittent phenomenon of the wind power production. We will consider in the following paragraph the abrupt and severe variations of this power.

Case 2: Variable wind energy

We will consider in this case the most unfavorable variations of the wind power:

During the first period of the day: the wind turbines produced the maximum of energy (150 MW) during the minimum load range and stopped during the peak load one (Figure 8-(a)),

During the second period of the day: a maximum production at the beginning, then null in the peak, finally a weak production (Figure 8-(b)).

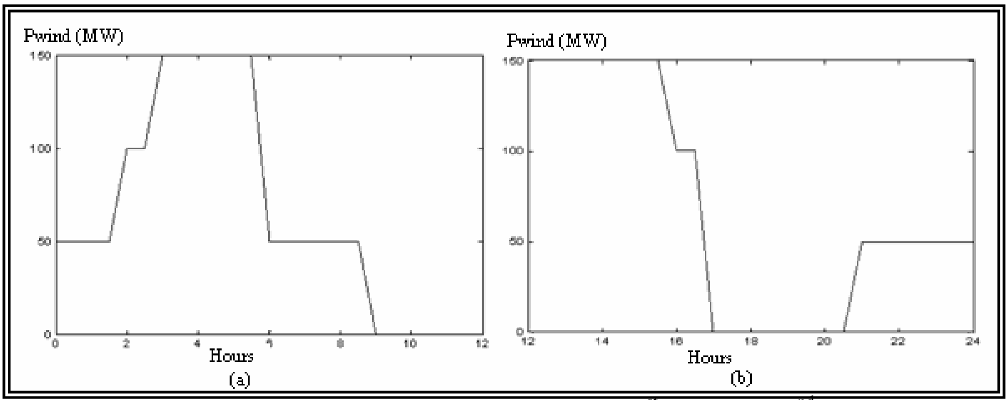


Figure 8: Profile of the wind turbine power during (a) the 1st period, (b) 2nd period

In the following, we discuss the effects of the integration of such wind power component on the power plant generation. Note that the worst wind profile is chosen to test the ability of the dispatching ANN model to take into account this high perturbation.

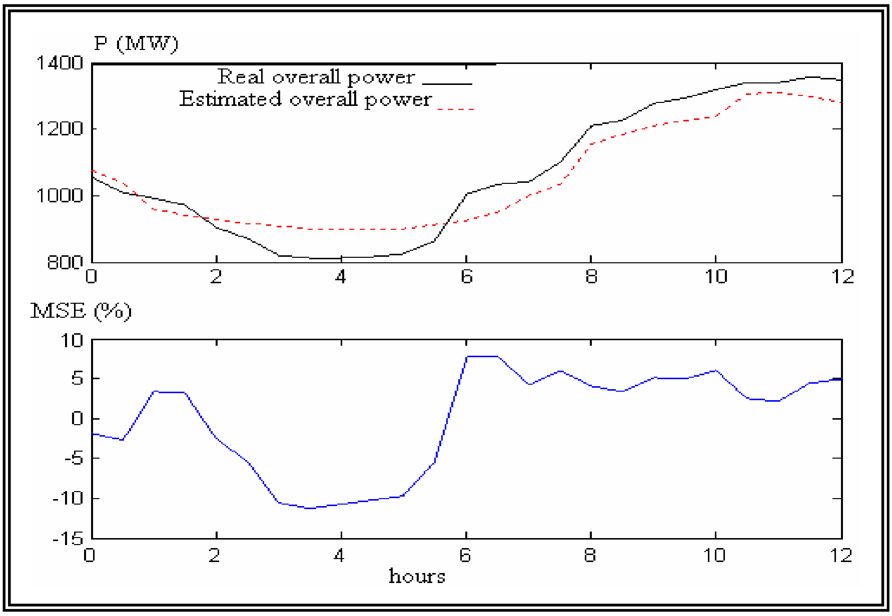


Figure 9: Total real and estimated power following the integration of intermittent P_{wind}: 1st period

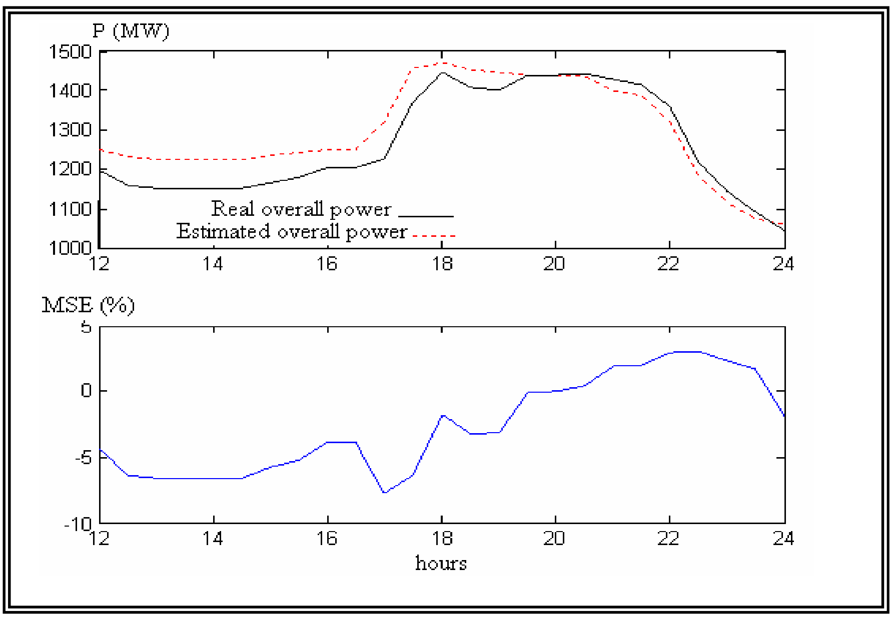


Figure 10: Total real and estimated power following the integration of intermittent P_{wind}: 2nd period

In figure 9 and figure10, we present the Mean Square Error (MSE) between the real and the estimated total power production (sum of all the outputs of the ANN); this error is more significant during the minimum load zone because the traditional power plants operated at the minimum of their production, so any other reduction leads to an over-cost of production. Even if this error seems acceptable, it is necessary to see the error in estimation

of the production of each power plant following the integration of intermittent wind energy. Indeed, the estimation of the global power is satisfactory, but sum power plants must produce an amount of power below the technical minimum or more than the technical maximum and this causes an impact on the cost.
Discrepancies among real and estimated power plant productions due to the wind power integration (figure 11) confirm the complexity and the high nonlinearity of the re-dispatching problem because some human errors (especially for security reasons) which do not obey some rules.
In figure 12, we represented the estimated production of three basic plants. Only the estimated production of rdsA is remarkable. The wind power integration to the dispatching provokes a variation of produced power of 80% during one hour and half involving an operation with the lower part of its minimal technical power, and consequently an over-cost of production.

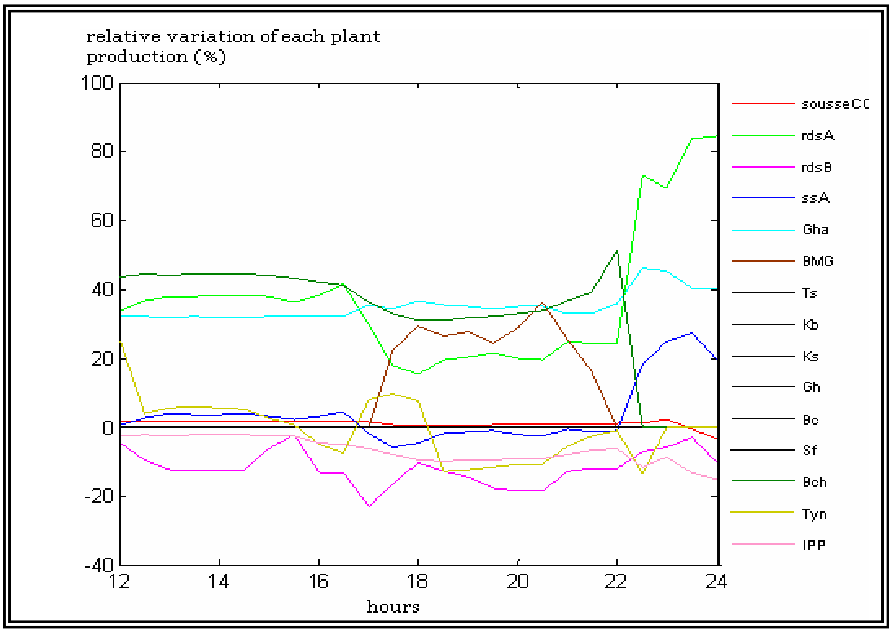


Figure 11: relative variation of each plant production

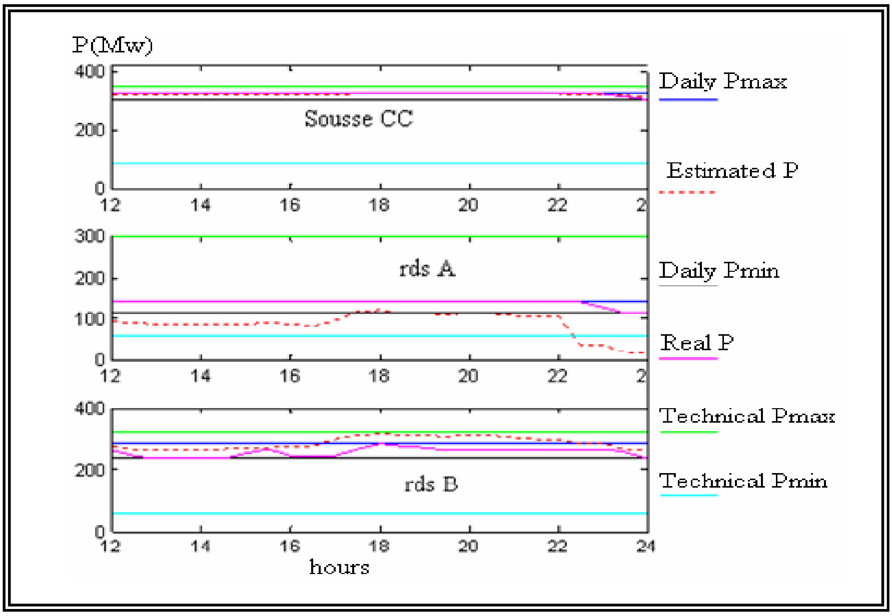


Figure 12: Power produced by each basic plant (sousseCC, rdsA, rdsB)

Conclusion

To integrate wind power production, an economic and safe dispatching method has been modeled by use of an ANN technique. The ANN dispatching model is tested for various types of days (ordinary working, special, holidays, and festival). The database is carried out from real situations based on human expertise. After the design of ANN of the dispatching by many learning processes, we integrated a wind power component neglected in the modeling phase. Different scenarios are tested to simulate the intermittent phenomenon. The reaction of the modeled dispatching with the integration of wind energy is characterized by an over-cost of production for some power plants. We are facing an evolutionary system in terms of number of traditional power stations, extension of the network, increase in the load and especially the growth of the wind energy production. This requires an evolutionary neuronal structure always depending on the exactitude of the prediction of the wind power production.

Acknowledgments

This work was supported by the PRF project (federated research project PRF02-ER03).The authors would like to thank Dr N. Dhouib and the staff of the STEG (Tunisian Electricity and Gas Company) for their contributions by supplying data.

References

[1] J. Kabouris, A.Koronides, A.Maissis, "Wind Power Integration intoElectricity Networks in Greece". Electronical conference, vol 3, pp 1157-1160, MELECON (2000).
[2] M.P.Palsson, T.Toftevaag, "Large-scale Wind Power Integration and Voltage Stability Limits in Regional Networks". IEEE Power engineering society summer Meeting, vol 2; pp 762-769, (2002)
[3] Ch.M.Huang, Y.Ch.Huang, "Combined Wavelet-Based Networks and Game-Theoretical Decision Approach for Real-Time Power dispatch". IEEE transactions on power systems, vol.17 n°.3,(2002)
[4] T.Guesmi, H.H.Abdallah, H. Ben Arbia, A.Toumi, "Optimisation Multi Objectif du Dispatching Economique/Environnemental par l'Approche NPGA", GEI 2006.
[5] D. Devara j, S. Duraira j, and P.S. Kannan, "Real Parameter Genetic Algorithm for Multiobjective reactive power dispath", International Journal of Power and Energy Systems vol 28,2008.

[6] Aurelio R. L. Oliveira, Secundino Soares, "Optimal Active Power Dispatch Combining Network Flow and Interior Approaches".IEEE transactions on power systems, vol.18, NO.4, (2003)
[7] Z.E,Aygen, M.Bagryanic, K.S. Seker, F.G.Bagryani, " An artificial network based application to reactive power dispatch problem".9th Mediterranean Electrotechnical Conference-pp 1080-1082, (1998)
[8] W.N.W Abdullah, H.Saibon, A.A.M Zain K.L.Lo, "Genetic algorithm for optimal reactive power dispatch". Energy Management and Power delivery Preceeding of EMPD'98 pp160-164.(1998)
[9] P. X. Zhang, B. Zhao, Y. J. Cao, S. J.Cheng, "A novel multi-objective genetic algorithm for economic power dispatch". Universities Power Engineering Conference 2004.vol 1, pp422-426,(2004).
[10] G. Dreyfuss : "Les réseaux de neurone". Mécanique Industrielle et Matériaux, n°51, septembre 1998.
[11] Soteris A.Kalogirou, "Artificial Intelligence in Energy and Renewable Energy Systems", Nova Publishers, 2006.
[12] Paul G.Harrald and Harrald and Mark Kamstra, “Evolving Artificial Neural Networks to Combine Financial Forecasts”, IEEE Transactions on Evolutionary computation, Vol. 1, N°. 1, pp40-52, (1997).
[13] Barbounis T.G, Theocharis J.B,. Alexiadis M.C, Dokopoulos P.S, “Long-term Wind Speed and Power Forecasting Using Local Recurrent Neural Network Models”, IEEE Transactions on Energy Conversion, Vol. 21, N° 1, pp273-281 (2006).
[14] Shuhui Li, Donald C. Wunsch, Edgar O’Hair,Michael G. Giesselmann, ”Comparative Analysis of Regression and Artificial Neural Network Models for Wind Turbine Power Curve Estimation”, Journal of Solar Energy Engineering, Vol. 123, pp 327-332, (2001).
[15] M.Carolin Mabel, E.Fernandez, “Analysis of wind power generation and prediction using ANN: a case study”, Elsevier, Renewable Energy 32, pp.2350–2360, 2007.
[16] Soteris A. Kalogirou,” artificial neural networks in renewable energy systems applications: a review”, Pergamon, Renewable & sustainable energy reviews, N°5, pp373-401, 2001.
[17] Peter Vas,” Artificial Intelligence Based Electrical Machines and Drives :Application of Fuzzy, Neural, Fuzzy Neural, and Genetic Algorithm based Techniques”, Oxford University Press, USA, 1999.

Appendices: Abbreviation

Combined Cycle:	sousse CC		
	IPP		
Thermal:	ssA		
	rdsA et rdsB		
	Gha		
Gaz :	BMG	Bc	
	Sf	Ts	Tyn
	Bch	Kb	
	Gh	Ks	