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A FUZZY LOGIC APPROACH TO UNIT COMMITMENT OF A POWER SYSTEM INTERCONNECTED WITH WECS

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ABSTRACT

The application of fuzzy logic for the optimal operation from both, economic and reliability perspective, of a Wind Energy Conversion System (WECS) interconnected to an autonomous electric power system is demonstrated. The daily scheduling of such systems is complicated due to forecasting uncertainties. In this paper, wind produced power, system demand, reserve requirements and operational cost are considered as fuzzy quantities and a fuzzy dynamic programming algorithm is developed to compose the optimal unit commitment schedule. The application of the method is demonstrated by means of a case study for the power system of Crete island.

1. INTRODUCTION

In conventional scheduling of an autonomous electric power system interconnected with a Wind Energy Conversion System (WECS), the wind produced power, the system demand and the unit availability are assumed to be known, since the forecasted values of the wind speed and the load demand are considered as crisp. The optimization problem is the determination of start-up, shut-down, and generation level of all units over a specified time period T, while the objective function to be minimized is the total cost, subject to system demand, reserve requirements and individual unit constraints (Bakirtzis 1988).

Load demand and particularly wind speed are highly stochastic variables so that their forecasted values suffer by a significant error. Stochastic models as well as a neural-network-based prediction model are developed, for both, wind power and load demand forecasting, in order to improve the forecasting accuracy (Balouktsis 1986, JOULE II 1995). However, when scheduling is performed on the basis of forecasted wind power and load demand values, the decision made may no longer be optimal since the effects of uncertainties propagate through the time horizon, significantly affecting the economics and reliability. The methodology proposed here takes these uncertainties into account using a fuzzy logic approach. The operational cost and the spinning reserve of the system are also considered as fuzzy quantities, as related to fuzzy hourly load and wind speed values. The fuzzy optimization procedure reaches an optimal unit commitment scenario where the constraints are satisfied to varying degrees according to decision maker priorities. This is opposed to conventional optimization where an optimal scenario is sought satisfying all the constraints crisply.

A case study based on the proposed methodology, for the power system of the island of Crete interconnected with WECS is presented. To evaluate the performance of the proposed fuzzy algorithm, conventional methods are also simulated and the results are compared.

2. THE FUZZY OPTIMIZATION PROBLEM

Fuzzy set theory is employed to model all the above described imprecisions. Thus, the proposed fuzzy dynamic programming algorithm uses fuzzy variables such as the total cost C, the load demand forecasting error ΔL_d, the wind speed forecasting error ΔV_w and the spinning reserve S. The task is the maximization of the degree to which all these constraints are satisfied. The optimal operation schedule is the one with the higher membership value in the fuzzy decision set D, which in fuzzy set notation is written as :

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$$D = C \cap \Delta Ld \cap \Delta Vw \cap S \tag{1}$$

The optimal schedule is determined for a time interval of T hours. A priority classification is mapped, separately for the conventional units and the WECS units, in order to reduce the computational effort needed. The priority list for the conventional units is formed either ordering them in increasing full-load operational cost or encoding the experience of the operators as in the case of WECS units (Burns 1975). According to this priority list, a unit is set out of operation only if all the above units in the list (higher cost) are out of operation.

For every hour H, the maximum WECS output power is calculated. The mathematical model for the WECS output power P(v) as a function of the wind speed v, is given by the relation :

$$P(v) = \begin{cases} 0 & v < V_{in} \\ P_r \left(\frac{v}{V_r}\right)^3 & V_{in} < v < V_r \\ Pr & V_r < v < V_{co} \\ 0 & V_{co} < v \end{cases} \tag{2}$$

where:

P_r is the WECS rated power, V_{in} is the cut-in wind speed, V_r is the rated wind speed and V_{co} is the cut-off wind speed. The hourly actual wind speed and load demand are also fuzzy as the sum of the corresponding forecasted value and the corresponding forecast error, and are described by the following equation :

$$V_{actual} = V_{forecasted} + \Delta V_w \qquad L_{actual} = L_{forecasted} + \Delta L_d \tag{3}$$

The values for the actual wind speed V_{actual} and load demand L_{actual}, for discrete membership values of the fuzzy sets ΔV_w and ΔL_d, are computed respectively. Then, the WECS output power is calculated. The optimal combination of wind generation (W/G) units to be connected to the grid, is constrained by the penetration limit of 30% of the total conventional generators power for each state (Kalaitzakis 1987, Papadopoulos 1988). The combinations of the wind generators selected from the W/G priority list are merged to the combinations of the conventional units selected from the conventional unit priority list, thus formulating the states of the system. The feasible states of the system for each hour are those which supply the required load demand and do not violate any of the constraints.

For every hour H and for each feasible state the expected total operational cost C and the membership values of the fuzzy sets C, S and D, are also calculated. The limitation of the number of paths M for the transition from each state of hour H-1 to the states of the next hour H, reduces the computational effort (Wood 1984). The M more interesting paths from each hour to the next are those with the higher membership value of the related states in the fuzzy decision set D. This is performed for each hour of the time interval T and the optimum time schedule is derived by backward tracing.

The proposed repetitive fuzzy dynamic programming algorithm is described by the following relation :

$$\mu_D(H,J) = \max_{\{N\}}\left(\min\left(\mu_C(H,J),\ \mu_{\Delta V_w}(H,J),\ \mu_{\Delta L_d}(H,J),\ \mu_S(H,J),\ \mu_D(H-1,J) \right)\right) \tag{4}$$

where, for every state J during the hour H, $\mu_D(H,J)$, $\mu_C(H,J)$, $\mu_{\Delta V_w}(H,J)$, $\mu_{\Delta L_d}(H,J)$, $\mu_S(H,J)$ are the membership values in the relevant fuzzy sets and N is the set of the feasible states during the hour H.

The fuzzy set C describes the possible range of the operational cost while the value μ_c indicates the membership grade of the operational cost in the set. The function μ_c is a numerical expression of the decision maker satisfaction for the cost level. When $\mu_c = 1$, there is full satisfaction. The proposed membership function for the cost is described by equation (5) :

$$\mu_C(H,J) = e^{-w\Delta C(H,J)} \qquad \Delta C(H,J) = \frac{COST(H,J) - COST_{min}(H,J)}{COST_{min}(H,J)} \tag{5}$$

where :

w = 0.64048 is a weight coefficient estimated by successive trials. The choice of the weight coefficient affects the resultant optimal commitment schedule and expresses the decision maker penalty for the increase of the cost. COST(H,J) is the total operational cost for the path up to the hour H and $COST_{min}(H,J)$ is the minimal total cost for the hour H.

The membership function of the fuzzy set ΔV_w denotes the range of variation of the forecasted wind speed. The error on the wind speed forecasting becomes less acceptable as it increases. The mean absolute errors for the forecasted wind speed are calculated separately for the positive and negative values M^+_w and M^-_w, with the repetitive use of the wind speed forecasting algorithm. The resulting mean absolute errors are described by means of linguistic variables according to the classification shown in Table 1. The variables M^+_w and M^-_w take one of the values $M^+_w(VL)$, $M^-_w(VL)$, $M^+_w(L)$, $M^-_w(L)$, $M^+_w(M)$, $M^-_w(M)$, $M^+_w(S)$, $M^-_w(S)$, $M^+_w(VS)$, $M^-_w(VS)$, where the labels VL, L, M, S and VS denote Very Large, Large, Medium, Small and Very Small. The membership function for the error on the wind speed forecasting is described by equation (6).

$$\mu_{\Delta V_w}(H) = \begin{cases} \dfrac{1}{1 + 1.723\left(\dfrac{\Delta v_w}{M_w^+}\right)^2} & \Delta v_w \geq 0 \\[2ex] \dfrac{1}{1 + 1.723\left(\dfrac{\Delta v_w}{M_w^-}\right)^2} & \Delta v_w < 0 \end{cases} \qquad \Delta v_w = \frac{V_{actual} - V_{forecasted}}{V_{forecasted}} \tag{6}$$

The membership function for the error on the load demand forecasting ΔL_d is derived by a similar approach to ΔV_w and is given by the equation :

$$\mu_{\Delta Ld}(H) = \begin{cases} \dfrac{1}{1 + 1.563\left(\dfrac{\Delta \ell_d}{M_d^+}\right)^2} & \Delta \ell_d \geq 0 \\[2ex] \dfrac{1}{1 + 1.563\left(\dfrac{\Delta \ell_d}{M_d^-}\right)^2} & \Delta \ell_d < 0 \end{cases} \qquad \Delta \ell_d = \frac{L_{actual} - L_{forecasted}}{L_{forecasted}} \tag{7}$$

The total required spinning reserve is taken as the 10% of the sum of the forecasted load demand and WECS output power (Papadopoulos 1988). As the total reserve decreases it becomes less acceptable. The membership function for the required spinning reserve is given by the equation :

$$\mu_s(H,J) = \begin{cases} 1 & \text{if } SR(H) \geq RQSR(H) \\ \exp\left(R\dfrac{SR(H) - RQSR(H)}{RQSR(H)}\right) & \text{if } SR(H) < RQSR(H) \end{cases} \tag{8}$$

where :

R = 1.02 is a weight coefficient, SR(H) is the total spinning reserve and RQSR(H) is the total required spinning reserve.

Table 1
Linguistic Description of the Mean Absolute Errors (MAE) of the Load Demand and Wind Speed Forecasts

Linguistic Description	Positive Errors	Negative Errors
VL	> 0,08	> -0,08
L	0,06 ... 0,08	-0,06 ... -0,08
M	0,04 ... 0,06	-0,04 ... -0,06
S	0,02 ... 0,04	-0,02 ... -0,04
VS	0,00 ... 0,02	0,00 ... -0,02

Table 2
Generating Unit Data

Unit type	Number of units	Station	Unit Name	Maxpower (MW)
Steam	1	Linoperamata	No1	6,2
Steam	2	Linoperamata	No2, No3	15
Steam	3	Linoperamata	No4, No5, No6	25
Diesel	4	Linoperamata	No1, No2, No3, No4	12,3
Gas	2	Linoperamata	No1, No2	16,2
Gas	1	Chania	No1	17,35
Gas	1	Chania	No4	26,6
Gas	1	Chania	No5	40,08
Gas	2	Chania	No6, No7	52,2

Table 3
The Membership Values for the Optimal Commitment Schedule

Hour	$\mu_{\Delta Ld}$	$\mu_{\Delta Vw}$	μ_S	μ_C	$\mu_D(H-1)$	μ_D
1	0,990	0,990	0,998	0,989	1,0	0,989
2	0,990	0,990	1,0	0,988	0,989	0,988
3	0,990	0,990	1,0	0,987	0,988	0,987
4	0,990	0,990	1,0	0,986	0,987	0,986
5	0,990	0,990	1,0	0,986	0,986	0,986
6	0,990	0,990	1,0	0,985	0,986	0,985
7	0,990	0,990	1,0	0,984	0,985	0,984
8	0,990	0,990	1,0	0,985	0,984	0,984
9	1,000	0,990	0,998	0,985	0,984	0,984
10	0,990	0,990	0,998	0,985	0,984	0,984
11	0,985	0,990	0,998	0,983	0,984	0,983
12	0,900	0,930	0,996	0,898	0,983	0,898
13	0,920	0,910	0,996	0,910	0,898	0,898
14	0,920	0,920	0,996	0,921	0,898	0,898
15	0,940	0,930	0,996	0,944	0,898	0,898
16	0,950	0,960	1,0	0,942	0,898	0,898
17	0,950	0,960	1,0	0,931	0,898	0,898
18	0,950	0,960	1,0	0,949	0,898	0,898
19	0,940	0,960	1,0	0,952	0,898	0,898
20	0,940	0,930	1,0	0,940	0,898	0,898
21	0,920	0,930	0,997	0,924	0,898	0,898
22	0,920	0,950	0,997	0,931	0,898	0,898
23	0,930	0,940	0,998	0,923	0,898	0,898
24	0,940	0,910	0,998	0,934	0,898	0,898

3. SIMULATION PROCEDURE

The simulation procedure consists of the following steps :

(a) The short-term forecasting of wind speed and load demand.

(b) The determination of the optimal time schedule in the fuzzy environment.

In this paper stochastic models and a neural-network-based prediction model are used for step (a) and the results are compared.

The stochastic forecasting model for the hourly load demand uses data for the load demand for every hour and day of a 10 years period and simulates the complex periodic fluctuation for the hourly mean load demand during a whole year period and a whole day period, according to the seasonal behaviour. The stochastic wind speed forecasting model of (Balouktsis 1986) is used, featuring an appropriate transformation for the cancellation of the annual and daily periodic fluctuations of the initial data.

In order to improve the forecasting accuracy, a neural-network-based prediction model is developed, for both, wind speed and load demand forecasting (JOULE II 1995, ELSAM 1993). The dynamic process to model is the future wind speed and load demand profile. An one output recurrent higher-order neural network (RHONN) is used iteratively to give forecasts for all time steps, while high-order terms up to two are taken into account and the neurons are fully interconnected via recurrent links. The model has been optimised by considering the forecast errors of all time steps and achieves an improvement of about 10% over the stochastic model for long time forecasting. Nevertheless, this improvement is not very beneficial to the proposed commitment method which filters properly the forecasting imprecisions.

The results of the forecasting routine for the simulating period are compared to the previous years measured values and their mean absolute errors are calculated and described by the use of linguistic variables.

In step (b) the optimum unit commitment algorithm is employed as described in Section 2. In the present work the states corresponding to membership values 1, 0.999, 0.998,... and 0.5 in the fuzzy sets ΔV_w and ΔL_d are examined for every hour.

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4. A CASE STUDY

The proposed fuzzy dynamic algorithm is applied to the electric power system of the island of Crete. The conventional power station consists of 6 steam turbines, 4 diesel units and 7 gas turbines. The WECS system consists of 30 wind generators of 1MW rated power each. The characteristics of the conventional units are illustrated in Table 2.

The fuzzy dynamic algorithm results are compared to a conventional algorithm results (Bakirtzis 1988). The conventional model computes the optimal unit commitment by minimisation of the objective cost function, neglecting the uncertainties on the load demand and the wind speed forecasting ($\mu_{\Delta V_w}= 1$, $\mu_{\Delta Ld}= 1$).

The forecasted load demand for the selected time interval of 24 hours is 3220.4 MWh while the wind energy contribution is 434.8 MWh. The resulting production cost following the conventional commitment schedule, is $425993.

Table 3 contains the values of the membership functions $\mu_{\Delta V_w}$, $\mu_{\Delta Ld}$, μ_C, μ_S, $\mu_D(H-1)$ and $\mu_D(H)$, for every hour of the proposed fuzzy optimal unit commitment schedule. The total production cost and the membership value μ_D of the proposed optimal unit commitment are $405119 and 0.898 respectively.

The total production cost depends on the shape of the membership functions $\mu_{\Delta V_w}$, $\mu_{\Delta Ld}$, μ_C, μ_S. The membership functions weight factors express the operators penalty for the increase in the total cost, as well as the penalty for the use of load demand and wind speed levels far away from the forecasted 'actual' ones. The total production cost can be further reduced using different weight factors at the price of a lower membership value of μ_D. However, a decision with a too low membership value μ_D and relatively low production cost, in practical applications is unacceptable since it implies that the load levels used are far away from the actual ones.

5. CONCLUSIONS

Results from the present study reveal that the proposed fuzzy dynamic programming is very effective in reaching an optimal commitment schedule which expresses the operators preferences on conflicting perspectives (production cost, reliability). The comparison of the conventional methodology with the proposed one proves the superiority of the former. Indeed, the production cost resulted by the proposed method is lower by 4.9% than the cost of the conventional one. This is achieved without any degradation of the required reliability of the system.

6. REFERENCES

Bakirtzis, A.G., and Dokopoulos, P.S. 1988. Short Term Generation Scheduling in a Small Autonomous System with Unconventional Energy Sources. IEEE Transactions on Power Systems, Vol 3, No 3.

Balouktsis, A., Tsanakas, D., and Vachtsevanos, G. 1986. Stochastic Simulation of Hourly and Daily Average Wind Speed Sequences. Wind Engineering, Vol 10, No 1.

Burns, R.M., and Gibson, C.A. 1975. Optimisation of Priority Lists for a Unit Commitment Program. Paper A 75 453-1, IEEE/PES Summer Meeting.

ELSAM, 1993. Wind Power Prediction Tool in Central Dispatch Centers. Progress Report 3 of the EU project JOU2-CT92-0083.

JOULE II 1995. Development and Implementation of an Advanced Control System for the Optimal Operation and Management of Medium-sized Power Systems with a Large Penetration from Renewable Power Sources. Final report of the EU project: JOU2-CT92-0053.

Kalaitzakis K.C., Vachtsevanos G.J., 1987. On the Control and Stability of Grid-connected Dispersed Sources. IEEE Trans. on Energy Conversion, Vol EC-2, No 4.

Papadopoulos, M., Papadias, B., and Malatestas, P. 1988. Penetration of Wind Turbines in Islands with Diesel Power Station. European Community Wind Energy Conference, Herning, Denmark.

Wood, A.J., and Wollenberg, B.F., 1984. Power Generation Operation & Control. Power Technologies, Inc. Schenectady, New York.