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A FUZZY DYNAMIC PROGRAMMING ALGORITHM FOR THE OPTIMAL OPERATION OF A POWER SYSTEM INTERCONNECTED WITH WECS

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ABSTRACT

A new approach 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 introduced. The forecasting of the load demand and the wind speed is based on fuzzy models. Thus, the uncertainty on the forecasted values is taken into account, resulting in better results compared to conventional methods, where the forecasted values are considered crisp. A fuzzy dynamic programming algorithm is used for the optimal unit commitment scheduling. A case study of the proposed algorithm is performed for the power system of Crete island.

1. INTRODUCTION

The more common conventional method for the optimal operation of a power system is the minimisation of the cost objective function of the system based on dynamic programming techniques [1]. A basic constraint for the operation of the system is the balance between the load demand and the generated power. Another constraint, because of unpredictable fluctuations on the load demand, is a minimum reliability of the operation, retained by an amount of spinning reserve. Thus, prediction of the load demand is required for at least 24 hours in advance, obtained by a suitable forecasting model . In case of WECS connected to the system, a part of the load demand is supplied by the wind generated power and therefore, the wind speed prediction is required also. A proper wind speed forecasting model is used [2].

The load demand and particularly the wind speed are very stochastic variables so that their forecasted values contain a significant error. The methodology proposed here takes these errors 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 values. A case study based on the proposed methodology, for the power system of the island of Crete interconnected with WECS is performed and the results are compared to other conventional methods.

2. THE FUZZY LOGIC METHOD

The proposed fuzzy dynamic programming model consists of the fuzzy set of the total cost C and the fuzzy variables which determine the constraints of the system, such as the load demand forecasting error ΔL_d, the wind speed forecasting error ΔV_w and the spinning reserve S. The stochastic nature of both, the load demand error and the wind speed error are expressed by fuzzy sets. The cost and the spinning reserve are also fuzzy sets, because they depend on the above fuzzy variables. Additional constraints for the system are the minimum start/stop time of the conventional units and the maximum permissible power penetration level from the WECS to the grid. The above constraints are considered to be crisp.

The optimal operation schedule is characterised by the higher membership value in the fuzzy decision set D, which is described by the following equation :

$$D = C \cap \Delta L_d \cap \Delta V_w \cap S \tag{1}$$

According to the above equation the optimal schedule can be expressed by the use of linguistic terms as follows :

IF the total cost is very low AND
the load demand is balanced with the generated power by both the conventional and the WECS units AND
the spinning reserve is adequate AND
the start/stop times are reasonable AND
the penetration level is not violated
THEN the resulting unit commitment is acceptable.

In the present work, the optimal schedule is determined for a time interval of 24 hours, but this is not a limitation resulting by the method, so any interval can be used. A combination of conventional and WECS units, is in operation during each hour. This combination is the **state** of the system. 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 is determined either ordering the conventional units in an increasing full load operational cost or encoding the experience of the operators [3]. According to the 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 particular hour H of the schedule interval and for every WECS unit, the maximum output power is calculated, considering the forecasted hourly wind speed. The optimal combination of wind generation (W/G) units to be connected to the grid, is the one with the maximum total power, taking into account that the total rated power of the wind generators of each state (combination of wind generators in operation) must be less than 30% of the total of the conventional generators for this state, according to the limit of the power penetration [4,5]. 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 the states which do not violate any of the constraints of the system. For every hour H of the schedule interval, the feasible states of the system are examined for r distinct error levels for both, the forecasted wind speed value and the forecasted load demand value. For each error level and for each feasible state for the hour H, the expected total operational cost C and the membership values to the fuzzy sets C, ΔV_w, ΔL_d, S and D, are calculated. A limited 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 [6]. 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 of the 24 hours and the optimum time schedule is derived by backward tracing.

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

$$\mu_D(H,J) = \max_{\{N\}}\Big(\min\big(\mu_C(H,J),\ \mu_{\Delta V_w}(H,J),\ \mu_{\Delta V_w}(H,J),\ \mu_{\Delta V_w}(H,J),\ \mu_{\Delta V_w}(H,J)\big)\Big) \tag{2}$$

where, for every state J during the hour H, it is:

$\mu_D(H,J)$ the membership value in the set D, for every combination of the error levels of the forecasted wind speed and the forecasted load demand.

$\mu_C(H,J)$ the membership value of the total cost, for every combination of the error levels of the forecasted wind speed and the forecasted load demand.

$\mu_{\Delta V_w}(H,J)$ the membership value of the forecasted wind speed error, for every error level of the forecasted wind speed.

$\mu_{\Delta L_d}(H,J)$ is the membership value of the forecasted load demand error, for every error level of the forecasted load demand.

$\mu_S(H,J)$ the membership value of the spinning reserve, for every combination of the forecasted wind speed and the forecasted load demand error levels.

$\mu_D(H\text{-}1,J)$ the membership value in the set D of each of the M states, during the hour H-1, for the transition from hour H-1 to the hour H.

{N} is the set of the feasible states during the hour H.

For the design of the proposed algorithm it is required the formulation of the membership functions of the fuzzy sets C, ΔV_w, ΔL_d and S.

3. DETERMINATION OF THE MEMBERSHIP FUNCTIONS

3.1 The Membership Function for the Fuzzy Objective Function of the Cost C

The membership function for the cost C denotes the preference for an operating time schedule with a minimal cost. The membership function is a numerical expression of the decision maker satisfaction for the cost level. If the membership value is $\mu_c = 1$, then the decision maker is fully satisfied with the cost, while if $\mu_c = 0$, he is not satisfied at all. The proposed membership value for the cost, for every feasible state J, can be written in the form :

$$\mu_C(H,J) = e^{-w\Delta C(H,J)} \tag{3}$$

where :

$$\Delta C(H,J) = \frac{COST(H,J) - COST_{min}(H,J)}{COST_{min}(H,J)} \tag{4}$$

COST(H,J) is the total cost for the path up to the hour H, for the state J, and for all error levels examined.

w = 0.64048 is a weight coefficient estimated by successive trials.

$COST_{min}(H,J)=Min_J(COST(H,J))$ is the minimal total cost for the hour H.

3.2 The Membership Function for the Error on the Wind Speed ΔV_w

The mathematical model for the WECS output power P(v) as a function of the wind speed v, is given by the relation :

$$P(v) = \begin{cases} 0 & v<V_{in} \\ Pr\left(\dfrac{v}{Vr}\right)^3 & V_{in}<v<V_r \\ Pr & V_r<v<V_{co} \\ 0 & V_{co}<v \end{cases} \tag{5}$$

where:

P_r the WECS rated power

V_{in} the cut-in wind speed

V_r the rated wind speed

V_{co} the cut-off wind speed

For the short-time forecasting of the wind speed a suitable model has been elaborated. [3]. The actual speed of the wind V_{actual} is the sum of the forecasted value and the forecast error ΔV_w, as described in the following relation :

$$V_{actual} = V_{forecasted} + \Delta V_w \tag{6}$$

The error on the wind speed forecasting and the actual wind speed are characterised by the fuzzy sets ΔV_w and V_{actual} respectively. The determination of the membership function of the fuzzy set for the forecasting error is sufficient for the determination of the fuzzy set for the actual wind speed V_{actual}.

The mean absolute errors for the forecasted wind speed are calculated with the repetitive use of the suitable wind speed forecasting algorithm. The error ΔV_w can be either positive or negative and for every hour is calculated the mean absolute error for all positive forecasting errors and the mean absolute error for all negative forecasting errors. The calculated mean absolute errors are described by means of linguistic variables according to the classification shown in Table 1. The mean absolute errors M^+_w and M^-_w for all positive and negative errors on the wind speed forecasting for every hour may 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 linguistic variables VL, L, M, S and VS denote Very Large, Large, Medium, Small and Very Small mean absolute error.

The membership function for the error on the wind speed forecasting is given by the relation:

$$\mu_{\Delta V_w}(H) = \begin{cases} \dfrac{1}{1+1.723\left(\dfrac{\Delta Vw}{M^+_w}\right)^2} & \Delta Vw \geq 0 \\ \dfrac{1}{1+1.723\left(\dfrac{\Delta Vw}{M^-_w}\right)^2} & \Delta Vw < 0 \end{cases} \tag{7}$$

where :

$$\Delta Vw = \frac{\Delta V_w}{V_{forecasted}} = \frac{V_{actual} - V_{forecasted}}{V_{forecasted}} \tag{8}$$

The value for the actual wind speed V_{actual} corresponding to each membership value $\mu_{\Delta V_w}(H)$ is computed by equations (7)

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

and (8). Then, the WECS output power is calculated using equation (5).

3.3 The Membership Function for the Error on the Load Demand ΔL_d

The actual demand L_{actual} is the sum of the forecasted value $L_{forecasted}$ and the forecasting error ΔL_d, as shown in the following equation :

$$L_{actual} = L_{forecasted} + \Delta L_d \tag{9}$$

As described for the wind forecast, the mean absolute errors for the load demand are calculated with the repetitive use of the demand forecasting algorithm and are described by the use of linguistic variables according to the classification shown in Table 1.

The membership function for the load demand forecasting error is given by the equation :

$$\mu_{\Delta Ld}(H) = \begin{cases} \dfrac{1}{1+1.563\left(\dfrac{\Delta\ell_d}{M^+_d}\right)^2} & \Delta\ell_d \geq 0 \\ \dfrac{1}{1+1.563\left(\dfrac{\Delta\ell_d}{M^-_d}\right)^2} & \Delta\ell_d < 0 \end{cases} \tag{10}$$

where :

$$\Delta\ell_d = \frac{\Delta L_d}{L_{forecasted}} = \frac{L_{actual} - L_{forecasted}}{L_{forecasted}} \tag{11}$$

The value of the actual load demand L_{actual}, corresponding to each membership value $\mu_{\Delta Ld}(H)$, is computed by equations (10) and (11).

3.4 The Membership Function for the Spinning Reserve Demand S

The spinning reserve required to ensure a minimum reliability of the system operation, depends on the fuzzy variables of the wind speed and the load demand. Therefore, it is characterised by the fuzzy set S.

The membership function for the required spinning reserve, for every feasible state J during the hour H, is calculated by the equation :

$$\mu_S(H,J) = \begin{cases} 1 & \text{if } SR(H) \geq RQSR(H) \\ \exp\left(R\dfrac{SR(H) - RQSR(H)}{RQSR(H)}\right) & \text{if } SR(H) < RQSR(H) \end{cases} \tag{12}$$

where :

R = 1.02 weight coefficient

SR(H) the total spinning reserve

RQSR(H) the total required spinning reserve

The total required spinning reserve RQSR(H) is the sum of 10% of the forecasted load demand and 10% of the total forecasted WECS output power for the state J during the hour H [5].

4. DESCRIPTION OF THE ALGORITHM

The specification of the optimal time schedule, as described in section 2, is a fuzzy dynamic programming problem. The data for both, the wind speed and the load demand are required for the solution. Thus, two successive stages are executed :

a. The short-term forecasting for the wind speed and the load demand.

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

Two separate algorithms are exploited for the execution of the above stages.

4.1 Forecasting Models

Stochastic models are used in the present paper for the forecasting of the load demand and the wind speed.

The forecasting model for the hourly load demand uses data for the load demand for every hour and every day of a 10 years period and simulates the complex periodic fluctuation for the hourly mean load demand during (a) a whole year period and (b) a whole day period, according to the season behaviour.

The wind speed forecasting model [3] uses an appropriate transformation for the cancellation of the annual and daily periodic fluctuations of the initial data.

The results of the forecasting routine, for the simulating period, are compared to the measured values for the previous years and the mean absolute errors on both, the wind speed values and the load demand values, are calculated for every hour, and are described by the use of linguistic values. Afterwards, the optimum time schedule algorithm (unit commitment algorithm) is performed in the fuzzy environment.

4.2 Optimal Unit Commitment Fuzzy Algorithm

For the determination of the optimal unit commitment for every hour H of the simulating period and for every feasible state J of the system, the membership value $\mu_D(H,J)$ in the fuzzy decision set D is calculated, as described in relation (2).

The optimal unit commitment is characterised by the maximum membership value in the fuzzy set D, at the end of the simulating period. The steps executed are as follows:

1. For every hour H of the simulating period, the system states, determined as described in Section (2), are studied for r different error levels on (a) the forecasted wind speed value (and consequently on the WECS output power) and (b) the forecasted load demand value. For every such an error level and for all the feasible system states during the hour H, the membership values $\mu_{\Delta Vw}$, $\mu_{\Delta Ld}$, μ_C, μ_S and μ_D are calculated. In the present paper, the positive and negative errors are examined on both the wind speed and the load demand, corresponding to membership values 1, 0.99, 0.98,..., 0.51 and 0.5 in the fuzzy sets ΔV_w and ΔL_d.

2. For the transition to the hour H, at the end of the hour H-1, a limited number of M possible states with the higher membership value in the fuzzy set D, is selected.

5. 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.

Table 2
Generating Unit Data

Unit type	Number of units	Station	Unit Name	Max power (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

The results from the application of the fuzzy dynamic algorithm are compared to the results from a conventional algorithm [1]. The conventional model computes the optimal unit commitment by the minimisation of the objective cost function, neglecting the uncertainty on the forecasting of the load demand and the wind speed ($\mu_{\Delta Vw}$= 1, $\mu_{\Delta Ld}$= 1).
The forecasted load demand for the selected time interval of 24 hours is 3020.5 MWh and the resulting production cost for the optimal commitment schedule, using the conventional dynamic algorithm, is $404240. Details on the hourly load demand, the wind speed, and the amount of spinning reserve for the optimal commitment schedules generated by the conventional dynamic algorithm and the proposed fuzzy dynamic algorithm are not given due to limited space.

Table 3
The Membership Values for the Optimal Commitment Schedule

Hour	μΔLd	μΔVw	μS	μC	μD(H-1)	μD
1	0.990	0.990	1.0	0.989	1.0	0.989
2	0.990	0.990	1.0	0.986	0.989	0.986
3	0.990	0.990	1.0	0.987	0.986	0.986
4	0.990	0.990	1.0	0.986	0.986	0.986
5	0.990	0.990	1.0	0.986	0.986	0.986
6	0.990	0.990	1.0	0.984	0.986	0.984
7	0.990	0.990	1.0	0.984	0.984	0.984
8	0.990	0.990	1.0	0.985	0.984	0.984
9	1.000	0.990	1.0	0.985	0.984	0.984
10	0.990	1.000	1.0	0.985	0.984	0.984
11	0.990	0.990	1.0	0.983	0.984	0.983
12	0.900	0.970	1.0	0.896	0.983	0.896
13	0.920	0.960	1.0	0.916	0.896	0.896
14	0.920	0.910	1.0	0.961	0.896	0.896
15	0.940	0.950	1.0	0.924	0.896	0.896
16	0.950	0.960	1.0	0.929	0.896	0.896
17	0.950	0.960	1.0	0.900	0.896	0.896
18	0.950	0.960	1.0	0.928	0.896	0.896
19	0.940	0.960	1.0	0.942	0.896	0.896
20	0.940	0.930	1.0	0.960	0.896	0.896
21	0.920	0.930	1.0	0.924	0.896	0.896
22	0.920	0.950	1.0	0.961	0.896	0.896
23	0.930	0.940	1.0	0.923	0.896	0.896
24	0.940	0.940	1.0	0.934	0.896	0.896

Table 3 contains the values of the membership functions $\mu_{\Delta Vw}$, $\mu_{\Delta Ld}$, μ_C, μ_S, μ_D(H-1) and μ_D(H), for every hour of the proposed optimal unit commitment schedule using the fuzzy dynamic algorithm. It is observed that the membership values for spinning reserve μ_S are equal to 1 for every hour. The existing spinning reserve for every hour is much greater than the required spinning reserve because this case study deals with the commitment during the off-peak season of Autumn. The total production cost and the membership value μ_D of the proposed optimal unit commitment are $384599 and 0.896 respectively.

This total production cost depends on the form of the membership functions of $\mu_{\Delta Vw}$, $\mu_{\Delta Ld}$, μ_C, μ_S. The weight factors for the membership functions express the penalty that the operators determine for the increase in the total cost as well as the penalty for the use of load demand levels and wind speed levels far away from the forecasted 'actual' ones. The total production cost can be reduced by using different weight factors for the membership functions at the price of having a lower membership value of μ_D. A decision with 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.

6. 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 case study is lower by 4.8% than the cost of the conventional one. This is achieved without any degradation of required reliability of the system.

7. REFERENCES

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