Intermittent wind generation in optimal power flow dispatching

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Abstract: A stochastic model of wind generation in an optimal power flow (OPF) dispatching program is presented. The model includes the error in wind power forecasts using a probability or relative frequency histogram. Compared with the deterministic OPF, the proposed model allows the coordination of wind and thermal power while accounting for (i) the expected penalty cost for not using all available wind power and (ii) the expected cost of calling up power reserves because of wind power shortage. The stochastic model is integrated in an extended conic quadratic OPF program in which wind driven generators are represented as induction machines. Simulation results are presented for cases where the forecasting error histogram is either derived from historical data or estimated by a bimodal normal distribution. The effect of the skewness of the error distribution on the optimal dispatch policy is studied.

1 Introduction

The increase in fuel prices coupled with environmental concerns has prompted countries to invest in renewable energy sources such as wind generation. Wind generation has been added to many power systems in Europe and the USA as an energy source, with substantial generation of expansion wind being planned. However, wind generation is intermittent, that is, the power produced by a wind plant varies as a function of wind speed. The uncontrollable nature of wind power introduces an additional cost of managing intermittency [1]. The minimisation of this cost requires the modelling of the wind’s variability in the economical operation of systems.

The economics of wind–thermal coordination has been studied under different scenarios including the operation of isolated networks [2] and markets governed by the Spanish [3] and British NETA rules [4]. In wind–thermal coordination models, which conform to the practice in the Hellenic interconnected system, the purchase of power from independent producers is governed by guaranteed and/or interruptible contracts [5]. In particular, the system operator is obliged to dispatch all available power produced by the wind plant through guaranteed contracts. Moreover, the wind generation output may be curtailed by interruptible contracts to avoid the violation of security constraints. Chen et al. [6] present a direct search approach to the solution of the wind–thermal coordination problem in the Taiwanese power system with operating conditions similar to those in [5]. Miranda and Hang [7] propose a solution with fuzzy wind constraints and attitudes of dispatchers. The interruptible contracts in [7] are modelled through compensation payments to private owners of wind parks if all available wind power is not utilised. Wang and Singh [8] use a fuzzy model similar to [7] and details its solution via particle swarm optimisation. An extension of the classical economic dispatch model, which includes wind energy conversion system generators, has been recently reported in [9].

This paper considers an optimal power flow (OPF) wind–thermal coordination model for networks operating under conditions similar to those reported in [6–9]. Without the loss of generality, it is assumed that wind power generators are privately owned by independent power producers. The objective function (1) of the OPF wind–thermal coordination covers the expected generation
cost of conventional units together with the expected operating costs associated with privately owned non-utility wind generators. The OPF objective cost consists of [9] (i) the cost of thermal power generation, (ii) the cost of purchase of wind power, (iii) the penalty cost because of the expected surplus wind power which is not utilised and (iv) the reserve power cost because of the expected deficit of wind power

\[ c(x) = \sum_{i=1}^{N_G} C_i(P_{Gi}) + \sum_{j=1}^{N_W} \left[ e_j P_{Wj} + c_{ESWPj} + c_{EDWPj} \right] \]

(1)

where \( P_{Gi} \) is the scheduled generation of thermal unit \( i \), \( P_{Wj} \) the scheduled generation of wind unit \( j \), \( C_i(P_{Gi}) \) is \( a_i P_{Gi}^2 + b_i P_{Gi} + c_i \) (fuel cost of a thermal generation unit \( i \)), \( \alpha_{Wj} \) the penalty cost coefficient for not using all available wind power from unit \( j \), \( c_{EDWPj} \) the cost coefficient for calling reserves to cover for wind unit \( j \), \( e_j \) the cost coefficient of wind unit \( j \), \( ESWPj \) the expected surplus wind power of unit \( j \), \( EDWPj \) the expected deficit wind power of unit \( j \), \( N_G \) the number of thermal units in the system and \( N_W \) the number of wind units in the system.

The wind power cost coefficient \( e_j \) corresponds to the fixed feed-in tariff for wind power in many European countries. According to [10], feed-in tariffs are defined by governments as the power purchase price that local wind units have to pay for wind power generation corresponding to a given forecast, simulate the relative frequency histogram of the available wind power. To underestimate the available wind power production. To simulate the relative frequency histogram of the available wind power forecasting error. The wind power forecast error for observation \( k \) is defined by

\[ e_{jk} = \frac{\omega_{jk} - \omega_{jk}}{\omega_{jk}} \times 100 \]

(4)

where \( \omega_{jk} \) is the available generation of wind unit \( j \) in observation \( k \) and \( \omega_{jk} \) the forecast generation of wind unit \( j \) in observation \( k \).

For instance, Fig. 1 shows the relative frequency histogram of the wind power forecasting error \( e_{jk} \) for the case where the power forecast is most likely to overestimate the available wind power production. Similarly, Fig. 2 corresponds to the case where the wind power forecast is most likely to underestimate the available wind power production. To simulate the relative frequency histogram of the available wind power generation corresponding to a given forecast, \( e_{jk} \) \( \omega_{jk} \) /100 is computed for all relative frequencies and added to the forecasted wind power.

2 Cost of wind intermittency in the OPF model

Let \( \rho(w) \) denote the probability density distribution of the available wind power from unit \( j \). If \( P_{Wj} \) is the scheduled wind power generation of unit \( j \), the expected surplus wind power is

\[ ESWPj = \int w_j \rho(w_j) dw_j \]  

(2)

where \([x]^+\) is the \( \max(0, x) \) and \( w_j \) the installed capacity of wind unit \( j \).

Similarly, the expected deficit wind power is

\[ EDWPj = \int w_j \rho(w_j) dw_j \]  

(3)

In practice, there are several approaches to estimate \( \rho(w) \). In one approach, an information database is used to obtain the relative frequency histogram of the wind power forecasting error. The wind power forecast error for observation \( k \) is defined by

\[ e_{jk} = \frac{\omega_{jk} - \omega_{jk}}{\omega_{jk}} \times 100 \]

(4)

where \( \omega_{jk} \) is the available generation of wind unit \( j \) in observation \( k \) and \( \omega_{jk} \) the forecast generation of wind unit \( j \) in observation \( k \).

For instance, Fig. 1 shows the relative frequency histogram of the wind power forecasting error \( e_{jk} \) for the case where the power forecast is most likely to overestimate the available wind power production. Similarly, Fig. 2 corresponds to the case where the wind power forecast is most likely to underestimate the available wind power production. To simulate the relative frequency histogram of the available wind power generation corresponding to a given forecast, \( e_{jk} \) \( \omega_{jk} \) /100 is computed for all relative frequencies and added to the forecasted wind power.
Another approach is useful if only the mean absolute percentage error (MAPE) is available from the forecasting tool [14]. The MAPE is defined by

$$\text{MAPE}_j = \frac{1}{N_c} \sum_{k=1}^{N_c} |\varepsilon_{jk}|$$

where $N_c$ is the number of observed cases. When only the MAPE is available, the forecasting error probability density distribution can be assumed to follow a bimodal normal distribution [14]. This distribution can be approximated by a probability histogram with 13 classes as shown in Fig. 3. The abscissa in Fig. 3 is $x_{jk} = \varepsilon_{jk}/\text{MAPE}_j$. Similar to the previous approach, the available wind power generation probability histogram corresponding to a given power forecast can be simulated by adding to the forecast the quantity $\text{MAPE}_j x_{jk} w_j/100$ computed for each of the thirteen classes ($k = 1, \ldots, 13$).

A third approach applies if a wind power forecast is not available. In this case, it is possible to approximately derive $p_j(w_j)$ from the knowledge of (i) the wind speed distribution at the installation site and (ii) the unit’s output power against the wind speed curve [9]. The wind speed variations over a period of 1 year are best described by a Weibull or Rayleigh probability density distribution [15] which can also be approximated by a probability histogram.

For wind–thermal coordination, the wind power forecast is assumed to be available and the third approach is not further considered in what follows.

The above approaches suggest that $p_j(w_j)$ can be estimated by a probability or relative frequency histogram represented by the set of ordered pairs $(w_{jk}, f_{jk}), k = 1, \ldots, M$. The ESWP$_j$ and EDWP$_j$ become

$$\text{ESWP}_j = \sum_{k=1}^{M} [w_{jk} - P_{Wj}]^t f_{jk}$$

$$\text{EDWP}_j = \sum_{k=1}^{M} [P_{Wj} - w_{jk}]^t f_{jk}$$

Using (6) and (7), the OPF objective (1) can be therefore written as

$$\text{minimise } \sum_{i=1}^{NG} C_i (P_{Gi}) + \sum_{j=1}^{NW} [\varepsilon_j P_{Wj} + \alpha_{Wj} \sum_{k=1}^{M} f_{jk}\sigma_{jk}]$$

subject to

$$t_{jk} \geq x_{jk}/\text{MAPE}_j; \quad t_{jk} \geq 0$$

$$s_{jk} \geq w_{jk} - P_{Wj}; \quad s_{jk} \geq 0$$

$$t_{jk} \geq P_{Wj} - w_{jk}; \quad t_{jk} \geq 0$$

### 3 Wind driven induction generators in the OPF model

Unlike conventional generating facilities based on synchronous generators, wind power plants employ induction machines which could be classified into the four groups based on their electrical topology [11]: (i) standard squirrel cage induction generator, (ii) wound rotor induction generator with variable rotor resistance, (iii) doubly fed induction generator and (iv) induction generator with full-size power converter. The induction generators in groups (i) and (ii) can only absorb reactive power. Moreover, this power is a function of the real power produced. On the other hand, the induction generators in groups (iii) and (iv) allow a wider variable speed operation and independent control of real and reactive power. As far as the mathematical modelling in OPF studies is concerned, the first two types of induction generators need to have their real and reactive powers constrained by a $P–Q$ curve, whereas the real and reactive outputs of the last two types can vary independently of each other within the operating limits of the $P–Q$ region. The $P–Q$ region associated with groups (iii) and (iv) can be modelled as in the case of conventional synchronous machines.
The asynchronous machine model considered herein is applicable to induction generators which are classified in the first two groups. The relation between the real and reactive power can be determined by the use of the simplified induction generator circuit in Fig. 4 [16]. In this circuit:

- $P = P_W > 0$ (the subscript $W$ is dropped to simplify notation)
- $Q = \text{reactive power supplied} < 0$ (the absorbed reactive power is $-Q$)
- $X_1 = \text{stator leakage reactance}
- X_2 = \text{rotor leakage reactance referred to the stator}
- X_m = \text{magnetising reactance}
- R_2 = \text{rotor resistance referred to the stator}
- s = \text{per-unit slip}

The magnetising losses are ignored and the stator losses are lumped with the line losses. It is also assumed that $X_m$ together with any shunt capacitor banks are included in the calculation of the network bus admittance matrix. Therefore the reactive power as defined in Fig. 4 does not account for the consumption by $X_m$.

The real power generated is

$$P = \frac{-V^2 R_2}{(R_2/s)^2 + X^2} > 0 \quad (11)$$

and the reactive power consumed is

$$-Q = \frac{V^2 X}{(R_2/s)^2 + X^2} > 0 \quad (12)$$

Equations (11) and (12) can be combined by eliminating $R_2/s$ to yield the following

$$P^2 + Q^2 + \frac{V^2 Q}{X} = 0 \quad (13)$$

Equation (13) indicates that for given values of the real power $P$ and the voltage $V$, there are two solutions for the reactive power

$$Q_1 = \frac{-V^2}{2X} \left[ 1 - \sqrt{1 - \left( \frac{2PX}{V^2} \right)^2} \right] \quad (14)$$

$$Q_2 = \frac{-V^2}{2X} \left[ 1 + \sqrt{1 - \left( \frac{2PX}{V^2} \right)^2} \right] \quad (15)$$

Fig. 5 shows that the locus of these solutions in the $P$-$Q$ plane is a semicircle with centre at $(0, -V^2/2X)$ and a radius of $V^2/2X$. It is obvious that the domain of variation of $P$ is

$$0 \leq P \leq \frac{V^2}{2X} \quad (16)$$

and the ranges of $Q_1$ and $Q_2$ are

$$\frac{-V^2}{2X} \leq Q_1 \leq 0 \quad (17)$$

$$\frac{-V^2}{X} \leq Q_2 \leq -\frac{P^2}{2X} \quad (18)$$

The critical point occurs at

$$P_{\text{max}} = \frac{V^2}{2X} \quad (19)$$

and

$$s = \frac{-R_2}{X} \quad (20)$$

In fact, the $Q_1$ characteristic is valid for

$$\frac{-R_2}{X} \leq s \leq 0 \quad (21)$$

![Figure 4](image1)

*Figure 4 Equivalent circuit of an induction generator*

![Figure 5](image2)

*Figure 5 $P$–$Q$ curve for a squirrel cage / wound rotor induction generator*
whereas $Q_2$ holds for

$$-\infty < s \leq \frac{-R_2}{X} \quad (22)$$

Therefore for a given generated power $P_i$, the induction machine can absorb one of two values of reactive power depending on whether the per-unit slip is less than or greater than $-R_2/X$. In practice, a wind unit is shut down for safety reasons when the wind speed is in excess of a predetermined cut-out value. It is therefore safe to assume that $s$ remains above $-R_2/X$ and the reactive power consumed is given by $-Q_1$ in (14). This conclusion is also supported by (6) in [17]. In fact, according to [15], only the operating points which correspond to (21) are stable. Therefore (13) for the model of the induction generator in the OPF has to be governed with the additional constraints

$$P \geq 0$$

$$-\frac{P^2}{2X} \leq Q \leq 0 \quad (24)$$

4 OPF program and solver

The OPF is a mathematical optimisation problem set up to minimise a scalar function subject to equality and inequality constraints. In the case of OPF dispatching with a wind power plant, the objective function is given by (8) subject to [16]

$$\sum P_i = 0 \quad \sum Q_i = 0 \quad \text{at each node } i \text{(net power injections)} \quad (25)$$

$$P_{j_{\min}} \leq P_j \leq P_{j_{\max}} \quad \text{for each generator } j \quad (26)$$

$$Q_{j_{\min}} \leq Q_j \leq Q_{j_{\max}} \quad \text{for each generator } j \quad (26)$$

$$V_{i_{\min}} \leq V_i \leq V_{i_{\max}} \quad \text{for each node } i \quad (27)$$

$$P_{m_{\min}} \leq P_{m_{\max}} \quad \text{for each circuit from node } m \text{ to node } n \quad (27)$$

Equations (9), (10), (13), (23) and (24) also apply as additional constraints for wind generators. In (28), the maximum allowed real power flow $P_{m_{\max}}$ reflects the stability limit, whereas the thermal limit is specified by the current-carrying capacity of the conductors $I_{m_{\max}}$. For short lines, the thermal limit dictates the maximum power transfer. However, practical stability considerations set the transfer limit for longer lines (in excess of 150 miles) [18]. Other constraints can include limits on the taps of tap-changing transformers and wind power penetration [19]. The above OPF includes only time-separated constraints. It is possible to extend it into a dynamic OPF by including time-related (ramping rate) constraints between the real power outputs of conventional generators in consecutive time intervals. Xie and Song [20] have shown that interior-point methods can exploit the structure of the dynamic OPF to solve it as a single optimisation problem.

In general, an OPF problem can be formulated using the voltage polar coordinates model [21], the voltage rectangular model [22] or the current mismatch formulation [23]. This paper represents the OPF problem using the extended conic quadratic format of power equations recently proposed in [12, 13]. This format is based on the following transformations ($V_i$ and $\theta_i$ are, respectively, the voltage magnitude and angle at node $i$)

$$R_{in} = V_i V_n \cos (\theta_i - \theta_n) \quad \text{for each circuit from node } i \text{ to node } n \quad (29)$$

$$T_{in} = V_i V_n \sin (\theta_i - \theta_n) \quad \text{for each circuit from node } i \text{ to node } n \quad (29)$$

$$u_i = \frac{V_i^2}{\sqrt{2}} \quad \text{at each node } i \quad (30)$$

The above transformations result in linear equations for the real and reactive power injections

$$P_i = \sqrt{2} G_{ii} u_i + \sum_{k=1}^{N} \left[ G_{ik} R_{kn} + B_{ik} T_{kn} \right] \quad \text{at each node } i \quad (31)$$

$$Q_i = -\sqrt{2} B_{ii} u_i - \sum_{k=1}^{N} \left[ B_{ik} R_{kn} - G_{ik} T_{kn} \right] \quad \text{at each node } i \quad (31)$$

subject to

$$2u_i u_n = R_{in}^2 + T_{in}^2 \quad \text{for each circuit from node } i \text{ to node } n \quad (32)$$

$$\theta_i - \theta_n = \tan^{-1} \left( \frac{T_{in}}{R_{in}} \right) \quad \text{for each circuit from node } i \text{ to node } n \quad (32)$$

where $G_{ii}$ is the real part of an element in the bus admittance matrix, $B_{ii}$ the imaginary part of an element in the bus admittance matrix and $N$ the number of nodes in the system.

The extended conic quadratic format requires some modifications in the constraint representation. For instance, (27) becomes

$$\frac{V_{i_{\min}}^2}{\sqrt{2}} \leq u_i \leq \frac{V_{i_{\max}}^2}{\sqrt{2}} \quad \text{for each node } i \quad (33)$$

and the induction generator constraints (13) and (24) are transformed into

$$P^2 + Q^2 + \frac{\sqrt{2} u Q}{X} = 0 \quad (34)$$

$$-\frac{u}{\sqrt{2}X} \leq Q \leq 0 \quad (35)$$

The real power flow and current magnitude squared (28) together with other dependent quantities can be also expressed as linear equations in terms of the transformed variables. Details can be found in [13, 24].
The mathematical optimisation techniques for solving the different models of the OPF problem are continually improving in terms of speed, accuracy and robustness. Recent research by the authors [13, 24] has shown that the extended conic quadratic format is well suited for a solution using primal-dual interior-point methods. In particular, [13] shows that this format entails the following advantages: (i) The non-zero entries of the Lagrangian Hessian matrix correspond only to the set of quadratic and arctangent constraints. The Hessian matrix can be therefore easily integrated within primal-dual interior-point optimisation methods. (ii) The linearity of the power injection and inequality constraint equations allows the use of linear programming scaling techniques for improving the numerical conditioning of the problem. The implementation details of the interior-point solver are documented in [25].

5 Numerical results

The OPF program for economic dispatching with a wind power plant has been programmed in MATLAB running on an Intel® Core™ 2 Duo Processor T5300 (1.73 GHz) PC with 1 GB RAM. Testing was carried out on two systems under different economical operating conditions.

5.1 69-node test system

The 69-node distribution network has five meshes and serves a total load of 1107.9 kW + j897.9 kVar [26]. The network is studied under the following assumptions:

- The distribution network operator owns two wind turbine generating units connected at nodes 14 and 48. The capacity of each wind unit is 250 kW.

- The distribution network operator purchases power from an independent power producer connected at node 1. The scheduled power is purchased at a price of \( b_i \$/kWh, whereas reserve power, which is called at short notice, has a higher price of \( c_R^j$/kWh. All other cost coefficients associated with wind power, that is \( c_j^i / 2 \) and \( c_W^j \), are zero.

- The forecasted power for each wind unit is 125 kW. Two cases are considered in relation to the forecasting error distribution:

   Case 1: The error relative frequency histograms for the wind units at nodes 14 and 48 are given in Figs. 1 and 2, respectively.

   Case 2: The error probability histogram for both units is given in Fig. 3 with \( \text{MAPE}_j = 16.55\% \), that is the MAPE is obtained from the distribution in Fig. 1 or equivalently Fig. 2.

The OPF function was run for different values of \( c_R^j / b_i \) varying from 1 to 10 in steps of 0.1. Fig. 6 shows the scheduled wind power from the unit at node 14 for cases 1 and 2. Fig. 7 is for the unit at node 48. The following conclusions can be drawn from this simulation:

- Although wind power is used at no cost, the scheduled wind power decreases with the increase in the price of purchasing power reserves. This dispatch policy reflects the fact that if wind power scheduling is probably to result in calling up significant power reserves at high cost, then the system operator is better off scheduling power from conventional units. As depicted in Figs. 6 and 7, the decrease rate is dependent on the distribution of the forecast error.

- The scheduled wind power for the case where the power forecast is most likely an overestimate of the available power production is less compared with the case where the available production can be greater or less than the forecast power with equal probability. This conclusion is demonstrated quantitatively in Fig. 6. It is consistent with the observation that the wind generator whose forecasting error histogram predicts a higher expected deficit wind power should be dispatched conservatively to reduce the

Figure 6 Wind power generation at node 14 against the normalised reserve purchase price (69-node system, case 1: overestimation relative frequency histogram, case 2: bimodal normal distribution)

Figure 7 Wind power generation at node 48 against the normalised reserve purchase price (69-node system, case 1: underestimation relative frequency histogram, case 2: bimodal normal distribution)
expected costs of purchasing power reserves. The reverse conclusion holds for Fig. 7.

5.2 30-node test system

The line and load data for the 30-node test system are available from [27]. The generator data including those of wind power units is given in [28]. Two wind units are installed. The first has a capacity of 15 MW and is connected at node 24 whereas the second has a capacity of 20 MW and feeds in power at node 27. In practice, each unit can represent the aggregate generation model of a wind farm consisting of several wind driven induction generators. The following cost coefficients are assumed for both wind units

\[ c_j = 3.5\$/\text{MWh}, \quad c_{Wj} = 3.0\$/\text{MWh}, \quad c_{Rj} = 4.0\$/\text{MWh} \]

The system is operated at 86% of the peak load in [27]. The wind power forecasts are assumed at half the power capacities, that is, 7.5 MW at node 24 and 10 MW at node 27. This simulation aims to study the effect of skewness of the forecast error probability distribution function on the wind power schedule. Towards this end, the probability density distribution is assumed to be triangular with its mode varying between \(-48\) and \(+48\)% in steps of \(4\%\). Fig. 8 shows the triangular probability density distribution function corresponding to a mode of \(-48\), \(0\), and \(+48\)%. In the OPF model, the distribution function is converted to a probability histogram with 25 interval classes.

Fig. 9 shows the variation of the scheduled power of each wind unit as the error distribution goes from being skewed to the right (\(-50\% < \text{mode} < 0\) in Fig. 8) to being skewed to the left (\(0 < \text{mode} < 50\%\) in Fig. 8). The corresponding expected total cost (8) is depicted in Fig. 10. The expected dispatch cost, that is, the expected total cost exclusive of the expected cost of managing wind power intermittency, is also shown. Fig. 11 shows the components of the expected cost of managing intermittency: the expected cost of calling up reserves and the expected cost of unused wind power. The following can be inferred from the above results:

- When the error distribution is skewed to the right, the wind power forecast most probably overestimates the wind power available and power reserves are likely to be called. To reduce the expected cost of power reserves that have a dominant price, the OPF program conservatively schedules the wind generation.
- When the error distribution is skewed to the left, the wind power forecast is most likely an underestimate of the available wind power.
wind power. In this case, the OPF schedules the wind power such that the cost of not using the available wind is reduced.

- The expected available wind power ∑ k=1 M P k , fj k w k increases as the skewness varies from right to left. The wind power scheduled by the OPF follows the same trend as the expected wind power available. For the case where the wind power price is competitive with conventional generation, the expected total cost decreases with the increase in expected wind power available.

- The OPF program produces wind–thermal coordination schedules which quantify the above conclusions.

5.3 Computational performance

As indicated in Sections 5.1 and 5.2, the 69-node system was studied for two cases, each involving 91 simulations, and the 30-node system was observed in 25 simulations. Table 1 shows the corresponding minimum, mean and maximum values of each of the following performance measures [25]:

- iter = number of interior-point iterations
- time = solution time in seconds
- pfeas = relative primal infeasibility
- dffeas = relative dual infeasibility
- opt = relative duality gap

The results indicate that the modifications in the OPF program do not impede convergence within a tight tolerance of 10⁻⁸ in around 0.15 s.

Table 1 Computational performance

<table>
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<th>Quantity</th>
<th>69-node system: case 1 / case 2</th>
<th>30-node system</th>
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<tr>
<td></td>
<td>min</td>
<td>mean</td>
</tr>
<tr>
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<tr>
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<td>0.14/0.14</td>
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<td>3.65 × 10⁻¹¹ / 4.14 × 10⁻¹¹</td>
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7 References


