Wind farm strategic investment considering forecast errors penalties in a nodal prices market

F. Foucault[1] R. Girard[1] G. Kariniotakis[1]

fiona.foucault@mines-paristech.fr robin.girard@mines-paristech.fr
georges.kariniotakis@mines-paristech.fr

[1]MINES-ParisTech, PERSEE: Center for Processes, Renewable Energies and Energy Systems, 1 rue Claude Daunesse, 06904 Sophia Antipolis Cedex, France.

Abstract

In this work, we determine the optimal investment strategy of a wind producer in a local prices environment, taking into account the penalties for real-time imbalances. We assume these imbalances come from forecast errors on the considered renewable production only. To do so, we solve a bilevel optimization problem. The upper level problem corresponds to the revenue of the considered producer, and the lower level problems correspond to the market clearings, taking place a day ahead of operations and on real-time. Indeed, we consider that imbalances penalties correspond to real-time prices such as is done in the American market PJM. Indeed, in a local prices framework, using real-time prices is a simple way to recover the financial amounts corresponding to the imbalances in power.

1 Introduction

The share of renewable energy sources in the energy mix of several countries worldwide is rapidly increasing. As regards the European Union (EU-27), the European Commission has set the target of having 20% of EU-27´ s energy consumption coming from renewable sources by 2020. Wind energy is anticipated to be a major contributor to this target with an installed capacity which is expected to extend from 121 GW by the end of 2013 in EU-27, to 230 GW by 2020 according to EWEA projections (see [1], [2]).

Such large-scale integration of wind energy raises several challenges in operating and managing power systems, as they are a great deal more subject to variability. And yet, the electricity being a non-storable product, the balance between production and consumption must be maintained. Therefore, it is now recognized that accurate short-term forecasts of wind farms´ power output over the next few hours to days are important factors for the secure and economic operation of power systems with high wind power penetration [3]. Today, significant R and D efforts are being undertaken to improve the performance of wind power prediction models and related weather forecast models. Increased overall wind power predictability is expected to be beneficial for several actors, such as transmission or distribution system operators, to efficiently perform functions such as estimating reserves, unit commitment, and congestion management.
In addition to increased predicitbility (forecast quality), adapting the incentive policies is a way to improve the renewable energy´ s adaptation to the system. This corresponds to the introduction of renewable production in the traditional electricity markets. In concrete terms, this means that deviations of the produced energy from the contracted energy (imbalance) especially due to forecast errors are exchanged at a different price called the imbalance price. This imbalance price is fixed in order to repay the network operator for his expenses to maintain the system´ s balance when generators do not produce the amount

contracted on day-ahead markets. Indeed, with growing integration of renewable energy, countries tend to shift from a feed-in tariff policy difficult to sustain in the long-run (given the fixed remuneration per kW.h, predictability does not play any role in decision-making for producers), to a management of imbalances with imbalance prices so that variability is regulated by prices whose design can be adapted. This direct translation of wind power forecast errors into a financial cost, as well as strategies for the reduction of this cost, have already been studied (see e.g. in [4, 5, 6, 7]). Yet it is still difficult to quantify the economic benefit of increasing predictability. The direct consequence of this is the difficulty in devising clear economic incentives aiming at greater predictability.

From the producer or the investor´ s point of view, this change of paradigm questions the usual decision-making process concerning the choice of location of wind farms. It is usually based on well-established ”resource assessment” study based on capacity factor. However, the costs incurred from forecast errors could damage benefits, all the more as the more wind farms are installed the less the choice among sites is large and the more complex the sites´ terrains are. Indeed, previous works like the benchmarking exercise performed in [8] have shown to what extent predictability is dependent on terrain complexity; the higher the complexity, the lower the predictability. It was shown also in [9] that predictability tends to decrease when wind speeds increase. Therefore, the wind power production investment issue has to deal with a new factor : the cost for imbalances from forecast errors.

This paper addresses this issue by proposing a model to derive optimal investment strategy taking into account penalties charged for imbalances due to forecast errors. It may enable to measure the impact of predictability in an energy mix with strong renewable penetration. The issue of predictability as a decision factor has been treated in [10] and the article [11] based on empirical, nowadays data. They deal with the new questions which are increasingly being asked by end-users: Can a compromise between resource potential and predictability be beneficial when choosing among two sites where to install a wind farm? Is some compromise to be found when choosing among two sites, let us say one with high potential but low predictability (i.e. a complex terrain site) and one with lower potential but higher predictability (i.e. a flat terrain site), so that such a compromise might lead to choosing the site with lower potential if the loss in revenue can be compensated by lower penalties? For these analyses, it has been shown that predictability had a limited impact on the revenue formation. However, in an energetic mix with a stronger renewable share, the results might be different.

This work is undertaken in a nodal pricing market. Indeed, today several local prices markets are emerging. Moreover, the growing share of renewable energy in the electricity mix should increase the local constraints on the network, all the more in a liberalized context where independent investors build capacity according to personal interest without a global perspective on the system. In this view, we consider a nodal day-ahead market, but we also take local prices into account to determine the imbalance prices, such as is done on the American PJM market[12], because this structure seems to follow the trend of the development of an integrated, continuous marketplace. However, in a first approach, we consider that the imbalances have to be dealt with locally, i.e. local reserve has to compensate for imbalances coming from difference between energy actually produced and the amount contracted on the day-ahead market. Moreover, in this paper we consider that imbalances occuring in real-time are only coming from wind power production forecast errors. Further work could interestingly benefit from emphasizing errors coming from conventional generators (linked to unexpected outages or strategic behaviors).

The actors concerned by this work could be independent power producers, wind farm developers, aggregators or virtual power plant operators who need to decide where to install a new wind (or solar) farm, or how to compose an optimal portfolio of wind farms to participate in an electricity market. In addition, penalties paid by producers who deviate from the day-ahead contract are settled by the transmission system operator and market operator, who will thus be concerned by the results of this paper.

To sum up, this paper may present an interest for investors and producers in order to help them choose the optimal strategy to maximize their revenue, but it also presents an interest for the power system and market operators, who may want to incite wind farm operators to adopt practices which increase predictability in order to lower the wind production´ s impact on the system. In this paper we propose a methodology to study the above questions, in a context of strong renewable penetration. In Section 2, we present the model which enables us to solve the problem. In section 3 we present the case study on which we carry out the optimization. In Section 4 we show results and in Section 5 we draw conclusions and give a few hints for future work.

2 The Model

2.1 Introduction to the revenue formation

We consider producers selling their forecasted production in a day-ahead market. A producer´ s revenue can be decomposed in two terms : the product of sales, given by the amount of energy sold on the day-ahead market times the spot price, and the imbalance cost, which can be positive or negative and is determined by the amount of error between the forecasted (assimilated to the amount bid, as all wind energy produced should be accepted, sold at a zero-price) and the actual amount of energy sold on the real-time market (which corresponds to the amount produced). This revenue term can therefore be expressed as :

$$Revenue = (\pi^c.E^c) + (\pi^*.d^*) \tag{1}$$

where
π^c is the spot price,
E^c is the energy contracted,
π^* is the imbalance price
$d^* = E^* - E^c$ is the error between the actual energy delivered and the bid, with E^* the contracted energy.

Low predictability is reflected through imbalance costs in the second term of the revenue expression.
There are several potential factors which may influence the magnitude of the imbalance price (which basically corresponds to the offer price of the last bid accepted on the real-time market, or the cost of loss of load if the demand is not satisfied):

→ The availability of interconnections with the exterior which brings flexibility to the system (storage is also another flexibility mean). However, we will not consider this aspect here;

→ The availability of low-cost balancing power such as hydropower. Basically it is this effect which we are interested in: how the coszt of reserve means affect the amount of imbalances;

→ The impact of renewable energy in the generation mix : the larger the share the bigger the imbalances and the costs of regulation when errors do not balance out; Here it will always be the case because divergence between day-ahead and real-time operations will come from the considered producer;

→ The size of the area or the level of aggregation: variability can be smoothened by compensating shortages in one area by the production in another.

2.2 Notation

Optimization variables
X_i represents the amount of capacity installed on node i (in MW).
P^c_{nt} represents the wind power contracted on the day-ahead market for node n for time period t.
e^*_{nt} represents the error between contracted and injected wind energy.
g_{it} represents the production of generator i for time period t.
f^{DA}_{kt} represents the power flow on line k resulting from day-ahead operations.
$\delta^{DA}_{o(k)t}$ $\delta^{DA}_{r(k)t}$ represent the voltage angle resulting from day-ahead operations, for the emitting and receiving node of line k, respectively.
$R_{nt\omega}$ represents the reserve production for node j at time period t.
LMP^{DA}_{nt} represents the day-ahead local marginal price at node n for time period t.
LMP^{RT}_{nt} represents the real-time local marginal price at node n for time period t.
Parameters
djt represents the demand j at time period t.
N represents the number of nodes of the grid considered.
T represents the number of time period considered.
Cinv represents the cost of investment per MW.
ci represents the marginal cost of production

for generator i.
cr represents the marginal cost or reserve means of production.
o(k) represents the emitting node of line k.
r(k) represents the receiving node of line k.
Bk represents the susceptance of line k.
X^{max} represents the maximal amount of capacity which can be installed at one node.
f_k^{max} represents the maximal power flow in line k.
g_i^{max} represents the maximal power production for generator i.
R_n^{max} represents the maximal power production of reserve generator n.
Data
Pred(n,t) represents the normalized production forecast.
Error(n,t) represents the normalized error between forecasted and observed wind energy.
Sets
Ω^G represents the set of generators.
Φ_n^G represents the set of generator installed at node n.
Φ_n^D represents the demand present at node n.
Ω^R represents the set of reserve generators.

2.3 The generic model

An investment decision (the capacity to install on each node considered) is based on an optimization to maximize the producer´ s revenue i.e. minimize his minus profit. This comes down to:

$$\begin{aligned} &minimize_{X=(X_1,\dots,X_N)} \\ &C_{inv}X - \sum_T \sum_N LMP_{nt}^{DA} P_{nt}^c \\ &+1/N \times \sum_T \sum_\Omega \sum_N e_{nt\omega}^* LMP_{nt\omega}^{RT} \end{aligned} \quad (2)$$

s.t

$$P_{nt}^c = X_n \times prev(n,t) \quad (3)$$

$$e_{nt\omega}^* = X_n \times erreur(n,t,\omega) \quad (4)$$

with

$$erreur(n,t,\omega) = prev(n,t) - prod(n,t,\omega) \quad (5)$$

and

$$0 \le X_n \le X^{max} \quad (6)$$

The error corresponds to the forecast production minus the actual, observed production.
s.t

$$minimize \sum_{i\in\Omega^G} c_i g_{it} \quad (7)$$

$\forall n$

$$\sum_{i\in\Phi_n^G} g_{it} - \sum_{o(k)=n} f_{kt}^{DA} + \sum_{r(k)=n} f_{kt}^{DA} + P_{nt}^c = \sum_{j\in\Phi_n^D} d_{jt} : LMP_{nt}^{DA} \quad (8)$$

$\forall k$

$$f_{kt}^{DA} = B_k(\delta_{o(k)t}^{DA} - \delta_{r(k)t}^{DA}) : \Phi_{kt}^{DA} \quad (9)$$

$$-f_k^{max} \le f_{kt}^{DA} \le f_k^{max} : (\Phi_{kt}^{DAmin}, \Phi_{kt}^{DAmax}) \quad (10)$$

$\forall i$

$$0 \le g_{it} \le g_i^{max} : (\varphi_{it}^{min}, \varphi_{it}^{max}) \quad (11)$$

$\forall n \backslash n : ref$

$$-\pi \le \delta_{nt}^{DA} \le \pi : (\xi_{nt}^{DAmin}, \xi_{nt}^{DAmax}) \quad (12)$$

n:ref

$$\delta_{nt}^{DA} = 0 : (\chi_{nt}) \quad (13)$$

s.t. $\forall t \forall \omega$

$$minimize \sum_{i\in\Omega^R} c_r R_{jt\omega} \quad (14)$$

$\forall n$

$$R_{nt\omega} = e_{nt\omega}^* : (LMP_{nt\omega}^{RT}) \quad (15)$$

$\forall n$

$$-R_n^{max} \le R_{nt\omega} \le R_n^{max} : (\Phi_{nt\omega}^{Rmin}, \Phi_{nt\omega}^{Rmax}) \quad (16)$$

(2) corresponds to the minus profit of the producer, considering a zero operational cost for wind turbines. In this objective function, the first term corresponds to the investment cost. Then the two following terms represent the revenue coming from sales on the day-ahead market and the real-time market, respectively. The last term can correspond to a revenue or

a loss according to the sign of $e^*_{nt\omega}$. When the amound bade is inferior to the power actually injected on the network, $e^*_{nt\omega}$ is positive, and the relevant term is a cost and vice versa. These revenue terms are non linear.
(3) means that the amount of wind energy bid on the day ahead market corresponds to normalized forecasts on the area times the installed capacity whereas (4) shows that the amount bid on the real-time market corresponds to actual normalized errors, coming from onsite observations times the installed capacity.

This optimization problem depends on two lower level problems, i.e. the market clearing, both day ahead and real-time, which produce the market prices. They deal with minimizing the global (on all nodes) cost of supplying energy (respectively7 and 14), whilst satisfying the demand (respectively 8 and 15). On the day-ahead market, conventional generators provide their offers(8), whereas on the real-time market(15), flexible generators provide reserve services. (10)represents the power flow limits on the network lines.(9),(12),(13) represent physical constraints on the power lines. (11)(16) represent the respective (conventional and reserve) units´ minimal and maximal output.

2.4 Methodology

We use a simplified model where the real-time problem is decorrelated from the day ahead problem. A simplifying hypothesis is to consider that the power flows remain the same as those obtained with the day ahead market clearing, so that imbalances have to be compensated on the nodes where they are generated. This enables to get rid of the non convex part of the objective function (coming from the dependance between day ahead and real-time.

To solve this optimization problem, we transform the lower level problems into constraints of the upper level problem using their Karush Kuhn Tucker (KKT) conditions. We are able to linearize the objective function using the strong duality theorem, and the non-linear constraints using the following relation :

$$\alpha \geq 0, \beta \geq 0, \alpha.\beta = 0 \tag{17}$$

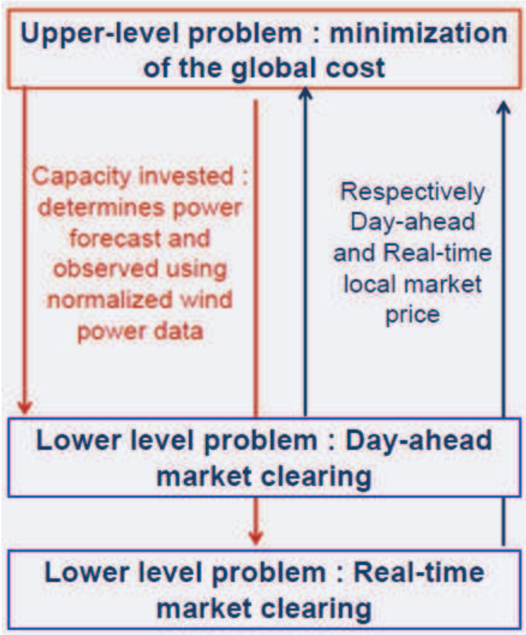

Figure 1: The problem considered

is equivalent to:

$$\alpha \geq 0, \beta \geq 0, \alpha \leq M.(1-\omega), \beta \leq M.\omega \tag{18}$$

3 The case study

3.1 The system

We use a simple 3 node system:

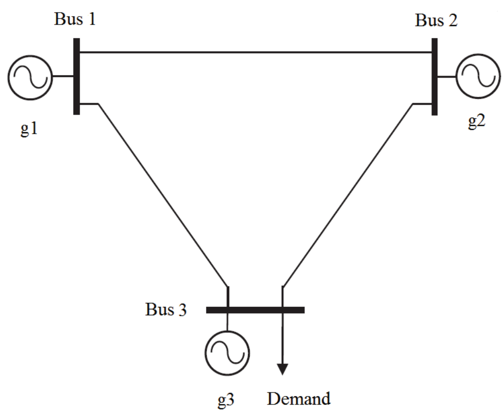

Figure 2: The system considered

3.2 The data

We use wind observation and forecast data for France for the February-March 2008 period (the investment term is scaled to match the data period). It is generated using MERRA reanalysis (NASA reanalysis) of wind speed at 50 m from ground, using a 50 km*50 km spatial resolution grid, and a hourly timestep. These wind speed data are used as input to a manufacturer power curve (which defines the relation between wind and the electrical power of a turbine).

In this work, we only use one scenario of renwable production, so that only one scenario is used to carry out the optimization for the real-time market clearing. Further work could benefit from adding other scenarios to improve the solution´ s robustness to different production and error levels.
Tthe french wind production data is available for a grid of 193 points, we divide the whole national demand data by the number of these grid points, and consider the data for the first three points. The wind production forecast error'mean bias is 0.6% (respectively 2, 0.03 and -0.02% for node 1,2 and 3 illustrated side by side in the following figure):

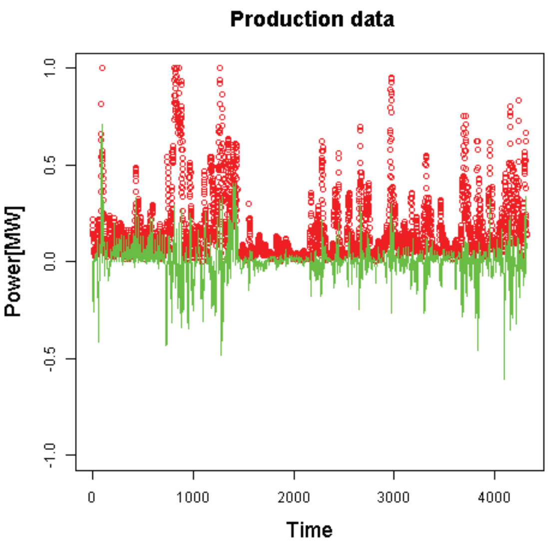

Figure 3: Wind power production (green) and forecast error (red) for the 3 nodes

The conventional units are considered to have a 20 MW capacity and the following caracteristics:

Node	Demand	Type	Cost(€/MWh)
1	0	Coal	20
2	0	Gas	35
3	60	Nuclear	7

All the lines´value is 9.412 p.u and their maximal capacity is 25 MW. The investment cost considered is 900 k€, distributed on 20 year amortization period so that $Cinv$ is 45 k€/MW for a year, which comes down to $45000 * 1440/8760 = 7397$ €/MW when adjusted to the February-March 2008 period considered for the wind production. We assume one reserve plant is installed on each node, whose cost is 40 €/MWh and whose installed capacity is 20 MW.

4 Results

4.1 Computational issues

The problem is solved using R´ s package Rcplex with IBM´ s optimization tool CPLEX on a 64 bits, 4Go of RAM computer.

4.2 Numerical results

Reserve cost(€/MWh)	Investment	Benefit (€)
0	15.5/0/5.1	66964
10	15.4/0/4.9	42401
40	0/0/0	0
100	0/0/0	0

The investment cost wears down the revenue. In a case where the investment cost is null, the investment could be beneficial with higher reserve costs:

Reserve cost(€/MWh)	Investment	Benefit (€)
0	17/46/44	561077
10	23.6/40.7/32.9	475088
40	10.5/51.6/33	266337
100	0/24/19.4	26728

5 Conclusion and perspectives

Taking into account the penalties for forecast errors in a realistic context does not enable to carry out a beneficial investment. Indeed, the investment, fixed cost and the reserve cost are wearing down the wind producer´revenue. With a realistic investment cost, the cost of reserve has to be lower than the cost of conventional units to have a positive benefit.

Further work could deal with the non-convex problem we have outlined, where the real-time market clearing depends on the day-ahead variables. Indeed, instead of assuming that the reserve only supplies the amount missing from wind power locally, we could have a new market clearing involving new power flows along the lines. In this work, only one scenario of renewable production was considered. Introducing more scenarios would enable us to determine more robust strategies, adaptable to various wind production and forecast errors such as those available for an investment decision.
Also, we have introduced the cost of reserve as a parameter of the problem and it would be interesting to have insights on the future cost of reserve to analyse how investment decisions might be affected (whether the cost of reserve increases due to renewable energy imbalances or decreases with a mutualization of ressources). Finally, this work would have a larger impact by modelling the imbalances coming from conventional generators (due to unexpected outages), or from other renewable producers already installed. This way the new renewable producer may benefit from counterbalancing the system´ s direction. This is expected to be more profitable in the case of imbalances from conventional generators or renewable energy with a different production profile in order not to have the same imbalance direction for the considered generator and the system.

6 Appendix

In the following we explain how the main problem was transformed in order to solve it using Cplex.

6.1 The upper level problem

Using the strong duality theorem on the two lower level problems, we are able to linearize the objective function:

$$minimize_{X=(X_1,\dots,X_N)}$$

$$\begin{aligned} C_{inv}X - \sum_T \Bigg[&- \sum_{i\in\Omega^G} c_i g_{it} \\ &+ \sum_N LMP^{DA}_{nt} \times \sum_{j\in\Omega^{Dn}} d_{jt} \\ &- \sum_{k\in\Omega^K} \left(\Phi^{max}_{kt} + \Phi^{min}_{kt}\right) \times f^{max}_k \\ &- \sum_{i\in\Omega^G} \varphi^{max}_{it} g^{max}_{it} \\ &- \sum_{n\in\Omega^{N}:ref} \pi \times \left(\xi^{max}_{nt} + \xi^{min}_{nt}\right) \Bigg] \\ &+ 1/N \times \sum_T \sum_\Omega \Bigg[\sum_N c_n R_{nt\omega} \\ &+ \sum_N R^{max}_n \left(\Phi^{Rmax}_{nt\omega} + \Phi^{Rmin}_{nt\omega}\right) \Bigg] \end{aligned} \tag{19}$$

We keep the upper level constraints (3), (4), (5) and (6).

6.2 Transformation of the lower level problems

We transform the lower level problems into constraints of the upper level problem using their Karush Kuhn Tucker (KKT) conditions. As they are formulated in an independant way, the formulation of their KKT conditions is straightforward.

For the day ahead market clearing, the first order conditions give:
$\forall i \in \Omega^G$

$$c_i - LMP^{DA}_{nt} - \varphi^{min}_{it} + \varphi^{max}_{it} = 0 \tag{20}$$

$\forall k \in \Omega^K$

$$LMP^{DA}_{o(k)t} - LMP^{DA}_{r(k)t} - \Phi_{kt} - \Phi^{min}_{kt} + \Phi^{max}_{kt} = 0 \tag{21}$$

$\forall n \backslash n : ref$

$$- \sum_{k|o(k)=n} B_{kt}\Phi_{kt} + \sum_{k|r(k)=n} B_{kt}\Phi_{kt} - \xi^{min}_{nt} + \xi_{max} = 0 \tag{22}$$

for $n : ref$

$$- \sum_{k|o(k)=n} B_{kt}\Phi_{kt} + \sum_{k|r(k)=n} B_{kt}\Phi_{kt} - \chi_{nt} = 0 \tag{23}$$

We also keep the constraints (8) and (9).
The positivity and complementary slackness conditions give for the day-ahead market clearing:

$$f_{kt}^{DA} + f_k^{max} \geq 0 \tag{24}$$

$$\Phi_{kt}^{DAmin} \geq 0 \tag{25}$$

$$(f_{kt}^{DA} + f_k^{max}).\Phi_{kt}^{DAmin} = 0 \tag{26}$$

$$f_k^{max} - f_{kt}^{DA} \geq 0 \tag{27}$$

$$\Phi_{kt}^{DAmax} \geq 0 \tag{28}$$

$$(f_k^{max} - f_{kt}^{DA}).\Phi_{kt}^{DAmax} = 0 \tag{29}$$

$$g_{it} \geq 0 \tag{30}$$

$$\varphi_{it}^{min} \geq 0 \tag{31}$$

$$g_{it}.\varphi_{it}^{min} = 0 \tag{32}$$

$$g_i^{max} - g_{it} \geq 0 \tag{33}$$

$$\varphi_{it}^{max} \geq 0 \tag{34}$$

$$(g_i^{max} - g_{it}).\varphi_{it}^{max} = 0 \tag{35}$$

$$\delta_{nt}^{DA} + \pi \geq 0 \tag{36}$$

$$\xi_{nt}^{DAmin} \geq 0 \tag{37}$$

$$(\delta_{nt}^{DA} + \pi).\xi_{DAnt}^{min} = 0 \tag{38}$$

$$\pi - \delta_{nt}^{DA} \geq 0 \tag{39}$$

$$\xi_{nt}^{DAmax} \geq 0 \tag{40}$$

$$(\pi - \delta_{nt}^{DA}).\xi_{nt}^{DAmax} = 0 \tag{41}$$

For the real-time market, the first order conditions give:

$$c_r - LMP_{nt}^{RT} - \varphi_{nt\omega}^{Rmin} + \varphi_{nt\omega}^{Rmax} = 0 \tag{42}$$

We also keep the equilibrium constraint (15).
The complementary slackness conditions give for the real-time market clearing:

$$R_{nt\omega} + R_n^{max} \geq 0 \tag{43}$$

$$\varphi_{nt\omega}^{Rmin} \geq 0 \tag{44}$$

$$(R_{nt\omega} + R_n^{max}).\varphi_{nt\omega}^{Rmin} = 0 \tag{45}$$

$$R_n^{max} - R_{nt\omega} \geq 0 \tag{46}$$

$$\varphi_{nt\omega}^{Rmax} \geq 0 \tag{47}$$

$$(R_n^{max} - R_{nt\omega}).\varphi_{nt\omega}^{Rmax} = 0 \tag{48}$$

6.3 Linearization of the constraints

The non-linear constraints coming from the complementarity conditions are linearized using (17):

$$f_{kt}^{DA} + f_k^{max} \leq M^p(1 - \omega_{kt}^{DAmin}) \tag{49}$$

$$\Phi_{kt}^{DAmin} \leq M^{\Phi p}(\omega_{kt}^{DAmin}) \tag{50}$$

$$f_k^{max} - f_{kt}^{DA} \leq M^p(1 - \omega_{kt}^{DAmax}) \tag{51}$$

$$\Phi_{kt}^{DAmax} \leq M^{\Phi p}(\omega_{kt}^{DAmax}) \tag{52}$$

$$g_{it} \leq M^p(1 - \omega_{it}^{min}) \tag{53}$$

$$\varphi_{it}^{min} \leq M^{\Phi p}(\omega_{it}^{min}) \tag{54}$$

$$g_i^{max} - g_{it} \leq M^p(1 - \omega_{it}^{max}) \tag{55}$$

$$\varphi_{it}^{max} \leq M^{\Phi p}(\omega_{it}^{max}) \tag{56}$$

$$\delta_{nt}^{DA} + \pi \leq M^p(1 - \omega_{nt}^{DAmin}) \tag{57}$$

$$\xi_{nt}^{DAmin} \leq M^p(1 - \omega_{nt}^{DAmin}) \tag{58}$$

$$\pi - \delta_{nt}^{DA} \leq M^p(1 - \omega_{nt}^{DAmax}) \tag{59}$$

$$\xi_{nt}^{DAmax} \leq M^p(\omega_{nt}^{DAmax}) \tag{60}$$

$$R_{nt\omega} + R_n^{max} \leq M^p(1 - \omega_{nt\omega}^{min}) \tag{61}$$

$$\varphi_{nt\omega}^{Rmin} \leq M^{\Phi p}(\omega_{nt\omega}^{min}) \tag{62}$$

$$R_n^{max} - R_{nt\omega} \leq M^p(1 - \omega_{nt\omega}^{max}) \tag{63}$$

$$\varphi_{nt\omega}^{Rmax} \leq M^{\Phi p}(\omega_{nt\omega}^{max}) \tag{64}$$

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