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Robust Optimization of Demand Response Power Bids for Drinking Water Systems

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HIGHLIGHTS

- The french mechanism for Demand Response in spot markets is presented.
- Water demand uncertainties are modeled.
- A chance constrained problem for Demand Response optimization has been formulated.
- Demand Response commitment is best respected when uncertainties are considered.
- Water systems are more profitable for Demand Response with uncertainty consideration.

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Peak electricity load
Water supply
Load shifting
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Water demand uncertainties

ABSTRACT

The development of smart grids represents a major breakthrough in the management of electric power and drinking water systems. On the one hand, smart grids have contributed to the development of energy efficiency and demand side management mechanisms such as Demand Response, making it possible to reduce peak load and adapt elastic demand to fluctuation generation. On the other hand, smart water networks and sophisticated Supervisory Control and Data Acquisition systems in the water industry have allowed one to optimize, control and monitor the water flow throughout its entire process. Being a highly energy intensive industry and having an electrical flexibility by the presence of storage elements such as tanks, drinking water systems have the ability to address energy efficiency mechanisms such as Demand Response. In this paper, the French demand response mechanism in spot power markets is presented. Then, a chance constrained problem is formulated to integrate water systems flexibility to power system operation, under water demand uncertainties. Numerical results are discussed based on a real water system in France, demonstrating the relevance of the approach in terms of financial benefits and risk management.

1. Introduction

Energy transition has introduced a series of new rules and constraints for the management of power systems. On the supply side, several countries around the world are experiencing a progressive integration of renewable energies in their energy mix. At the same time and on the demand side, the world is experiencing a rapid increase in electricity consumption [1], mainly due to the development of new usages of electricity (heat pumps, electric vehicles, etc.). Given the limited storage capacity of electricity, balancing in real time the power system is a very difficult task. In fact, physical equilibrium between load and generation has traditionally been managed by transmission system operators through a flexible portfolio of different generation units. However, with the massive integration of intermittent generation, the power network becomes more and more exposed to instabilities, reducing the flexibility of this portfolio and leading to an increase of peak load phenomenon.

In France, electricity consumption is highly driven by weather conditions, especially in winter because of the preponderance of electric heating in households. During cold winters, a decrease of 1° Celsius in temperature implies an increase of 2300 MW in electricity demand [2]: this is the thermo-sensibility phenomenon. For instance, in the situation illustrated in Fig. 1, a peak of consumption of 102 GW occurred on the 8th February 2012 at 7:00 pm, which alerted the French

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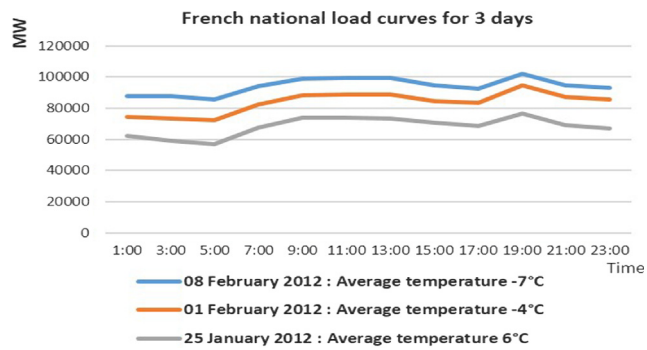

Fig. 1. Load curves before and during the cold spell: impact of temperature (source: RTE).

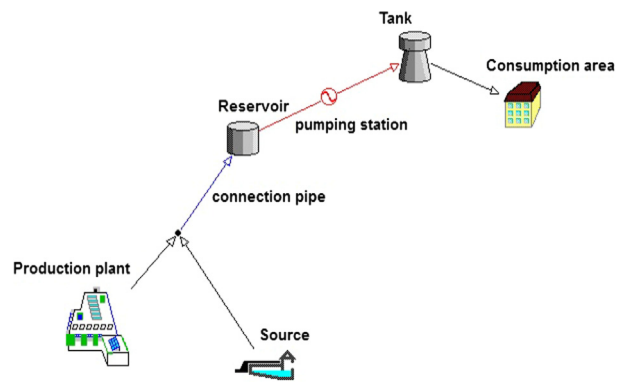

Fig. 2. Example of a simple drinking water system.

Transmission System Operator RTE (Réseau Transport d'électricité) and showed the need to develop efficient methods for the active management of demand.

Demand response (DR), defined as the change in the power consumption of an electric utility customer in response to a given signal, has been part of the flexible portfolio of transmission system operators since a long time. It participates in balancing the power system at peak moments in the same way peak generation units does, and is becoming more and more interesting and attractive with the development of smart grid technologies [3].

Industrial processes are believed to be the best candidates for DR, especially the ones that have storage units. They can adapt their energy consumption to the needs of the electric grid, in return of a remuneration that compensates them for the economic cost of their load shedding [4,5]. Since the industrial sector comprises 42% of the world's electricity consumption [6], addressing industrial load control is critical and remains a major challenge for both authorities and industrials: the French industry consumes around 21% of the total annual electricity produced in France [7] and the German industry around 50% [8]. In a context of deregulation of energy markets and rising energy costs, optimizing these costs becomes a major challenge for manufacturers. DR can prove to be a win-win approach for both the power system and the industrial sector [9].

This paper deals with the particular case of a highly energy-intensive industrial sector: the drinking water industry. We present the opportunities and constraints for drinking water systems (DWSs) to participate in efficient DR mechanisms in France. We evaluate the economic benefits for water utilities of optimizing pump scheduling and DR trading operations under Time of Use (ToU) power procurement contracts. Uncertainties about water demand are taken into account in the mathematical model, making it possible to propose power reductions in the spot market while ensuring satisfaction of water demand under a wide range of scenarios.

The paper is organized as follows. DWSs and their electric flexibility are first introduced in Section 2, and DR mechanisms in France are discussed in Section 3. The optimization problem for scheduling DR in the day-ahead market for DWSs is then formulated in Section 4. In Section 5, we present simulation results based on a real drinking water system in France. Finally, some conclusions and future research directions are discussed in Section 6.

2. Drinking water systems and electric flexibility

DWSs are designed to produce, transport and distribute water from sources to consumption areas. A drinking water supply system typically includes:

- Water sources;
- Water treatment and production plants;
- Storage facilities such as tanks and reservoirs;
- Connection elements such as pipes and valves;
- Pumping stations including fixed and variable-speed pumps.

A drinking water cycle generally begins with the collection of water from sources to be processed in treatment and production plants. After its production, water is stored in reservoirs. Pumping stations then pump water to tanks that serve to distribute the water under gravity (without any pumping operation) to final consumption areas (Fig. 2).

Nowadays, the water industry is facing major changes in its business environment. Efforts to preserve water resources involve developing more efficient ways to improve the efficiency of water networks by reducing water leakages. Furthermore, providing a good quality of water to all consumers is one of the major concerns of public authorities. A key factor to address successfully these challenges will be to reduce costs by improving the efficiency of capital investment and operations [10]. In this context, energy-efficient water supply operations could contribute to the reduction of investment, maintenance and operating costs for the management of drinking water networks.

Water distribution systems can account for up to 5% of a city's total electricity consumption [11], and more than two thirds of this consumption is used by electric pumps [12]. The optimization of energy costs is, therefore, among the main concerns of water utilities in a context of deregulation of energy markets and high price volatility. Energy optimization can be achieved by four complementary means:

- Strategic power procurement contract optimization: among all the market offers, choosing the most suited ones given the constraints and the mode of operation of the water network.
- Load shifting optimization: optimization of the pump scheduling in order to benefit from the most advantageous (cheapest) time rates and reduce energy consumption during peak times.
- Pump efficiency optimization: operating pumps near their best efficiency point (BEP).
- Optimization of pump maintenance operations (preventive maintenance).

In a DWS, pump schedules can be determined using several mathematical optimization models, which will be discussed in Section 4. Storage units such as tanks and reservoirs provide some flexibility that can be exploited for securing water supply and optimizing the pump scheduling. Indeed, pump operators store water without immediate need in tanks and reservoirs during off-peak hours (cheapest electricity price periods), in order to have a reserve of water ensuring a level of autonomy to supply consumers with water during peak hours, or in anticipation of unexpected unavailability of pumps. We can thus assimilate water reservoirs to electric batteries, as they implicitly allow for electricity storage. Fig. 3 illustrates this situation. Pumping water to fill a reservoir at off-peak hours makes it possible to store a quantity v of water during a period d_t and its equivalent in energy

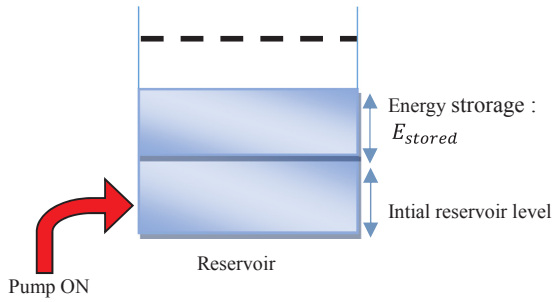

Fig. 3. Reservoirs and electricity storage.

storage$E_{stored} = P_{pump} * d_t$, where P_{pump} is the electric power of the pump. This energy conserved in the form of water can be used later to supply end-users with water during periods of stress on the power system, without resorting to using the energy of pumps.

In addition, some pumps can be of variable speed, which gives them the ability to adapt their flow rate, pressure and thus their energy consumption to the needs.

This flexibility (storage facilities and variable-speed pumps) can be used to give another dimension to the pump-scheduling problem, because of its ability to address energy efficiency mechanisms such as DR. With the development of smart grids and sophisticated Supervisory Control and Data Acquisition (SCADA) systems in the water industry, water utilities now have the ability to optimize, control and monitor the water flow throughout its entire process. The optimal use of water equipment and available energy market data could allow water systems to interact in real time with energy markets and participate in punctual balances of the electric grid, in return of remunerations. However, this process can be hampered by financial remunerations that are often not attractive enough to encourage the development of DR in the industrial sector [13]. A major challenge is to find strategies that are economically viable for water utilities, as well as ecologically and operationally beneficial to the power system. In this context, our objective is to find an optimal operating schedule of pumps allowing us to:

- Minimize electricity costs due to pumping operations;
- Maximize the revenues earned from trading DR via appropriate mechanisms;
- Help the Transmission System Operators to manage imbalances in the electric grid and to reduce peak electricity demands.

Some previous important related studies on drinking water systems in demand side management have discussed the opportunities for water systems to reduce peak electricity demand [14–16], while others deal with some energy efficiency operations in DWS [10,17]. In the United Kingdom, *Menke et al.* [18–20] considered the design of the local DR markets, particularly frequency response and reserve power mechanisms operated by the British transmission system operator National Grid. They proposed a mathematical model making it possible to optimize participation of DWSs in these mechanisms, proving both economic and ecological benefits [18]. The relevance of using variable speed pumps to improve DR participation has also been demonstrated [20]. Simulations were done using a benchmark water network and numerical results were discussed for a range of pump usage rates and a range of overall rewards for the provision of DR using historical statistics provided by National Grid. Integration of energy flexibility for water systems in power system operation has also been evaluated by some authors [21,22]. The new contributions presented in our article compared to previous work are the following:

- The DR market considered in our study is the French day-ahead wholesale market, which allows a direct participation of DR as a resource. This is a new DR mechanism in France and the only one to regulate DR on spot markets in Europe. Our study proposes to model its constraints.
- Water demand uncertainties are considered in the modeling of the problem in order to propose power reductions on the spot market covering potential real-time water demand forecasting errors.
- A chance constrained problem for the pump scheduling problem with DR consideration and uncertain water demands has been formulated. Then, an original heuristic has been developed to solve the problem.
- A real water system in France with real operational constraints has been used for simulations.
- The importance of considering uncertainties in the day-ahead decision-making problem has been demonstrated. For this purpose, numerical results are discussed from a financial aspect, an operational aspect relating to the management of the water system, and a risk management aspect.

The next section presents the different DR markets in France, and discusses the particular market considered for our study.

3. Demand Response in the French markets

The general context of DR in the French energy markets will first be discussed in Section 3.1. The specific mechanism considered in this paper will then be described in Section 3.2.

3.1. General context

In all liberalized electricity markets, peak generation units face problems of economic viability. As a consequence of regulatory policies, energy markets do not remunerate these generation units well in comparison with their investment, operation and maintenance costs. Maintaining operation of some fossil fuel power plants is thus unprofitable. To face this problem called “the missing money issue in energy-only markets” [23,24], several countries started integrating DR in their local markets, as well as some other capacity payment mechanisms, in order to secure the electric power system at peak times and improve its reliability. On the other hand, advancements in smart grid technologies have made it possible to apply several strategies to optimize DR in energy markets. We then see the emergence of new actors in electricity markets called “DR operators”, or “DR aggregators”. These operators offer the possibility to aggregate DR potential and constraints of many customers, and propose the total DR capacity on markets [25]. Furthermore, the implementation of smart technologies like advanced metering infrastructures, the progressive change in market rules by regulatory agencies and the removal of barriers for DR participation in electricity markets encourage an active involvement of demand-side management around the world and capture its potential benefits in electricity markets [25,26].

Some countries around the world like USA, Spain, Finland and Norway offer dynamic energy pricing in retail markets [27]. This type of pricing is based on spot prices (D-1 markets) and reflects the supply-demand equilibrium of the market. There exists a large literature on dynamic pricing concluding that it improves competitiveness at retail level and promotes the development of DR and energy efficiency mechanisms [28–31]. In France, only ToU power procurement contracts with peak/off-peak hours pricing options are proposed in retail markets. However, this country remains among the most developed in the field of demand-side management (see Fig. 4) thanks to the active involvement of the transmission and distribution system operators RTE and ENEDIS, the French regulatory commission CRE, suppliers and DR operators [32,33]. This active involvement is motivated by the thermo-sensitive nature of the French electricity consumption, by the high nuclear dependence, and by the increasing desire of public authorities to reduce gradually the nuclear rate.

The DR mechanisms available in France can be divided into two

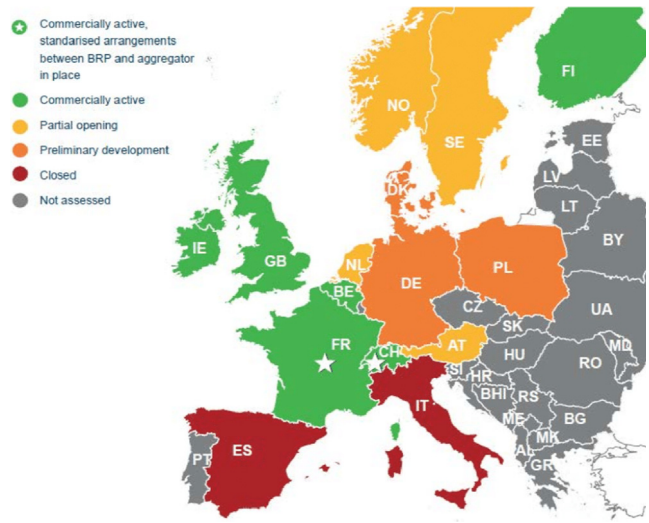

Fig. 4. Map of explicit Demand Response development in Europe today (source: Smart Energy Demand Coalition 2017).

different categories: those with engagement of availability (capacity) and those without any engagement of availability (energy). Energy mechanisms make it possible to sell the energy not consumed by a consumer, either in the day-ahead spot market or in real time (balancing market) to RTE. These mechanisms contribute to manage punctual imbalances on the power grid and to reduce peak power load. In contrast, capacity mechanisms were designed to provide a commitment of availability for RTE over a fixed period (one year in general for rapid reserves, call for tenders and capacity obligation mechanism), enabling it to improve power system's reliability and manage different uncertainties and constraints: network congestion, generator failure, anticipation of peak demand, etc.

In this paper, the participation of water systems in the spot power market is considered under the "Notification d'Echange de Blocs d'Effacement" (NEBEF) mechanism. This mechanism has been chosen for two reasons:

- It is a recent mechanism in France and, to the best of our knowledge, no study has tried to formulate its constraints and optimize its participation;
- It does not require any commitment over a medium time horizon since the decision of participation is only made one day ahead.

The principle and the constraints of the mechanism will first be described. The mathematical model allowing us to optimize the participation of DWSs will then be discussed.

3.2. *The NEBEF mechanism*

The NEBEF mechanism is applicable since April 2014 in France. It makes it possible to sell energy curtailment of an energy consumer, called a DR block, in the day-ahead spot power market via a Demand Side Management Operator (DSMO). The DSMO is composed of the DR aggregator and the consumer himself. The DR block is sold at the market price, which corresponds to the intersection of the market's supply and demand curves. The DSMO must then compensate financially the supplier of the site with energy curtailment for the energy injected into the network and valued by the DSMO on the market [34]. The amount of compensation is regulated in order to avoid any prior agreement of the supplier, and depends on the season, time, and type of day (working or non-working). This compensation is compulsory so that it does not impact wholesale and retail market conditions. The final incentive for the DSMO is the difference, when positive, between the spot price and compensation (see Fig. 5).

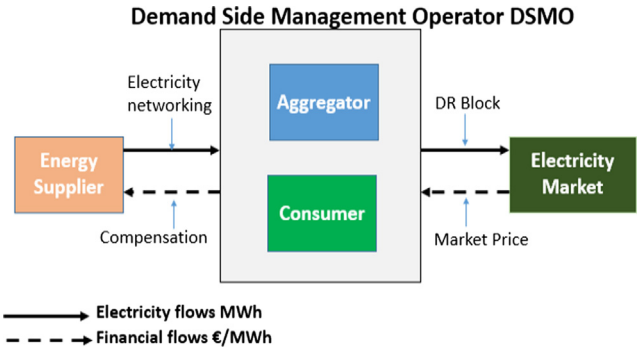

Fig. 5. NEBEF process.

For example, for a DR power of 200 KW, the process could be summarized as follows:

- The DSMO sells on day D-1 the DR power 200 KW on the spot market, without prior agreement from the supplier of the site with energy curtailment (the energy supplier of the consumer participating in the DR program). The DSMO is paid at the spot market price for the power 200 KW.
- Then, the DSMO pays the supplier to compensate for the power (200 KW) they have injected into the power network. This price is regulated.
- The final incentive for the DSMO is the difference between the spot price and compensation, multiplied by the power 200 KW and the duration of the event.
- Finally, benefits are shared between the DR aggregator and the consumer.

In Europe, France is the only country that allows DR to participate directly to D-1 (spot) markets as a resource [35]. However, the same kind of discussions has taken place before in the USA: Should DR be paid market price? With what impact on suppliers? In response to these questions, the Federal Energy Regulatory Commission (FERC) issued Order 745 in March 2011, declaring that DR must be paid market price for energy when such resources have the capability to balance supply and demand as an alternative to a generating resource and when their dispatch is cost-effective [36]. The main difference between the two mechanisms is that the American one does not oblige DSMOs to financially compensate the suppliers.

Offers through the NEBEF mechanism were intensive at the end of 2016, due to high wholesale market prices as a consequence of high nuclear plant unavailability and low temperatures. The total volume traded was 4 GWh in the month of November [33].

For the NEBEF mechanism, the time-step considered is 30 min. Each DR bid on the spot market must constitute at least 100 kW of power reduction. In addition, DR bids cannot exceed a maximum of two hours per block [37]. The duration between two DR bids must not be less than the maximum duration of the two bids [37].

In order to quantify the real load curtailed by the DR operator during a DR event, RTE compares two curves [37]:

- **Reference curve**: the minimum between the mean electric load just before (past reference) and just after (post reference) the DR event, over a period of time equal to that of the DR event.
- **DR curve**: mean electric load during the DR event.

The load curtailed is equal to the difference between the reference curve and the DR curve (Fig. 6). This method of estimation is called the *corrected double-reference* method, because it takes into account the load before and after DR events.

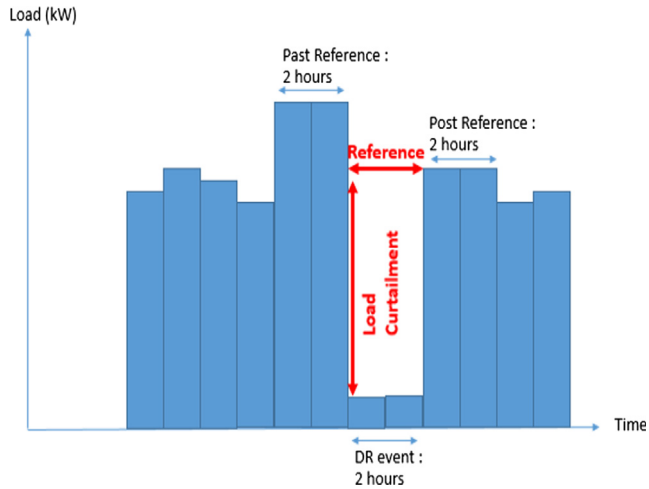

Fig. 6. Illustration of reference periods.

4. Mathematical model

This section presents the mathematical model used to optimize participation of DWSs in the NEBEF mechanism. The optimal pump scheduling problem without DR consideration will first be discussed in Section 4.1, and the model of the pump scheduling problem with DR participation will then be presented in Section 4.2.

4.1. Optimal pump scheduling problem

Optimal pump scheduling problem has been addressed in the literature for a very long time. It is a NP-Hard problem [38] and it has been addressed via different modeling schemes and optimization methods [39]. It has been shown to reduce the energy cost of DWS up to 20%, either by optimizing load shifting according to different energy prices or by improving operational pump efficiency [40]. Due to the presence of binary variables and nonlinear hydraulic constraints, which make calculations more difficult, only automatized control programs have the computational capacity to determine a least-cost schedule in real-time [41]. This problem has given rise to advanced research on optimization algorithms (see [42,43,40]). The mathematical approaches are either heuristic or exact, in which case they ensure global optimality but can often only be used for small instances due to high computational complexity. The optimization problem for scheduling DWS pumps can be, in general, formulated as follows [18]:

Minimize Pumping Costs
Subject to:

- Physical constraints of reservoirs and pipes
- Hydraulic constraints of pumps and pipes
- Mass balance at network nodes
- Operational constraints of the network
- Regulatory constraints of the network

Physical constraints correspond to storage minimum and maximum operational filling level of tanks and reservoirs, as well as maximum flow rate that can pass through a pipe. They can be written as linear equations on the state variables. Operational constraints correspond to specific operating modes of each water system: they include water quality, priority of use of equipment, continuous functioning of production plants [38], etc. In general, they can all be modeled by linear constraints.

Regulatory constraints generally refer to conditions of use of water resources imposed by public authorities.

Mass balance constraints, neglecting compressibility effects and using steady-state approximations of hydraulic conditions, are equivalent to volume balance constraints. They impose the equality between the sum of the incoming flows and the sum of the outflows at each network node. Note that water demands at nodes are part of the mass balance constraints.

Finally, hydraulic constraints correspond to the fundamental equations for pipes, called the head-loss or potential flow-coupling equations [41]. Due to the non-linearity of the constraints generated by these quadratic equations, prior linearization by piecewise affine functions or the use of a hydraulic simulator like EPANET is required [44]. For our study, we used a hydraulic simulator to evaluate the hydraulic coherence of the obtained solutions. The forecasted water demand profile in demand nodes was injected into the hydraulic model of the system using EPANET, allowing us to estimate the head losses in pipes as well as the flow rate of the pumps. These hydraulic simulation results were used to update the flow rates of pumps.

Since all these types of constraints and considerations are often encountered in the literature [18,38,39], we will refer to them as the *DWS classical constraints*.

4.2. Pump scheduling problem with Demand Response

We propose to model the optimal participation of a DWS in the DR NEBEF mechanism. We assume that the water utility acts on the market as a DR operator and seeks to maximize its own profits. We schedule both the biddings of the water utility on the spot market and the operation of pumps one day ahead in order to maximize the total profitability. This day-ahead scheduling problem is advantageous in terms of available computational time compared to the real-time pump scheduling where optimal schedules should be found in few minutes.

4.2.1. Problem formulation

We model DR in the objective cost function of the DWS as follows:

Minimize Electric **Costs - DR Benefits**
Subject to:

- DWS classical constraints.
- NEBEF constraints.

Electric Costs are related to power supply contract that links the water utility to the energy supplier. They are fixed contracts over a time horizon with two prices per season (peak hours and off-peak hours). DR benefits correspond the financial profits related to DR power transactions on the spot market, which vary daily and depend on the market situation.

The time-steps are discretized to one-hour interval periods in order to speed up computational times. We consider that we can take a position in the spot market at each period t. Each market position is a pair (go/no go, Power), where “no go” corresponds to no bid on period t and “go” to a bid with the corresponding power “Power” and paid at market price. We consider deterministic scenarios for the modeling of market prices in our objective cost function. Under this assumption, each DR bid corresponds to an accepted bid and is paid market price (price uncertainties are neglected by considering deterministic scenarios). In other words, we assume that market prices are well anticipated by the water utility and that the main issue is to decide whether or not to bid on the market. For this purpose, historical French market scenarios for 2016 are considered, available on the website of the electricity exchange EPEX SPOT [45].

However, planning one day ahead (day D-1) the amount of electricity consumption to be reduced (in day D) during peak times represents a challenge for water utilities due to the uncertainties about water demands over the network. It requires well-formulated operating schedules for pumps and risk-management to ensure that the water level in tanks remains in the operational range at minimum cost. In addition, a minimum of financial viability is required to water utilities in order to participate in DR schemes. Indeed, the water utility could be

considered as an electricity producer aiming to sell an amount of its electricity on the spot market in day D-1. However, its clients demand for day D is uncertain and therefore must be taken into account in its decision making.

For the modeling of water demand uncertainties, it is assumed that one has a set Ω containing a history of N water demand realizations $\{d_t^i,\ t = 1\cdots T\}_{i=1\cdots N}$ for the system.

The following notations are then used for the model:

- $x_{i,t}$ $x_{i,t}$: state of the pump i at period t (1, 0)
- $C_{i,t}$: power cost when pump i is ON at period t (linked to power supply contracts).
- $P_{i,t}$: power activated by pump i at period t.
- y_t : binary variable indicating the position taken on the spot market at period t (go/no go).
- P_{max}: maximal contractual power of the DWS.
- P_t^{DR}: electric power (DR block) put on sale (bid) on the spot market at period t (in kW).
- P_{min}^{DR}: minimum DR bid allowed for NEBEF (in kW)
- r_t: market spot price at period t (in €/kWh).
- ρ_t: compensation price at period t (in €/kWh)
- $s_{i,t}$: level of reservoir i at period t
- s_i^{min}: minimum level of security for reservoir i
- s_i^{max}: maximum level of security for reservoir i
- $d_{i,t}^{for}$: forecasted demand of reservoir i at period t

We write the objective function as follows *(Obj):*

$$\underset{x_{i,t},y_t,P_t^{DR}}{\text{minimize}} \sum_{i,t} C_{i,t} * x_{i,t} - P_t^{DR} * y_t * (r_t - \rho_t)(Obj)$$

The decision variables are$x_{i,t}$, P_t^{DR} and y_t. The objective function aims at making, for each step time t, a trade-off between electric consumption by activating the pumps, and energy curtailment by selling the energy not consumed on the spot market. Naturally, if the model does not find any economic interest in bidding on the spot market, the vector $\{y_t, t = 1\cdots.T\}$ should be equal to zero and the problem gets back to the classical pump scheduling problem.

The operation of the water system would then be scheduled based on power costs $C_{i,t}$ for pumping operations, and the difference between spot price and compensation for DR energy selling on the market.

We introduce the following new variables for a better modeling and understanding of the constraints:

$$\alpha_t = y_t * (1 - y_{t+1}) \tag{1}$$

DR bid at period t but not at period t + 1.

$$\beta_t = y_t * (1 - y_{t-1}) \tag{2}$$

DR bid at period t but not at period t − 1.

$$e_t = y_t * y_{t+1} \tag{3}$$

DR bid at period t and t + 1 (two consecutive periods

These variables are introduced because that past and post reference periods depend on the bid duration. The constraints of the NEBEF mechanism as described in Section 3.2 are modeled as follows:

$$\forall\ t = 1\cdots T,\ P_{min}^{DR} \le P_t^{DR} \le P_{max} \tag{4}$$

$$\forall\ t = 1\cdots T-2,\ y_t + y_{t+1} + y_{t+2} \le 2 \tag{5}$$

$$\forall\ t = 1\cdots T-1,\ |P_t^{DR} - P_{t+1}^{DR}| \le P_{max} * (1 - e_t) \tag{6}$$

$$\left|\left(\sum_i P_{i,t}x_{i,t} - \sum_i P_{i,t+1}x_{i,t+1}\right)\right| \le P_{max} * (1 - e_t) \tag{7}$$

$$\forall\ t = 2\cdots T,\ \sum_i P_{i,t-1}x_{i,t-1} \ge \left(\sum_i P_{i,t}x_{i,t} + P_t^{DR}\right) * \beta_t \tag{8}$$

$$\forall\ t \le T-1,\ \sum_i P_{i,t+1}x_{i,t+1} \ge \left(\sum_i P_{i,t}x_{i,t} + P_t^{DR}\right) * \alpha_t \tag{9}$$

$$\forall\ t = 2\cdots T$$

$$\left|\left(\sum_i P_{i,t-2}x_{i,t-2} - \sum_i P_{i,t-1}x_{i,t-1}\right)\right| \le P_{max} * (1 - e_t) \tag{10}$$

$$\forall\ t = 0\cdots T-3,$$

$$\left|\left(\sum_i P_{i,t+2}x_{i,t+2} - \sum_i P_{i,t+3}x_{i,t+3}\right)\right| \le P_{max} * (1 - e_t \tag{11}$$

Eq. (4) represents the minimum power reduction in kW allowed for the NEBEF mechanism while Eq. (5) represents the two hours maximum duration of a DR bid. Eqs. (6) and (7) reflect the fact that the DR bids containing two consecutive periods (two hours for the block$e_t = 1$) must be uniform: they should have the same amount of energy curtailment. Eq. (8) models the end of the past reference period and Eq. (9) models the beginning of the post reference period. Finally, Eqs. (10) and (11) model the duration of reference periods in the case of a 2-hour DR bid (e_t=1).

A first formulation of the problem is the minimization of the objective function (*Obj*), under the DWS classical constraints and constraints (4–11), verified for any water demand realization in Ω:

$$\underset{x_{i,t},y_t,P_t^{DR}}{\text{minimize}} \sum_{i,t} C_{i,t} * x_{i,t} - P_t^{DR} * y_t * (r_t - \rho_t)$$

Subject to: (P_0)

- DWS classical constraints $\forall\ d \in \Omega$.
- Constraints (4–11) $\forall\ d \in \Omega$

Formulation (P_0) is very robust. Indeed, robustness comes from the fact that the constraints must be verified for all water demand scenarios, which strongly limits the flexibility and the DR potential of the system. To overcome this problem, a tolerance value $p \in [0, 1]$ is set and the problem is replaced by a probabilistic problem, noted (P_1), in which we impose the respect of all constraints with a probability p (over a proportion p of the historic scenarios)

$$\underset{x_{i,t},y_t,P_t^{DR}}{\text{minimize}} \sum_{i,t} C_{i,t} * x_{i,t} - P_t^{DR} * y_t * (r_t - \rho_t)$$

Subject to: (P_1)

- P (DWS classical constraints $\forall\ d \in \Omega$) ≥ p
- P (Constraints (4–11) $\forall\ d \in \Omega$) ≥ p.

Problem (P_1) consists on minimizing the objective function (*Obj*) with all constraints satisfied for at least $[p.\ N]$ water demand scenarios. Since demand areas are considered as network nodes, Problem (P_1) can be considered as a chance-constrained problem (CCP) on mass balance violation on demand nodes: tanks and reservoirs must be able to respond to at least $[p.\ N]$ water demand scenarios.

4.2.2. Problem simplification

As mentioned in the previous section, Problem (P_1) belongs to the family of CCP, in which constraints must be satisfied at a certain confidence level p [46]. Generally, there are two methods to solve a CCP: by transforming the CCP into a deterministic model [47,48], or by stochastic simulation [49].

Let A be the set of subsets of Ω of cardinal at least equal to $[p.\ N]$,

$$A = \{I \subset \Omega,\ card(I) \ge [p.\ N]\}$$

and $J(I)$ the function defined as

$$J(I) = \text{minimum} \sum_{i,t} C_{i,t} * x_{i,t} - P_t^{DR} * y_t * (r_t - \rho_t)$$

Subject to: (P_I)

- DWS classical constraints $\forall\ d \in$ I.

- Constraints (4–11) $\forall\ d \in \mathrm{I}$.

(P_I) is the optimization problem whose constraints must be verified for all water demand realizations in set I. Minimizing function $J(I_p)$, for I_p belonging to set A, amounts to finding a set of water demand scenarios of cardinal at least $[p.\ N]$, respecting all the constraints and minimizing the objective function *(Obj)*. Problem (P_1) is then equivalent to:

$$(P_1) \Longleftrightarrow \min_{I \subset A} J(I)$$

This equivalence allows the transformation of the chance-constrained problem into a robust linear programming problem [50,51].

4.2.3. Problem resolution

Problem (P_1) is solved in two stages:

1. Selection of the set of demand scenarios $I_p \subset A$;
2. Resolution of problem(P_{I_p}).

4.2.3.1. Demand scenarios selection. Naturally, to solve Problem (P_1), it would be necessary to solve the subproblems (P_I) for each subset $I \subset A$, and then to retain the set I_p minimizing the function $J(I_p)$. However, since the set A is very large, the selection of the scenarios I_p will be performed using a heuristic. A minimal function $J(I)$ is correlated to a narrow set of uncertain demands I. Indeed, if the difference between the minimum and the maximum demands in the set I is large, the optimization problem (P_I) becomes over-constrained which will have a significant impact on the economic cost. The proposed heuristic is such that the chosen set of scenarios I_p has a minimal surface between their maximum and minimum envelopes. In other terms, this amounts to calculating a minimum area band containing at least $[p.\ N]$ scenarios.

The area of the demand curves was approximated by a Riemann sum using the rectangle method. The following optimization model $(P_{minArea})$is proposed, which from N water demand scenarios, returns $[p.\ N]$ scenarios such that the area between its maximum and minimum envelopes is minimal.

$$\min_{y,z,a} \sum_{t=1}^{24} (y_t - z_t)$$

Subject to: $(P_{minArea})$

- $\forall\ t = 1 \cdots T y_t \geq d_t^i.\ a_i\ \forall\ i$
- $\forall\ t = 1 \cdots T z_t \leq d_t^i.\ a_i + (1 - a_i) * \bar{d_\Omega}\ \forall\ i$
- $\sum_{i=1}^{N} a_i = [p.\ N]$
- $a_i \in \{0, 1\}\ \forall\ i = 1 \cdots N$

In the above equations, a_i is the binary variable indicating if a scenario i is selected or not, y_t the upper bound on all demand scenarios at time t and z_t the lower bound on all demand scenarios at time t. The resolution of $(P_{minArea})$ determines the set I_p and problem (P_{I_p}) can then be addressed.

4.2.3.2. Resolution of problem P_{I_p}. Let us denote by $d_{i,t,p}^{min}$ and $d_{i,t,p}^{max}$, respectively, the minimum and maximum water demand values over the set of scenarios I_p at time t for demand zone i. Satisfying all the constraints (DWS classical constraints and constraints (4–11)) for all scenarios in I_p is equivalent to meeting the constraints for the two extreme values of demand (minimum and maximum) for each period t. In order to ensure this, maximum and minimum safety levels of each reservoir should be corrected by the difference between extreme demands ($d_{i,t,p}^{min}$ and $d_{i,t,p}^{max}$) and forecasted demand $d_{i,t}^{for}$ as follows (12):

$$s_i^{min} + d_{i,t,p}^{max} - d_{i,t}^{for} \leq s_{i,t+1} \leq s_i^{max} + d_{i,t,p}^{min} - d_{i,t}^{for} \tag{12}$$

Eq. (12) then allows the management of tanks between their two corrected security levels as shown in Fig. 7. These new security levels are variable over time depending on the difference between forecasted and extreme water demands. The final optimization problem resulting in participation of DWS in the NEBEF mechanism while anticipating uncertainties with a degree of robustness $p \in [0, 1]$ can be written as a combination of the objective function(*Obj*), constraints (4–12) and DWS classical constraints as follows (P_{I_p}):

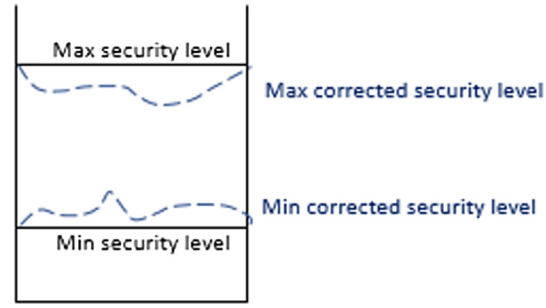

Fig. 7. Corrected security levels for uncertainties management.

$$\underset{x_{i,t}, y_t, P_t^{DR}}{\text{minimize}} \sum_{i,t} C_{i,t} * x_{i,t} - P_t^{DR} * y_t * (r_t - \rho_t)$$

Subject to: (P_{I_p})

- DWS classical constraints
- Constraints (4–12).

However, problem (P_{I_p}) cannot be solved by linear programming due to nonlinearities in constraints (9) and (10) and in the second term of the objective function. To solve this problem, the following linearization approach (proposition 1) is used:

Proposition 1. *The two following formulations are equivalent:*

$$\begin{cases} z = x * y \\ x \in \{0, 1\} and 0 \leq y \leq U(y \end{cases} \quad \begin{cases} z \leq U(y) * x \\ z \leq y \\ z \geq y - U(y) * (1 - x) \\ z \geq 0 \end{cases}$$

The proof of Proposition 1 is directly obtained by distinguishing the cases × = 0 and × = 1:

- *For × = 0, z is equal to 0 in the left formulation and z is also equal to 0 in the right formulation ($z \leq 0$ and $z \geq 0$);*
- *For × = 1, z is equal to y in the left formulation, and z is also equal to y in the right formulation ($z \leq y$ and $z \geq y - U(y) * (1 - 1) = y$).*

Finally, problem P_0 with maximum robustness has been replaced by problem P_1 with a degree of robustness $p \in [0, 1]$. The latter problem, difficult to solve by conventional optimization methods, has been solved in two steps through a heuristic.

5. Results and discussion

In this section, we examine three aspects from DR via the NEBEF mechanism for DWSs:

1. Water demand profiles and uncertainties management using a benchmark water network.
2. Optimal day-ahead water system management with DR consideration, according to market price scenarios;
3. The relevance of taking into account uncertainties in the real-time operational management of the water system.

5.1. Price scenarios and Benchmark network

For price scenarios, data from autumn and winter 2016 during working days were considered for two main reasons:

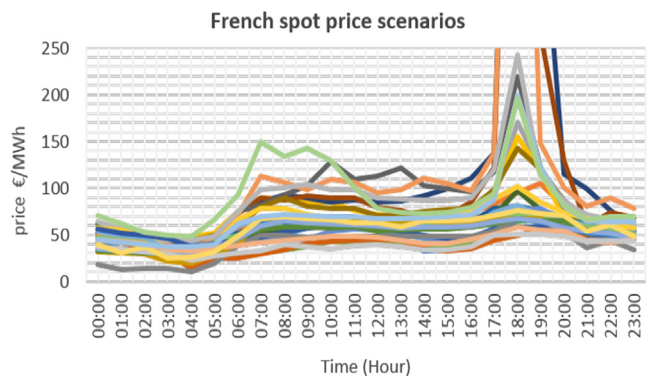

Fig. 8. Some spot price scenarios used for simulations [45].

- There is more stress on the power grid so there is a need for DR due to peak electricity demands as a consequence of the massive use of electric heating in households.
- These months correspond to off-peak periods for water demand (peak periods occur during summer), and then a greater potential of electrical flexibility.

For simulations, data prices for the year 2016 were used [45]. The price paid to the supplier of the site participating in the NEBEF mechanism, called compensation, is established by RTE [37] after approval of the French energy regulatory commission. The price was 56.1 €/MWh at peak hours (06:00–20:00.) and 41 €/MWh at off-peak hours (00:00–06:00 and 20:00–00:00) for winter and autumn 2016. Spot prices are available in the Epex Spot website [45].

As shown in Fig. 8, spot prices have two daily peaks: in the morning between 07:00 and 09:00 and in the afternoon between 18:00 and 20:00. We note that French spot prices experienced particular spikes in November 2016 (07/11, 08/11, 09/11, 14/11 and 15/11 of the year 2016) as a consequence of a large cold wave coupled with a historically low nuclear availability [52]. In winter, spot prices are usually higher than compensation prices, which shows the interest of load shedding. Therefore, DR via NEBEF mechanism is encouraged to replace the high-cost high-emissions peak generation units.

To evaluate and discuss numerical results of simulations, a real drinking water system in France was used as benchmark (see Fig. 9). The system has about 1300 km of network and contains 15 storage units, 11 pumping stations and one water production plant. Given the different operational constraints of the water network, the maximum contractual power of the system is 4000 kW and the minimum power is 300 kW (minimum power is due the compulsory continuous operation of production plant). The system includes two variable-speed pumping stations and two storage units with large storage capacity (more than three times the daily water demand of the corresponding consumption area), which brings flexibility to the system. It is recalled that a variable speed pump operates on a continuous range from a threshold q^{thr}. Pump operators carry out a daily management of the water network starting at 06:00 with almost full tanks (> 85% of their maximum storage capacity). Finally, system operators wish to participate in a one maximum DR event per day, which would be that of the evening peak (18:00 to 20:00) since it is the period in which spot prices are the highest.

Electricity tariffs used for the water system include supply and delivery (transport and distribution) energy costs. These are long-term energy supply contracts between the water utility and energy suppliers. These are tariffs with uniform prices during peak hours (06:00 to 20:00) and off-peak hours (20:00 to 06:00).

To model the energy consumption of pumps, their energy-efficiency curves were used. Finally, vector$C_{i,t}$ is the product of electricity tariffs by pump energy consumption.

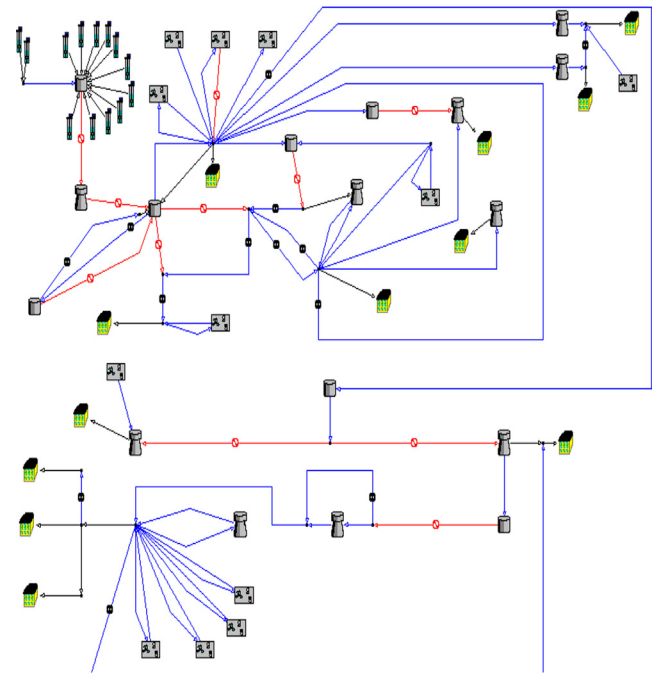

Fig. 9. Benchmark network: pumping stations are shown in red, blue lines correspond to pipes, green elements to production plants, grey elements to storage units and yellow/brown elements to demand zones.

5.2. Water demand profiles and uncertainty consideration

The average water demand of the system in winter is about 50,000 m^3/day with some time profile variations depending on the demand area. The water demand profile is similar to that of electricity demand. Indeed, two particular peak periods are observed per day, and are the morning peak (08:00 to 10:00) and the evening peak (20:00 to 22:00). The studied system contains only residential demand areas. The water demand history includes only working days of the months of October, November and December since it corresponds to high electricity demand periods when the power system needs DR.

Parameters influencing water demand include weather, type of day and geographic area. Indeed, the water demand profile may be very different from one region to another (residential, agricultural, industrial, etc.), even with the same weather conditions. The non-working days demand profile is generally shifted one to two hours compared to that of working days.

Figs. 10 and 11 display 32 historical realizations of water demand

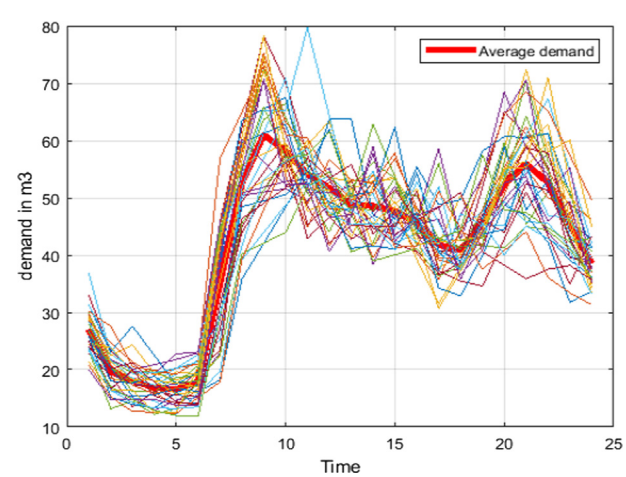

Fig. 10. Hourly water demand profiles for demand area 1.

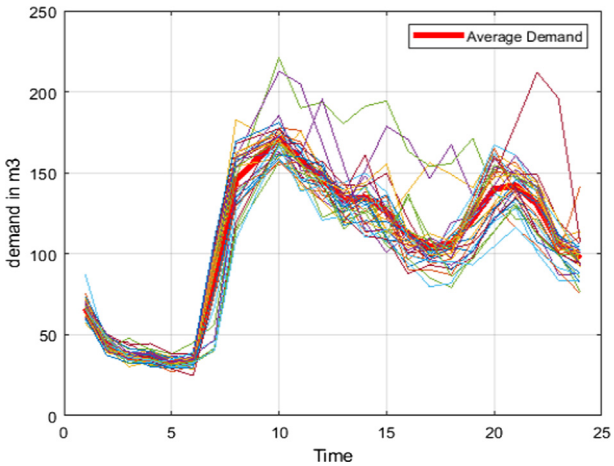

Fig. 11. Hourly water demand profiles for demand area 2.

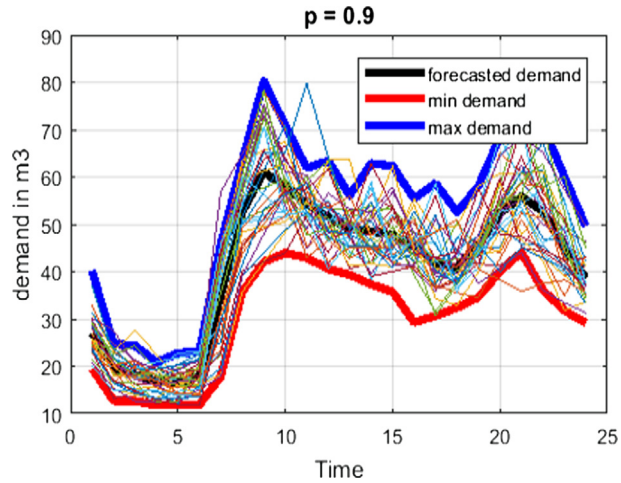

Fig. 13. Extreme water demands with p = 0.9 for demand area 1.

for two domestic demand areas belonging to the studied system in winter 2016. The displayed scenarios correspond to working days. Demand area 1 has greater historical variability as compared to zone 2, making the demand forecasting more complicated. Demand area 2 has very stable demand profiles, with the exception of few extreme scenarios.

Figs. 13 and 12 show the minimum and maximum profiles used for uncertainties management for probability values of p=0.7 and p=0.9. The blue and red curves were constructed after solving the problem ($P_{minArea}$), selecting the scenarios on which the band is calculated. On the other hand, forecasted demand curve was calculated by taking an arithmetic mean over the historical demand scenarios. We note that the maximum demand curve remained almost unchanged from the case with $p = 0.7$ to the one with $p = 0.9$, while the minimum curve has moved down. The interval between these two extreme demands is then the uncertain demand set: it would be managed by tanks and reservoirs through the modification of their security levels as explained before (Eq. (12)).

5.3. Optimal day-ahead water system management

In this section, optimal day-ahead water system management with DR participation is evaluated. For this purpose, problem (P_{I_p}) has been solved for different observed spot price scenarios for winter 2016. For each resolution, the obtained schedule was injected into the EPANET hydraulic simulator to confirm that the flows, pressures and head losses are consistent with our initial estimations.

Three probability values for water demand uncertainties were considered: $p = 0$ (without uncertainties), $p = 0.7$ and $p = 0.9$. These values were chosen because bids strategies are constant for $p < 0.7$ given system's flexibility. DR bids, allowed only for the evening peak 18:00 to 20:00 (imposed by water system operators), are denoted by P_p^{DR}. Simulations were performed using the CPLEX optimization solver [53]. Numerical results include optimal DR power bids on the spot market as well as tank and reservoir filling strategies allowing to maximize the economic utility of the system while respecting various constraints and anticipating water demand uncertainties with the corresponding probability p.

The function of evolution of optimal DR power bids is obviously growing with market price (Fig. 14). The function is concave and the slope is decreasing with the price, which is due to the decrease of the water system's flexibility. The optimal DR power is:

- Very sensitive for prices between 0 and 100 €/MWh since the water system still has enough flexibility to react to the price signal. DR bids strategies for $p = 0$ and $p = 0.7$ are the same because the available flexibility is sufficient to deal with water demand uncertainties without changing the bid strategy. However, bids strategies for $p = 0.9$ are lower.
- Minimally sensitive for prices between 100 and 400 €/MWh since the water system has only reduced available flexibility. DR bids strategies for different probability values are different which is explained by the reduced available flexibility to deal with water demand uncertainties.
- Constant for prices $>$ 400 €/MWh since the water system used its maximum DR power capacity. In this case each DR bid strategy is constant.

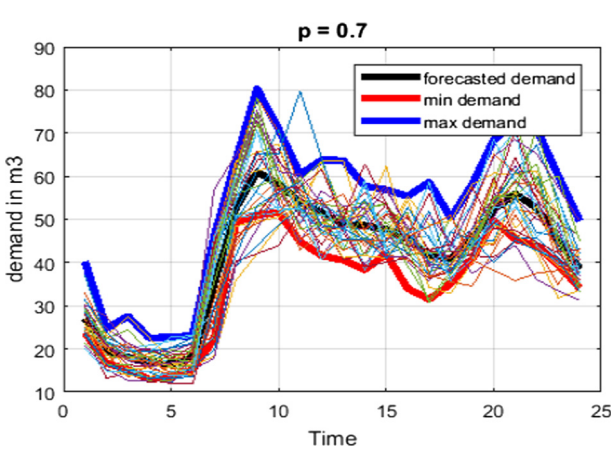

Fig. 12. Extreme water demands with p = 0.7 for demand area 1.

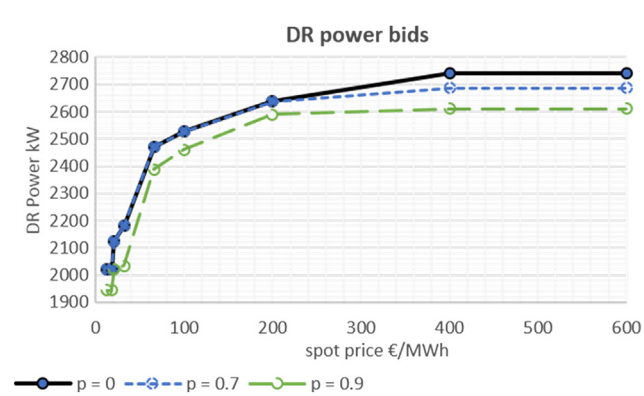

Fig. 14. Optimal DR bids with uncertainties consideration.

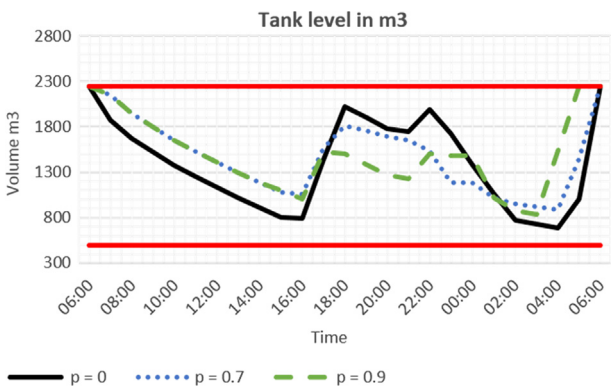

Fig. 15. Tank level variation with different probability values.

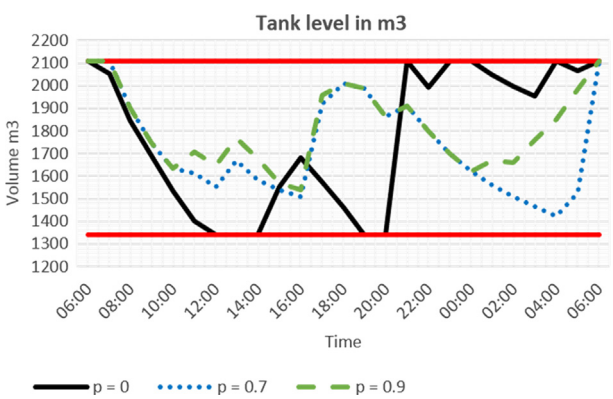

Fig. 16. Tank level variation with different probability values.

As shown in Figs. 15 and 16, pumping operations are minimized for the water system during peak hours to meet demand at minimum cost while tank levels gradually decrease. However, a higher activity of pumps is observed at off-peak hours (20:00 to 06:00) to take advantage of cheapest electricity tariffs and to fill tanks to their target levels at 06:00.

A pump participates in a DR program if it has been activated during reference periods (past and post reference periods) and turned-off during the DR period. For fixed-speed pumps, a pump is either participating or not in the DR program, depending on the flexibility of the tank it supplies. Fig. 17 shows that the second fixed-speed pump of the pumping station had been stopped during the reference periods with uncertainties consideration, which is a consequence of a lack of flexibility of the tank it supplies. However, variable-speed pumps improve DR potential by adapting the pumping flow to the flexibility of the downstream tank. As shown in Fig. 18, the pumping-flow of the variable speed pump had been adapted to the modified reservoir safety

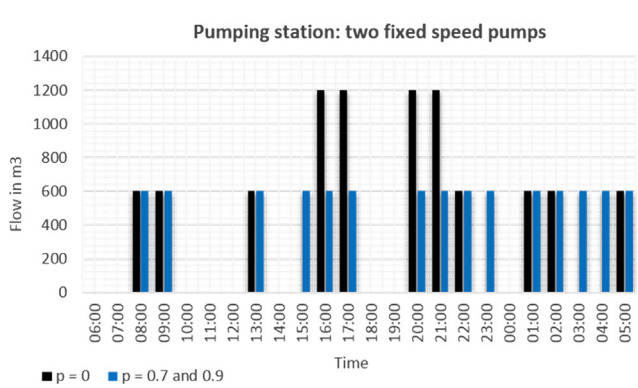

Fig. 17. Fixed speed pumps for DR provision.

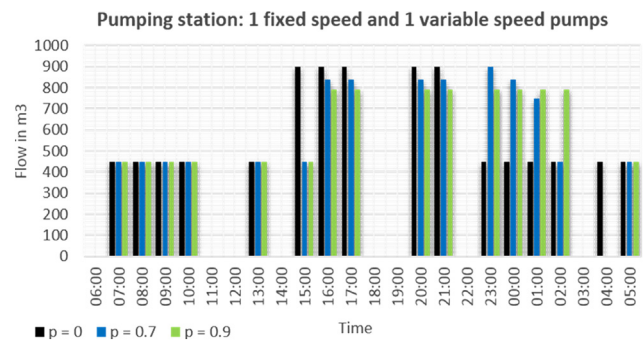

Fig. 18. Variable speed pumps and impact on DR potential.

levels for each probability value p, without stopping it completely.

Without uncertainties consideration, the flexibility of the water system is maximal since the tank storage level is entirely used to optimize system's operation while anticipating DR events (full line in Figs. 15 and 16). However, the consideration of uncertainties tightens tanks safety levels, limiting the flexibility of the of the upstream pumping station and then the potential of DR. It is noted that water system flexibility naturally decreases with the probability value p. The tank of Fig. 15 (Tank 1 serving around 5000 persons) has a larger effective volume (difference between maximum and minimum safety levels) than the one of Fig. 16 (Tank 2 serving around 3800 persons), resulting in a greater flexibility.

5.4. Optimal real-time water system management

In this section, we study the real-time management of the water system for different water demand realizations. The DR power, which was sold on the spot market in day D-1, must be reduced in day D (real-time) according to the market transaction (time, duration and power). Otherwise, financial penalties, known as imbalance prices, would be applied by RTE to balance the power grid [37].

Because of unexpected water consumption in real time, the water utility may not be able to reduce power for DR as expected in the day-ahead transaction. In order to highlight the relevance of taking into account water demand uncertainties in the day-ahead market decision making, the real-time management of the water system was studied for two types of spot market decisions: without taking into account uncertainties (p = 0), and with uncertainties consideration (p > 0). The values $p = 0$, $p = 0.7$ and $p = 0.9$ were used in the simulations. By DR energy-deficient volume, we mean the amount of energy that the water utility could not reduce in real-time for the DR event according to the day-ahead market transaction.

The following approach was adopted:

- Random generation of 100 water demand scenarios;
- For each water demand scenario generated, resolution of real-time water system optimization problem, with an imposed constraint of respecting the DR power P_p^{DR} sold in day D-1 (three resolutions $p = 0p = 0.7$ and $p = 0.9$ for each scenario).
- For each resolution, calculation, if any, of DR energy-deficient volume and overall cost (pumping cost – DR benefits + DR financial penalties if any DR energy failure);
- Out of the 100 random water demand scenarios generated, calculation of the average overall cost, the percentage of respect of the DR power P_p^{DR} and the average DR energy-deficient volume in kWh.

The random generation of 100 water demand scenarios was done according to the following procedure, with steps 3, 4 and 5 repeated 100 times:

1. Calculation of daily water demand by summing the hourly water

demand for each historical scenario.

2. Calculation of the normalized water demand profile for each historical scenario, by dividing the hourly demand profile by its daily water demand.
3. Generation of a random number α between the maximum and the minimum daily water demand of the historical scenarios.
4. Generation of a random normalized water demand profile $d_{i,t}^{rand}$.
5. Multiplication of $d_{i,t}^{rand}$ by α.

Each random demand scenario was then an input to the real-time water system optimization problem, which was solved each time for the values $p = 0$, $p = 0.7$ and $p = 0.9$. The DR power P_p^{DR} was an input to each problem.

We denote by T^{past} the past reference period 16:00 to 18:00, T^{post} the post reference period 20:00 to 22:00, T^{DR} the DR period 18:00 to 20:00 and V^{def} the DR energy-deficient volume, penalized by a coefficient C^{def}. The real-time optimization problem could be written as follows ($P_{RealTime}$):

$$\underset{x_{i,t},V^{def}}{\text{minimize}} \sum_{i,t} C_{i,t} * x_{i,t} + V^{def} * C^{def}$$

Subject to: ($P_{RealTime}$)

- DWS classical constraints
- $\forall\ t_1 \in \{T^{past}, T^{post}\}, \forall\ t_2 \in T^{DR}$:

$$\sum_i P_{i,t_1} x_{i,t_1} \geq P_p^{DR} + \sum_i P_{i,t_2} x_{i,t_2} - V^{def}$$

In this real-time optimization problem, the objective is to minimize pumping costs as well as balancing costs if any DR energy failure. Variable decisions are the state of pumps $x_{i,t}$ and the energy-deficient volume V^{def}. Constraints are similar to the classical DWS ones, with an additional constraint imposing the reduction of the DR power P_p^{DR} and allowing a defective volume V^{def} if the DR constraint could not be respected. Numerical resolutions were performed using the CPLEX optimization solver.

Fig. 19 and Table 1 represent, respectively, the cost distribution and main average numerical results resulting from the optimization approach. Balancing prices were taken from the balancing price history available on RTE website [54]. The following observations can be made from Fig. 19 and Table 1:

- The percent of respect of the DR power with the desired probability is guaranteed: 85% of water demand realizations allowing to respect the DR power for $p = 0.7$, 100% for $p = 0.9$ with only 49% for $p = 0$.
- In the case where the DR power could not be reduced, the DR energy-deficient volume is lower in the case of $p = 0.7$, thanks to a lower DR power commitment.
- The average economic benefit is higher in the case of $p = 0.7$. This is due to financial balancing penalties, which makes the real-time management with uncertainty consideration more interesting economically. Indeed, the very low average DR energy failure 27 kWh does not penalize much the system for $p = 0.7$. However, the case $p = 0.9$ costs a little more than the one with $p = 0.7$, but less than the case without uncertainties consideration. This is due to a lower DR remuneration in the market, but is associated with the highest rate of DR power constraint satisfaction.

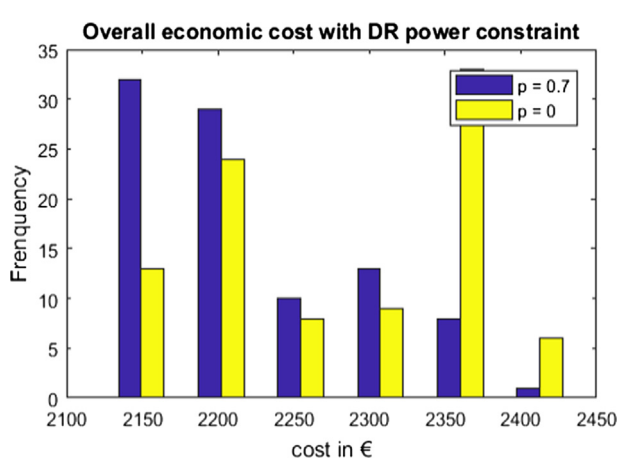

Fig. 19. Cost distribution over 100 random water demand scenarios for p = 0 and p = 0.7.

Table 1
Average results from the real-time optimization over 100 random water demand scenarios.

Situation	Average economic cost €	Standard deviation	% DR power respect	Average failed DR energy
p = 0	2,278 €	81 €	49%	136 kWh
p = 0.7	2,255 €	69 €	85%	27 kWh
P = 0.9	2,271 €	72 €	100%	0 kWh

Results presented in this subsection highlighted the relevance of considering uncertainties on water demands in the pump scheduling problem with DR consideration. Economic as well as operational performances were found to be better on average considering 100 water demand scenarios randomly generated. In the example studied, the management without uncertainties consideration implied a non-respect of the DR power constraint 51% of the time. There is not only an economic impact because of a higher economic cost, but also an impact about confidence of the transmission system operator RTE in future market transactions.

In this case study, the average economic cost is very close for all situations. However, operational risks (DR power commitment, DR energy-deficient volume) are much better managed when uncertainties are considered.

5.5. Discussion and future work

For the day-ahead scheduling problem, DR power bids are increasing with market price and decreasing with the probability of uncertainties handling p. For low spot prices, DR power decisions are very close (equal for low probability values) for different probability values because of the significant available flexibility of the system. For high spot prices, the DR power bids are higher and thus the system flexibility decreases, which implies that the DR power bid decreases with probability of uncertainties consideration. Variable-speed pumps make it possible to optimize DR power decisions on the market by adapting the pumping rate flow to the flexibility of the downstream tank.

In the second part of the study, the relevance of uncertainty consideration in the real-time management of the system has been demonstrated. Indeed, the expected cost for the day-ahead scheduling problem is increasing with probability (optimal expected cost is with $p = 0$ due to a maximal flexibility). However, the random generation of 100 water demand scenarios and the real-time optimization showed that the water system is more profitable when uncertainties are considered in the day-ahead scheduling problem. Indeed, uncertainties consideration allows us to guarantee the respect of DR power reduction with the desired probability p. In addition, the average economic cost is more interesting compared to the case $p = 0$. This is because of a minimal failure in DR energy reduction and consequently, very few additional balancing costs.

For real operational applications, the proposed mathematical model should be coupled to a SCADA such as Topkapi data connector [55]. This coupling makes it possible to centralize water system management, by sending the obtained schedule from the optimization solver to

different water system equipment, and recovering the state of tanks and the availability of pumps to update the mathematical model [56].

The choice of the probability level for water demands risk management should be made by water system operators according to their risk aversion. A strategy of maximum security (p = 0.9) would cost more than a strategy where we have a lower but still acceptable level of security (p = 0.7). An interesting continuation of this research work would be to find the optimal level of robustness p to fix for water utilities. In other words, how much would the water utility be willing to pay for a 1% increase of real-time DR power constraint satisfaction?

Finally, we plan as future work to include the management of multiple water systems through a centralized mathematical model. The approach will be to aggregate the flexibility of several independent water systems in order to propose large quantities of power reductions in energy markets.

6. Conclusion

In this article, we discussed the potential of Demand Response mechanisms in the drinking water industry, considered as a huge electricity consumer. Among the obstacles hindering the development of Demand Response in industry are economic viability and operational risks management. The mathematical model proposed in this article makes it possible to manage the two aspects simultaneously. Indeed, the formulation of the objective function allows us to maximize the economic profitability of the system. On the other hand, uncertainties on water demands were taken into account to secure the operation of the water system in real-time regarding water demand hazards. Numerical results obtained on a benchmark water system show the relevance of the model regarding water demands risk management and economic performances.

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