Decentralized Participation of Flexible Demand in Electricity Markets—Part II: Application With Electric Vehicles and Heat Pump Systems

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***Abstract*—Realizing the significant demand flexibility potential in deregulated power systems requires its suitable integration in electricity markets. Part I of this work has presented the theoretical, algorithmic and implementation aspects of a novel pool market mechanism achieving this goal by combining the advantages of centralized mechanisms and dynamic pricing schemes, based on Lagrangian relaxation (LR) principles. Part II demonstrates the applicability of the mechanism, considering two reschedulable demand technologies with significant potential, namely electric vehicles with flexible charging capability and electric heat pump systems accompanied by heat storage for space heating. The price response sub-problems of these technologies are formulated, including detailed models of their operational properties. Suitable case studies on a model of the U.K. system are examined in order to validate the properties of the proposed mechanism and illustrate and analyze the benefits associated with the market participation of the considered technologies.**

***Index Terms*—Demand side participation, electric heat pumps, electric vehicles, electricity pool markets, Lagrangian relaxation.**

Nomenclature

The main mathematical symbols used throughout this paper, additional to the ones defined in Part I, are given below:

A. Electric Vehicle (EV) Local Sub-Problem

P_t^{ev}	Electric power demand of EV at t (kW).
$P^{ev,max}$	Maximum electric power capacity of EV battery and grid connection's power electronics (kW).
E_t	Electric energy in EV battery at the end of t (kWh).
E^{cap}	Electric energy capacity of EV battery (kWh).
E^{min}	Minimum electric energy in EV battery (kWh).
E^{max}	Maximum electric energy in EV battery (kWh).
E_t^{tr}	Electric energy requirements of EV for driving purposes at t (kWh).
η^{ch}	Charging efficiency of EV battery and grid connection's power electronics.
η^{el}	Hourly electric energy efficiency of EV battery.
T^{gr}	Set of hours when the EV is connected to the grid.

B. Electric Heat Pump (EHP) System Local Sub-Problem

T_t^{m}	Building's structure temperature at $t(^\circ\mathrm{C})$.
T_t^{out}	Building's outdoor temperature at $t(^\circ\mathrm{C})$.
T_t^{in}	Building's indoor temperature at $t(^\circ\mathrm{C})$.
T_t^{set}	Desired building's indoor temperature at $t(^\circ\mathrm{C})$.
Q_t^{tot}	Total heat power supplied to building at t (kW).
Q_t^{ig}	Internal heat power gains of the building due to the human, lighting and equipment presence at t (kW).
Q_t^{hp}	Heat power output of EHP at t (kW).
$Q_t^{hp,max}$	Heat power capacity of EHP at t (kW).
P_t^{hp}	Electric power demand of EHP at t (kW).
$P_t^{hp,max}$	Electric power capacity of EHP at t (kW).
COP_t	Coefficient of performance of EHP at t.
Q_t^{st}	Heat power input ($Q_t^{st} > 0$) /output ($Q_t^{st} < 0$) of heat storage at t (kW).
$Q_+^{st,max}$	Charging heat power capacity of heat storage (kW).
$Q_-^{st,max}$	Discharging heat power capacity of heat storage (kW).
U_t	Heat energy in heat storage at the end of t (kWh).
U^{cap}	Heat energy capacity of heat storage (kWh).
U^{min}	Minimum heat energy in heat storage (kWh).
U^{max}	Maximum heat energy in heat storage (kWh).
η^{th}	Hourly thermal energy efficiency of heat storage.

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C. Generation Participants' Characteristics

P_j^{max} Maximum generation of generation participant j (GW).

MC_j^{min} Minimum marginal cost value of generation participant j $(£/\mathrm{MWh})$.

MC_j^{max} Maximum marginal cost value of generation participant j $(£/\mathrm{MWh})$.

I. Introduction

DEMAND side integration in electricity markets is the key towards the realization of its significant flexibility potential in deregulated power systems [1]–[3]. Approaches to achieve such integration in the existing literature exhibit significant limitations. Centralized mechanisms raise communication, computational and privacy issues while dynamic pricing schemes fail to realize the actual value of demand flexibility since the economic implications of demand response are not encapsulated in the posted prices. In this two-part paper, a novel pool market clearing mechanism is proposed, combining the solution optimality of centralized mechanisms and the decentralized demand participation structure of dynamic pricing schemes.

In mathematical terms, the proposed mechanism is based on *Lagrangian relaxation* (LR) principles and involves a two-level iterative process, composed of a number of independent local surplus maximization sub-problems, expressing the market participants' price response, coordinated by a global price update algorithm, expressing the market operator's effort to reach an optimal clearing solution. When this process cannot reach a feasible solution due to non-convexities in participants' price response, it is modified by suitable heuristic methods (*LR heuristics*) achieving high-quality feasible solutions.

Part I [4] presented the theoretical and mathematical foundations and outlined an implementation framework of the proposed mechanism. Non-convex characteristics in the price response of reschedulable demand participants (RDP) were identified and their impacts on the ability of the basic LR structure to reach feasible solutions were analyzed. In order to deal with the implications of such non-convexities, a simple yet effective LR heuristic method was developed, complying with the decentralized demand participation objective and limiting the creation of new peaks by the concentrated shift of reschedulable demand to the same low-priced periods by imposing a suitable relative maximum demand limit on RDP.

The scope of Part II is to demonstrate the applicability of the mechanism considering two reschedulable demand technologies with significant penetration and flexibility potential:

a) *Electric vehicles (EV) with flexible charging capability*. Environmental and energy security concerns, along with recent developments in automotive and battery technologies have paved the way for the electrification of the transport sector [5]–[8]. The EV demand flexibility potential is significant due to their inherent ability to store electrical energy in their batteries, their stationary character (parked for more than 90% of the time according to [5]) and their low energy consumption requirements with respect to the significant energy and power capacities of their batteries.

b) *Electric heat pump (EHP) systems accompanied by heat storage for space heating*. Space heating loads currently constitute the largest part of energy demand in the domestic and commercial sector of the U.K. [9], [10]. As with the transport sector, environmental and energy security concerns have justified the electrification of heat supply, primarily based in the U.K. on the replacement of traditional gas/oil-fired heating systems with the promising and energy efficient EHP technology [10]. Different flexibility potentials are associated with such loads, such as the allowance of indoor temperature variation by the users within their specified thermal comfort level boundaries or the incorporation of some form of heat storage (e.g., hot water tanks) in the heating system, with the latter exhibiting a more significant potential and attracting the authors' interest due to its ability to preserve the desired level of service (i.e., temperature) delivered to the users.

The local price response sub-problems corresponding to these reschedulable demand technologies are mathematically formulated incorporating models of their operational properties. Suitable case studies involving the integration of these technologies in a model of the U.K. system are examined in order to: a) validate and analyze the effectiveness of the proposed mechanism [4] in efficiently determining high quality solutions of the market clearing problem and b) illustrate, analyze and compare benefits emerging from the market participation of these demand technologies through the proposed mechanism.

The rest of Part II is organized as follows. Section II derives a mathematical formulation of the price response sub-problems corresponding to the considered reschedulable demand technologies. Section III briefly presents the different case studies examined while illustrative results are provided and explained in Section IV. Finally, Section V discusses conclusions and future extensions of this work.

II. Flexible EV and EHP Systems Price Response Sub-Problems

The formulation of reschedulable demand technologies' price response sub-problems should include suitable models of their users' preferences and their operational constraints. As discussed in Part I [4], consumers' benefit functions are assumed constant and consumers' preferences are expressed solely in the form of constraints. This assumption is justified by a) the theoretical and practical difficulties of benefit functions' derivation due to the significant uncertainties related to the human valuation of electrical energy and b) the fact that the considered demand technologies involve explicit storage components enabling demand flexibility without affecting the level of service delivered to the users: provided that their EV can carry out the desired journeys and their room temperature is kept at the desired levels, the users have little concern over the electric demand patterns of their EV and EHP systems respectively. Given this assumption, the RDP technologies' price response sub-problems are formulated as payment minimization problems.

As part of the LR heuristic method proposed in [4, Section V-B], the extra constraint (14) therein, limiting the maximum hourly power demand of RDP to a fraction ω of their respective technically feasible limits, is included in the formulation of their sub-problems and the latter are solved for a set Ω [4, (13)] of different values of the factor ω. It has been assumed that if a value of the set is so restrictive for an EV or an EHP system that does not allow the satisfaction of its local operational constraints, its optimal price response for this value is set equal to the optimal price response corresponding to the immediately higher value of the set. Since the value $\omega = 1$ is always an element of Ω, the feasibility of the price response sub-problem is guaranteed (given that the technically feasible maximum limit ensures this feasibility).

A. EV With Flexible Charging Capability

The considered vehicles are fully electric. The constraints of the local sub-problem are related to the users' driving requirements, the operational properties of the EV, its battery and its grid connection, as well as the availability of a grid connection when the EV is stationary. The price response sub-problem is formulated as follows:

$$\min_{P_t^{ev},\forall t\in[1,24]} \sum_{t=1}^{24} \lambda_t * P_t^{ev}. \quad (1)$$

Constraints:

$$E_t = \eta^{ch} * P_t^{ev} * 1h + \eta^{el} * E_{t-1} - E_t^{tr}, \quad \forall t \in [1,24] \quad (2)$$

$$E^{min} \le E_t \le E^{max}, \forall t \in [1,24] \quad (3)$$

$$0 \le P_t^{ev} \le \omega * P_t^{max}, \forall t \in [1,24] \quad (4)$$

$$\text{where } P_t^{max} = \begin{cases} P^{ev,max} & \text{if } t \in T^{gr} \\ 0 & \text{otherwise} \end{cases}$$

$$E_0 = E_{24}. \quad (5)$$

Constraint (2) expresses the energy balance in the EV battery, including charging losses, self-discharging energy losses and the energy required for driving purposes; the latter is derived by combining the users' driving requirements in terms of travel times and distances and the EV's energy consumption per unit of distance travelled. Constraint (3) corresponds to the minimum and maximum limits of the battery's energy content related to its maximum depth of discharge and state of charge ratings respectively. Constraint (4) represents the limit of the battery's power input, which depends on the electric power capacity of the battery and the grid connection's power electronics, on whether the EV is connected to the grid and on the value of the factor ω.

The EVs' demand rescheduling ability is spread beyond the examined (daily) market horizon. Decisions regarding the demand responses in a certain day will affect corresponding decisions and subsequently potential payments in the next day(s). Incorporation of such out-of-horizon effects in the formulation requires suitable probabilistic models incorporating predictions regarding operational parameters and prices beyond the day-ahead horizon. For the sake of simplicity such effects are not considered and the battery energy content at the start and the end of the daily horizon are assumed equal (5).

B. EHP Systems With Heat Storage for Space Heating

The structure of the considered space heating system is depicted in Fig. 1. The constraints of the price response sub-problem are related to the users' thermal comfort requirements, the dynamic thermal behavior of the building heated and the operational properties of the installed heat pump and heat storage appliances.

Buildings' dynamic thermal response is modelled through a second-order equivalent electric circuit [11], [12] characterized by five lumped parameters whose values depend on the building geometry and the thermal properties of its materials. As discussed in [12], proper manipulation of the differential equations expressing the thermal balance in this circuit results in the linear

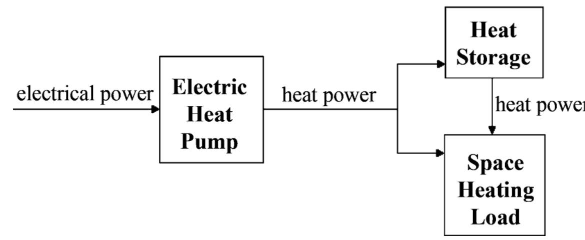

Fig. 1. Structure of considered space heating system.

formulation (6) expressing the building's thermal behavior constraints, where $\varphi_a, \varphi_b, \varphi_c, \varphi_d, \Psi_a, \Psi_b, \Psi_c, \Psi_d$ are functions of the equivalent circuit lumped parameters:

$$\begin{bmatrix} T_t^{in} \\ T_t^{m} \end{bmatrix} = \begin{bmatrix} \varphi_a & \varphi_b \\ \psi_a & \psi_b \end{bmatrix} \begin{bmatrix} T_{t-1}^{in} \\ T_{t-1}^{m} \end{bmatrix} + \begin{bmatrix} \varphi_c & \varphi_d \\ \psi_c & \psi_d \end{bmatrix} \begin{bmatrix} T_{t-1}^{out} \\ Q_{t-1}^{tot} \end{bmatrix} \quad (6)$$

$$Q_t^{tot} = Q_t^{hp} + Q_t^{ig} - Q_t^{st}. \quad (7)$$

Regarding the EHP model, constraint (8) represents the limits of the electric input and thermal output, including the effect of the factor ω. EHP thermal and electric power capacities are functions of outdoor and indoor temperatures [13]; linear correlations are assumed in this work (9), where constants q_a, q_b, q_c, p_a, p_b, p_c depend on the EHP technical characteristics. The ratio of its thermal output over its electric input is known as Coefficient of Performance (10)[13]:

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} < \begin{bmatrix} P_t^{hp} \\ Q_t^{hp} \end{bmatrix} < \begin{bmatrix} \omega * P_t^{hp,max} \\ Q_t^{hp,max} \end{bmatrix} \quad (8)$$

$$\begin{bmatrix} Q_t^{hp,max} \\ P_t^{hp,max} \end{bmatrix} = \begin{bmatrix} q_a \\ p_a \end{bmatrix} + \begin{bmatrix} q_b \\ p_b \end{bmatrix} T_t^{out} + \begin{bmatrix} q_c \\ p_c \end{bmatrix} T_t^{in} \quad (9)$$

$$COP_t \equiv \frac{Q_t^{hp}}{P_t^{hp}} = \frac{Q_t^{hp,max}}{P_t^{hp,max}}. \quad (10)$$

Regarding the heat storage operation, constraint (11) expresses the thermal energy balance in the storage including energy losses, constraint (12) represents the minimum and maximum limits of the storage's energy content—related to its maximum depth of discharge and state of charge, respectively—and constraint (13) corresponds to its maximum heat power charging and discharging rates. Moreover, the heat power input of the storage is lower than the heat power output of the EHP (14), as the former is charged by the latter (Fig. 1):

$$U_t = \eta^{th} * U_{t-1} + Q_t^{st} * 1h \quad (11)$$

$$U^{min} \le U_t \le U^{max} \quad (12)$$

$$-Q_-^{st,max} \le Q_t^{st} \le Q_+^{st,max} \quad (13)$$

$$Q_t^{st} \le Q_t^{hp}. \quad (14)$$

Finally, users' thermal comfort requirements are defined in terms of the desired indoor temperature at each hour:

$$T_t^{in} = T_t^{set}. \quad (15)$$

As with EV, out-of-horizon effects are not considered and a periodic daily continuation is assumed:

$$\begin{bmatrix} T_0^{out} \; T_0^{in} \; T_0^{m} \end{bmatrix} = \begin{bmatrix} T_{24}^{out} \; T_{24}^{in} \; T_{24}^{m} \end{bmatrix} \quad (16)$$

$$\begin{bmatrix} Q_0^{hp} \; Q_0^{ig} \; Q_0^{st} \; U_0 \end{bmatrix} = \begin{bmatrix} Q_{24}^{hp} \; Q_{24}^{ig} \; Q_{24}^{st} \; U_{24} \end{bmatrix}. \quad (17)$$

TABLE I
GENERATION PARTICIPANTS' CHARACTERISTICS

Technology	Maximum generation P_j^{max}(GW)	Marginal cost function	
		MC_j^{min} (£/MWh)	MC_j^{max} (£/MWh)
Wind	3.5	0	0
Nuclear	10.8	0	0
Base Gas	14.9	24	36
Base Coal	15.9	28	42
Hydro	1.1	40	60
Interconnections	3.0	48	72
CHP	2.3	64	96
Marginal Gas	11.6	72	108
Marginal Coal	12.5	80	120
Peakers	7.0	160	240

TABLE II
EXAMINED SCENARIOS FOR EV AND EHP FLEXIBILITY EXTENT

Name	Description
Base	No demand flexibility, both EV and EHP are inflexible
EV-X%	X% of EV flexible
EHP-S-X%	X% of EHP flexible with U^{cap} = 10% * U^{dem}
EHP-L-X%	X% of EHP flexible with U^{cap} = 50% * U^{dem}
Both-S-X%	X% of EV and X% of EHP with U^{cap} = 10% * U^{dem} flexible
Both-L-X%	X% of EV and X% of EHP with U^{cap} = 50% * U^{dem} flexible

The price response sub-problem is formulated as follows:

$$\min_{P_t^{hp}, Q_t^{st}, \forall t \in [1,24]} \sum_{t=1}^{24} \lambda_t * P_t^{hp}. \quad (18)$$

Constraints: (6)–(15), $\forall t \in [1, 24]$ and (16)–(17)

III. CASE STUDIES

The examined case studies involve the application of the proposed market mechanism to a model of the U.K. system on a typical winter day. Due to the scope of this paper, a simplified yet representative model of the generation side is employed. Ten generation participants are assumed, each representing the population of generation units of a different power generating technology in the U.K., and characterized by their maximum generation capability—assumed equal to the total installed capacity of the respective technology, as derived by [14] and [15]—and their assumed linear marginal cost function (expressed by the line connecting points $(0, MC_j^{min})$ and (P_j^{max}, MC_j^{max}))(Table I). Nuclear and wind units are assumed inflexible with their hourly productions determined by their maximum generation capability and their predicted outputs, respectively.

Different scenarios for the penetration and flexibility extent of the considered demand technologies are examined. In terms of penetration, 3 different scenarios are considered where 10%, 20% and 30% of light to medium size vehicles are EV and the respective percentage of domestic and commercial buildings are space-heated by EHP systems. For each penetration scenario, different scenarios of EV and EHP flexibility are considered (Table II), explained in more detail in the following sections.

A. EV Data, Assumptions, and Flexibility Scenarios

Original data regarding the size and the average driving patterns of the U.K. light to medium size vehicle fleet is taken from [16], [17]. Based on this data, each EV is assumed to make two journeys per day. Their energy consumption rate is assumed 0.15 kWh/km travelled [18]. These assumptions along with data from [16] and [17] are inputted to a data processing stage which groups the EV fleet into a set of types, each defined by the combination of the start time, end time and electrical energy requirement of each of its two daily journeys; an example of an EV type is presented in Table III.

TABLE III
EXAMPLE OF EV TYPE PRODUCED BY DATA PROCESSING STAGE

1st journey			2nd journey			Number of EV of this type
Start time	End time	Required energy (kWh)	Start time	End time	Required energy (kWh)	
8	8	1.99	17	18	4.39	51605

Based on [5]–[8], the values for the rest of the parameters are assumed $E^{max} = E^{cap} = 15$ kWh, $E^{min} = 0.2 * E^{cap}$, $P^{ev,max} = 3$ kW, $\eta^{ch} = 0.93$ and $\eta^{el} = 1$ for every EV, and EV are assumed connected to the grid during the period between the end of their second and the start of their first journey, in line with the home-charging scenario, deemed as the most plausible in the literature [7], [8]. Under this assumption, $E^{max} - E^{min} \geq \sum_{t=1}^{24} E_t^{tr}$ should be satisfied for every EV, so that they are able to fulfil their driving requirements.

In the Base flexibility scenario, EV are assumed inflexible, starting charging their batteries immediately after their second journey with $P_t^{ev} = \min\left(P^{ev,max}, (E^{max} - E_{t-1})/(\eta^{ch} * 1h)\right)$. Cases with EV flexibility (Table II) involve X% of the total number of EV exhibiting flexible charging capability and participating in the market through the price response sub-problem (1)–(5), assuming $E_0 = 0.5 * E^{cap}$.

B. EHP Systems Data, Assumptions, and Flexibility Scenarios

EHP systems for space heating are assumed installed in domestic and commercial buildings of different structures (detached, semi-detached, terrace, flat dwellings and hotels, offices, retail stores, respectively), sizes and insulation levels. The *Energy Plus building energy simulation software* [19] is used to determine the values of the five parameters of the second-order thermal response model and the internal heat gains for each of those different building types [12]. Moreover, the buildings are assumed to be spread across three different U.K. areas (North, Midlands and South), for which typical winter day outdoor temperature profiles are considered [12]. Data regarding the total number of each of the examined building types in each of the three considered areas is taken from [20] and [21].

During hours when the buildings are occupied, T_t^{set} is assumed constant and equal to 22°C for all buildings. When the buildings are unoccupied, T_t^{set} is reduced to a desired setback value, which varies for the different buildings. Values of the design parameters $q_a, q_b, q_c, p_a, p_b, p_c$ for different EHP models are taken from [22] and the model installed in each building is selected based on the latter's maximum heat power demand. The assumed values for the heat storage parameters are $U^{max} = U^{cap}, U^{min} = 0.3 * U^{cap}, U_0 = 0.5 * U^{cap}, Q_+^{max} = Q_-^{max} = U^{cap}/1h$ and $\eta^{th} = 0.99$ for every building.

In the Base flexibility scenario, EHP systems are not accompanied by heat storage and the inflexible EHP demand keeps the indoor temperature at the desired levels. Cases with EHP flexibility (Table II) correspond to a different combination of 1) the percentage X% of EHP systems accompanied by heat

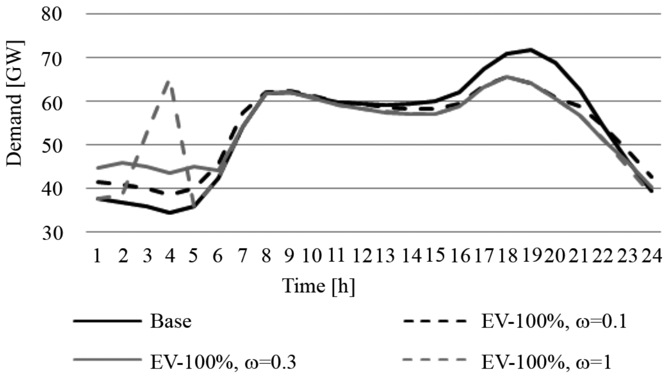

Fig. 2. Impact of EV flexibility on demand profile for different values of ω (30% EV/EHP penetration).

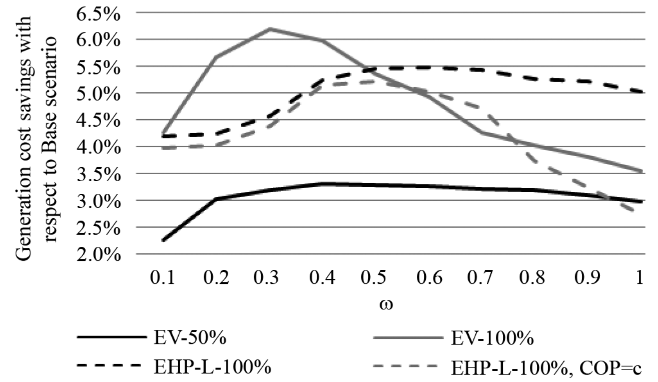

Fig. 3. Impact of EV/EHP flexibility on generation costs for different values of ω and different COP models (30% EV/EHP penetration).

storage and thus exhibiting flexibility and 2) the storage capacity, expressed as a fraction of the daily heat energy consumption U^{dem} in the respective building; in practical terms, this capacity will be limited by restrictions related to the available space for storage installations.

IV. Results

A. Validation of Proposed Market Mechanism

In order to limit the creation of new demand peaks by the concentrated shift of reschedulable demand to the same low-priced hours and thus produce high quality solutions of the market clearing problem, the LR heuristic method proposed in Part I [4] perturbs the price response of reschedulable loads by limiting their maximum power demand to a fraction ω of their respective technically feasible limits. In order to heuristically determine a high quality market clearing solution, a set of K different responses (corresponding to K different values of ω) are received from reschedulable loads and K respective solutions are determined (through the scheduling of the generation side) at each iteration of the clearing mechanism.

Figs. 2 and 3 present the demand profiles and generation cost savings (with respect to the Base scenario) corresponding to the best solution for the different employed values of ω assumed (0.1, 0.2, … , 1) in cases with EV flexibility. Not perturbing EV response (equivalent to $\omega = 1$) allows large EV demand shifts to the lowest-priced hours, yielding a significant new demand peak in early morning. A very low value of ω (0.1) on the other hand restricts the EV flexibility to shift their demand to lower-priced periods so much that part of their demand is satisfied at medium-priced periods and the off-peak valley of inflexible demand (hours 23–7) characterized by lower prices is not sufficiently filled; therefore, generation cost savings are lower than the technically available EV flexibility allows. The most suitable value of lies between these two extremes ($\omega = 0.4$ for EV-50% and $\omega = 0.3$ for EV-100%), enabling flatter demand (and price) profiles and higher generation cost savings. As justified by Fig. 3 and Table IV, as the extent of EV flexibility and EV penetration increases: 1) the new demand peak created in the case corresponding to $\omega = 1$ is larger and thus the value of the proposed LR heuristic -quantified as the % improvement in generation cost savings when the best value of ω is employed with respect to $\omega = 1$- is enhanced and 2) the most suitable value of ω is reduced since a stricter restriction needs to be set on the available flexibility of each EV in order to achieve a higher-quality solution.

TABLE IV
Properties of Proposed LR Heuristic in Cases With EV Flexibility

Penetration scenario	Flexibility scenario	Best value of ω	Value of proposed LR heuristic method
10%	EV-20%	0.6	0.17%
	EV-50%	0.5	0.81%
	EV-100%	0.4	3.27%
20%	EV-20%	0.5	0.46%
	EV-50%	0.4	3.14%
	EV-100%	0.3	32.62%
30%	EV-20%	0.4	0.92%
	EV-50%	0.4	11.74%
	EV-100%	0.3	75.12%

When flexible EHP systems are considered, a significant new demand peak is not created for $\omega = 1$ even in the case with the largest flexibility extent (EHP-L-100%, Fig. 4); therefore, the value of the proposed LR heuristic (giving 0.6 as the most suitable value of ω in EHP-L-100%) is not as significant as in the case of EV, as shown in Fig. 3 (best ω does not improve generation cost savings with respect to $\omega = 1$ as significantly as in the EV case). This is due to the operational diversity of the EHP associated with the correlation of their COP with indoor and outdoor temperatures (9)–(10). Since the same EHP thermal power output requires less electric power input when the COP is higher, flexible EHP systems determine the optimal periods for their storage charging based on the combination of prices and indoor/outdoor temperatures. Given that the considered buildings exhibit different indoor and outdoor temperature profiles, the optimal charging periods for the different EHP systems exhibit significant diversity and thus do not yield a large new peak at the lowest-priced hours. This was justified by examining an additional case, where this correlation between COP and indoor/outdoor temperatures is neglected and a constant $COP = c$ is assumed for each EHP; the diversity in EHP response is lost, the demand profile exhibits significant new peaks (Fig. 4) and the value of the proposed LR heuristic becomes very significant, as shown in Fig. 3 (generation cost savings for the best value $\omega = 0.5$ are almost double as high with respect to $\omega = 1$).

As discussed in Part I [4], the convergence properties of the employed Lagrangian multipliers' update algorithm will have a significant impact not only on the total time for solving the clearing problem but also on the communication costs of the mechanism, as the number of required iterations corresponds to the number of required message exchanges between the market operator and the decentralized demand participants. As

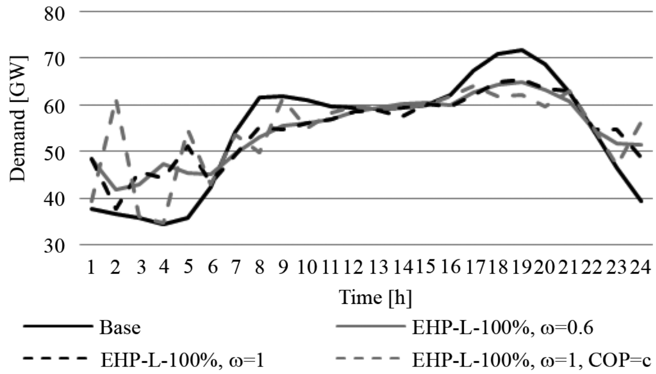

Fig. 4. Impact of EHP flexibility on demand profile for different values of ω and different COP models (30% EV/EHP penetration).

TABLE V
NUMBER OF REQUIRED ITERATIONS OF MARKET CLEARING ALGORITHM (30% EV/EHP PENETRATION)

Flexibility scenario	Poor initialization		Good initialization	
	ε = 0.5%	ε = 1%	ε = 0.5%	ε = 1%
EV-50%	1	1	1	1
EV-100%	4	1	1	1
EHP-S-50%	1	1	1	1
EHP-S-100%	1	1	1	1
EHP-L-50%	3	1	1	1
EHP-L-100%	5	4	3	2
Both-S-50%	1	1	1	1
Both-S-100%	21	6	9	3
Both-L-50%	11	4	7	3
Both-L-100%	46	18	13	9

explained in [4], the initialization quality of the update process can greatly influence the number of required iterations. Finally, a combined termination criterion for the iterative mechanism was proposed; the mechanism terminates when 1) the relative duality gap (RDG) is lower than a tolerance value ε or 2) a maximum number of iterations R is reached.

The case studies were executed with two tolerance values $\varepsilon = 0.5\%$ and $\varepsilon = 1\%$ while the value of R was set to 100. Furthermore, two initialization cases were tested. In the first one (poor initialization case), the initial multipliers $\boldsymbol{\lambda}^1$ were determined by the solution of the generation scheduling problem with the Base scenario demand profile, i.e., by neglecting the potential impact of reschedulable demand on prices; in the second one (good initialization case), the tth element of $\boldsymbol{\lambda}^1$ was calculated as the average of its tth element in the poor initialization case and the tth element of the multiplier vector corresponding to the optimal market clearing solution. The number of iterations required for the two values of ε and the two initialization cases are given in Table V.

When the extent of demand flexibility is relatively small, its impact on the price profile is not significant; therefore, even when the initialization ignores this impact, few iterations are required for convergence and the initialization quality does not have a significant impact. When however the degree of flexible demand is relatively high, the number of iterations gets significantly larger and a good initialization technique—including suitable prediction of the flexible demand's impact—becomes critical. In these cases, the increase of ε can also reduce significantly the required number of iterations but comes with the cost of higher uncertainty on the optimality of the market clearing solution [4], a trade-off which needs to be properly balanced by the market operator.

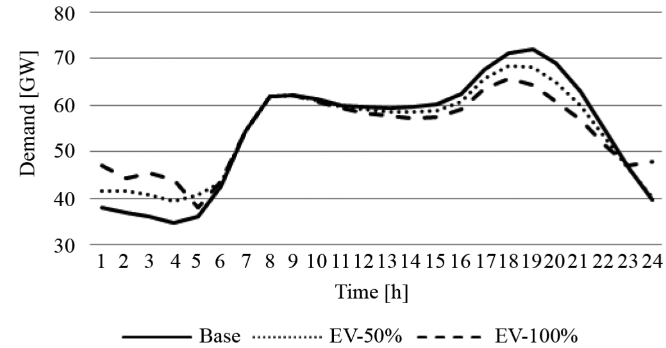

Fig. 5. Impact of EV flexibility on demand profile (30% EV/EHP penetration).

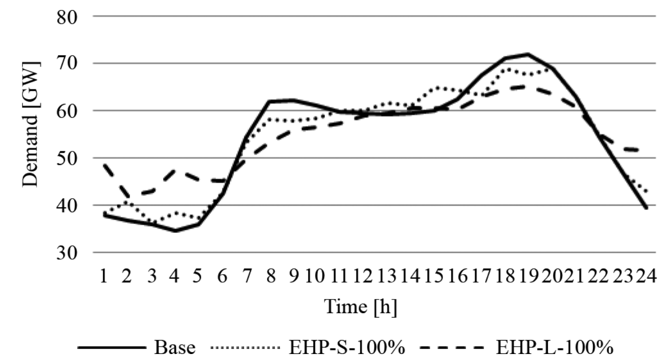

Fig. 6. Impact of EHP flexibility on demand profile (30% EV/EHP penetration).

B. *Benefits of Flexible Demand's Market Participation*

The demand profiles corresponding to the best solution—with the most suitable value of ω—in cases with EV flexibility are depicted in Fig. 5. The shift of flexible EV demand from high-priced (peak) afternoon/evening hours to low-priced (off-peak) night/early morning hours results in a flattening effect in the demand (and price) profile. This effect is enhanced as the number of flexible EV is increased as more demand migrates from peak to off-peak hours.

The respective profiles for cases with EHP flexibility are presented in Fig. 6. Flexible EHP systems shift their electrical demand towards more favorable hours by increasing the EHP heat power production and filling the available heat storage at low-priced hours while reducing the EHP production and utilizing the stored heat energy at high-priced hours. Therefore, as in the cases of EV flexibility, a flattening effect is introduced in the demand (and price) profile. It is worth noting however that the daily electrical energy demand increases with the introduction of flexibility due to the energy losses in the heat storage. When the heat storage capacity is larger, flexible EHP systems can take better advantage of the lowest prices of the day at night/early morning hours by satisfying a larger part of their daily heat energy demand through electricity purchases in that period, and the flattening effect is enhanced despite the fact that the storage losses and thus the daily energy demand increase.

Table VI presents the impacts of demand flexibility on different system indices in some of the examined scenarios. The flattening of the demand profile leads to significant savings in generation costs, due to the increasing shape of the aggregate

TABLE VI
DEMAND FLEXIBILITY IMPACTS ON SYSTEM INDICES (IN% REDUCTION WITH RESPECT TO BASE SCENARIO) (30% EV/EHP PENETRATION)

Flexibility scenario	Generation costs	Demand peak	Flexible demand payments
EV-50%	3.31%	4.92%	59.81%
EV-100%	6.20%	8.63%	55.67%
EHP-S-50%	0.85%	3.11%	5.12%
EHP-S-100%	1.52%	4.14%	5.02%
EHP-L-50%	3.29%	6.61%	18.24%
EHP-L-100%	5.47%	9.38%	10.18%
Both-S-50%	4.07%	8.44%	19.01%
Both-S-100%	7.22%	10.99%	15.69%
Both-L-50%	5.98%	11.12%	22.81%
Both-L-100%	8.08%	14.48%	11.48%

hourly marginal cost function of the generation side (Table I); these savings emerge despite the fact that the daily electrical energy demand remains constant (EV flexibility scenarios) or even increases (EHP flexibility scenarios) with the introduction of flexibility at the demand side. The migration of flexible demand away from high-priced peak hours leads to significant demand peak reductions. These beneficial impacts on generation costs and demand peak are enhanced as the extent of demand flexibility increases. Flexible demand's payments exhibit large reductions, since it is rescheduled towards hours with lower prices. It is noted that as the X% of EV and EHP exhibiting flexibility increases, their % payments' savings are reduced due to their increasing effect on off-peak prices towards which they are rescheduled.

Although the comparison between the impacts of the two flexible demand technologies depends on their assumed parameters' values, penetration and flexibility scenarios, useful conclusions can be drawn by comparing for example scenarios EV-100% and EHP-L-100%. The % savings in flexible EV payments are much higher than the respective savings of flexible EHP systems due to the greater flexibility of EV, justified by the fact that: 1) the battery capacity of each EV is higher than its daily driving energy requirements, while the heat storage capacity of each building is lower than is daily heat energy requirements and 2) in contrast with EV, introduction of flexibility in EHP systems results in notable energy losses. However, the same savings are higher in absolute terms for the flexible EHP systems (the average payments' savings in £ per flexible EHP system in EHP-L-100% are almost double as high as the respective savings per flexible EV in EV-100%) due to their greater energy intensity. Finally, even though EHP-L-100% exhibits higher demand peak reduction and greater improvement of the load factor (the latter is 84.32% in EHP-L-100% and 82.89% in EV-100%) due to the greater energy intensity of EHP systems, it also exhibits slightly lower generation cost savings due to the higher daily energy demand caused by the heat storage losses.

Figs. 7 and 8 illustrate the generation cost savings and demand peak reduction with respect to the Base scenario for different EV/EHP penetration and flexibility scenarios. Due to the temporal patterns of vehicles' and heating systems' use by consumers, in a scenario where EV and EHP do not exhibit flexibility, as their penetration increases, both morning and evening demand peaks' increase is disproportionately higher than the increase in total energy consumption [18]; thus the

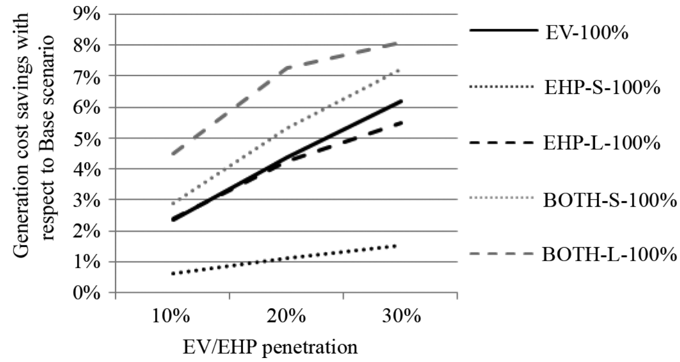

Fig. 7. Impact of EV/EHP flexibility on generation costs for different EV/EHP penetration scenarios.

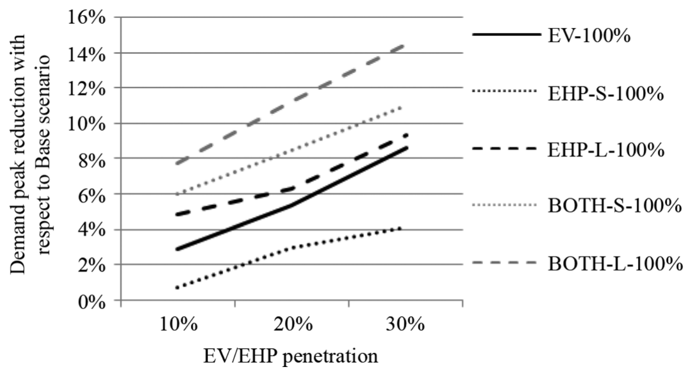

Fig. 8. Impact of EV/EHP flexibility on demand peak for different EV/EHP penetration scenarios.

benefits brought by each demand flexibility scenario in terms of generation cost savings and demand peak reductions increase with an increasing EV/EHP penetration.

V. CONCLUSIONS

A novel pool market mechanism is proposed in this two-part paper in order to realize the demand flexibility potential in a market-oriented and decentralized fashion. Part II demonstrates the applicability of the mechanism considering two flexible demand technologies with significant potential, EV with flexible charging capability and EHP systems accompanied by heat storage for space heating. Their price response sub-problems are formulated including models of their operational properties, and case studies on a model of the U.K. system with different scenarios regarding their penetration and flexibility extent are examined.

In terms of the mechanism properties, the results illustrate that the LR heuristic method proposed in Part I [4] enables the production of a high quality solution by setting a suitable restriction to the maximum hourly demand of reschedulable loads, accounting for the trade-off between the avoidance of new peaks' creation (caused by the concentrated shift of reschedulable demand to the same low-priced periods) and the sufficient flattening of the inflexible demand profile. In cases with EV flexibility the size of these potential new demand peaks and thus the value of the proposed method are significant; as the EV penetration and flexibility increases, the value of the method is enhanced and the optimal solution requires a stricter restriction on the available flexibility of each EV. In cases involving flexible EHP systems on the other hand, their natural diversity associated with the correlation of the heat pump's COP with indoor and outdoor temperatures prevents the creation of significant new demand peaks and the value of the proposed method is smaller.

Regarding the communication requirements of the mechanism, when the extent of demand flexibility is relatively small, few message exchanges between the market operator and the flexible demand participants are required to reach a solution with a low relative duality gap (0.5%) even when the Lagrangian multipliers' initialization ignores the impact of this flexibility. When however the degree of flexible demand is high, the initialization process should include suitable prediction models of such impact in order to limit the significant number of required message exchanges.

In terms of demand flexibility benefits realized through the proposed mechanism, the results show that the EV and EHP flexibility results in a flattening effect and peak reduction in demand and price profiles and yields significant savings in generation costs. These benefits are shown to increase not only with an increasing extent of EV/EHP flexibility but also with an increasing EV/EHP penetration, demonstrating the increased potential of demand flexibility in a future with a wide electrification of transport and heat sectors.

Future work will incorporate detailed models of the generation side, network and security constraints in the market clearing problem in order to further investigate the impact of demand flexibility in cases of different generation system's characteristics, increased wind generation penetration and network congestion. Furthermore, other flexible demand technologies and flexibility patterns, interacting with the level of service delivered to the users (e.g., EHP systems with indoor temperature margins, wet appliances with reschedulable initiation time, etc.) will be examined from the same perspective. Finally, suitable cost/benefit analyses will be carried out in order to compare the economic benefits of flexible demand market participation with the investment required for introducing flexibility in the demand assets and practically realizing the proposed mechanism.

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