Investigating the Ability of Demand Shifting to Mitigate Electricity Producers' Market Power

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***Abstract*—Previous work on the role of the demand side in imperfect electricity markets has demonstrated that its self-price elasticity reduces electricity producers' ability to exercise market power. However, the concept of self-price elasticity cannot accurately capture consumers' flexibility, as the latter mainly involves shifting of loads' operation in time. This paper provides for the first time theoretical and quantitative analysis of the beneficial impact of demand shifting (DS) in mitigating market power by the generation side. Quantitative analysis is supported by a multi-period equilibrium programming model of the imperfect electricity market, accounting for the time-coupling operational constraints of DS as well as network constraints. The decision making process of each strategic producer is modeled through a bi-level optimization problem, which is solved after converting it to a Mathematical Program with Equilibrium Constraints (MPEC) and linearizing the latter through suitable techniques. The oligopolistic market equilibria resulting from the interaction of multiple independent producers are determined by employing an iterative diagonalization method. Case studies on a test market reflecting the general generation and demand characteristics of the GB system quantitatively demonstrate the benefits of DS in mitigating producers' market power, by employing relevant indexes from the literature.**

***Index Terms*—Bi-level optimization, demand shifting, electricity markets, equilibrium programming, market power.**

I. Nomenclature

A. Indices and Sets

$t \in T$	Index and set of time periods
$n, m \in M$	Indexes and set of nodes
M_n	Set of nodes connected to node n through a transmission line
$i \in I$	Index and set of producers
$i-$	Index of producers other than producer i
$j \in J$	Index and set of demands
I_n, J_n	Set of producers and demands connected to node n
$b \in B$	Index and set of generation blocks
$c \in C$	Index and set of demand blocks
V^{LL}	Set of decision variables of lower level problem
V	Set of decision variables of MPEC model

B. Parameters

$\overline{F}_{n,m}$	Capacity of transmission line (n, m) (MW)
$x_{n,m}$	Reactance of transmission line (n, m) (p.u.)
$\lambda_{i,b}^G$	Marginal cost of block b of producer i (£/MWh)
$\overline{g}_{i,b}$	Maximum power output limit of block b of producer i (MW)
$\lambda_{j,t,c}^D$	Marginal benefit of block c of demand j at period t (£/MWh)
$\overline{d}_{j,t,c}$	Maximum power input limit of block c of demand j at period t (MW)
α_j	Load shifting limit of demand j (%)

C. Variables

$\theta_{n,t}$	Voltage angle at node n and period t (rad)
$k_{i,t}$	Strategic offer variable of producer i at period t
$g_{i,t,b}$	Power output of block b of producer i at period t (MW)
$d_{j,t,c}$	Power input of block c of demand j at period t (MW)
$d_{j,t}^{sh}$	Change of power input of demand j at period t due to load shifting (MW)
$\lambda_{n,t}$	Lagrangian multiplier associated with nodal demand-supply balance constraint or equivalently locational marginal price at node n and period t (£/MWh)
$\mu_{i,t,b}^-, \mu_{i,t,b}^+$	Lagrangian multipliers associated with the power output constraints of block b of producer i at period t (£/MW)
$\nu_{j,t,c}^-, \nu_{j,t,c}^+$	Lagrangian multipliers associated with the power input constraints of block c of demand j at period t (£/MW)
ξ_j	Lagrangian multiplier associated with the energy neutrality constraint of demand j (£/MW)
$\pi_{j,t}^-, \pi_{j,t}^+$	Lagrangian multipliers associated with the constraints of the change of power input of demand j at period t due to load shifting (£/MW)
$\rho_{n,m,t}^-, \rho_{n,m,t}^+$	Lagrangian multipliers associated with the capacity constraints of transmission line (n, m) (£/MW)
$\sigma_{n,t}^-, \sigma_{n,t}^+$	Lagrangian multipliers associated with the voltage angle constraints at node n and period t (£/rad)
φ_t	Lagrangian multiplier associated with the voltage angle value at the reference node (£/rad)

D. Functions

$GP_{i,t}$	Profit of producer i at period t (£/h)
$DU_{j,t}$	Utility of demand j at period t (£/h)
SW_t	Social welfare at period t (£/h)

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II. Introduction

A. Background and Motivation

AFTER the deregulation of the energy sector, electricity markets are better described in terms of imperfect instead of perfect competition. In this setting, market participants do not necessarily act as price takers. Electricity producers owning a large share of the market or units at strategic locations of the transmission network are able to influence the electricity prices and increase their profits beyond the competitive equilibrium levels, through *strategic bidding*. This *market power* exercise results in increased price levels and consumers' payments as well as loss of social welfare [1].

Previous works [1]-[3] have identified various measures to mitigate producers' market power, such as a) promoting the separation of dominant producers in order to limit the market share of each producer; b) encouraging the entry of new participants in order to foster competition; and c) imposing price caps and bidding restrictions on producers.

Furthermore, enhancing demand side responsiveness is also regarded as a very promising measure towards more competitive markets. Previous work has demonstrated that the *self-price elasticity* of demand reduces electricity producers' ability to exercise market power, as demand is reduced at high market prices and thus limits the volume of electricity sold by strategic producers [4]-[9]. A theoretical explanation of this effect is presented in [4]-[5]. Authors in [6]-[7] employ a *Supply Function Equilibrium* (SFE) model to determine the market equilibria with different levels of demand's self-price elasticity and define a number of market power indexes in order to quantitatively analyze the impact of elasticity. In [8], the same authors model the effect of two demand response programs, namely *time-of-use pricing* and *economic load response program*, on the self-price elasticity of demand and subsequently on the extent of market power exercised by strategic producers. Finally, an *agent-based* electricity market model is employed in [9] to assess the benefits of different self-price elasticity levels in mitigating market power.

However, a large number of researchers have stressed that consumers' flexibility regarding electricity use cannot be fully captured through the concept of self-price elasticity. Instead of simply avoiding using their loads at high price levels, consumers are more likely to shift the operation of their loads from periods of higher prices to periods of lower prices [4]. In other words, load reduction during certain periods is accompanied by a *load recovery effect* during preceding or succeeding periods. This shift of energy demand from high- to low-priced periods drives a demand profile flattening effect. Although numerous studies have investigated the impacts of *demand shifting* (DS) on various aspects of power system operation and planning [10]-[15], its impact in imperfect electricity markets has not been comprehensively explored yet. Paper [16] is the first piece of work that includes the DS flexibility in an imperfect electricity market model through also considering the cross-price elasticity of the demand side. However, no theoretical or quantitative analysis of the specific impacts of demand shifting on strategic producers' market power is provided. Furthermore, the imperfect electricity market is modeled through an agent-based approach which is not capable of determining oligopolistic market equilibrium solutions and thus the actual value of demand flexibility. On the other hand, although authors in [6]-[8], [17]-[25], [28] adopt mathematically rigorous equilibrium programming models, their single-period setting is not suitable for investigating the impact of DS, as it cannot capture the relevant time-coupling characteristics of the demand side.

B. Scope and Contributions

This paper aims to fill this knowledge gap by providing both theoretical and quantitative analysis of the beneficial impact of DS in mitigating market power by the generation side. Theoretical analysis is supported through a simplified two-period example without network constraints. Quantitative analysis is supported by a *multi-period equilibrium programming* model of the imperfect electricity market. Each strategic producer's decision making is modeled through a *bi-level optimization* problem. The upper level represents the profit maximization problem of the producer and the lower level represents endogenously the market clearing process, accounting for the time-coupling operational constraints of DS as well as network constraints. This bi-level problem is solved after converting it to a *Mathematical Program with Equilibrium Constraints* (MPEC), and linearizing the latter through suitable techniques. The *oligopolistic market equilibria* resulting from the interaction of multiple independent producers are determined by employing an *iterative diagonalization* method.

Case studies on a test market with day-ahead horizon and hourly resolution operating over a 16-node transmission network quantitatively demonstrate the benefits of DS in mitigating producers' market power, by employing relevant indexes from the literature. It should be noted that although existence of and convergence to oligopolistic market equilibria are not generally guaranteed, an equilibrium has been reached within a relatively small number of iterations in every examined case study.

More specifically, the novel contributions of this paper are the following:

- A multi-period equilibrium programming model of imperfect electricity markets is formulated, accounting for the time-coupling operational characteristics of DS as well as network constraints. In contrast to the agent-based model employed in [16], this approach determines oligopolistic market equilibria in a mathematically rigorous fashion.

- Theoretical analysis of the beneficial impact of DS in mitigating market power by strategic producers is provided through a simplified two-period example without network constraints. This example demonstrates that DS reduces the extent of exercised market power at peak periods and increases it at off-peak periods, with the former reduction dominating the latter increase and resulting in an overall positive impact.

- Quantitative analysis of this beneficial impact is provided through case studies with the developed equilibrium programming model on a test market reflecting the general characteristics of the GB system. The results provide evidence of the beneficial impact of DS through the quantification of relevant market power indexes.

- In cases where the network over which the market operates is congested, the extent of the beneficial impact of DS on the overall market efficiency as well as the impact on producers and demands at different areas are demonstrated to depend on the location of DS in the network.

C. Paper Structure

The rest of this paper is organised as follows. Section III details the developed equilibrium programming model. Section IV provides a theoretical example of the beneficial impact of DS on electricity producers' market power. Case studies and quantitative results are presented in Section V. Finally, Section VI discusses conclusions and future extensions of this work.

III. Modeling Imperfect Electricity Market with Demand Shifting

A. Modeling Assumptions

For clarity reasons, the main assumptions behind the proposed model are outlined below:

1) The considered market is a pool-based energy-only market, which is cleared by the market operator through the solution of a social welfare maximization problem.
2) In order to account for the effect of the transmission network, the market clearing process incorporates a DC power flow model and yields *locational marginal prices* (LMP) $\lambda_{n,t}$ for each node n and time period t.
3) For presentation clarity reasons and without loss of generality, we assume that each producer i owns a single generation unit. Each producer submits to the market an increasing step-wise offer curve, consisting of a number of blocks.
4) Following the model employed in [6], [18], [20], [22], the strategic behavior of producer i at period t is expressed through a decision variable $k_{i,t} \geq 1$. If $k_{i,t} = 1$, producer i behaves competitively and offers its actual marginal costs $\lambda^G_{i,b}, \forall b$ to the market at t. If $k_{i,t} > 1$, producer i behaves strategically and offers higher than its actual marginal costs ($k_{i,t} * \lambda^G_{i,b}, \forall b$) to the market at t. Producer i should determine the value of $k_{i,t}$ by accounting for the trade-off between higher market clearing price and lower clearing quantity. More specifically, a higher $k_{i,t}$ will tend to increase market prices at t, but at the same time it will tend to decrease the quantity sold by producer i at t, since producers with lower submitted offers may replace i in the merit order and / or the demand side may reduce demand at t.
5) Each demand submits to the market a decreasing (capturing the effect of demand's self-price elasticity) step-wise bid curve, consisting of a number of blocks [9]. The price / quantity bids are time-specific parameters, capturing the differentiated preferences of consumers across different time periods.
6) A generic, technology-agnostic model is employed for the representation of DS flexibility. According to this model, demand at each time period can be reduced / increased within certain limits, and DS is energy neutral within the market horizon i.e. the total size of demand reductions is equal to the total size of demand increases (load recovery), assuming without loss of generality that DS does not involve energy gains or losses.
7) Demand participants are assumed competitive entities revealing their true characteristics to the market, as the focus of this paper is on the impact of DS on the market power potential of the generation side, and not on the market power potential of the demand side.

B. Bi-level Optimization Model of Strategic Producer

Following the approach employed in [17]-[28], the decision making process of each strategic producer i is modeled through the bi-level optimization model (1)-(12). The upper level (UL) problem determines the optimal offering strategies maximizing the profit of the producer and is subject to the lower level (LL) problem representing the market clearing process. These two problems are coupled, since the offering strategies determined by the UL problem affect the objective function of the LL problem while the LMP and generation dispatch determined by the LL problem affect the objective function of the UL problem.

(Upper level)

$$\max_{\{k_{i,t}\}} \sum_{t,b} \left[\left(\lambda_{(n:i \in I_n),t} - \lambda^G_{i,b} \right) g_{i,t,b} \right] \quad (1)$$

subject to:

$$k_{i,t} \geq 1, \ \forall t \quad (2)$$

(Lower level)

$$\min_{V^{LL}} \sum_{t,b} k_{i,t} \lambda^G_{i,b} g_{i,t,b} + \sum_{i-,t,b} k_{i-,t} \lambda^G_{i-,b} g_{i-,t,b} - \sum_{j,t,c} \lambda^D_{j,t,c} d_{j,t,c} \quad (3)$$

where:

$$V^{LL} = \{ g_{i,t,b}, d_{j,t,c}, d^{sh}_{j,t}, \theta_{n,t} \} \quad (4)$$

subject to:

$$\sum_{(j \in J_n),c} d_{j,t,c} + \sum_{j \in J_n} d^{sh}_{j,t} - \sum_{(i \in I_n),b} g_{i,t,b} + \sum_{m \in M_n} \frac{\theta_{n,t} - \theta_{m,t}}{x_{n,m}} = 0 : \lambda_{n,t}, \forall n, \forall t \quad (5)$$

$$0 \leq g_{i,t,b} \leq \overline{g}_{i,b} : \mu^-_{i,t,b}, \mu^+_{i,t,b}, \forall i, \forall t, \forall b \quad (6)$$

$$0 \leq d_{j,t,c} \leq \overline{d}_{j,t,c} : \nu^-_{j,t,c}, \nu^+_{j,t,c}, \forall j, \forall t, \forall c \quad (7)$$

$$\sum_t d^{sh}_{j,t} = 0 : \xi_j, \forall j \quad (8)$$

$$-\alpha_j \sum_c d_{j,t,c} \leq d^{sh}_{j,t} \leq \alpha_j \sum_c d_{j,t,c} : \pi^-_{j,t}, \pi^+_{j,t}, \forall j, \forall t \quad (9)$$

$$-\overline{F}_{n,m} \leq \frac{\theta_{n,t} - \theta_{m,t}}{x_{n,m}} \leq \overline{F}_{n,m} : \rho^-_{n,m,t}, \rho^+_{n,m,t}, \forall n, \forall m \in M_n, \forall t \quad (10)$$

$$-\pi \leq \theta_{n,t} \leq \pi : \sigma^-_{n,t}, \sigma^+_{n,t}, \forall n, \forall t \quad (11)$$

$$\theta_{1,t} = 0 : \varphi_t, \forall t \quad (12)$$

The objective function (1) of the UL problem constitutes the profit of producer i. This problem is subject to the limits of the strategic offer variables (2) and the LL problem (3)-(12). The latter represents the market clearing process, maximizing the *perceived social welfare* (since the producers do not generally offer their actual marginal costs) or *quasi social welfare* [22] (3), subject to nodal demand-supply balance constraints (5) (the Lagrangian multipliers of which constitute the LMP), the operational constraints of the generation side (6) and the demand side (7)-(9), and network constraints (10)-(12).

The time-shifting flexibility of demand j is expressed by (8)-(9). The variable $d_{j,t}^{sh}$ represents the change of demand with respect to the baseline level $\sum_c d_{j,t,c}$ at period t due to load shifting, taking negative / positive values when demand is moved away from / towards t. Constraint (8) ensures that DS is energy neutral within the market horizon (Section III-A). Constraint (9) expresses the limits of demand change at each period due to load shifting as a ratio α_j ($0 \le \alpha_j \le 1$) of the baseline demand; $\alpha_j = 0$ implies that demand j does not exhibit any time-shifting flexibility, while $\alpha_j = 1$ implies that the whole load of demand j can be shifted in time. The utility of demand j at period t is given by (13).

$$DU_{j,t} = \sum_c \lambda_{j,t,c}^D d_{j,t,c} - \lambda_{(n:j\in J_n),t}\left(\sum_c d_{j,t,c} + d_{j,t}^{sh}\right) \tag{13}$$

While the energy payment (second term) depends on the final demand after any potential load shifting, the benefit (first term) is assumed to depend only on the baseline demand (a reduction in the baseline demand reduces the perceived benefit). This assumption expresses the flexibility of the consumers to shift the operation of some of their loads without compromising the satisfaction they experience.

C. MPEC Model of Strategic Producer

In order to solve the above bi-level optimization problem, the LL problem is replaced by its *Karush-Kuhn-Tucker* (KKT) optimality conditions, which is enabled by the continuity and convexity of the LL problem. This converts the bi-level problem to an MPEC which is formulated as:

$$\max_V \sum_{t,b}\left[\left(\lambda_{(n:i\in I_n),t} - \lambda_{i,b}^G\right) g_{i,t,b}\right] \tag{14}$$

where:

$$V = \{k_{i,t}, V^{LL}, \lambda_{n,t}, \mu_{i,t,b}^-, \mu_{i,t,b}^+, \nu_{j,t,c}^-, \nu_{j,t,c}^+, \xi_j, \pi_{j,t}^-, \pi_{j,t}^+, \rho_{n,m,t}^-, \rho_{n,m,t}^+, \sigma_{n,t}^-, \sigma_{n,t}^+, \varphi_t\} \tag{15}$$

subject to:

(2), (5), (8), (12)

$$k_{i,t}\lambda_{i,b}^G - \lambda_{(n:i\in I_n),t} - \mu_{i,t,b}^- + \mu_{i,t,b}^+ = 0, \forall t, \forall b \tag{16}$$

$$k_{i-,t}\lambda_{i-,b}^G - \lambda_{(n:i-\in I_n),t} - \mu_{i-,t,b}^- + \mu_{i-,t,b}^+ = 0, \forall i-, \forall t, \forall b \tag{17}$$

$$-\lambda_{j,t,c}^D + \lambda_{(n:j\in J_n),t} - \nu_{j,t,c}^- + \nu_{j,t,c}^+ - \alpha_j\pi_{j,t}^- - \alpha_j\pi_{j,t}^+ = 0, \forall j, \forall t, \forall c \tag{18}$$

$$\lambda_{(n:j\in J_n),t} + \xi_j - \pi_{j,t}^- + \pi_{j,t}^+ = 0, \forall j, \forall t \tag{19}$$

$$\sum_{m\in M_n}\frac{\lambda_{n,t}-\lambda_{m,t}}{x_{n,m}} + \sum_{m\in M_n}\frac{\rho_{n,m,t}^+ - \rho_{m,n,t}^+}{x_{n,m}} - \sum_{m\in M_n}\frac{\rho_{n,m,t}^- - \rho_{m,n,t}^-}{x_{n,m}} + \sigma_{n,t}^+ - \sigma_{n,t}^- + (\varphi_t)_{n=1} = 0, \forall n, \forall t \tag{20}$$

$$0 \le \mu_{i,t,b}^- \perp g_{i,t,b} \ge 0, \forall i, \forall t, \forall b \tag{21}$$

$$0 \le \mu_{i,t,b}^+ \perp \left(\overline{g}_{i,b} - g_{i,t,b}\right) \ge 0, \forall i, \forall t, \forall b \tag{22}$$

$$0 \le \nu_{j,t,c}^- \perp d_{j,t,c} \ge 0, \forall j, \forall t, \forall c \tag{23}$$

$$0 \le \nu_{j,t,c}^+ \perp \left(\overline{d}_{j,t,c} - d_{j,t,c}\right) \ge 0, \forall j, \forall t, \forall c \tag{24}$$

$$0 \le \pi_{j,t}^- \perp \left(d_{j,t}^{sh} + \alpha_j \sum_c d_{j,t,c}\right) \ge 0, \forall j, \forall t \tag{25}$$

$$0 \le \pi_{j,t}^+ \perp \left(\alpha_j \sum_c d_{j,t,c} - d_{j,t}^{sh}\right) \ge 0, \forall j, \forall t \tag{26}$$

$$0 \le \rho_{n,m,t}^- \perp \left(\overline{F}_{n,m} + \frac{\theta_{n,t}-\theta_{m,t}}{x_{n,m}}\right) \ge 0, \forall n, \forall m \in M_n, \forall t \tag{27}$$

$$0 \le \rho_{n,m,t}^+ \perp \left(\overline{F}_{n,m} - \frac{\theta_{n,t}-\theta_{m,t}}{x_{n,m}}\right) \ge 0, \forall n, \forall m \in M_n, \forall t \tag{28}$$

$$0 \le \sigma_{n,t}^- \perp \left(\pi + \theta_{n,t}\right) \ge 0, \forall n, \forall t \tag{29}$$

$$0 \le \sigma_{n,t}^+ \perp \left(\pi - \theta_{n,t}\right) \ge 0, \forall n, \forall t \tag{30}$$

The objective function of the MPEC is identical to the objective function of the UL problem. The set of decision variables (15) includes the decision variables of the UL and the LL problem as well as the Lagrangian multipliers associated with the constraints of the LL problem. The KKT optimality conditions of the LL problem correspond to equations (16)-(30).

D. MILP Model of Strategic Producer

The above MPEC formulation is non-linear and thus any solution obtained by commercial solvers is not guaranteed to be globally optimal. The objective of this section is to transform this MPEC to a *mixed-integer linear problem* (MILP) which can be efficiently solved to global optimality using commercial branch-and-cut solvers [27]-[29]. More specifically, the above MPEC includes two types of non-linearities. The first one involves the bilinear terms $\sum_{t,b}\lambda_{(n:i\in I_n),t}g_{i,t,b}$ in the objective function (14). Adopting the linearization approach proposed in [26], which exploits the *strong duality theorem* and some of the KKT equalities, these bilinear terms are replaced with the following linear expression:

$$\sum_{j,t,c}\left(\lambda_{j,t,c}^D d_{j,t,c} - \nu_{j,t,c}^+ \overline{d}_{j,t,c}\right) - \sum_{i-,t,b}\left(k_{i-,t}\lambda_{i-,b}^G g_{i-,t,b} + \mu_{i-,t,b}^+ \overline{g}_{i-,b}\right) - \sum_{n,(m\in M_n),t}\left(\rho_{n,m,t}^- + \rho_{n,m,t}^+\right)\overline{F}_{n,m} - \sum_{n,t}\left(\sigma_{n,t}^- + \sigma_{n,t}^+\right)\pi \tag{31}$$

The second non-linearity involves the bilinear terms in the *complementarity conditions* (21)-(30), which can be expressed in the generic form $0 \le \mu \perp p \ge 0$, with μ and p representing generic dual and primal terms respectively. The linearization approach proposed in [30] replaces each of these conditions with the set of mixed-integer linear conditions $\mu \ge 0$, $p \ge 0$, $\mu \le \omega M^D$, $p \le (1-\omega)M^P$, where ω is an auxiliary binary variable, while M^D and M^P are large positive constants. The set of decision variables of the MILP formulation includes the set (15) as well as the auxiliary binary variables introduced for linearizing (21)-(30).

The values of the parameters M^D and M^P should be suitably selected in order to achieve not only accurate but also computationally efficient solution of the MILP. More specifically, M^D and M^P should be large enough in order to avoid imposing additional upper bounds on the decision variables and thus resulting in an inaccurate solution of the MILP. On the other hand, extremely large values should be avoided as they hinder the convergence of branch-and-cut solvers and result in large computational times [25]-[26]. Suitable values of the parameters M^P corresponding to primal terms can be more easily determined based on the bounds of primal variables which correspond to explicit physical limits. For example, the parameter M^P corresponding to the primal term of the complementarity constraint (21) is set equal to the maximum power output limit $\overline{g}_{i,b}$ which physically limits the primal variable $g_{i,t,b}$. Suitable selection of the parameters M^D corresponding to dual terms is more challenging since the dual variables do not exhibit explicit physical limits. In this context, the heuristic approach presented in [26] has been employed to tune parameters M^D.

E. Determining Market Equilibrium

The above MPEC / MILP model expresses the decision making problem of a single strategic producer. In order to determine the oligopolistic market equilibrium under the participation of multiple strategic producers, recent work has employed two distinct approaches. Under the first one, which was employed in [22]-[25], the KKT conditions of all producers' MPEC problems are combined into a single optimization problem, known as *Equilibrium Program with Equilibrium Constraints* (EPEC), the solutions of which generally constitute market equilibria. The main drawback of this approach is its modeling and computational complexity, mainly associated with the significant non-linearities of the EPEC formulation.

The second one employs an iterative approach, which is known as *diagonalization*, was introduced in the mathematical paper [31] and was employed in [6], [17]-[21]. At each iteration, each producer i solves its respective MILP problem - accounting for the offering strategies $k_{i-,t}$ of the rest of the producers as fixed parameters and equal to their values in the previous iteration- until the iterative approach converges i.e. the offering strategies of all producers remain constant with respect to the previous iteration. As discussed in [17]-[21], this convergence state corresponds by definition to a *pure strategy Nash equilibrium* of the oligopolistic market, since none of the producers can increase their profits by unilaterally modifying their offering strategies. Given that the computational challenges of EPEC formulations become even more significant in the multi-period, time-coupling and network-constrained framework of this paper, the authors have decided to employ the iterative diagonalization approach.

As discussed in the literature, existence and uniqueness of Nash equilibria are not generally guaranteed [17]-[25], [28], [32]. Furthermore, if multiple Nash equilibria exist, a *global Nash equilibrium* may exist, where the profits of all competing players are higher than their respective profits in all other Nash equilibria [32]. Finally, the iterative diagonalization approach is not generally guaranteed to converge to an equilibrium, even if equilibria exist [17]-[19], [23], [25]. However, an equilibrium has been reached within a relatively small number of iterations in every examined case study (Section V). This finding, along with the focus of this work on investigating the impact of DS on producers' market power, sets a detailed analysis of existence, uniqueness, globality and convergence to an equilibrium out of the scope of this paper.

IV. Theoretical Analysis of Impact of Demand Shifting on Producers' Market Power

This section provides a theoretical example demonstrating the beneficial impact of DS on the extent of generation market power, in a simplified market representation involving only two periods (one peak and one off-peak period), no network constraints and inelastic demand. As discussed in Section II and demonstrated in [10]-[15], DS drives flattening of the demand profile by reducing demand during peak time periods and increasing it during off-peak time periods.

Fig. 1 illustrates the impact of this demand flattening effect on the extent of market power exercised by strategic producers in the investigated example. The two curves represent in a simplified fashion the aggregate offer curves of the generation side -characterized by increasing slopes [1]-under competitive and strategic behavior. The price intercept and the slope of each segment of the strategic curve are higher than the respective parameters of the competitive curve (Section III-A). DS reduces peak demand from d_2 to d_2' and increases off-peak demand from d_1 to d_1'. The intersections of the offer curves with the vertical demand bid curves (given that demand is assumed inelastic) determine the market clearing prices in the respective cases. The price increments $\Delta\lambda$ represent the increase of the market clearing prices driven by the exercise of market power in the respective cases. As demonstrated in Fig. 1, this price increase is much higher during the peak period due to the increasing slope of the offer curve.

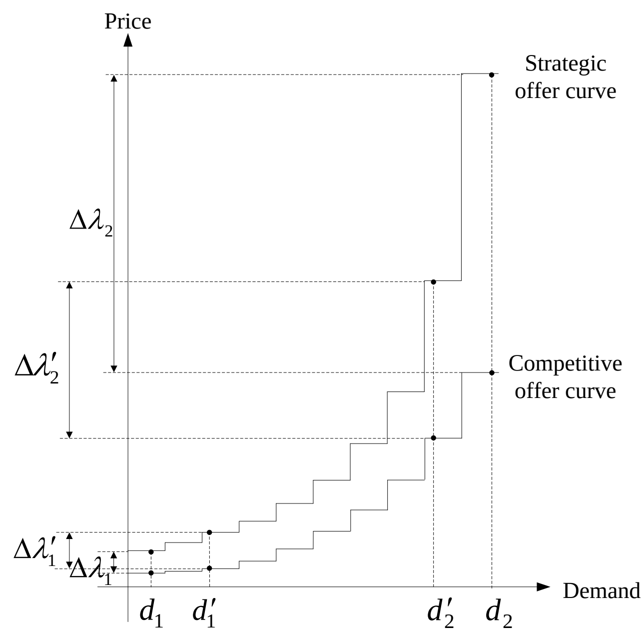

Fig. 1. Impact of demand shifting on the extent of market power exercised by the generation side.

Fig. 1 demonstrates that DS reduces the price increment at the peak period from $\Delta\lambda_2$ to $\Delta\lambda_2'$ while it increases it at the off-peak period from $\Delta\lambda_1$ to $\Delta\lambda_1'$. Although the peak demand reduction is equal to the off-peak demand increase, i.e. $d_2 - d_2' = d_1' - d_1$ (given the assumed energy neutrality constraint (8)), the price increment reduction at the peak period is higher than its increase at the off-peak period, i.e. $\Delta\lambda_2 - \Delta\lambda_2' > \Delta\lambda_1' - \Delta\lambda_1$, due to the increasing slope of the offer curve. This effect also applies to the resulting producers' profit increments (as quantitatively explored in Section V) and implies that DS results in an overall reduction of the extent of market power exercised by the generation side.

V. Case Studies

A. Test Data and Implementation

The examined studies quantitatively demonstrate the beneficial impact of DS on the market power exercised by electricity producers in a test market with day-ahead horizon and hourly resolution, operating over a 16-node model of the GB transmission network (Fig. 2) [33]. Nodes 1-6 correspond to Scotland while nodes 7-16 correspond to England.

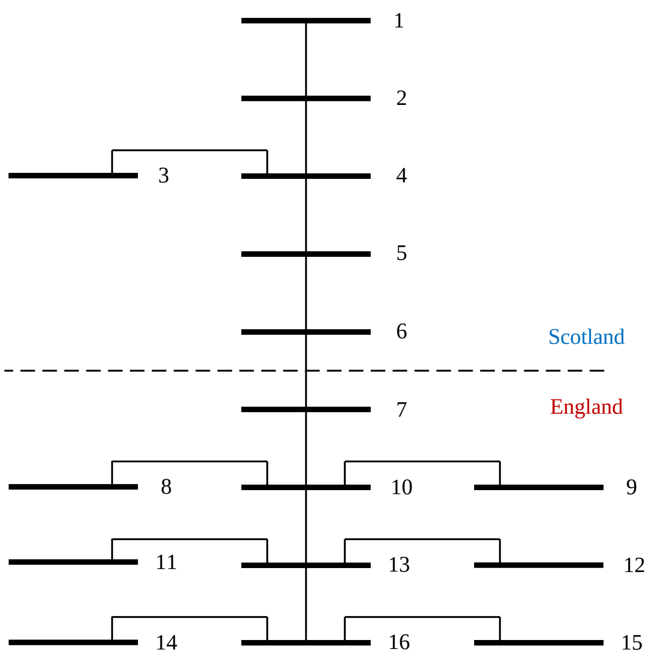

Fig. 2. 16-node model of GB transmission network.

The market includes 7 electricity producers, with their location provided in Table I and their cost and maximum output data derived from [34]-[35]. The merit order of the units owned by the producers is presented in Table I (1 indicating the unit with the lowest marginal costs) and reflects the actual situation in the GB system, where Scotland is characterized by cheaper generation.

TABLE I
Location and Merit Order of Producers

Producer i	1	2	3	4	5	6	7
Node	3	5	6	9	11	15	16
Merit order	1	3	5	2	4	6	7

The market also includes 13 demand participants, with their location and relative size (expressed as % of the total system demand and assuming that it remains identical for every time period) presented in Table II. This table reflects the actual situation in the GB system, where the largest demand centres are located in England. The time-specific benefit and maximum input data of these demands are derived from [34]-[35]. Different scenarios are examined regarding the time-shifting flexibility of the demand side, as expressed by parameter α_j.

TABLE II
Location and Relative Size of Demands

Demand j	1	2	3	4	5	6	7	8	9	10	11	12	13
Node	1	2	4	5	6	7	8	9	11	12	14	15	16
Size (%)	1.8	2.0	3.6	5.6	0.8	19	14.1	5.6	5.9	6.3	10.4	2.6	22.3

The developed equilibrium programming model has been coded and solved using the optimization software FICO™ Xpress [36] on a computer with a 6-core 3.47 GHz Intel(R) Xeon(R) X5690 processor and 192 GB of RAM. A market equilibrium has been reached within a relatively small number of iterations in every examined case study.

B. Impact of Demand Shifting: Uncongested Network

This section considers a case where the network capacity limits are neglected and therefore the network is not congested. For different DS flexibility (assumed identical for every demand, i.e. $\alpha_j = \alpha, \forall j$) scenarios, two cases are compared: i) a case of perfectly competitive market (indicated by the superscript c in the remainder), where all producers behave competitively at all time periods, i.e. $k_{i,t} = 1, \forall i, \forall t$, and ii) a case of imperfect, oligopolistic market (indicated by the superscript s in the remainder), where the offering strategies of the producers are determined based on the developed equilibrium model (Section III). In order to quantitatively characterize the extent of market power exercised by the generation side, relevant indexes from the literature [6]-[7] are employed.

Fig. 3 presents the hourly system demand for different DS flexibility scenarios in the oligopolistic market case. As discussed before, DS drives flattening of the demand profile by reducing demand during peak time periods and increasing it during off-peak time periods, although the daily energy consumption remains the same.

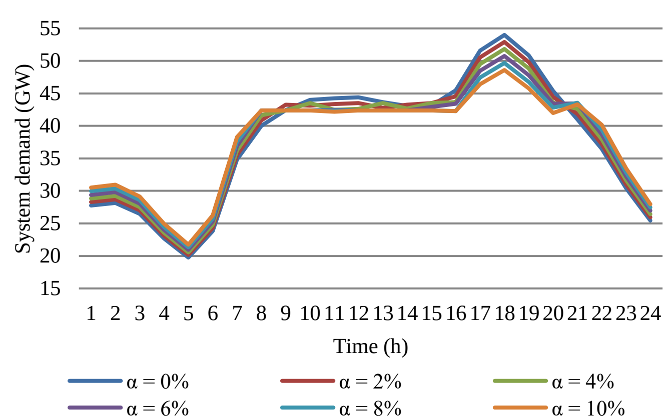

Fig. 3. Hourly system demand for different DS flexibility scenarios in the oligopolistic market case.

Fig. 4 presents the increment of market prices driven by the exercise of market power for different DS flexibility scenarios. As qualitatively illustrated in Section IV, DS reduces the price increment at peak periods and increases it at off-peak periods, with the former reduction being significantly higher than the latter increase and resulting in an overall positive impact.

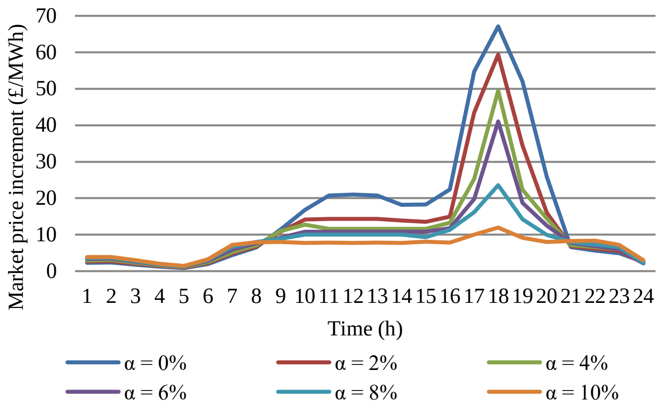

Fig. 4. Hourly market price increment driven by the exercise of market power for different DS flexibility scenarios.

This positive impact is justified through the quantification of the *average Lerner index* (AveLI) (32), which expresses the average increment of market prices driven by the exercise of market power; as illustrated in Fig. 5, AveLI is reduced with increasing DS flexibility.

$$AveLI = \underset{n,t}{\text{average}} \frac{\lambda_{n,t}^{s} - \lambda_{n,t}^{c}}{\lambda_{n,t}^{s}} (\%) \tag{32}$$

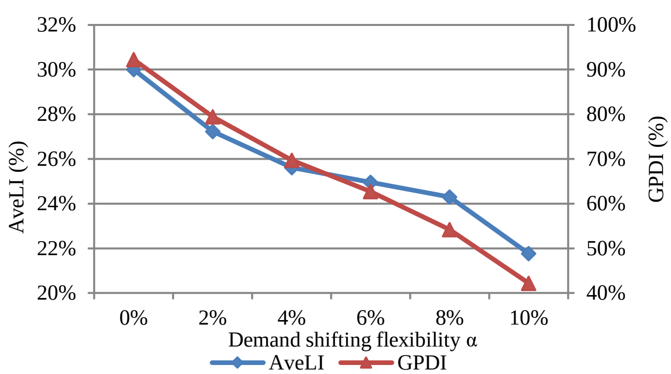

Fig. 5. Average Lerner index (AveLI) and generation profit deviation index (GPDI) for different DS flexibility scenarios.

This reduction of producers' ability to manipulate market prices has also an impact on their additional profit driven by the exercise of market power. Fig. 6 presents the aggregate increment of all producers' hourly profit for different DS flexibility scenarios. Following the trend characterising the price increments, DS reduces the hourly profit increment during peak periods and increases it during off-peak periods, with the former reduction being significantly higher than the latter increase. As a result, the total profit increment driven by the exercise of market power is significantly reduced. This reduction is justified through the quantification of the *generation profit deviation index* (GPDI) (33); as illustrated in Fig. 5, GPDI is reduced with increasing DS flexibility, implying that the latter reduces the additional profit driven by the exercise of market power.

$$GPDI = \frac{\sum_{i,t} GP_{i,t}^{s} - \sum_{i,t} GP_{i,t}^{c}}{\sum_{i,t} GP_{i,t}^{c}} (\%) \tag{33}$$

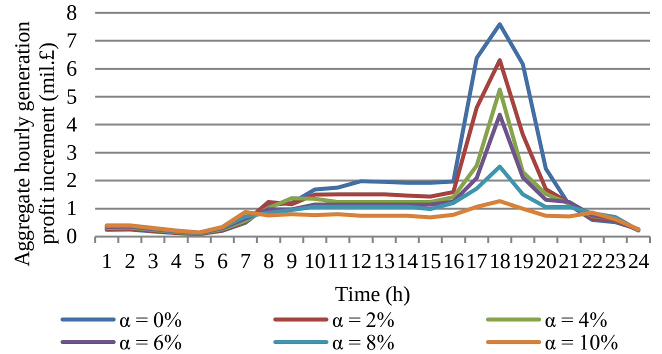

Fig. 6. Aggregate hourly generation profit increment driven by the exercise of market power for different DS flexibility scenarios.

The reduction of the generation market power has also beneficial effects on demand utility and social welfare, which are justified by the quantification of the *demand utility deviation index* (DUDI) (34) and the *market inefficiency index* (MII) (35), respectively.

$$DUDI = \frac{\sum_{j,t} DU_{j,t}^{s} - \sum_{j,t} DU_{j,t}^{c}}{\sum_{j,t} DU_{j,t}^{c}} (\%) \tag{34}$$

$$MII = \frac{\sum_{t} SW_{t}^{s} - \sum_{t} SW_{t}^{c}}{\sum_{t} SW_{t}^{c}} (\%) \tag{35}$$

Fig. 7 demonstrates that the absolute values of DUDI and MII are both reduced with increasing DS flexibility. The absolute DUDI reduction implies that DS reduces the demand utility loss driven by the exercise of market power, and thus enables consumers to more efficiently preserve their economic surplus against producers' strategic behavior. The absolute MII reduction implies that DS reduces the social welfare loss driven by the exercise of market power and thus enhances the overall efficiency of the market.

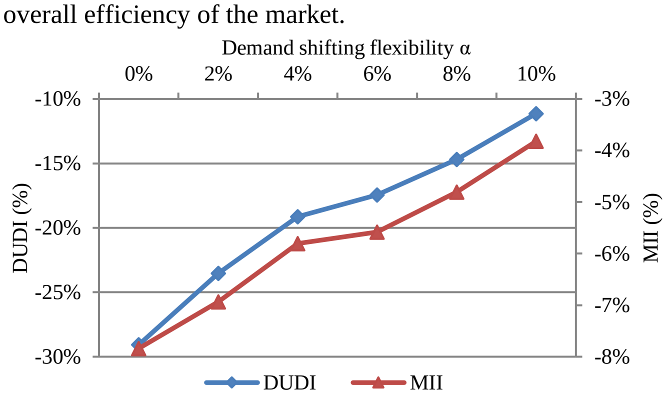

Fig. 7. Demand utility deviation index (DUDI) and market inefficiency index (MII) for different DS flexibility scenarios.

Table III provides an overview of the computational performance of the developed equilibrium programming model for each of the examined case studies, by presenting a) the total computational time, b) the number of iterations of the diagonalization approach, and c) the average computational time per iteration of the diagonalization approach (which reflects the computational time for the solution of the MILP decision making problems of the strategic producers). It can be concluded that the computational performance of the equilibrium programming model does not exhibit a clear trend with respect to the extent of demand shifting flexibility in the system.

TABLE III
COMPUTATIONAL PERFORMANCE OF EQUILIBRIUM PROGRAMMING MODEL IN CASE STUDIES OF SECTION V-B

DS flexibility	Total CPU time (sec)	Number of iterations	Average CPU time per iteration (sec)
$\alpha = 0\%$	3050	14	218
$\alpha = 2\%$	3253	17	191
$\alpha = 4\%$	3478	15	232
$\alpha = 6\%$	3894	22	177
$\alpha = 8\%$	2991	14	214
$\alpha = 10\%$	3518	23	153

C. Impact of Demand Shifting: Congested Network

In this section the impact of network congestion and the location of DS flexibility are investigated by examining the following cases:

U: Network capacity limits are neglected and therefore the network is uncongested, under both competitive and oligopolistic market settings. The demand side has no shifting flexibility.

U-DS-SC: The network is uncongested and demands in Scotland have shifting flexibility.

U-DS-EN: The network is uncongested and demands in England have shifting flexibility.

U-DS-SC&EN: The network is uncongested and demands in both Scotland and England have shifting flexibility.

C: Network capacity limits are taken into account; in this case the line (6,7) connecting Scotland and England gets congested during some peak hours (reflecting the actual situation in the GB system), under both competitive and oligopolistic market settings. The demand side has no shifting flexibility.

C-DS-SC: Line (6,7) is congested and demands in Scotland have shifting flexibility.

C-DS-EN: Line (6,7) is congested and demands in England have shifting flexibility.

C-DS-SC&EN: Line (6,7) is congested and demands in both Scotland and England have shifting flexibility.

Given that England is characterized by significantly higher demand than Scotland (Table II), in order to provide a meaningful analysis regarding the impact of the location of DS flexibility in the network, the overall extent of DS flexibility is assumed identical in cases U-DS-SC, U-DS-EN, U-DS-SC&EN, C-DS-SC, C-DS-EN and C-DS-SC&EN and equivalent to the $\alpha = 6\%$ scenario of Section V-B. In cases U-DS-SC&EN and C-DS-SC&EN, it is assumed that demands in Scotland and England exhibit the same extent of DS flexibility i.e. they equally share the overall DS flexibility.

Fig. 8-9 present the GPDI and DUDI corresponding to producers and demands in Scotland and England, and Fig. 10 presents the MII, for each of the above cases. First of all, let us examine cases without DS flexibility, in order to understand the effects of network congestion which are highly relevant for the subsequent analysis. When the network is uncongested, the locational prices are identical in the two areas, while congestion in line (6,7) yields a locational price differential between the two areas [1], as illustrated in Fig. 11. More specifically, during periods when the line is congested, England -characterized by more expensive generation and higher demand- exhibits higher price than the one observed in the uncongested case, while Scotland -characterized by cheaper generation and lower demand- exhibits lower price than the one observed in the uncongested case.

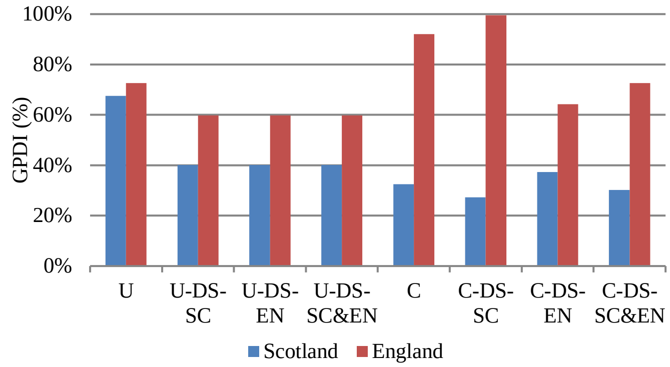

Fig. 8. Generation profit deviation index (GPDI) corresponding to producers in Scotland and England for each of the examined cases.

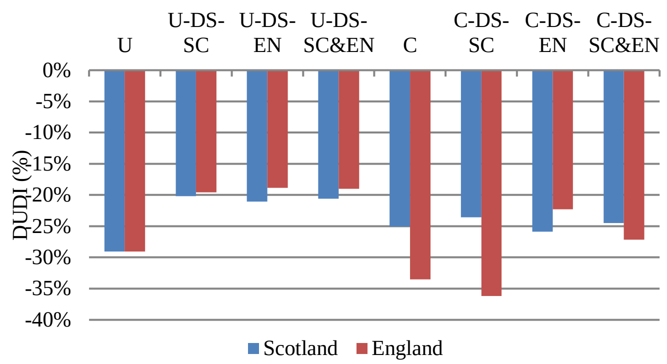

Fig. 9. Demand utility deviation index (DUDI) corresponding to demands in Scotland and England for each of the examined cases.

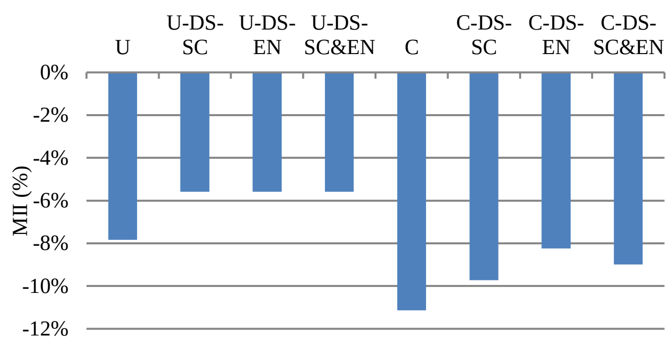

Fig. 10. Market inefficiency index (MII) for each of the examined cases.

Producers' market power is more significant at higher price levels due to the increasing slope of the offer curve (Section IV). Therefore, congestion increases the GPDI and the absolute value of DUDI corresponding to producers and demands in England, while it reduces the GPDI and the absolute value of DUDI corresponding to producers and demands in Scotland, as observed in Fig. 8-9. In other words, congestion creates a more favourable setting for producers in England and demands in Scotland, and a less favourable setting for producers in Scotland and demands in England. The overall impact of congestion on the efficiency of the market is negative (as justified by the increase of the absolute value of MII in Fig. 10), since the negative impact on producers' market power in the higher-priced area (England) dominates the positive impact in the lower-priced area (Scotland). These findings verify the conclusions of previous work [6], [18]-[20], [22], [25] that network congestion favours market power exercise by strategically-located producers and aggravates the overall impacts of market power exercise.

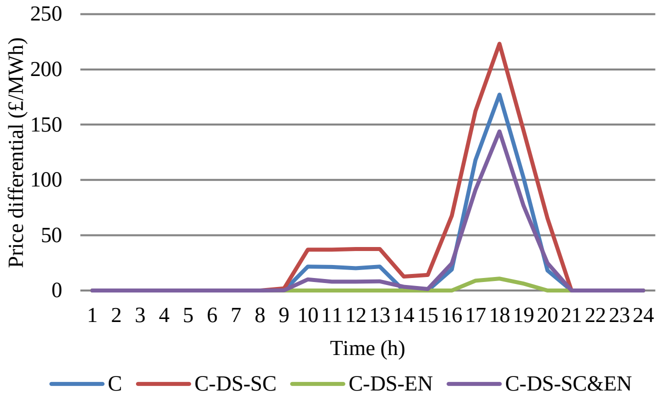

Fig. 11. Price differential between Scotland and England for each of the cases with network congestion in the oligopolistic market case.

Let us now examine the impact of introducing DS flexibility in the market. When the network is uncongested, producers' market power is reduced (Section V-B), resulting in a reduction of the MII as well as the GPDI and the absolute value of DUDI for producers and demands in both areas. Furthermore, the location of DS flexibility does not have an impact on the market outcome and thus cases U-DS-SC, U-DS-EN and U-DS-SC&EN exhibit the same indexes' values (Fig. 8-10).

When the network is congested though, the location of DS flexibility affects the market outcome significantly. Fig. 12-13 present the aggregate increment of the hourly profit corresponding to producers in Scotland and England for each of the cases with network congestion. When demands in Scotland have shifting flexibility, the flattening effect on Scotland's demand profile aggravates congestion on line (6,7), by increasing the number of hours that the line is congested and the price differential between the two areas, with respect to case C (Fig. 11). As a result, the hourly profit increment corresponding to producers in Scotland / England is significantly reduced / increased during peak hours when the network gets congested (Fig. 12-13). Therefore, the GPDI and the absolute value of DUDI corresponding to producers and demands in Scotland are reduced, while the GPDI and the absolute value of DUDI corresponding to producers and demands in England are increased, as observed in Fig. 8-9. In other words, DS flexibility in Scotland creates a less favourable setting for producers in Scotland and demands in England, and a more favourable setting for producers in England and demands in Scotland.

On the other hand, when demands in England have shifting flexibility, the flattening effect on England's demand profile relieves congestion on line (6,7), by reducing the number of hours that the line is congested and the price differential between the two areas, with respect to case C (Fig. 11). As a result, the hourly profit increment corresponding to producers in Scotland / England is significantly increased / reduced during peak hours when the network gets congested (Fig. 12-13). Therefore, the GPDI and the absolute value of DUDI corresponding to producers and demands in Scotland are increased, while the GPDI and the absolute value of DUDI corresponding to producers and demands in England are reduced, as observed in Fig. 8-9. In other words, DS flexibility in England creates a less favourable setting for producers in England and demands in Scotland, and a more favourable setting for producers in Scotland and demands in England.

Finally, the case C-DS-SC&EN (where demands in Scotland and England equally share the overall DS flexibility) exhibits intermediate results between the C-DS-SC and the C-DS-EN cases (Fig. 8-13), given that the above discussed effects of DS in Scotland and England are now combined.

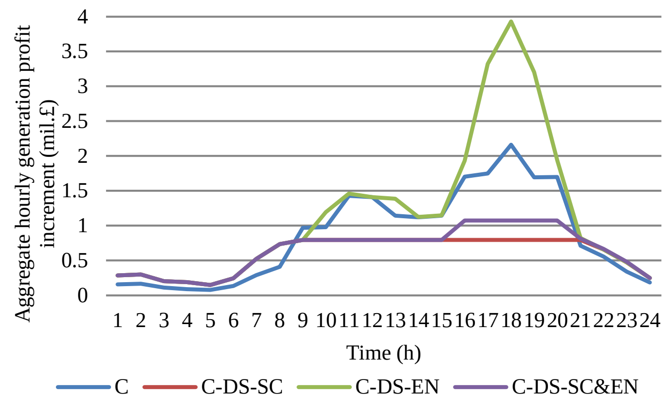

Fig. 12. Aggregate hourly generation profit increment corresponding to producers in Scotland for each of the cases with network congestion.

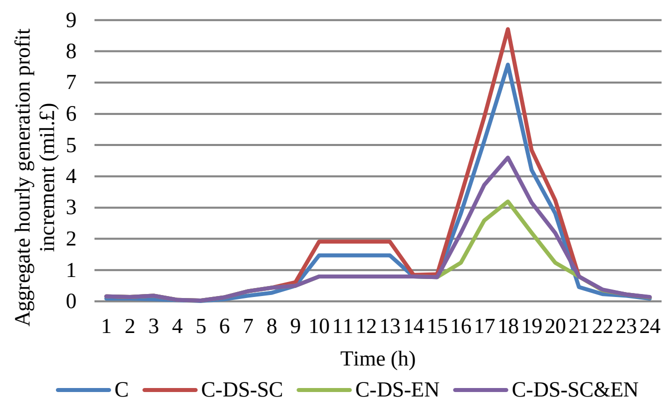

Fig. 13. Aggregate hourly generation profit increment corresponding to producers in England for each of the cases with network congestion.

The overall impact of DS on the efficiency of the market is positive irrespectively of its location, as the absolute value of MII is reduced in all C-DS-SC, C-DS-EN and C-DS-SC&EN cases with respect to the C case (Fig. 10). However, this positive impact is higher when it is located in the higher-priced area (England) where producers' market power potential is more significant and lower when it is located in the lower-priced area (Scotland) where producers' market power potential is less significant, while the case C-DS-SC&EN exhibits an intermediate impact. In other words, the benefits of DS in mitigating producers' market power depend on its location in cases of network congestion.

Table IV provides an overview of the computational performance of the developed equilibrium programming model for each of the examined case studies. It can be concluded that both the number of iterations and the average computational time per iteration (and therefore the total computational time) are higher when the network is congested.

TABLE IV
COMPUTATIONAL PERFORMANCE OF EQUILIBRIUM PROGRAMMING MODEL IN CASE STUDIES OF SECTION V-C

Case	Total CPU time (sec)	Number of iterations	Average CPU time per iteration (sec)
U	3050	14	218
U-DS-SC	3902	22	177
U-DS-EN	3846	22	175
U-DS-SC&EN	3917	22	178
C	8758	30	292
C-DS-SC	10732	36	298
C-DS-EN	9142	33	277
C-DS-SC&EN	9719	34	286

VI. CONCLUSIONS AND FUTURE WORK

This paper has provided for the first time theoretical and quantitative analysis of the beneficial impact of demand shifting flexibility in mitigating market power by strategic producers in electricity markets. Theoretical analysis of this impact has been supported through a simplified two-period example without network constraints. This example has demonstrated that DS reduces the extent of exercised market power at peak periods and increases it at off-peak periods, with the former reduction dominating the latter increase and resulting in an overall positive impact. These effects are not captured in previous works modeling consumers' flexibility solely through their self-price elasticity, which results in a simple demand reduction at periods of high prices and does not capture the realistic consumers' flexibility to shift the operation of their loads from periods of higher prices to periods of lower prices.

Quantitative analysis has been supported by a multi-period equilibrium programming model of the imperfect electricity market, accounting for the time-coupling operational characteristics of DS as well as network constraints. Case studies with the developed model on a test market reflecting the general generation and demand characteristics of the GB system have quantitatively demonstrated the benefits of DS in mitigating producers' market power, by employing relevant indexes from the literature. In cases without network congestion, the location of DS flexibility does not have an impact on producers' market power exercise, but an increasing DS flexibility is shown to i) reduce strategic producers' ability to manipulate market prices, and as a result ii) reduce strategic producers' additional profit driven by the exercise of market power, iii) allow consumers to more efficiently preserve their economic surplus against producers' strategic behavior, and iv) reduce the social welfare loss and thus enhance the overall efficiency of the market. In cases with network congestion, DS flexibility still has an overall positive impact on market efficiency, but the extent of this benefit as well as the impact on producers and demands at different areas depends on the location of DS flexibility in the network, an effect which has not been explored in previous works.

Future work aims at enhancing the presented model in four directions. First of all, beyond the generic, technology-agnostic representation of DS flexibility employed in this paper, detailed representations of different residential and commercial flexible demand technologies, including electric vehicles, electric heat pumps and smart appliances, will be incorporated in the model. This will enable a comprehensive analysis of the value of different demand response initiatives in imperfect electricity markets.

Secondly, the presented model is deterministic, assuming that strategic producers have accurate projections of their competitors' strategic offers and the extent of DS flexibility. Future work aims at incorporating uncertainties that strategic producers face regarding these parameters, thus reformulating the developed model as a stochastic equilibrium programming model, and investigating the role and value of DS flexibility in this context.

Furthermore, this paper has assumed that demand participants are competitive entities revealing their true characteristics to the market, as the focus has been set on the impact of DS on producers' market power. Future work will model strategic demand participants, misreporting their actual DS flexibility to the market in order to increase their surpluses, and will explore the impacts of such strategic behavior on the market outcome.

Finally, the developed equilibrium programming model as well as similar models in the existing literature [6]-[8], [17]-[28], neglect the complex unit commitment constraints of the generation side, due to their inherent inability to deal with binary decision variables in the lower level of the strategic producers' bi-level optimization problems. However, these complex operating properties may affect the market outcome and the value of demand flexibility, as the latter may have a significant impact on the scheduling patterns and offering strategies of different producers. In this context, future work will explore mathematical techniques enabling (approximate) incorporation of these complex constraints in the developed model without deteriorating significantly its computational performance.

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VIII. Biographies

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