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The role of demand response in mitigating market power - A quantitative analysis using a stochastic market equilibrium model

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Abstract: *Market power is a dominant feature of many modern electricity markets with an oligopolistic structure, resulting in increased consumer cost. This work investigates how consumers, through demand response (DR), can mitigate against market power. Within DR, our analysis particularly focusses on the impacts of load shifting and self-generation. A stochastic mixed complementarity problem is presented to model an electricity market characterised by oligopoly with a competitive fringe. It incorporates both energy and capacity markets, multiple generating firms and different consumer types. The model is applied to a case study based on data for the Irish power system in 2025. The results demonstrate how DR can help consumers mitigate against the negative effects of market power and that load shifting and self-generation are competing technologies, whose effectivity against market power is similar for most consumers. We also find that DR does not necessarily reduce emissions in the presence of market power.*

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1. INTRODUCTION

Many modern, deregulated wholesale electricity markets are still characterised by an oligopolistic structure on the generation side. As a result, the exertion of market power (MP) by electricity generation companies, leading to increased consumer costs and social welfare losses, has been a concern and research topic since the 1990s.

Much of the research in the past has focused on the sources of market power, the proposition of different indices (e.g., based on market shares/concentration) for analysing market power or simulation analysis to estimate price making behaviour (for an overview, see David and Wen, 2001; Karthikeyan et al., 2013). Moreover, researchers have proposed alternative approaches to mitigate market power, including the limitation of individual market players' shares (Green and Newbery, 1992), the expansion of transmission and generation capacity or price caps (Blumsack et al., 2002), the ease of market entry (Dalton et al., 1997), or increasing demand side flexibility (Borenstein and Bushnell, 1999; Caves et al., 2000), e.g., through demand response (DR). As for the latter, DR is a large topic of research, within which Albadi and El-Saadany (2008) distinguish between (i) load reduction/shedding, (ii) load shifting and (iii) customer owned distributed self-generation. Numerous studies exist that analyse the impact of DR on power systems operation (e.g., Su and Kirschen, 2009; Hu et al., 2016) and planning (e.g., De Jonghe et al., 2012; Bertsch et al., 2018; Devine et al., 2019), all in a perfect market context. However, studies analysing the impact of DR on imperfect markets are rare. The main body of research in this area is limited to reflecting the consumers' demand flexibility through self-price elasticity, i.e. load shedding, only (e.g., see Hobbs et al., 2000; Li and Shahidehpour, 2005; Neuhoff et al., 2005). The only exceptions known are Shafie-Khah et al. (2016) and Ye et al. (2017), considering the cross-price elasticity of consumers' electricity demand, hence capturing the time-coupling characteristics of load shifting. However, Shafie-Khah et al. (2016) use an agent-based model to simulate the imperfect market rather than a mathematically thorough equilibrium programming model. In contrast, Ye et al. (2017) focus on analysing the impact of load shifting on market power of generators using a mathematical program with equilibrium constraints (MPEC) in an energy only market context.

In general, analysing the impact of DR on imperfect markets, and in doing so going beyond the mere consideration of self-price elasticity, is a highly relevant research topic for different reasons. On the one hand, such analyses will help understand the role DR (embracing shifting, shedding and self-generation) can take in mitigating market power; hence help understand how market efficiency can be increased. On the other hand, this is important when assessing the value of DR, or demand side flexibility more generally, which may be underestimated when only considering DR in a perfect market context.

To date, however, existing research on the impact of DR on market power does not consider self-generation in addition to load shifting or shedding, i.e. a comprehensive picture of the impact of DR is missing. Moreover, research considering shedding through self-price elasticity does usually not capture the fact that elasticity is not constant (i) between consumer groups, (ii) over time or (iii) over different amounts of load reduction (Devine and Bertsch, 2018) (for instance, small load reductions may only lead to low-cost effects such as reduced illumination, whereas larger load reductions may lead to higher losses for different groups of consumers (Ruppert et al., 2015)). In addition, existing research in this field is limited to energy only market settings and does not account for the stochasticity of renewable generation, despite the fact that the importance of stochastic modelling of variable renewable generation is well established in the literature (see Ambec and Crampes, 2012), in particular for a high-renewable scenario such as the one examined in this paper.

We therefore present a stochastic Mixed Complementarity Problem (MCP), where the individual optimisation problems of each player are solved simultaneously and in equilibrium. MCPs have been used to model various types of energy markets (Hobbs, 2001; Huppmann, 2013; Lynch and Devine, 2017; Devine et al., 2016). MCPs allow both primal variables (e.g., power generation) and dual variables (e.g., prices) to be constrained together (Gabriel et al., 2012) while also allowing players with constrained optimisation problems to be modelled as either price-takers or price-makers, hence, incorporating market power into such models (Gabriel et al., 2005; Lee, 2016).

Using this model, the present paper fills several gaps in the literature. First, our model considers load shifting, load shedding and self-generation on the demand side when analysing the impact of DR on market power. Moreover, it distinguishes between residential and industrial/commercial consumer groups with and without solar PV or controllable micro-generation, all of whom have the objective of minimising their costs. This is in contrast to most existing literature, where system demand is modelled as one time series rather than distinguishing between consumer groups. In addition, in relation to the generating firms, our model considers revenues from an energy market, a quantity-based capacity market and an additional feed-in premium (FIP) for any renewable generation. This modelling of three different revenue streams on the supply side is more representative of modern electricity markets and represents an important advance on the state-of-the-art. Finally, our model accounts for the stochasticity of the renewable generation.

All firms in the model maximise their profits by optimising the hourly dispatch of their portfolio. When modelling market power, we consider an oligopoly with a competitive fringe where the two largest firms, the integrated firm and the specialised midload firm, exert market power and are price-makers. The remaining firms are modelled as price-takers. Traditionally, price-makers have been modelled using simple linear demand curves ($Demand = A - B \times Price$). However, in this work, we model price-makers by combining a supply-demand equation specific to a consumer group with the KKT conditions of that group (Devine and Bertsch, 2018).

The overarching research questions addressed through model-based analyses in this paper are: To which extent can DR help mitigate the impact of MP on...

1. ... costs for different consumers?
2. ... generator profits?
3. ... carbon emissions?

We apply the model developed to a case study based on data for the Irish power system in 2025. This system has a high penetration of wind power and a significant presence of smart meters (Comission for Energy Regulation, 2014). As in Bertsch et al. (2018), we hypothesise that there will be an aggregator who acts on behalf of the consumers Burger et al. (2017); Good et al. (2017) using the smart metering infrastructure with the objective of minimising their energy supply costs since, in reality, most consumers would not want to decide themselves whether or not and when to shift or shed any load.

The remainder of this paper is structured as follows: In section 2, we introduce the mathematical model. In section 3, we describe the data while, in section 4, we present our results. In section 5, we discuss the findings and draw conclusions.

2. METHODOLOGY

Table 1: Indices and sets.

$f \in F$	Generating firms
$t \in T$	Generating technologies
$p \in P$	Time periods
$k \in K$	Consumers groups
$s \in S$	Scenarios
$h \in H$	Time steps in storage/load shifting period
$p' \in P' = \{1, \lvert H \rvert + 1, 2\lvert H \rvert + 1, \ldots\} \subseteq P$	Index representing starting points for storage period

Note: sets contain a finite amount of non-zero natural numbers.

Table 2: Variables.

Firms' primal variables	
$gen_{f,t,p,s}$	Generation from firm f with technology t in period p and scenario s
$cap^{\text{bid}}_{f,t}$	Capacity bid of firm f with technology t
Consumers' primal variables	
$g^{\text{ls}}_{k,p,s}$	Load shedding from consumer group k in period p and scenario s
$g^{\text{up}}_{k,p,s}$	Electricity stored for later time point from consumer group k in period p and scenario s
$g^{\text{down}}_{k,p,s}$	Electricity used from storage from consumer group k in period p and scenario s
$g^{\text{micro}}_{k,p,s}$	Micro generation from consumer group k in period p and scenario s
$g^{\text{pv}}_{k,p,s}$	PV generation from consumer group k in period p and scenario s
Dual variables	
$\gamma_{p,s}$	System price for time period p and scenario s
κ	Unit capacity price
$\lambda^{\#}_{.}$	Lagrange multipliers associated with constraint # of the firms' problem
$\mu^{\#}_{.}$	Lagrange multipliers associated with constraint # of the firms' problem consumers' problem

Note: '.' is used as a place-holder as the subscripts for both Lagrange multipliers vary depending the on constraint.

Table 3: Parameters.

PR_s	Probability associated with scenario s
MTC_t	Maintenance cost form generating technology t
$CAP_{f,t}$	Generating capacity for firm f with technology t
$D^{\text{REF}}_{k,p}$	Reference demand for consumer group k in period p and scenario s
$LOSS_k$	Storage loss factor for consumer group k
$G^{\text{LS,MAX}}_k$	Maximum load shedding for consumer group k in any time period or scenario
INT^{STOR}_k	Electrical storage/ load shifting capacity for consumer group k
INT^{MICRO}_k	Micro generation capacity for consumer group k
INT^{PV}_k	PV generating capacity for consumer group k
FAC^{STOR}_k	Percentage of electrical storage capacity electricity consumer group k can use in each period and scenario
$NORM^{\text{PV}}_{p,s}$	PV generating profile for period p and scenario s
$NORM^{\text{G}}_{f,t,p,s}$	Generating profile for firm f with technology t in period p and scenario s
$TARGET$	Capacity target for overall market
X_t	Feed-In premium for technology t
X^{PV}	Feed-In premium for PV
$PM_{f,t}$	Binary parameter used to indicate whether firm f's generating unit for technology t is a price making unit ($PM_{f,t}$ = 1) or price taking unit ($PM_{f,t}$ = 0).
DR_t	De-rating factor for technology t
$A^{\cdot}_{\cdot}$	Intercept associated with marginal cost functions
$B^{\cdot}_{\cdot}$	Slope associated with marginal cost functions
$C^{\text{PV}}_{k,p}$	Marginal cost of using PV generation for consumer group k in period p

Table 4: Functions.

$C^{\text{GEN}}_t(.)$	Marginal cost function for technology t
$C^{\text{LS}}_{k,p}(.)$	Load shedding operational cost for consumer group k in period p
$C^{\text{MICRO}}_{k,p}(.)$	Operational cost of using micro generation for consumer group k in period p

In this section, the methodology is presented. We utilise a stochastic MCP to represent an electricity market with two types of players: generation firms and electricity consumer groups. The model is similar to the model developed in Bertsch et al. (2018) but with the following differences:

1. Generation firms may be modelled as either price-takers or price-makers, i.e., the model can incorporate market power.

2. We only consider operational decisions and do not consider investment and decommissioning decisions. This is because the focus of the paper is to understand how operational decisions on the demand side, such as load shifting and micro-generation, can mitigate market power on the supply side.

Firms receive revenues from energy and capacity markets as well as a FIP and seek to maximise profits. As in Bertsch et al. (2018), the capacity payment mechanism we consider is a quantity based mechanism. Firms may hold multiple generating units of baseload, mid merit, peakload and wind technology. They are distinguished by the generation portfolio they hold and by the ability to exercise market power.

On the demand side, we consider a number of different consumer groups, including commercial/industrial as well as residential consumers. Consumers minimise the cost of meeting their demand. They do so by utilising a range of possible demand-side flexibility measures, such as load shedding, load shifting, PV generation or thermal micro-generation. We do not model individual consumers but rather consider different consumer groups, in a similar manner to that outlined in Bertsch et al. (2018), whose decisions represent the aggregate actions of consumers in these groups. Consumer groups are distinguished by different levels of demand-side flexibility capability, by their demand profiles and by the ability to self-generate electricity through PV modules or thermal micro-generation.

The stochasticity of the model arises from the uncertainty surrounding wind and PV power. Thus, each scenario in our model corresponds to different RES generation profiles, i.e. varying levels of wind and solar power availability at each point in time, which are correlated, both temporally and spatially (Bertsch et al., 2018).

Each of the generation firms and consumer groups considered have separate optimisation problems that are connected through market clearing conditions. The stochastic MCP is made up of these market clearing conditions along with the Karush-Kuhn-Tucker (KKT) conditions for optimality from each of the players. Thus, the MCP solves the optimisation problem of each player simultaneously and in equilibrium.

Throughout this section the following conventions are used: lower-case Roman letters indicate indices or primal variables, upper-case Roman letters represent parameters (i.e., data, functions), while Greek letters indicate prices or dual variables. The variables in parentheses alongside each constraint in this section are the Lagrange multipliers associated with those constraints.

2.1 Firm f's problem

Firm f maximises its expected profits (revenues less cost) by choosing the amount of generation, the quantity of capacity bid. Firm f considers revenues received from a capacity and an energy market as well as a FIP for RES generation. Its costs consist of generation costs and any costs incurred for maintaining its units.

Firm f's optimisation problem is:

$$\max_{\substack{gen_{f,t,p,s},cap^{\text{bid}}_{f,t},\\ exit_{f,t}}} \sum_{t,p,s} \Big(PR_s \times gen_{f,t,p,s} \times \left(\gamma_{p,s} + X_t - C^{\text{GEN}}_t(gen_{f,t,p,s})\right)\Big) - \sum_t \left(CAP_{f,t} \times MTC_t\right) + \sum_t DR_t \times \kappa \times cap^{\text{bid}}_{f,t}, \tag{1a}$$

subject to:

$$gen_{f,t,p,s} \leq CAP_{f,t} \times NORM^{\text{G}}_{f,t,p,s}, \;\; \forall t,p,s, \;\; (\lambda^1_{f,t,p,s}), \tag{1b}$$

$$cap^{\text{bid}}_{f,t} \leq CAP_{f,t}, \;\; \forall t, \;\; (\lambda^2_{f,t}), \tag{1c}$$

where the marginal cost of generating with technology t is

$$C^{\text{GEN}}_t(x) \quad = \quad A^{\text{GEN}}_t + B^{\text{GEN}}_t x, \tag{2}$$

which means the overall cost of generating electricity with technology t is quadratic. Constraints (1b) and (1c) constrain the amount of energy generated by and the capacity bid of firm f. In addition, each of firm f's primal (decision) variables are also constrained to be non-negative.

The capacity price paid for each unit of capacity bid accepted is κ. It is exogenous to firm f's problem but is a variable of the overall problem, determined via the market clearing condition (8b). The energy price at each period and scenario is $\gamma_{p,s}$. If firm f is a price taker then its decision variables cannot affect this price (i.e., $\frac{\partial \gamma_{p,s}}{\partial gen_{f,t,p,s}} = 0$). In this case, $\gamma_{p,s}$ is exogenous to firm f's problem but is a variable of the overall problem, determined via the market clearing condition (8a). If firm f's generating unit for technology t is assumed to be a price-maker unit, then its generation decision variable for that unit ($gen_{f,t,p,s}$) can affect the energy price. As a result, we derive the following relationship between the energy price and generation:

$$\begin{aligned} gen_{f,t,p,s} = & \sum_k \left(D^{\text{REF}}_{k,p} + g^{\text{up}}_{k,p,s} - LOSS_k g^{\text{down}}_{k,p,s} - g^{\text{pv}}_{k,p,s}\right) \\ & - \sum_k \frac{\gamma_{p,s} - A^{\text{LS}}_{k,p} + \mu^1_{k,p,s} + \mu^8_{k,p,s}}{B^{\text{LS}}_{k,p}} \\ & - \sum_k \frac{\gamma_{p,s} - A^{\text{MICRO}}_{k,p} + \mu^4_{k,p,s} + \mu^8_{k,p,s}}{B^{\text{MICRO}}_{k,p}} \\ & - \left(\sum_{\hat{f},t} \frac{\gamma_{p,s} + X_t - A^{\text{GEN}}_t + \lambda^1_{\hat{f},t,p,s}}{B^{\text{GEN}}_t}\right) + \frac{\gamma_{p,s} + X_t - A^{\text{GEN}}_t + \lambda^1_{f,t,p,s}}{B^{\text{GEN}}_t}, \end{aligned} \tag{3}$$

where the parameters and variables not mentioned already are parameters and variables from the consumers' problem (section 2.2) and hence exogenous to firm f's problem. Equation (3) is determined by combining market clearing condition (8a) with the KKT conditions that determine how consumers shed their load (10a), utilise micro-generation (10d), and the KKT conditions that determine how firms generate (9a) (all except firm f's unit t). The remaining KKT conditions cannot be used as they cannot be substituted into (8a). For price-making firms, this relationship is substituted into firm f's objective function (1a) leading to

$$\frac{\partial \gamma_{p,s}}{\partial gen_{f,t,p,s}} = -\left(\frac{1}{\sum_k \frac{1}{2B^{\text{LS}}_{k,p}}} + \frac{1}{\sum_k \frac{1}{2B^{\text{MICRO}}_{k,p}}} + \frac{1}{\left(\sum_{\hat{f},t} \frac{1}{2B^{\text{GEN}}_t}\right) - \frac{1}{2B^{\text{GEN}}_t}}\right). \tag{4}$$

Equation (4) represents firm f's conjectural variation of how it believes it can influence $\gamma_{p,s}$ with its generation decisions. If firm f is a price-taker, then its problem is convex assuming B^{GEN}_t $\forall t$. If firm f's generating unit for technology t is a price-maker, then its problem is strictly convex, assuming $B^{\text{GEN}}_t > 0$, $B^{\text{LS}}_{k,p} > 0$, and $B^{\text{MICRO}}_{k,p} > 0$, $\forall k, p, t$.

The firms' KKT conditions are presented in appendix A.1. Note: $PM_{f,t}$ is a binary parameter that is used in the KKT conditions to indicate whether firm f's generating unit for technology t is a price making unit ($PM_{f,t} = 1$) or price taking unit ($PM_{f,t} = 0$).

2.2 Consumer group k's problem

Consumer group k's optimisation problem is the same as that presented in Bertsch et al. (2018) where each consumer group minimises the cost of meeting their expected demand. As part of their optimisation problem, they may choose to (partially) shed their load or to (partially) self-generate using solar PV or thermal micro generation. For PV generation, they receive a FIP. Consumer group k may also shift some of their demand and obtain less from the grid. We consider shifting in the same way as electrical storage where consumers may obtain electricity from electrical storage.

Consumer group k's optimisation problem is:

$$\begin{aligned}\min_{\substack{g^{\text{ls}}_{k,p,s}, g^{\text{up}}_{k,p,s}, g^{\text{down}}_{k,p,s},\\ g^{\text{micro}}_{k,p,s}, g^{\text{pv}}_{k,p,s}}} \sum_{s,p} PR_s \Big(& \gamma_{p,s} \times \left(D^{\text{REF}}_{k,p} - g^{\text{ls}}_{k,p,s} + g^{\text{up}}_{k,p,s} - (1 - LOSS_k) g^{\text{down}}_{k,p,s} - g^{\text{micro}}_{k,p,s} - g^{\text{pv}}_{k,p,s} \right) \\ & - X^{\text{PV}} \times g^{\text{pv}}_{k,p,s} + g^{\text{ls}}_{k,p,s} \times C^{\text{LS}}_{k,p}(g^{\text{ls}}_{k,p,s}) + g^{\text{micro}}_{k,p,s} \times C^{\text{MICRO}}_{k,p}(g^{\text{micro}}_{k,p,s}) + g^{\text{pv}}_{k,p,s} \times C^{\text{PV}}_{k,p} \Big)\end{aligned} \tag{5a}$$

subject to

$$g^{\text{ls}}_{k,p,s} \leq G^{\text{LS,MAX}}_k, \ \forall p, s, \ (\mu^1_{k,p,s}), \tag{5b}$$

$$g^{\text{up}}_{k,p,s} \leq FAC^{\text{STOR}}_k \times INT^{\text{STOR}}_k, \ \forall p, s, \ (\mu^2_{k,p,s}), \tag{5c}$$

$$g^{\text{down}}_{k,p,s} \leq FAC^{\text{STOR}}_k \times INT^{\text{STOR}}_k, \ \forall p, s, \ (\mu^3_{k,p,s}), \tag{5d}$$

$$g^{\text{micro}}_{k,p,s} \leq INT^{\text{MICRO}}_k, \ \forall p, s, \ (\mu^4_{k,p,s}), \tag{5e}$$

$$g^{\text{pv}}_{k,p,s} \leq NORM^{\text{PV}}_{p,s} \times INT^{\text{PV}}_k, \ \forall p, s, \ (\mu^5_{k,p,s}), \tag{5f}$$

$$\sum_{e=p'}^{p'+h-1} \left(g^{\text{up}}_{k,e,s} - g^{\text{down}}_{k,e,s} \right) \leq INT^{\text{STOR}}_k, \ \forall s, p', h, \ (\mu^6_{k,p',h,s}), \tag{5g}$$

$$\sum_{e=p'}^{p'+h-1} \left(g^{\text{down}}_{k,e,s} - g^{\text{up}}_{k,e,s} \right) \leq 0, \ \forall s, p', h, \ (\mu^7_{k,p',h,s}), \tag{5h}$$

$$g^{\text{ls}}_{k,p,s} + (1 - LOSS_k) g^{\text{down}}_{k,p,s} + g^{\text{micro}}_{k,p,s} + g^{\text{pv}}_{k,p,s} \leq D^{\text{REF}}_{k,p} + g^{\text{up}}_{k,p,s}, \ \forall p, s, \ (\mu^8_{k,p,s}), \tag{5i}$$

The marginal cost functions associated with load shedding and micro generation are:

$$C^{\text{LS}}_{k,p}(x) = A^{\text{LS}}_{k,p} + B^{\text{LS}}_{k,p} x, \tag{6}$$

$$C^{\text{MICRO}}_{k,p}(x) = A^{\text{MICRO}}_{k,p} + B^{\text{MICRO}}_{k,p} x. \tag{7}$$

Constraint (5b) limits the amount of electricity consumer group k can shed. Similarly, constraints (5c) and (5d) limit the amount of their demand they increase and decrease, respectively, i.e., these constraints limit the amount of electricity they can shift/store. Constraints (5e) and (5f) limit the amount of electricity consumer group k can self-generate from micro- and PV generation, respectively.

Constraint (5g) ensures consumer group k cannot, over a $|H|$-timestep period, store/shift more electricity than its storage capacity. Constraint (5h) ensures consumer group k cannot, over the same $|H|$-step time period, use more electricity for meeting demand than what has already been stored/shifted. Constraints (5g) and (5h) also ensure that any electricity stored/shifted in a $|H|$-timestep period cannot be used in any other $|H|$-timestep period. In Section 4, we set $|H| = 48$ as we believe this storage (load shifting) horizon is reasonable given the daily trough and peak structure of electricity demand.

Constraint (5i) ensures any electricity generated by consumer group k must be less than their reference demand (the demand consumers have in absence of any demand side flexibilities). In other words, constraint (5i) ensures consumer group k's own generation cannot be used to meet other consumers' demand.

Consumer group k's problem is convex, assuming all values for $B^{\text{LS}}_{k,p}$ and $B^{\text{MICRO}}_{k,p}$ are non-negative. Its KKT conditions are the same as those presented in Appendix A.2 of Bertsch et al. (2018).

2.3 Market clearing conditions

The optimisation problems of each player are connected via the following market clearing conditions:

$$\sum_{f,t} gen_{f,t,p,s} = \sum_{k} \left(D^{\text{REF}}_{k,p} - g^{\text{ls}}_{k,p,s} + g^{\text{up}}_{k,p,s} - LOSS_k g^{\text{down}}_{k,p,s} - g^{\text{micro}}_{k,p,s} - g^{\text{pv}}_{k,p,s}\right),\ \forall p,s,\ (\gamma_{p,s}), \quad (8a)$$

$$\sum_{f,t} DR_t \times cap^{\text{bid}}_{f,t} = TARGET,\ (\kappa), \quad (8b)$$

Market clearing condition (8a) ensures that the total amount of electricity generated by the firms must equal the sum of the consumers' demand. Consumers' demand consists of their reference demand plus any electricity they shift/store less any electricity they shed or generate themselves. Reference demand represents consumers' demand in the absence of any demand response. Equation (8b) ensures that the sum of capacity bids from firms, times a derating factor[1], must equal the capacity target.

Assuming each of the players' optimisation problems are convex, the KKT conditions are both necessary and sufficient for optimality (Gabriel et al., 2012). Thus, the stochastic MCP consists of the KKT conditions of all players in addition to the market clearing conditions. The problem is solved in GAMS using the PATH solver.

3. MODEL INPUTS

In the previous section we presented the MCP used in this work. In this section, we describe the model's input data. As our case study considers the future Irish power system, we base our data for 2025 on EirGrid (2017). Firstly, in section 3.1, we describe the demand-side data. Secondly, in section 3.2, we present the conventional supply side data while, finally, in section 3.3, the renewable generation data is considered.

3.1 Demand side data

The consumer groups considered in this work include residential consumers in addition to commercial/industrial consumers. Figure 1 displays the reference demand ($D^{\text{REF}}_{k,p}$) of the industrial and residential consumer groups on a typical day. It shows that the residential demand profile has a peak that is more pronounced than the industrial one. Based on EirGrid (2017), we assume total annual electricity demand of 33.6 TWh and peak demand of 5655 MW.

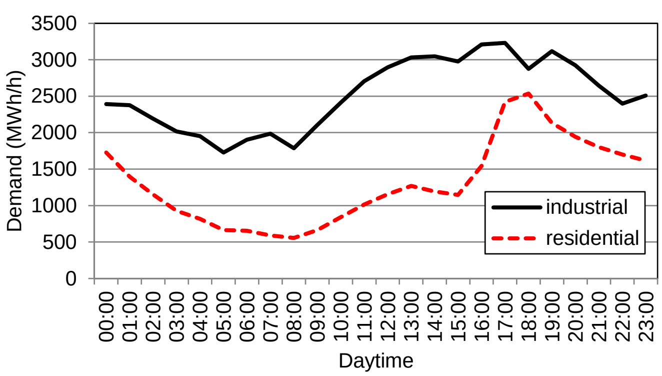


Figure 1: Reference demand of industrial and residential consumers on a typical day

In total, we consider six different consumer groups, three residential and three commer-

[1]The derating factor in this work reflects the proportion of its overall capacity a technology can provide to meet the capacity target.

cial/industrial. The difference between the groups is in the amount of installed micro-generation and PV capacity they hold, as described by Table 5. For the different test-cases analysed in section 4, we consider micro-generation capacities that are 0%, 33%, 67% and 100% of the values presented in Table 5, which corresponds to 0%, 3%, 7% and 10% of the system level peak demand, respectively. For PV generation, the installed capacities remain fixed across the test cases.

Table 5: Consumer group characteristics.

Group	Type	PV Capacity (MW) (INT_k^{PV})	Micro-Generation Capacity (MW) (INT_k^{MICRO})	Shifting Capacity (MW) (INT_k^{STOR})	% of overall demand
1	Industrial	0	0	2749	53.9%
2	Industrial	0	500	413	10.5%
3	Industrial	50	0	69	1.4%
4	Residential	0	0	2324	31.4%
5	Residential	0	100	106	1.4%
6	Residential	50	0	106	1.4%

Each consumer group can shift their load and Table 5 displays the total amount they can decrease their demand by over a 48-hour period, without increasing again it in that same time horizon. These values are taken from Bertsch et al. (2018). The percentage values of these capacities each consumer group can shift in each individual hour (FAC_k^{STOR}) varies from 0% to 20%. Following Nolan et al. (2017), we assume the quantity target for the capacity market is 1.2 times the system peak demand, i.e. $TARGET = 1.2 \times 5655$ MW = 6786 MW.

3.2 Conventional power generation data

On the supply side, we consider five power generating firms with different generation portfolios. These include specialised baseload, mid merit, peakload and renewable firms in addition to an integrated firm with generation capacity across all of these technologies. Based on EirGrid (2017), the maximum capacities by technology and firm are presented in Table 6.

Table 6: Maximum geneartion capacity (MW) by firm ($CAP_{f,t}$).

Technology	firm 1	firm 2	firm 3	firm 4	firm 5
Existing baseload	900	200	-	-	-
Existing mid merit	800	-	1250	-	-
Existing peakload	200	-	-	500	-
New baseload	750	-	-	-	-
New mid merit	500	-	800	-	-
New peakload	300	-	-	-	-
Wind	2400	-	-	-	2400

The firms' optimisation problems considers quadratic cost functions for the conventional generators as described in section 2.1. In other words, the marginal costs at the intercept increase with the power output of each generator according to the marginal cost slope $B_t^{\text{GEN}} = 0.000213$ (see

Grigg, 1996).

To derive marginal power generation costs at the intercept, we follow Bertsch et al. (2018) and assume power plant efficiencies of 30% for existing baseload generators, 50% for existing mid merit generators and 32% for existing peakload generators[2]. To calculate marginal costs of the new technologies at the intercept, we assume efficiencies of 45% for baseload, 60% for mid merit and 40% for peakload. The marginal costs in Table 7 were calculated using gas, coal and CO_2 prices of the corresponding futures markets for 2017 as obtained from the European Energy Exchange (www.eex.com). For this purpose, we used the average market results of the futures markets for 2017 as traded during 2016. Coal and CO_2 prices are used to calculate variable generation costs of baseload generation, while gas and CO_2 prices are used for determining the variable costs of peakload and mid merit generation, i.e., peakload generators are assumed to be open cycle gas turbines while mid merit generators are assumed to be combined cycle gas turbines (CCGT).

Table 7: Techno-economic input data of supply side technologies.

Technology	Fixed O & M costs (€/MW y) (MTC_t)	Marginal power gen. costs at intercept (€/MWh$_{el}$) (A_t^{GEN})	Spec. CO_2 emissions (t CO_2/MWh$_{el}$)
Existing baseload	41,667	49	1.17
Existing mid merit	27,778	41	0.36
Existing peakload	23,148	63	0.56
New baseload	41,667	32	0.78
New mid merit	27,778	34	0.30
New peakload	23,148	51	0.45

3.3 Renewable power generation data

The variable sources of renewable electricity generation considered in this paper are wind and solar PV. As with Bertsch et al. (2018) and Lynch et al. (2019), data from the MERRA2 reanalysis (Bosilovich et al., 2016) were used to generate input data for these two sources. Note that wind and solar PV are not only variable but also uncertain and their uncertainties are correlated since both depend on the meteorological conditions. Therefore accounting for these correlations is important when providing input data for the stochastic MCP.

The analysis is based on hourly MERRA2 data on surface incoming shortwave flux, wind speed and air temperature for the years 1981 to 2015 inclusive. This data was transformed to wind and solar capacity factors. For solar PV, the transformation follows Ruppert et al. (2016) and Schwarz et al. (2018) using parameters for Ireland, described in Bertsch et al. (2017). For wind, the transformation

[2]In an Irish context, these efficiencies may lead to existing baseload generation having higher variable power generation costs than existing mid merit generators.

is based on the method from Cradden et al. (2017) and Cannon et al. (2015) and the wind speed to capacity factor curve by Ofgem (2013). For computational reasons, the hourly wind and solar capacity factor time series of 35 years were then clustered into six representative years.

Details of the renewable data generation and the clustering procedure are described in Bertsch et al. (2018) while the probabilities and chosen years of occurrence are summarised in Table 8. To ensure that the spatial and temporal correlations between wind and PV are preserved, we use these historical wind and PV data as a basis for our analysis. As Table 5 indicates, we consider 50 MW of solar PV capacity, which are installed on the demand side. Furthermore, Table 6 shows that we consider 4800MW of installed wind capacity. We base these assumptions around installed RES-E capacity estimates for 2025 from EirGrid (2017).

Table 8: Representative years chosen for RES scenarios and corresponding probabilities of occurrence (see Bertsch et al., 2018).

Year	1983	1998	2001	2003	2004	2015
Probability of occurrence	0.486	0.286	0.086	0.086	0.029	0.029

We assume a FIP payment of $X_t = X^{\mathrm{PV}} = 23$ €/MWh for wind and PV generation. These values are obtained from Farrell et al. (2017). A FIP is not considered for any other technology. For both wind and solar we assume a marginal generating cost of zero.

4. RESULTS

In this section, we present the results of our work, focusing on how DR can help mitigate the impact of MP on consumer costs, firms' profits and emission levels. As described in the previous section, we exogenously vary the amount of installed micro-generation capacity consumers have and the percentage of their total load shifting capacity they can use in each hour. In addition, we also consider test cases where the market is perfectly competitive, i.e., all players are price takers, and test cases where market power is present. For the cases with market power, we consider an oligopoly with a competitive fringe. The price making oligopolists are the integrative firm and the specialised mid-merit firm. The price taking competitive fringe includes firms 2, 4 and 5.

When describing the results, we focus on load shifting and its interactions with micro-generation. While consumers are also capable of shedding their load, as described in the previous section, the results show minimal amounts of this behaviour. In the perfect competition cases, we see no load shedding throughout the market. In the market power cases, residential consumers also choose not to shed any of their demand while the maximum average amount of the load that industrial consumers choose to shed is 2.7MWh in a particular peak hour. These results can be explained by the capacity portfolio considered in this case study, which is large enough to meet consumers peak demand. Consequently, we do not concentrate on load shedding in the results to follow.

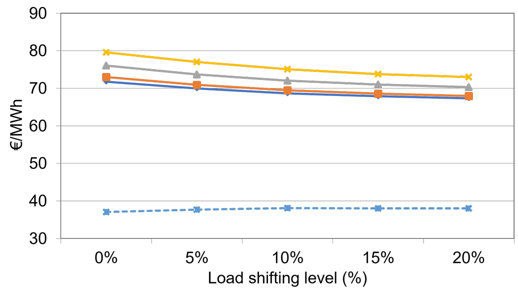
This section is organised as follows: in section 4.1 we present the consumer costs results whereas in section 4.2 we describe the results in relation to the generating firms' profits. Finally, in section 4.3, the emissions results are presented.

4.1 Consumer costs

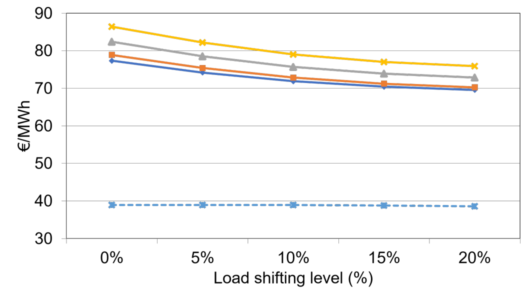
Figure 2 displays expected consumer cost (weighted average by demand) for each of the consumer groups in the absence and presence of market power for different levels of load shifting and micro-generation capacity. These values are calculated using equation (5a) and by dividing by each group's total yearly demand. When market power is present in the market, Figure 2 shows that costs increase substantially for each of the consumer groups and that DR can generally help mitigate against these effects.

More specifically, increasing the amount of micro-generation in the market decreases the costs for each group. This is despite the fact that only consumer groups 2 and 5 have micro-generation capacity. These results suggest that micro-generation can help restrict generation firms' ability to exert market power and thus benefit all consumer groups even if they do not hold such capacity themselves. Figure 2 also shows that, while there are noticeable differences between the 0MW, 200MW and 400MW cases, there is little difference between the 400MW and 600MW cases, in terms of consumer costs. This suggests that once a significant amount of micro-generation is installed on the system (400MW in this case), the marginal benefits of micro-generation decrease.

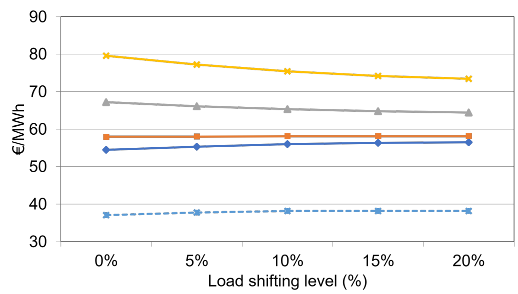
As for load shifting, Figures 2a, 2b, 2e and 2f show that, in the presence of market power, shifting can also reduce costs of consumers, particularly of those without their own micro-generation. This holds for industrial consumer groups 1 and 3 in addition to residential consumer groups 4 and 6, and regardless of the level of micro-generation in the system. The relative cost decrease, from 0% load shifting to 20%, is greater for residential consumers than industrial consumers. The percentages are 6%, 7%, 10% and 12% for groups 1, 3, 4 and 6, respectively (assuming 600MW of micro-generation). These results can be explained by the consumers' load curves (Figure 1) and the price duration curves (Figure 3b). Residential consumers' peak demand is far more pronounced than that of industrial consumers. Hence, shifting some of their demand from the peak to off-peak time periods, allows residential consumers to make higher savings.



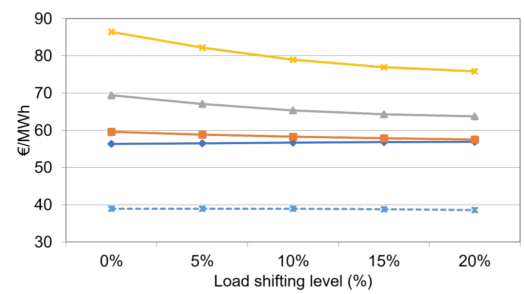
(a) Consumer group 1 (Industrial, w/o PV, w/o Micro-gen)



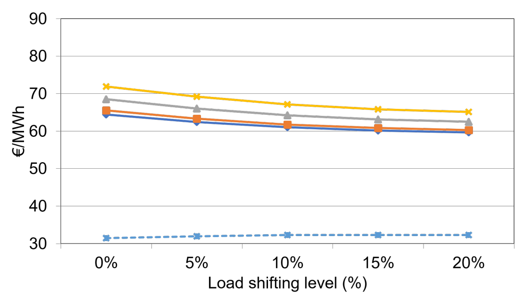
(b) Consumer group 4 (Residential, w/o PV, w/o Micro-gen)



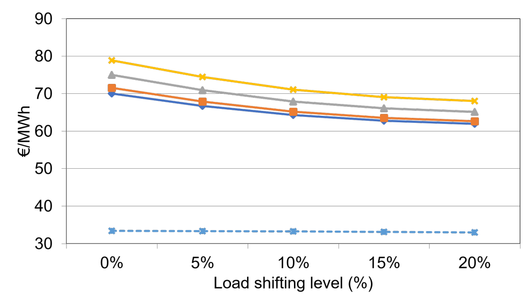
(c) Consumer group 2 (Industrial w Micro-gen)



(d) Consumer group 5 (Residential w Micro-gen)



(e) Consumer group 3 (Industrial w PV)



(f) Consumer group 6 (Residential w PV)

600 MW   400 MW   200 MW   0 MW   600 MW (No MP)

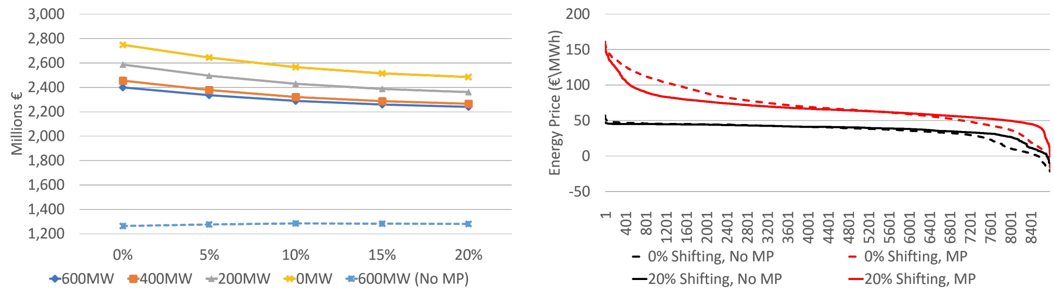
Figure 2: Expected consumer cost (weighted average by demand) for different levels of load shifting, both with (continuous lines) and without (dashed lines) market power. The legend describes the different micro-generation levels, which broadly correspond to 0%, 3%, 7% and 10% of system level peak demand.

For consumers with their own micro-generation, Figures 2c and 2d show that load shifting can also help reduce their costs. However, this is only when these consumers have low levels of or no micro-generation. When consumer groups 2 and 5 have 400MW of micro-generation installed, these results show that load shifting does not reduce their costs anymore. In fact, for industrial group 2, load shifting slightly increases their costs, when 600MW of micro-generation and market power are present. These lacks of reduction can be explained by the fact that micro-generation only becomes profitable to utilise when prices are high. Consequently, when prices are high, micro-generation reduces consumer costs without the need to increase off-peak prices and costs, which is in contrast to load shifting.

Comparing load shifting and micro-generation as to how they can help mitigate against the consumer cost increase resulting from market power, our findings show that these technologies compensate one another, i.e. the effect of load shifting decreases when the level of micro-generation in the system increases and vice versa. Moreover, we find that the relative effects of micro-generation and shifting generally have a similar magnitude (varying between 6-14%), where micro-generation has a slightly higher relative cost reduction effect for industrial consumers, whereas shifting has a slightly higher effect for residential consumers. This finding holds except for the consumers that have their own micro-generation (i.e. consumer groups 2 and 5). For these two consumer groups, the relative cost reduction of micro-generation in the presence of market power is significantly higher (varying between 25-35%), whereas the relative effect of shifting is lower (0-8%).

Moreover, Figure 2 also shows that consumers with installed PV capacity (groups 3 and 6) have smaller expected average costs when compared with consumers with no PV or micro-generation (groups 1 and 4). This holds regardless of the level of micro-generation, load shifting or market power presence in the overall market. It also holds when we compare residential groups 5 and 6. Likewise, when industrial groups 2 and 3 are compared, we observe similar results when there are 0MW and 200MW of micro-generation and when there is no market power present in the market. However, in contrast, when there are 400MW and 600MW of micro-generation and market power in the market, group 2 has lower average costs than group 3. This can be explained by the fact that PV and peak demand are negatively correlated. Thus, in peak demand time periods, intermittent PV generation is less likely to be able to meet demand. In contrast, micro-generation is most beneficial to consumers in such high demand time periods. This finding suggests that relatively large amounts of micro-generation are superior to PV in reducing the high prices resulting from market power.

In addition, Figure 3a displays the total consumer costs summed across the different groups'



(a) Total expected consumer costs **(b) Price duration curve (600MW of micro-generation)**

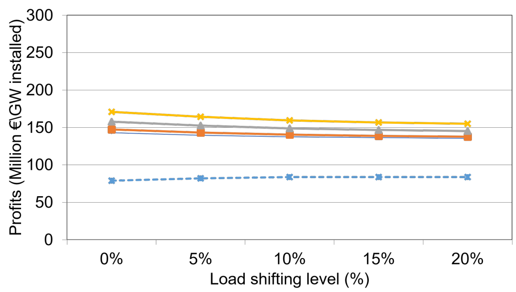
Figure 3: Total consumer costs and price duration curves, with (MP) and without (No MP) market power.

objective functions. As mentioned above, it generally shows that both load shifting and micro-generation can help reduce consumer costs, hence contribute to mitigating the impact of market power on consumers. Despite this, it is also important to note, that even when there is 600MW of installed micro-generation and consumers are able to shift 20% of total shifting capacity in each hour, consumer costs are still significantly higher than in the perfect competition case.

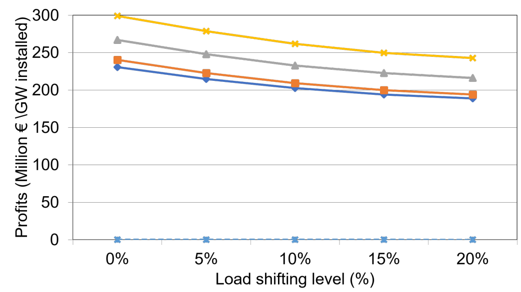
On a side note, in a perfectly competitive market, load shifting slightly increases the expected costs of industrial consumers (groups 1-3), which is in contrast to the findings for the imperfect competition case discussed previously. For residential consumers, however, load shifting also leads to a slight cost reduction when there is no MP present. These differences can again be explained by the relatively flatter nature of industrial consumers' demand (see Figure 1). In addition, Figure 3b shows that, in the absence of MP, the decrease in peak prices caused by load shifting is not as big as the increase in off-peak prices, which is in contrast to the imperfect competition case. Consequently, because their demand is relatively flatter, industrial consumers do not reap the benefits of load shifting, in the absence of market power. In fact, their costs increase as a result of the residential consumers' shifting.

4.2 Firms' profits

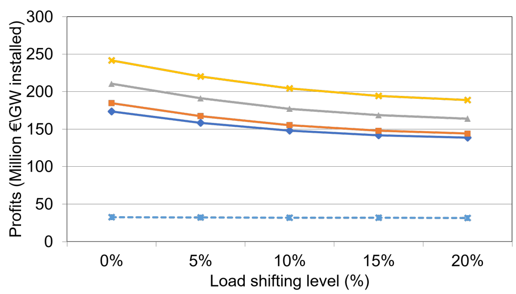
Figure 4 displays the expected profits for each of the generating firms, as described by equation (1a). When market power is present in the market, Figure 4 shows that each firms' expected profits increase substantially. This is despite the fact that only firms 1 and 3 have the ability to exert market power. In the market power cases, firm 1 and 3 reduce the generation they would otherwise provide to the market. This allows/forces more expensive generating units of these and other firms to come online more often. Consequently, system energy prices increase, to the benefit of all firms.



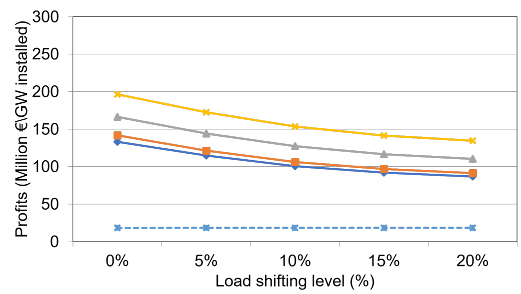
(a) Firm 1 (Integrated firm)



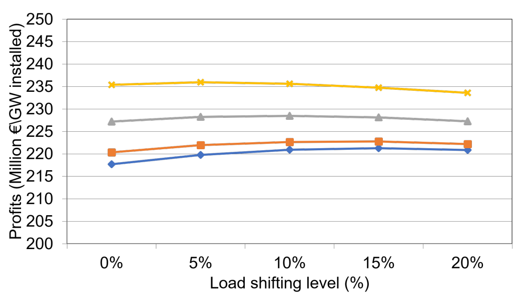
(b) Firm 2 (Baseload firm)



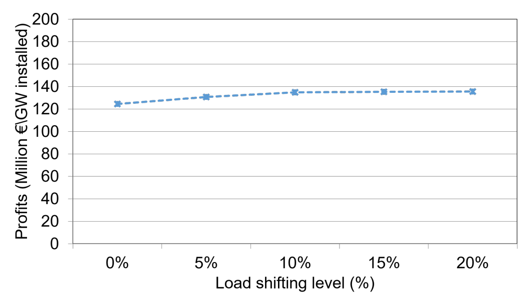
(c) Firm 3 (Mid merit firm)



(d) Firm 4 (Peakload firm)



(e) Firm 5 (Wind only firm, market power cases)



(f) Firm 5 (Wind only, no market power case)

600 MW 400 MW 200 MW 0 MW 600 MW (No MP)

Figure 4: Expected firm profits (per GW installed) for different levels of load shifting, both with (continuous lines) and without (dashed lines) market power. The legend describes the different micro-generation levels, which broadly correspond to 0%, 3%, 7% and 10% of system level peak demand.

Similar to the effects described in section 4.1, Figure 4 generally shows that DR can help mitigate the impact of market power. More specifically, when market power is present, increasing the amount of micro-generation in the system reduces expected profits for each of the five firms. This holds regardless of the level of load shifting. Micro-generation allows consumers to reduce the demand they place on the firms, which reduces firms 1 and 3's price-making ability and, consequently, system prices. However, Figure 4 shows that this decrease in firms' profits becomes minimal when the consumers increase the amount of micro-generation from 400MW to 600MW. As above, this results suggests a saturation effect in micro-generation's ability to reduce the effects of market power.

As for load shifting, Figures 4a - 4d show that, in the presence of market power, shifting decreases expected profits for firms 1 - 4 respectively. This holds regardless of the level of micro-generation in the market. Firms' ability to exert market power is strongest at times of high demand. Load shifting allows consumers to decrease their peak demand, which reduces the price-making ability of firms 1 and 3 and, consequently, prices and profits.

In contrast, Figure 4e shows that the renewable only firm's expected profits initially increase as a result of load shifting being introduced into a market where market power is present. As with the perfect competition cases, this is because load shifting increases off-peak demand and prices and decreases wind curtailment. However, as the level of load shifting increases further, Figure 4e shows that firm 5's profits turn and start to decrease again. As Figure 3b illustrates, load shifting also decreases peak prices. This effect is greater when some firms are exerting market power. Thus, the initial benefits of load shifting from firm 5's perspective (driven by reduced wind curtailment and increased offpeak prices) become overshadowed by the reduced peak prices. These results suggest that, in the presence of market power, relatively small amounts of load shifting can increase the profitability of renewable generation while larger amounts can reduce this effect. Furthermore, the most favourable level of load shifting for firm 5 in such a market, depends on the level of micro-generation. For example, when there is 0MW of micro-generation, the most favourable percentage of load shifting capacity for firm 5 is 5%, whereas this value is 15% when there is 600MW of micro-generation present. This can be explained by micro-generation's ability to mitigate the effects of market power and reduce peak prices. As the capacity of micro-generation in the system increases, there is less MP in the system; hence the downside effect of load shifting during peak hours decreases, while the upside effect during offpeak hours remains. As a result, for larger amounts of micro-generation in the system, firm 5 only benefits from the positive impacts load shifting brings.

Moreover, it is important to note that the integrated firm (firm 1) also has a significant portfolio of wind generation. However, Figure 4 shows its expected profit curves are in contrast to firm 5's. Firm 1's decreasing profit curves are dominated by the reduced profits of its conventional units, as explained above.

Comparing load shifting and micro-generation as to how they can help mitigate against the generation firms' profit increase, our results show that the effect of load shifting decreases when the level of micro-generation in the system increases and vice versa, i.e. these are compensating technologies. The relative effects of micro-generation and load shifting on the profits of the specialised conventional firms generally have a similar magnitude (between 18-23% for baseload generation, between 20-28% for mid-merit generation and between 31-36% for peakload generation), where micro-generation has a slightly higher relative profit reduction effect for baseload and mid-merit generation, whereas there is no clear effect difference for peakload generation. The relative profit reduction effects are much smaller for the integrated and renewable-only firms, where micro-generation leads to profit reductions of 12-16% and 5-8% for the integrated and renewable-only firm respectively, whereas load shifting leads to a relative profit decrease of 5-9% and 0-2% for the integrated and renewable-only firm respectively.

On a side note, when the market is perfectly competitive, Figures 4b - 4d show that load shifting has a relatively small impact on profits for firms 2 - 4, respectively. Although not visible in Figure 4d, firm 4's expected profits increase slightly as the level of load shifting increases. This is caused by an increase in capacity prices and the fact that, in the absence of market power, firm 4 only participates in the capacity market. The price increase in the capacity market is a result of decreasing profits of conventional generation in the energy market. As we assume a competitive, quantity-based capacity market, this leads to a capacity price increase, i.e. the capacity market compensates the reduced profits in the energy market (for further details, see Bertsch et al., 2018). In contrast, firm 3's expected profits slightly decrease as a result of increasing load shifting, in the absence of market power. Despite earning increased revenue from the capacity market, this decrease can be explained by the reduced peak hour energy prices; see Figure 3b. Moreover, as firm 3 is a mid-merit only firm, it does benefit from the increase in off-peak demand and prices as it is still not profitable for them to generate in those hours.

In contrast to firms 2 - 4, Figures 4a and 4f show that increasing the percentage of load shifting capacity from 0% to 10%, increases both firm 1's and 5's expected profits in the absence of market power. This is because firms 1 and 5 are the only firms that have wind generation capacity. Consequently, the increase in off-peak demand and prices, allows these firms to reduce wind

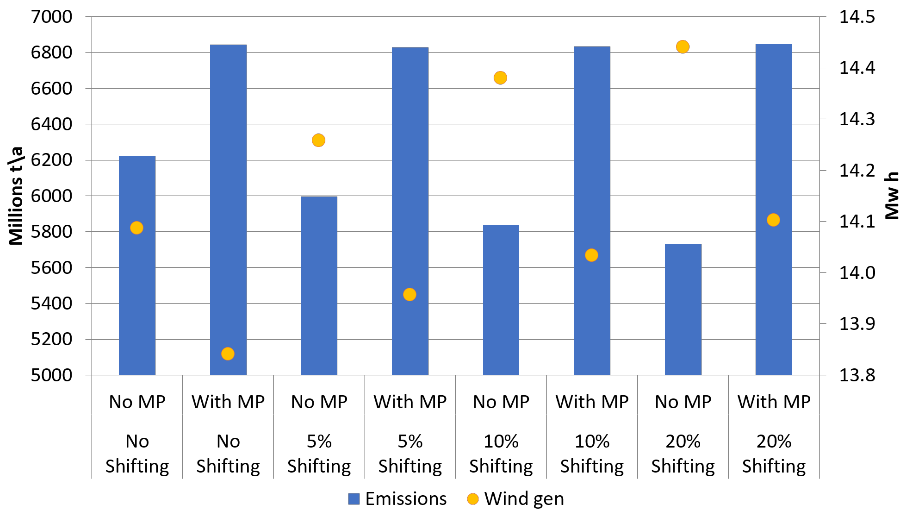


Figure 5: Expected emissions and wind generation (600MW of micro-generation).

curtailment and further utilise their wind portfolio. For firm 1, this is despite the reduced profit its conventional generation units suffer as a result of the reduced peak-hours demand and prices. When the hourly load shifting capacity increases from 10% to 20%, in the absence of market power, Figures 4a and 4f show that the expected profits of firms 1 and 5 do not increase substantially. This result suggests that the marginal effect of developing load shifting technologies reduces once there is already a considerable amount of it present.

4.3 Emissions

Finally, Figure 5 displays the expected levels of emissions and wind generation for different load shifting cases, both in the presence and absence of market power. The results show that overall wind generation levels are lower in non-competitive market conditions. This is because, when firm 1 is a price-making firm, it reduces its wind generation in order to force/allow more expensive generating units into the market, which are more emission-intensive at the same time. Hence, when price-making firms own renewable generation, their price-making behaviour can lead to increased system emissions as a side effect.

Moreover, Figure 5 shows that, as load shifting increases, so does the amount of wind generation. This result concurs with Lynch et al. (2019) and is because load shifting increases off-peak demand and thus reduces wind curtailment. However, Lynch et al. (2019) only consider a perfectly competitive market, whereas Figure 5 shows that the increase in wind generation, as a result of load shifting, also holds when market power is present. Interestingly though, while wind generation increases, we observe that emissions do not decrease as the level of load shifting increases when market power is present. As opposed to the perfect competition case, when firm 1 is able to exert market power, it does not use wind generation solely to meet the increased off-peak demand resulting from load shifting. It also utilises its conventional units, in particular its baseload units, which have a high emission factor. In addition, even if firm 1 only ramps up its baseload units to the minimum possible extent, this will increase system prices so that firm 2 (the price-taking baseload-only firm) will dispatch its emission-intensive baseload unit, too. Overall, the increase in baseload generation in off-peak hours is greater than the decrease seen in peak hours. Consequently, while load shifting increases wind generation, it can also increase baseload generation, when market power is present.

These findings are in contrast to the perfect competition case. In the absence of market power, Figure 5 shows that increasing levels of load shifting will not only increase wind generation (particularly in offpeak hours) and decrease conventional peak generation, but also decrease emissions. This is because in a perfectly competitive market, the increase in off-peak demand is primarily met by wind.

To summarise, these results suggest that, while DR may help mitigate the impact of MP on wind generation, its potential in mitigating against the negative effects of MP on emissions is limited in the considered case. In a perfectly competitive market, however, DR may also be useful in reducing emissions.

5. DISCUSSION AND CONCLUSIONS

In this work, we present a stochastic mixed complementarity problem to model an electricity market characterised by an oligopoly with a competitive fringe. We use the model to investigate the interactions between demand response and market power. More specifically, applying the model to a stylised version of the 2025 Irish power system, we examine to which extent DR can help mitigate the impact of market power on consumer costs, generating firm profits and carbon emissions. Our model generally distinguishes between load shifting, load shedding and self-generation (micro-generation) within DR, where we focus on the results for load shifting and micro-generation in this paper. In relation to the research questions set out in section 1, we can summarise three main findings of our research.

First, DR can generally help mitigate against substantially increasing costs for all consumer groups when market power is present. This finding includes load shifting and micro-generation and also holds for those consumers who do not necessarily own micro-generation capacity themselves.

When comparing load shifting and micro-generation within DR in terms of their contribution to mitigating against the effects of market power, our findings show that the effect of micro-generation decreases when the level of load shifting in the system increases and vice versa. Hence, we conclude that these are competing technologies. In addition, the analysis presented reveals that the relative effects of micro-generation and shifting generally have a similar magnitude. An exception from this finding are consumers that own micro-generation themselves. For these consumers, the relative cost reduction of micro-generation in the presence of market power is significantly higher than that of load shifting. Despite these benefits of DR, however, it is also important to note that even for the highest capacities of micro-generation and load shifting considered in this paper, consumer costs are still significantly higher than in the perfect competition case. At the same time, saturation effects could be observed for both micro-generation and load shifting, which suggests that the potential of DR in mitigating against the impact of market power on consumer costs is limited.

Second, in the presence of market power, all firms' expected profits increase substantially, despite the fact that only two firms have the ability to exert market power. In this case, DR can generally help mitigate against the profit increase by generation firms. More specifically, we find that DR is most effective in mitigating increased profits of peakload generators, followed by mid-merit and baseload generators. The profits of the renewable-only and integrated firms are less affected by DR. In addition, the analysis in this paper reveals that, with the exception of peakload generators, micro-generation turns out to be more effective than load shifting in mitigating profit increases. Despite the benefits of DR demonstrated in this paper, however, it is important to note that even for the highest capacities of micro-generation and load shifting considered as part of the case study, the generation firms' profits are still significantly higher than in the perfect competition case. At the same time, the analysis has shown saturation effects for both micro-generation and load shifting, which suggests that the potential of DR in mitigating against the impact of market power on generators' profits is limited.

Third, while DR helps increase the level of wind generation in the system, it does not help reduce emissions in the considered case study when market power is present. When firms dispatch their assets more strategically, it becomes financially rewarding for them not to fully utilise their wind units but to also use their carbon-intensive baseload units. This finding is in contrast to the perfect competition case, where increasing levels of load shifting will not only increase wind generation in offpeak hours and decrease conventional generation in peak hours, but also decrease emissions. The reason is that, in a perfectly competitive market, the increase in off-peak demand is primarily met by wind.

Concerning the impact of DR on consumer costs in the presence of market power, our estimated total expected consumer costs (see Figure 3a) correspond to annual residential consumer savings of about €20-80 per household (assuming approximately 1.5 million households in Ireland). In the absence of market power, Bertsch et al. (2018) estimate significantly lower savings of around €2-5 per household and year. The difference of more than a factor of 10 between these two estimates is related to the value of market power mitigation through load shifting. In other words, when analysing the value of DR, this difference shows that it is important to consider market power effects and how DR can help mitigate against these when modelling power markets.

Some of the literature cautions against significant investments in demand response technologies (Allcott, 2011; Feuerriegel and Neumann, 2016) as the savings may not outweigh the costs. However, the findings of this work clearly demonstrate how DR can act to mitigate against the negative impacts that market power can have on consumers. This conclusion aligns well with Zarnikau and Hallett (2008), Zarnikau (2010) and Walawalkar et al. (2008) who each discuss the benefits of demand response in relation to increasing electricity market efficiency and competitiveness. Interestingly, however, this paper also shows that load shifting should not be the only DR technology considered when seeking how to best mitigate against market power since micro-generation has also proven to reduce consumer costs reliably. In fact, from the perspective of an individual consumer, owning controllable micro-generation capacity that can be used for self-generation has been shown to be more effective than PV-based self-generation or load shifting when it comes to mitigating the impact of market power.

These findings will be of interest to policymakers who are concerned over market power in their relevant electricity market, particularly, if their aim is to reduce consumer costs. However, such policymakers should also note that load shifting does not necessarily decrease carbon emissions when market power is present. However, while the findings of this paper have clearly demonstrated the benefits of DR in relation to mitigating market power impacts, the analysis has also shown that DR alone will not be sufficient to ensure market competitiveness. The finding that micro-generation turns out to be the most effective technology for mitigating market power in our case study is obviously driven, at least to some extent, by the model input data. This does not imply automatically that all consumers becoming self-sufficient would be an efficient way to mitigate market power. What it does suggest though is that an increasing number of market participants that can provide generation to the market helps mitigate against market power.

Critically reflecting on our approach, we wish to acknowledge some limitations. While the model's data is based on the projected Irish power system for 2025, the case study is stylised in nature. Furthermore, we do not consider investment decisions by either the generating firms (e.g., in new generation) or by the consumers (e.g., in extra PV or micro-generation). In addition, when determining price-making ability, we assumed a fixed conjectural variation, i.e. when modelling price-making firms, we assume that the ratio between these firms' generation output and the corresponding influence on energy prices is fixed. Finally, while we do consider uncertain wind and solar profiles, a rolling-horizon optimisation approach may more accurately reflect operational decision making (Devine et al., 2016). Future research will seek to address these limitations.

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A. KARUSH-KUHN-TUCKER CONDITIONS

This appendix presents the Karush-Kuhn-Tucker (KKT) conditions for optimality for the two types of players modelled in this work. These conditions, along with the market clearing conditions (8), make up the mixed complementarity problem. The 'perp' notation $0 \leq a \perp b \geq 0$ is equivalent to $a \geq 0$, $b \geq 0$ and $a.b = 0$.

A.1 Firms' KKT conditions

The firms' KKT conditions are

$$0 \leq gen_{f,t,p,s} \quad \perp \quad -PR_s\Bigg(\gamma_{p,s} + X_t + PM_{f,t}\frac{\partial \gamma_{p,s}}{\partial gen_{f,t,p,s}}\Big(\sum_{\bar{t}\in T} gen_{f,\bar{t},p,s}\Big) - \frac{\partial C^{\text{GEN}}_{f,t}}{\partial gen_{f,t,p,s}}\Bigg) + \lambda^1_{f,t,p,s} \geq 0, \ \forall f,t,p,s, \tag{9a}$$

$$0 \leq cap^{\text{bid}}_{f,t} \quad \perp \quad DR_t \times \kappa + \lambda^2_{f,t} \geq 0, \ \forall f,t, \tag{9b}$$

$$0 \leq \lambda^1_{f,t,p,s} \quad \perp \quad -gen_{f,t,p,s} + (CAP_{f,t} - exit_{f,t}) \times NORM^{\text{G}}_{f,t,p,s} \geq 0, \ \forall f,t,p,s, \tag{9c}$$

$$0 \leq \lambda^2_{f,t} \quad \perp \quad -cap^{\text{bid}}_{f,t} + CAP_{f,t} - exit_{f,t} \geq 0, \ \forall f,t. \tag{9d}$$

A.2 Consumers' KKT conditions

The consumers' KKT conditions are

$$0 \leq g^{\text{ls}}_{k,p,s} \quad \perp \quad -PR_s\big(\gamma_{p,s} - \frac{\partial C^{\text{LS}}_{k,p}}{\partial g^{\text{ls}}_{k,p,s}}\big) + \mu^1_{k,p,s} + \mu^8_{k,p,s} \geq 0, \ \forall k,p,s, \tag{10a}$$

$$0 \leq g^{\text{up}}_{k,p,s} \quad \perp \quad PR_s\gamma_{p,s} + \mu^2_{k,p,s} + \sum_{e=p-\hat{p}+1}^{|H|}\big(\mu^6_{k,\hat{p},e,s} - \mu^7_{k,\hat{p},e,s}\big) - \mu^8_{k,p,s} \geq 0, \ \forall k,p,s, \tag{10b}$$

$$0 \leq g^{\text{down}}_{k,p,s} \quad \perp \quad -PR_s\gamma_{p,s} + \mu^3_{k,p,s} - \sum_{e=p-\hat{p}+1}^{|H|}\big(\mu^6_{k,\hat{p},e,s} - \mu^7_{k,\hat{p},e,s}\big) + (1 - LOSS_k)\mu^8_{k,p,s} \geq 0, \forall k,p,s, \tag{10c}$$

where

$$\hat{p} = \max\{p' | \hat{p} \leq p\},$$

$$0 \leq g^{\text{micro}}_{k,p,s} \quad \perp \quad -PR_s\big(\gamma_{p,s} - \frac{\partial C^{\text{MICRO}}_{k,p}}{\partial g^{\text{micro}}_{k,p,s}}\big) + \mu^4_{k,p,s} + \mu^8_{k,p,s} \geq 0, \ \forall k,p,s, \tag{10d}$$

$$0 \leq g^{\text{pv}}_{k,p,s} \quad \perp \quad -PR_s\big(\gamma_{p,s} + X^{\text{PV}} - C^{\text{PV}}_{k,p}\big) + \mu^5_{k,p,s} + \mu^8_{k,p,s} \geq 0, \ \forall k,p,s, \tag{10e}$$

$$0 \leq \mu^1_{k,p,s} \quad \perp \quad -g^{\text{ls}}_{k,p,s} + G^{\text{LS,MAX}}_k \geq 0 \ \forall k,p,s, \tag{10f}$$

$$0 \leq \mu^2_{k,p,s} \quad \perp \quad -g^{\text{up}}_{k,p,s} + FAC^{\text{STOR}}_k \times INT^{\text{STOR}}_k \geq 0 \ \forall k,p,s, \tag{10g}$$

$$0 \leq \mu^3_{k,p,s} \quad \perp \quad -g^{\text{down}}_{k,p,s} + FAC^{\text{STOR}}_k \times INT^{\text{STOR}}_k \geq 0 \ \forall k,p,s, \tag{10h}$$

$$0 \leq \mu^4_{k,p,s} \quad \perp \quad -g^{\text{micro}}_{k,p,s} + INT^{\text{MICRO}}_k \geq 0 \ \forall k,p,s, \tag{10i}$$

$$0 \leq \mu^5_{k,p,s} \quad \perp \quad -g^{\text{pv}}_{k,p,s} + INT^{\text{PV}}_k \times NORM^{\text{PV}}_{p,s} \geq 0 \ \forall k,p,s, \tag{10j}$$

$$0 \leq \mu^6_{k,p',h,s} \quad \perp \quad -\sum_{e=p'}^{p'+h-1} \big(g^{\text{up}}_{k,e,s} - g^{\text{down}}_{k,e,s}\big) + INT^{\text{STOR}}_k \geq 0 \ \forall k,p',s,h, \tag{10k}$$

$$0 \leq \mu^7_{k,p',h,s} \quad \perp \quad \sum_{e=p'}^{p'+h-1} \big(g^{\text{up}}_{k,e,s} - g^{\text{down}}_{k,e,s}\big) \geq 0 \ \forall k,p',s,h, \tag{10l}$$

$$0 \leq \mu^8_{k,p,s} \quad \perp \quad -g^{\text{ls}}_{k,p,s} - (1 - LOSS_k)g^{\text{down}}_{k,p,s} - g^{\text{micro}}_{k,p,s} - g^{\text{pv}}_{k,p,s} + D^{\text{REF}}_{k,p} + g^{\text{up}}_{k,p,s} \geq 0 \ \forall k,p,s. \tag{10m}$$

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