Demand side management: a case for disruptive behaviour

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Abstract. The UK electricity system is undergoing a significant transformation. Increasing penetration of renewable generation and integration of distributed energy resources (DERs) such as electrical storage, solar PV and wind generators challenge the traditional way of balancing electricity in the grid, whereby supply matches demand. Demand-side management (DSM) has been shown to offer a promising solution to the above problem. However, models proposed in literature typically consider an isolated system whereby a single aggregator coordinates homogeneous consumers. As a result potential externalities of DSM are overlooked. This work explores the value of DSM in the context of an interacting electricity system, where utilities compete for cheap electricity in the wholesale market. A stylised model of the electricity system is proposed based on the UK, whereby a traditional supplier competes with a 'green' supplier in the wholesale market. The modelling was able to show that competitive behaviour by electric utilities achieved by means of shifting consumer demand can lead to increased demand peaks in the system and thus higher electricity prices for certain periods during the year. Moreover, the vertically integrated utility benefited more from instructing consumer coordination compared to 'green' utility, which suggests the vulnerability of the 'green' utility to electricity price volatility.

Keywords: demand side management, competing utilities, smart grid, DER, electricity system transition, DSM

List of Abbreviations

CM Cost minimising

DF Demand flattening

DSM Demand side management

GS Green supplier

ICT Information and communications technology

PV Photovoltaic

SRMC Short run marginal cost

TS Traditional supplier

UK United Kingdom

List of symbols

$\epsilon^T(t)$ Uplift set by the TS for on top of p^T_{SRMC}

η^T Efficiency of an electricity generator of TS

$\mathcal{A}$ Set of all consumers

$\mathcal{A}^T, \mathcal{A}^G$ Subsets of consumers signed up with TS and GS

$\pi^T(t), \pi^G(t)$ Retail price for electricity set by TS and GS in day t

a Consumer index

b_i^a Non-deferrable consumer electricity demand in period i

B_i^S Total electricity demand of supplier S in dailiy period i

c^T_{var}, c^G_{var} Variable operating and maintenance cost for a generator of TS and GS

d_i^a Net consumer electricity demand in period i

D_i^S Net electricity demand of supplier S in daily period i

e^a Consumer storage capacity

f_i^a Flexible consumer electricity demand in period i

f_i^{a+}, f_i^{a-} Consumer storage charge and discharge profiles in daily period i

f^a_{min}, f^a_{max} Consumer storage minimum and maximum charging power constraints

I Total number of daily periods

i Daily period counter

$L_i(t)$ Total system electricity demand in daily period i and day t

$p_i(t)$ Wholesale electricity price in daily period i and day t

p^T_{fuel} Price of fuel used by TS to generate electricity

$p^T_{SRMC}(t), p^G_{SRMC}(t)$ Short run marginal cost of electricity generation for TS and GS

$Q^{gen}_i(t)$ Generated power by TS in daily period i of day t

$Q^{sold}_i(t)$ Power sold by TS in daily period i of day t

R_i Renewable power generated by GS in period i

S Supplier index, where T represents TS and G represents GS

T Total number of simulated days

t Day counter

$z(t)$ Electricity price offer set by TS in day t

1 Introduction

Climate policy amongst other triggers such as lowering costs for ICT , storage and micro generation technology are driving changes within the UK power system.

On the supply side, the UK has seen a significant growth in the deployment of renewable power generators over the last decade, in particular wind and solar [12]. On the demand side, a number of technologies have been entering the market, such as small scale batteries, electric vehicles [4], heat pumps and microgeneration units (especially rooftop solar PV)[13]. Consumers are also becoming more active due to increasing proliferation of smart power metering and management technology. The government is planning to equip every household with smart meters for electricity and gas by 2020 [3]. The changes on the supply and demand sides of the electricity system are causing concern for the grid, as it becomes more difficult to coordinate variable supply with unpredictable demand.

Demand side management (DSM) can offer a promising solution to balancing the electricity grid. Certain technologies like electric vehicles or electrical storage can be scheduled to operate during times of high renewable supply. A number of coordination methodologies have been proposed in the literature (see Section 2). However, such models typically ignore the interactions between the aggregators in the wholesale market. In reality, electricity suppliers compete in the wholesale market for cheap electricity. It is then possible to imagine that electricity companies may manipulate consumer demand in order to gain a competitive advantage. Consequently, it becomes uncertain how this will impact the system as a whole.

This project is concerned with investigating how DSM may impact the security of the grid. We pose the following question: *"Are there conditions under which DSM can be disruptive to the grid?"*. In order to answer it we develop a stylised model of the electricity based on the UK setting, whereby two types of suppliers (a traditional and green) compete in the wholesale electricity market.

In the following report Section 2 gives an overview of the previous work in the domain of DSM and provides motivation for research; Section 3 describes the proposed model; Section 4 covers model calibration and initial set-up; Section 5 provides result interpretation and analysis; and Section 6 gives a summary of the conclusions and suggestions for areas of improvement.

2 Relevant work

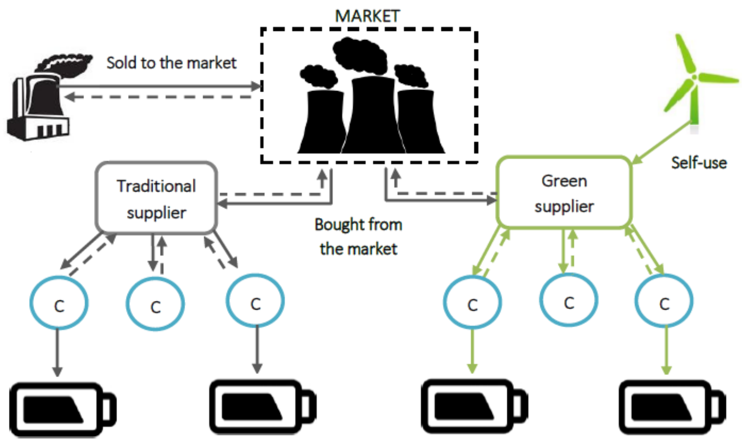
The idea of using demand side flexibility to compensate for intermittent supply is not new [14]. However, due to the lack of communication technology the work remained preliminary and thus untested in simulation settings. Recent developments in communication and data management tools (smart meters, mobile internet, cloud computing) alongside rapid integration of renewables have reignited academic interest in demand-side control as a means to compensate for variable supply. The new DSM models assume the presence of software agents which can optimise electricity usage on behalf of the consumer. Compared to the traditional DSM schemes aimed at human behaviour, software agents are able to perform complex calculations faster using tools such as machine learning and optimisation. There is a large body of research focusing on different ways of performing DSM (see [1] and [18]). A major shortcoming of these models is that the system under consideration often represents an idealistic setting where a set of homogeneous consumers are being coordinated by a single aggregator, e.g. [17] and [7]. On the other hand whole system models like in [15] tend to assume perfect consumer and market behaviour in order to perform global optimisation. Consequently, the dynamic interactions between autonomous consumers and suppliers are lost.

In reality, electricity suppliers interact in the wholesale market in order to supply consumers with very different demand profiles and flexibility resources. Following these gaps in research, we propose a dynamic model which would highlight the benefits and potential issues concerning DSM in the context of the wholesale electricity market.

3 The Model

The following model is motivated by the recent changes in the retail electricity market in the UK. Two types of electricity suppliers compete for cheap electricity: a vertically integrated utility owning dispatchable power generation capacity (TS)[5] and a 'new' independent supplier owning renewable generation capacity – a 'green supplier'(GS)[6]. At this stage there exist two agents representing each type: TS and GS. The consumers are modelled to possess small scale batteries with Tesla Power Wall specifications due to commercial availability of the technology [16]. Figure 1 shows main interactions between model agents.

Fig. 1: Graphical representation of model interactions.



Key: → *powerflow* ⇢ *cashflow* $C - consumer$

Whereas GS can offer greener electricity, it is unable to fulfill its consumer demand without going to the market (where TS profits from selling electricity). TS can choose how much it wants to generate, since if the prices offered in the market are lower than the cost of running the power plant, TS will choose not to generate. Finally, both suppliers may utilise smart coordination mechanisms in order to influence the flexible demand of their consumers (see Section 3.1). The two suppliers compete on the retail price they can offer to the consumers which is calculated as the break-even cost of supplying them with electricity, i.e. suppliers do not include a mark-up on the wholesale price of electricity[7].

[5] This type of a suppliers represents one of the 'Big Six' energy utilities operating in the UK market.

[6] These companies represent the new entrants in the UK electricity market like Ecotricity and Good Energy.

[7] This serves as a step for further development of the model where the consumers are able to switch suppliers.

3.1 The Agents

The following model runs on 24 hour basis with all decisions being made a day ahead. We define a daily period counter $i = 1, ..., I$, where I stands for the total number of daily periods (here 24 hours) and a day counter $t = 1, ..., T$, where T stands for the total number of simulated days (here 365 or one year). The following section describes the intra-day calculations where we drop the day counter t for clarity of notation. The t index is present when the calculations concern day specific calculations.

Consumers. Consumer agents represent residential households. We consider a set of consumers $\mathcal{A}$, where each agent $a \in \mathcal{A}$ has an hourly demand profile d_i^a. We use standard residential demand profiles provided by the National Grid [5]. The demand profile can be split into a non-deferrable part (b_i^a) and a flexible part (f_i^a), s.t.

$$d_i^a = b_i^a + f_i^a, \qquad \forall i \in [1, I],$$

where f_i^a represents the battery storage profile and is calculated as the difference between charging and discharging profiles f_i^{a+} and f_i^{a-}. Conceptually, non-deferrable demand corresponds to those activities where consumption cannot be shifted in time such as cooking or watching TV. Flexible demand can be shifted in time subject to consumer storage specifications, which in our case include battery storage capacity e^a (kWh) and minimum and maximum charging power constraints, f_{min}^a and f_{max}^a (kW). Battery charging efficiency is assumed to be zero.

Each day the supplier may deploy a coordination strategy, in which case it will negotiate the storage profile with the consumer prior to physical electricity delivery (See 3.1).

Suppliers. Suppliers are energy companies responsible for providing consumers signed up with them with electricity. We use index $S \in \{T; G\}$ to differentiate between the traditional (TS) and the green supplier (GS). Hence, we identify two subsets of consumers: $\mathcal{A}^T \subseteq \mathcal{A}$ (those signed up with TS) and $\mathcal{A}^G \subseteq \mathcal{A}$ (those signed up with GS). We assume that the size of the two consumer sets is the same, i.e. $|\mathcal{A}^T| = |\mathcal{A}^G|$.

Suppliers' objective is to fulfill energy demand of its consumers B_i^S, which is calculated as the sum of individual consumer demand profiles, i.e.

$$B_i^S = \sum_{a \in \mathcal{A}^S} d_i^a \qquad \forall i \in [1, I] \quad \text{and} \quad S \in \{T, G\}. \tag{1}$$

GS has renewable resources and hence needs to satisfy net demand D_i^G, which is calculated as the difference between consumer demand B_i^G and the renewable generation profile R_i:

$$D_i^G = max(0, B_i^G - R_i) \qquad \forall i \in [1, I].$$

In-line with UK regulations, TS cannot utilise power from own resources and has to fulfill consumer demand solely from the market. Hence, for TS net demand is the same as the total demand calculated in (1):

$$D_i^T = B_i^T \qquad \forall i \in [1, I].$$

Now, an assumption is made that GS does not sell electricity in the market since it wants to maximise the use of its own renewable resources which come almost free in the short run. For GS, R_i is constrained purely by the installed capacity of the wind generator cap^G and the weather[8].

The traditional supplier sells electricity in the wholesale market at a price $z(t)$ calculated daily as

$$z(t) = p_{SRMC}^T + \epsilon^T(t). \tag{2a}$$

The first term in (2a) p_{SRMC}^T is known as the short run marginal cost (SRMC) of generator type T and is calculated as [9]

$$p_{SRMC}^T = c_{var}^T + \frac{p_{fuel}^T}{\eta^T}, \tag{2b}$$

where,
c_{var}^T – variable operating and maintenance cost for a generator of supplier T and set constant for the whole period,
p_{fuel}^T – price of fuel used by supplier T to generate electricity,
η^T – efficiency of an electricity generator of supplier T.

The second term in (2a) $\epsilon^T(t)$ is referred to as an 'uplift' and essentially represents the company's revenue from selling electricity in the wholesale market. The strategy for how TS learns to adjust the uplift is described in Section 3.1.

For the green supplier (2b) is reduced to $p_{SRMC}^G = c_{var}^G$ since wind is free.

Finally, at the end of day t, both types of suppliers calculate the break-even retail price of electricity. For TS, the price is calculated as follows:

$$\pi^T(t) = \frac{\sum_{i=1}^I Q_i^{sold,T}(t) \cdot p_{SRMC}^T - Q_i^{sold,T}(t) \cdot z(t) + D_i^T(t) \cdot p_i(t))}{B_i^T(t)}, \tag{3}$$

where,
$Q_i^{sold,T}(t)$ – electricity sold by TS in daily period i of day t,
$z(t)$ – the asking price for a unit of electricity set by TS in day t,
$p_i(t)$ – wholesale market price for a unit of electricity in daily period i of day t,
$B_i^T(t)$ – the total power supplied to consumers by TS in daily period i of day t, and
$D_i^T(t)$ – the total power purchased by TS from the market in daily period i of

[8] In order to model the generation capacity of the GS we take historical electricity supply profile from a 1.8MW wind farm in Wales [9, 10].

[9] The short run marginal cost normally changes during the period of operation of the power plant but for the purpose of our simulation it is kept constant.

day t.

We can split (4) into three parts: cost of running the generator, profit made in the market and the cost of purchasing additional electricity.

The amount of power TS sells, $Q_i^{sold,T}$ is limited by the amount of power TS decided to generate for the day ahead $Q_i^{gen}(t)$, which itself is limited by the installed generation capacity cap^{TS}, i.e.

$$Q^{gen}(t) \leq cap^T \qquad \forall t \in [1, T].$$

The TS sets $Q^{gen}(t)$ acording to Algorithm 1.

For GS (4) is reduced to

$$\pi^G(t) = \frac{\sum_{i=1}^I R_i(t) \cdot p_{SRMC}^G(t) - D_i^G(t) \cdot p_i(t))}{B_i^G(t)}, \tag{4}$$

where,
$R_i(t)$ – renewable generation profile for GS in daily period i of day t,
$p_i(t)$ – wholesale market price for a unit of electricity in daily period i of day t,
$B_i^G(t)$ – the total power supplied to consumers by GS in daily period i of day t, and
$D_i^G(t)$ – the total power purchased by GS from the market in daily period i of day t.

Calculating the retail price at break-even cost enables us to compare the competitiveness of the two utilities.

TS learning. As will be seen in the next section, it is critical for TS to set the offer and dispatch capacity. Hence, we propose Algorithm 1 to allow the TS to learn the best strategy. The algorithm is based on the method developed by [2] which uses reinforcement learning to teach the agents the best strategy to adopt in the market in terms selecting the offer price $z(t)$ and the generation capacity $Q^{gen}(t)$. The idea is that the agent experiments with strategies for the first ten simulation days, after which the exploration time is reduced to 50% with the remaining time dedicated to selecting the best available strategy.

Supplier coordination. We consider two decentralised coordination strategies, whereby the supplier is signaling its consumers on how to schedule storage. The two algorithms are based on the method developed by [7] but have been adapted to consumers with batteries rather than electric vehicles.

The first coordination algorithm is designed to reduce the variance of the demand profile and hence we call it 'demand flattening' or DF (Figure 2, left).

The second coordination algorithm is designed to minimise the cost of electricity purchased from the market and hence we call it 'cost minimising' or CM (Figure 2, right). The suppliers receive a prediction of day-ahead prices from the market as described in (5) in the next section.

Algorithm 1 TS learning algorithm

Require: Retail price $\pi(t)$, offer $z(t)$ and generation capacity $Q^{gen}(t)$ from day t and the matrix for storing results,

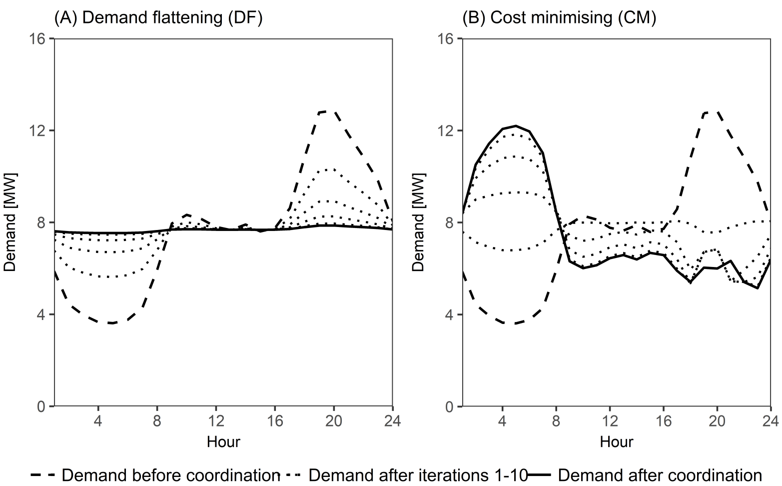
$$\mathcal{M} = \begin{bmatrix} \pi(1) & Q^{gen}(1) & z(1) \\ \vdots & \vdots & \vdots \\ \pi(10) & Q^{gen}(10) & z(10) \end{bmatrix}.$$

Ensure: Supplier generation capacity $Q^{gen}(t+1)$ and offer $z(t+1)$ for day-ahead.

Generate five random values a_1, a_2, a_3, a_4, a_5, s.t. $a_1, a_2, a_3, a_4 \in \mathcal{U}(0.9, 1.1)$ and $a_5 \in \mathcal{U}(0, 1)$
if $t \leq 10$ **then**
  $\mathcal{M}_{t,1} \leftarrow \pi(t), \mathcal{M}_{t,2} \leftarrow Q^{gen}(t), \mathcal{M}_{t,3} \leftarrow z(t)$
  $Q^{gen}(t+1) \leftarrow \min(cap^T, Q^{gen}(t) \cdot a_1), z(t+1) \leftarrow z(t) \cdot a_2$
else
  Sort the strategy matrix $\mathcal{M}$ in order of ascending retail prices, s.t. $\forall\ m_{k1}, m_{(k+1)1} \in \mathcal{M}, \quad m_{k1} \leq m_{(k+1)1} \forall, \quad k \in [1, 9]$
  if $a_5 \leq 0.5$ **then**
    $Q^{gen}(t+1) \leftarrow \mathcal{M}_{1,2}, z(t+1) \leftarrow \mathcal{M}_{1,3}$
  else
    $Q^{gen}(t+1) \leftarrow Q^{gen}(t) \cdot a_3, z(t+1) \leftarrow z(t) \cdot a_4$
return $Q^{gen}(t+1), z(t+1)$

For both algorithms the supplier negotiates the demand profile with the consumers over a number of iterations whilst the consumers imposes electrical storage constraints.

Fig. 2: Demonstration of the two decentralised coordination mechanisms deployed in the model by suppliers.



3.2 The Market

The market represents a pool of electricity generation companies which sell power. These maybe independent generators or vertically integrated companies also possessing a retail business (like in the case of TS). The generators bid available capacity into the market at a set offer per unit of energy. The cheaper units of electricity get sold first with more expensive units reserved for times of higher electricity demand. Hence, electricity prices are positively correlated with system's demand for electricity. The market is cleared at the price of the marginal unit of electricity – the last unit of generation needed to fulfill system demand.

In this model, the market receives the sum of the electricity demand profile from the two suppliers in each time period i and day t, i.e.

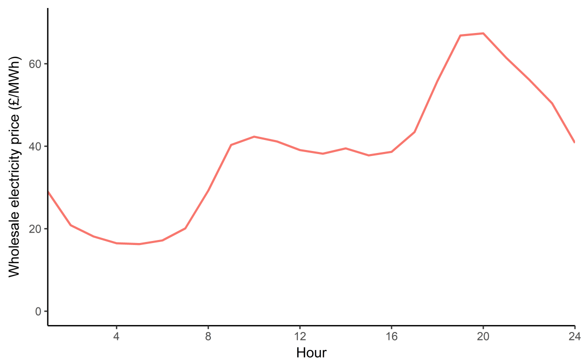
$$L_i(t) = D_i^T(t) + D_i^G(t). \tag{5}$$

The market price $p_i(t)$ is set at a level of the last unit of marginal generation capacity needed to fulfill the demand, $L_i(t)$. For simplicity, we assume a linear relationship between system demand and prices:

$$p_i(t) = k \cdot L_i(t). \tag{6}$$

Figure 3 shows an example of the prices profile calculated by the market.

Fig. 3: Example of wholesale electricity prices prediction.



The TS is able to sell electricity in the market, however only if the price offered $z(t)$ is lower than the clearing price $p_i(t)$ as calculated in (6). If the offer is too high the supplier is unable to sell but still has to pay the minimum cost of running the power plant. In order to decide on the best strategy the TS deploys the learning Algorithm 1 as described in section 3.1.

4 Experimental set-up

The model described in this paper is highly stylised and hence, in order the capture real-life interactions, it was critical to set the parameters.

Firstly, it was decided that 30,000 consumers (aggregated to 30 modelled agents) was a sufficient number to capture the needed model interactions without compromising on the speed of the simulation. Consumers were equally split between the TS and GS in order to make the retail prices comparable. The regression coefficient in (6) was adjusted to 2.9 in order to achieve the same level of market prices compared to the historical value of £40/MWh in the *base case* – when no utility coordinated (meaning that storage was not operated) [6].

The SRMC for a traditional supplier was set at £14/MWh (to represent a coal power plant) and at £1.5/MWh for the green supplier. It was assumed that all of consumers signed with each supplier were in possession of a battery with capacity of 6.4kWh, charging power of 3kW and 100% efficiency.

The purpose of this project was two-fold. Firstly, to investigate under which strategies the suppliers benefited through offering a lower retail price compared to their opponent. Secondly, whether any of the strategies resulted in a negative effect to the system through increased demand peaks. Hence, we consider six combinations of supplier coordination strategies referred to as 'scenarios' (Table 1). Demand flattening (DF) coordination represents the more idealistic DSM case (often considered in academic work) whereby suppliers serve the grid by smoothing demand peaks. Cost minimising (CM) coordination represents a more aggressive DSM case whereby suppliers actively try to minimise the cost of electricity.

We adopt the notation such that the first item in the brackets represents the strategy adopted by the TS (in capital letters) and the second item represents GS strategy (in small letters).

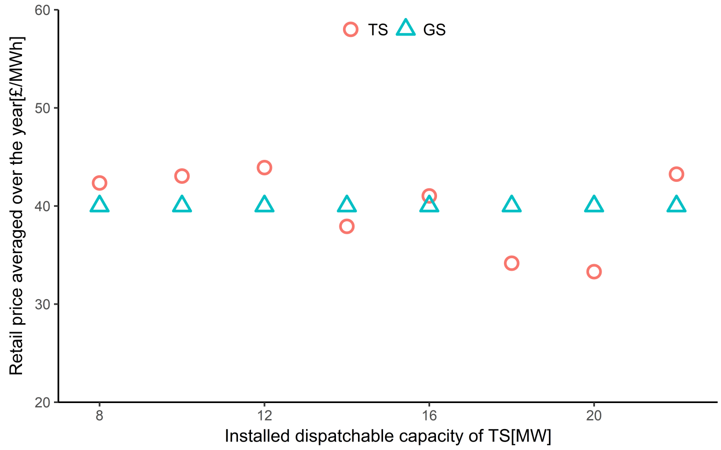
Table 1: Matrix representation of the simulation scenarios.

TS coordination	GS coordination	notation
none	none	(NC, nc)
DF	DF	(DF, df)
DF	none	(DF, nc)
none	DF	(NC, df)
CM	CM	(CM, cm)
CM	none	(CM, nc)
none	CM	(NC, cm)

During the preliminary run it was found that the model was very sensitive to the amount of installed generation available to suppliers. Figure 4 demonstrates how the retail prices for TS change in response to different values of cap^T. The model is calibrated in order to obtain an equal level of retail prices in the base case, which is achieved when TS has 16 MW of installed capacity and GS has 1.8 MW of wind generation (Figure 4)[10].

[10] In fact we leave the retail price achieved by TS marginally higher to make it more difficult for the company to compete

Fig. 4: Comparison of retail prices for TS and GS under different scenarios of installed dispatchable capacity for TS, Case: base case (NC,nc), GS in possession of 1.8 MW wind capacity.



For each run we compare the competitiveness of the two suppliers by tracking their average daily retail prices during the year of simulation, $\pi^T(t)$ and $\pi^G(t)$. In order to assess the impact on the system we also monitor the system demand, $L_i(t)$ – a proxy for carbon intensity of the grid and an indicator for the security of the electricity transmission system. Please refer to Appendix A for the overall model flow [11].

5 Results and analysis

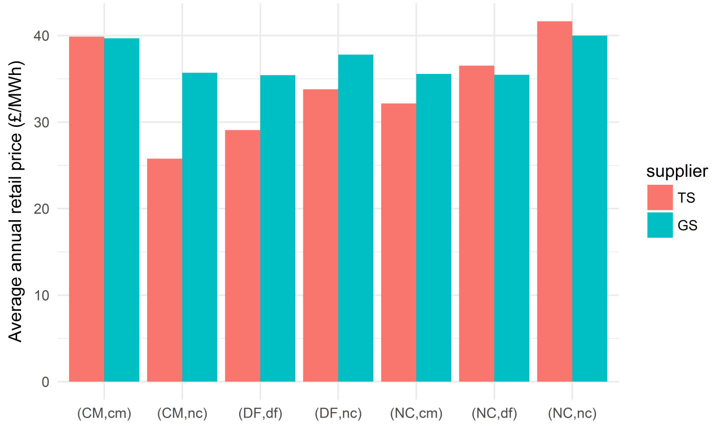
Figure 5 shows the comparison of average retail prices in the seven scenarios considered above. Out of all scenarios with coordination, the highest retail price was obtained when both suppliers performed cost minimising coordination, i.e. scenario (CM,cm). This might seem counter intuitive, however such observations can take place as a result of herding behaviour, when suppliers shift demand to the same periods of low electricity prices creating new demand peaks and price hikes. Whilst the retail price achieved by GS is marginally lower, the TS performs better than in the base case scenario (NC,nc).

It is interesting to note that TS benefited more from performing coordination. Apart from the scenario (NC,df) and (CM,cm) (discussed above), all others led to the TS achieving a lower retail price as compared to GS.

The highest price reduction for TS relative to base case took place in scenario (CM,nc) when GS did not coordinate whilst TS cost minised. In a mirror scenario, when only GS performed cost minimisation in (NC,cm) TS still achieved a lower retail price level. This is due the ability of the traditional supplier to adjust the generation capacity and the offer of power to be sold in the market

[11] The model code is also available on request.

Fig. 5: Comparison of average annual retail prices achieved by suppliers.



enabling it to profit from selling electricity at higher prices (Figure 6). This acts as a hedging strategy for TS against volatile market prices. The GS has no such ability making it exposed to the market risk.

Fig. 6: Electricity dispatch capacity and offer set by traditional supplier in experimental scenario (CM,cm).

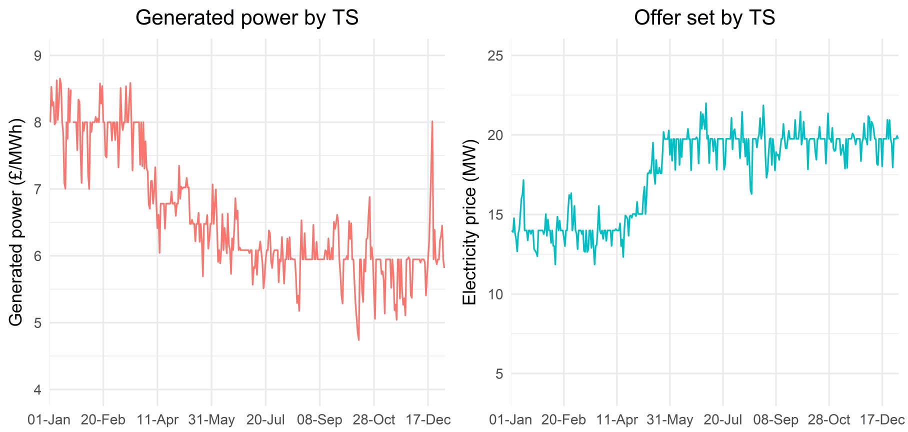
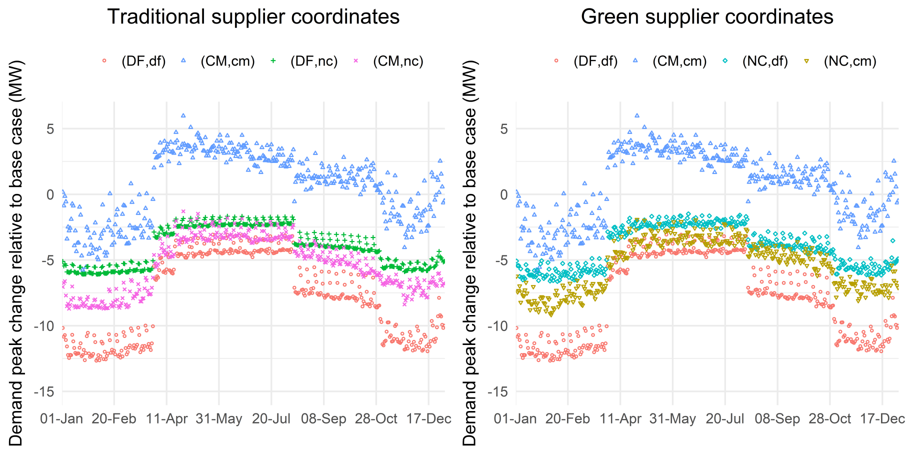


Figure 7 shows the change in daily system demand peak relative to the base case when no supplier coordinated (NC,nc), where a negative value suggests a decrease and a positive value an increase.

It can be seen that in all demand response cases apart from when both suppliers cost minimised (CM,cm), the system benefitted from a reduction in demand peaks. When suppliers performed cost minimising coordination (CM,cm) the system peaks increased by as much as 6MW, with the highest increases taking place in the summer months. This is likely due to the fact that overall demand is lower in those months and so any shift in demand is more noticeable compared to the winter. The cases when only one supplier cost minimised (i.e. (CM,nc) and (NC,cm)) also led to higher demand peaks compared to DF coordination cases. Especially in the summer months, the peaks almost approached base case scenario, suggesting that with higher level of flexibility these may surpass them leading to peak increases.

Fig. 7: Change in daily demand peaks relative to base case (NC,nc) by experimental scenario.



6 Conclusion and further work

In this work we investigated how a traditional supplier (TS) and a green supplier (GS) can compete for consumers by utilising DSM strategies. We considered different combinations of suppliers performing one of the three demand coordination mechanisms: demand flattening (DF), cost minimising (CM) or no coordination (NC). In each scenario we investigated the performance of suppliers and the system by monitoring retail prices and system demand.

The modelling was able to show that the traditional supplier benefitted more from performing coordination in all scenarios apart from the case when it did not coordinate and GS performed demand smoothing (NC,df). Even in the case when electricity prices were high for both suppliers as a result of herding in scenario (CM,cm) TS managed to reduce the price gap in the retail prices relative to the base case (NC,nc). This is because cost minimising coordination led to a higher level of electricity wholesale prices allowing TS to increase the offer in the market and profit from selling electricity. Hence, for TS it did not matter what coordination strategy to adopt as it still performed better or as well as in the base case. On the other hand GS was obliged to perform demand flattening coordination in order to compete. This exposes the vulnerability of GS to electricity price volatility compared to vertically integrated utilities.

Nevertheless, cost minimising behaviour resulted in an adverse effect of increased demand peaks in the system. This suggests that competitive behaviour of utilities by means of shifting consumer demand can lead to higher capacity requirements and more volatile electricity prices for the whole system.

There are a number of limitations which we aim to address in the future:

- Increase the number of suppliers bidding in the market
- Equip consumers with the ability to choose supplier
- Introduce better learning algorithm to the suppliers
- Introduce uncertainty to the demand and supply sides
- Introduce heterogeneous consumers
- Equip consumers with the ability to generate electricity

Demand response can offer a promising solution in balancing variable supply with flexible demand and help transition the UK electricity system to a cleaner more sustainable one. However, if not controlled it could lead to negative effects for the whole system and all stakeholders involved. Thus, in order to extract the maximum amount of benefit out of DSM a relevant regulatory framework is likely to be required in the future. For example, electricity supplier pricing strategies could be regularly reviewed so as to ensure that they are not incentivizing consumer behavior that works against overall electricity system performance.

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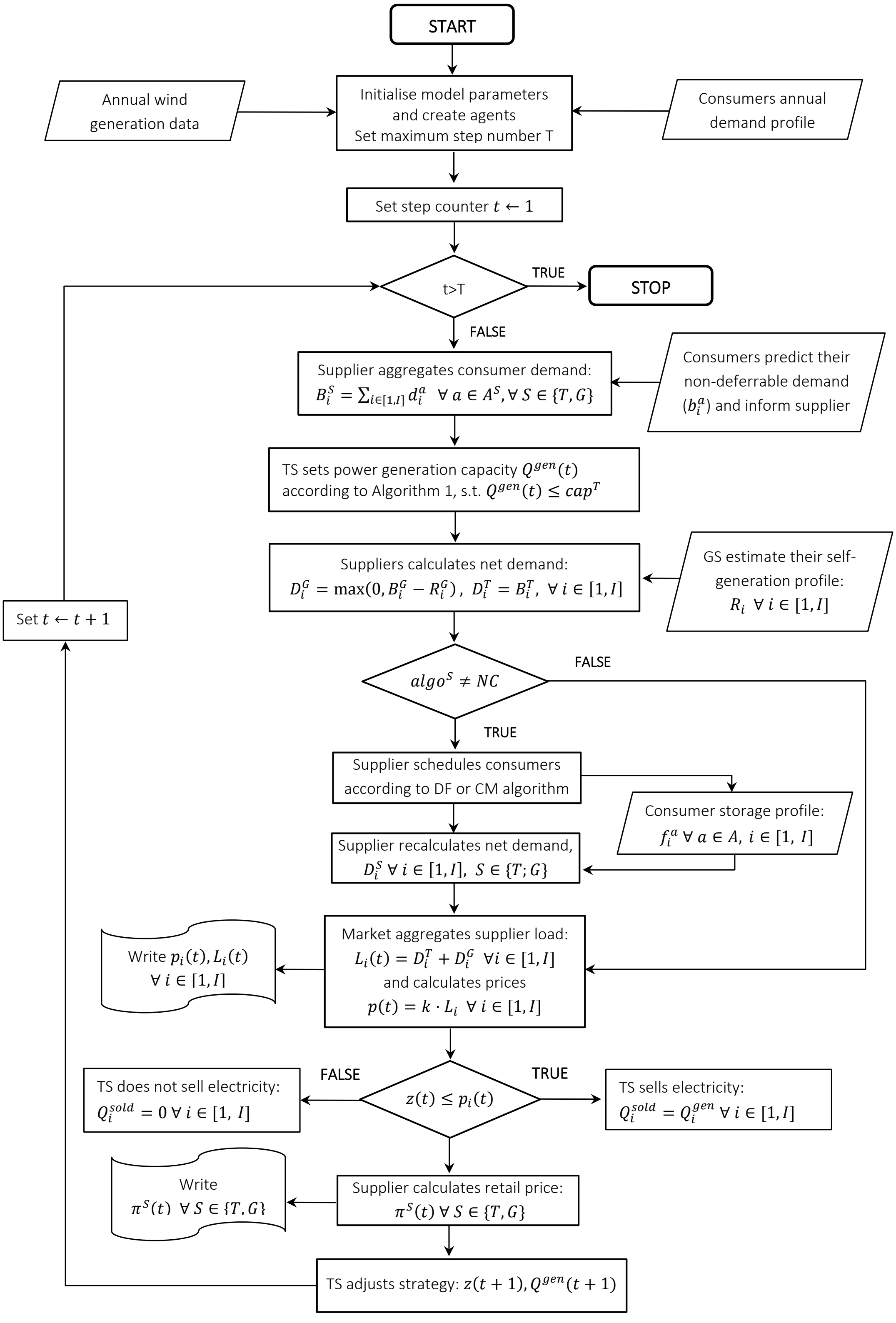
A Model flow diagram


START
Annual wind generation data
Initialise model parameters and create agents
Set maximum step number T
Consumers annual demand profile
Set step counter $t \leftarrow 1$
t>T
TRUE
STOP
FALSE
Supplier aggregates consumer demand:
$B_i^S = \sum_{i\in[1,I]} d_i^a \ \forall a \in A^S, \forall S \in \{T,G\}$
Consumers predict their non-deferrable demand (b_i^a) and inform supplier
TS sets power generation capacity $Q^{gen}(t)$ according to Algorithm 1, s.t. $Q^{gen}(t) \leq cap^T$
Suppliers calculates net demand:
$D_i^G = \max(0, B_i^G - R_i^G),\ D_i^T = B_i^T,\ \forall i \in [1,I]$
GS estimate their self-generation profile:
$R_i \ \forall i \in [1,I]$
Set $t \leftarrow t+1$
$algo^S \neq NC$
FALSE
TRUE
Supplier schedules consumers according to DF or CM algorithm
Consumer storage profile:
$f_i^a \ \forall a \in A,\ i \in [1,\ I]$
Supplier recalculates net demand,
$D_i^S \ \forall i \in [1,I],\ S \in \{T;G\}$
Write $p_i(t), L_i(t)$ $\forall i \in [1,I]$
Market aggregates supplier load:
$L_i(t) = D_i^T + D_i^G \ \forall i \in [1,I]$
and calculates prices
$p(t) = k \cdot L_i \ \forall i \in [1,I]$
TS does not sell electricity:
$Q_i^{sold} = 0 \ \forall i \in [1,\ I]$
FALSE
$z(t) \leq p_i(t)$
TRUE
TS sells electricity:
$Q_i^{sold} = Q_i^{gen} \ \forall i \in [1,I]$
Write $\pi^S(t) \ \forall S \in \{T,G\}$
Supplier calculates retail price:
$\pi^S(t) \ \forall S \in \{T,G\}$
TS adjusts strategy: $z(t+1), Q^{gen}(t+1)$