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The role of power-to-gas in the future energy system: how much is needed and who wants to invest?

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Abstract: Energy systems based on renewables have an increasing demand for flexibility. In this paper, we consider the potential of power-to-gas to provide flexibility and enhance the system integration of renewables. Existing research on power-to-gas typically analyses the system effects of a predetermined power-to-gas unit without endogenising the investment decision. Moreover, insights related to the market and portfolio effects of power-to-gas are rare. To this end we present a stochastic mixed complementarity problem, which models the optimisation problems of different market players individually. The players we consider include power generating firms with different generation portfolios and different consumer groups. Firms earn revenues from an energy market, a quantity-based capacity market and a feed-in premium for renewable generation. They maximise their profits by optimising the operation of existing assets and making investments in new generation assets and in power-to-gas. We find that firms with renewable generation benefit from investing in power-to-gas. While the technology itself is loss-making, power-to-gas particularly increases demand and hence prices in low-load hours. Therefore, renewable generation becomes more profitable, which justifies the investment. However, the price increase results in higher costs to consumers so the overall transfer from consumers to wind generators increases in the presence of power-to-gas.

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1. Introduction

Modern electricity generation systems have seen a significant increase in variable renewable generation, such as wind and photovoltaic solar, in recent years, primarily in response to government targets. This in turn increases the level of variability in the electricity supply (Bertsch et al., 2016). Increased flexibility in other sources of electricity supply, and also demand, is therefore desirable in order to accommodate the increased variability (Albadi and El-Saadany, 2008; Palensky and Dietrich, 2011; De Jonghe et al., 2012; Siano, 2014; Clastres and Khalfallah, 2015; Broberg and Persson, 2016).

Specific technology investments are often proposed in order to accommodate this increased variability in electricity supply. These include electricity storage (Barton and Infield, 2004), demand-side management (Strbac, 2008) and electricity transmission and interconnection (Lynch et al., 2012; Spiecker et al., 2013). Another technology that has the potential to accommodate surplus renewable generation on the system is power-to-gas. The power-to-gas technology uses electricity to perform electrolysis on water, splitting the water molecules into hydrogen and oxygen molecules. The hydrogen can be used directly in industrial applications, as a transport or heating fuel or injected directly into the natural gas grid (provided the total amount injected is sufficiently low). The hydrogen can also be combined with carbon dioxide to create methane. Benjaminsson et al. (2013) and Gahleitner (2013) provide useful summaries of the technical and cost characteristics of the technology, along with case studies.

The literature on power-to-gas can be broadly grouped into several categories. The first calculates the levelised cost of electricity (LCOE) or net present value (NPV) of power-to-gas, particularly in high renewable energy systems. Examples include Breyer et al. (2011); Guandalini et al. (2015); Lombardi et al. (2011); Schiebahn et al. (2015); Hlusiak and Breyer (2012). Given that these studies are focused on the LCOE or NPV of the technology, there is no consideration of the potential impact of power-to-gas on the profitability of other generation technologies, or vice versa. Furthermore there are many assumptions made about the costs of the technology and the operational decisions of the power-to-gas operator.

The second strand of literature concerns specific business cases or case studies of various applications of power-to-gas, see for example Buchholz et al. (2014); Breyer et al. (2015b); Qadrdan et al. (2015). These papers again tend to focus on the costs and revenues of the power-to-gas technology itself, potentially in conjunction with investment in a complementary technology. However, they do not consider the system-wide effects of power-to-gas investment. The investment decision in power-to-gas is exogenously-determined.

There are several studies that consider the impact of power-to-gas within an energy system, including systems with one hundred per cent renewable generation. Examples include Breyer et al. (2015a); Palzer and Henning (2014); Henning and Palzer (2014); Moeller et al. (2014); Varone and Ferrari (2015). These studies tend to focus on the potential for surplus renewable generation to be consumed by power-to-gas units, rather than focusing on the optimal operation of the entire system. Investments in various technologies are also typically determined exogenously.

Finally some studies do consider the optimal operation of generation units on the system, along with the power-to-gas unit(s). Examples include Jentsch et al. (2014); de Boer et al. (2014) and Ahern et al. (2015), all of which consider operational decisions of a system with an exogenously-determined installation of power-to-gas. These studies all operate on a cost-minimisation basis. Vandewalle et al. (2015) also perform a cost-minimisation exercise on the Belgian electricity, gas and carbon sector through an operational model, but do attempt to determine the optimal investment in power-to-gas. However the investment in power-to-gas itself is not a control variable of the model; rather the results of the operational model are used to determine the optimal investment. In his study for Germany, Heffels (2015) does consider the investment in power-to-gas as an endogenous variable using a deterministic cost-minimisation model, i.e. there is no distinction between different market players and their portfolios.

Overall, there is no examination in the literature of the market or portfolio effects of investment in power-to-gas, namely the potential for power-to-gas investment to render another technology more or less profitable. The consideration of portfolio effects in least-cost electricity systems, rather than focusing solely on the cost of each technology in isolation, was pioneered by Awerbuch (Awerbuch and Berger, 2003; Awerbuch, 2006; Awerbuch and Yang, 2007). The approach was continued in the context of liberalised electricity markets based on marginal-cost pricing, see for example Roques et al. (2008); Lynch et al. (2013); Tietjen et al. (2016). While this literature focuses on both the risk and return of a given portfolio, it is important to consider the potential for a given technology to render another technology more or less profitable on average, as well as considering the variation of those profits.

The work presented here addresses several gaps in the literature. In contrast to the (mostly deterministic) cost-minimisation modelling performed in the literature to date, we model a stylised electricity market as a stochastic mixed complementarity problem (s-MCP), which accounts for the stochasticity of the renewable generation. The s-MCP considers different players in energy markets and models their optimisation problems individually. On the demand side, we distinguish between residential and industrial/commercial consumers, both of whom have the objective of minimising their costs. On the supply side, we consider a number of different generation firms that earn revenues from an energy market and a quantity-based capacity market. Moreover, firms earn an additional feed-in premium (FIP) on top of the market price for their renewable generation. The firms' objective is to maximise their profits. We consider operational decisions of each of the generation firms, but also allow firms to determine their optimal investment into new technologies, including power-to-gas, as well as optimal retirement of existing units. Thus the optimal portfolio of technologies is arrived at endogenously, including the optimal investment in power-to-gas. In order to determine the interaction of power-to-gas and variable renewable technology, and in recognition of the fact that investment in renewable generation is driven primarily by policy decisions rather than market outcomes, we exogenously determine the level of installed wind capacity and consider the resulting investment decisions in power-to-gas.

The paper proceeds as follows. Section 2 outlines the modelling approach taken. Section 3 presents the stylised electricity system chosen and describes the input data. Section 4 presents the main results, section 5 discusses the findings and section 6 concludes.

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
$i \in I$	Iterations of Benders Decomposition algorithm

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
$inv_{f,t}$	Investment in new generation capacity for firm f with technology t
$exit_{f,t}$	Decommissioning of old generation capacity for firm f with technology t
$gen^{\text{P2G}}_{f,p,s}$	Gas produced by firm f in timestep p and scenario s
inv^{P2G}_{f}	Capacity of power-to-gas firm f invests in
Consumers' primal variables	
$g^{\text{ls}}_{k,p,s}$	Load shedding 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
$\lambda^{\#}_{\cdot}$	Lagrange multipliers associated with constraint # of the firms' problem
$\mu^{\#}_{\cdot}$	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.

In this section, the methodology is discussed. We utilise a stochastic MCP to represent an electricity market with two types of players: generation firms and electricity consumer groups. The model is very similar to the model developed in Bertsch et al. (2018). The most significant difference is the consideration of investment and operation decisions of power-to-gas units.

Firms receive revenues from energy and capacity markets as well as a FIP and seek to maximise their profits. They may hold multiple generating units of baseload, mid merit, peakload and wind technology. Firms are distinguished by the initial generation portfolio they hold but may invest in additional capacity of any technology. Firms may also invest in power-to-gas capacity. In addition, all firms are modelled as price-takers, i.e., we assume that no firm may exert market power. Firms may also earn revenues from a capacity market. As in Bertsch et al. (2018) the capacity payment mechanism we consider is a quantity based mechanism.

Table 3: Parameters.

PR_s	Probability associated with scenario s
MTC_t	Maintenance cost form generating technology t
$CAP_{f,t}$	Initial generating capacity for firm f with technology t
$D_{k,p}^{\text{REF}}$	Reference demand for consumer group k in period p and scenario s
$G_k^{\text{LS,MAX}}$	Maximum load shedding for consumer group k in any time period or scenario
INT_k^{MICRO}	Micro generation capacity for consumer group k
INT_k^{PV}	PV generating capacity for consumer group k
$NORM_{p,s}^{\text{PV}}$	PV generating profile for period p and scenario s
$NORM_{f,t,p,s}^{\text{G}}$	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
DR_t	De-rating factor for technology t
$A_{\cdot}$	Intercept associated with marginal cost functions
$B_{\cdot}$	Slope associated with marginal cost functions
$C_{k,p}^{\text{PV}}$	Marginal cost of using PV generation for consumer group k in period p
IC_t^{GEN}	Investment in generating technology t cost
CAP_f^{P2G}	Initial power-to-gas capacity
EFF	Efficiency of converting electrical energy to gas
C^{GAS}	Price of gas

Table 4: Functions.

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

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, 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 and their demand profiles.

The stochasticity of the model arises from the uncertainty surrounding wind and PV power (Bertsch et al., 2018). 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. 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, investment in new capacity and decommissioning of existing capacity. However, in this paper, firm f must also choose the capacity of power-to-gas in which it wishes to invest and, if this quantity is non-zero, how much gas it wishes to produce (and thus how much electricity it consumes). Firm f considers revenues received from a capacity and an energy market as well as a FIP for RES generation. In addition, it also considers any revenues it earns from the gas it produces. Its costs consist of generation costs, investment costs and any costs incurred for maintaining its units. Furthermore, firm f's costs also include the cost of generating electricity for power-to-gas. Firm f's optimisation problem is:

$$
\begin{aligned}
\max_{\substack{gen_{f,t,p,s}, cap^{\mathrm{bid}}_{f,t},\\ inv_{f,t}, exit_{f,t}\\ gen^{\mathrm{P2G}}_{f,p,s}, inv^{\mathrm{P2G}}_{f}}} \quad & \sum_{t,p,s} \Big(PR_s \times gen_{f,t,p,s} \times \big(\gamma_{p,s} + X_t - C^{\mathrm{GEN}}_t(gen_{f,t,p,s})\big)\Big) - \\
& \sum_{t} \Big(IC^{\mathrm{GEN}}_t \times inv_{f,t} + \big(inv_{f,t} + CAP_{f,t} - exit_{f,t}\big) \times MTC_t \Big) + \\
& \sum_{p,s} \Big(PR_s \big(C^{\mathrm{GAS}} \times gen^{\mathrm{P2G}}_{f,p,s} - \gamma_{p,s} \times (1/EFF) \times gen^{\mathrm{P2G}}_{f,p,s}\big)\Big) \\
& - IC^{\mathrm{P2G}} \times inv^{\mathrm{P2G}}_f + \sum_t DR_t \times \kappa \times cap^{\mathrm{bid}}_{f,t},
\end{aligned}
\tag{1a}
$$

subject to:

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

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

$$gen^{\text{P2G}}_{f,p,s} \leq EFF \times (CAP^{\text{P2G}}_{f} + inv^{\text{P2G}}_{f}),\ \ \forall t,p,s,\ \ (\lambda^{3}_{f,p,s}), \tag{1d}$$

where the parameter EFF represents the efficiency of converting electrical energy to gas within a power-to-gas unit while C^{GAS} represents the price of gas. 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. Constraint (1d) ensures that, for each timestep and scenario, firm f cannot produce more gas than the capacity of its power-to-gas unit. The parameter CAP^{P2G}_{f} represents firm f's initial power-to-gas capacity before any investment. Firm f's optimisation problem is convex if all values for B^{GEN}_{t} are non-negative. The KKT conditions of firm f's problem are discussed in Appendix A.

2.2. Consumer group k's problem

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. We do not consider any load shifting or storage options on the demand side as the focus is on understanding the potential role of power-to-gas. Considering other flexibility measures would lead to distortions in this analysis. However, investigating whether demand side storage and power-to-gas are competing or complementary technologies should be subject to future research.

Consumer group k's optimisation problem is:

$$\begin{aligned} \min_{\substack{g^{\text{ls}}_{k,p,s}, g^{\text{micro}}_{k,p,s}, \\ g^{\text{pv}}_{k,p,s}}} \sum_{s,p} PR_s \Big(& \gamma_{p,s} \times \big(D^{\text{REF}}_{k,p} - g^{\text{ls}}_{k,p,s} - g^{\text{micro}}_{k,p,s} - g^{\text{pv}}_{k,p,s} \big) - X^{\text{PV}} \times g^{\text{pv}}_{k,p,s} \\ & + g^{\text{ls}}_{k,p,s} \times C^{\text{LS}}_{k,p}(g^{\text{ls}}_{k,p,s}) + g^{\text{micro}}_{k,p,s} \times C^{\text{MICRO}}_{k,p}(g^{\text{micro}}_{k,p,s}) + g^{\text{pv}}_{k,p,s} \times C^{\text{PV}}_{k,p} \Big) \end{aligned} \tag{3a}$$

subject to

$$
\begin{aligned}
g^{\text{ls}}_{k,p,s} &\leq G^{\text{LS,MAX}}_{k},\ \forall p,s,\ (\mu^{1}_{k,p,s}), && (3b)\\
g^{\text{micro}}_{k,p,s} &\leq INT^{\text{MICRO}}_{k},\ \forall p,s,\ (\mu^{2}_{k,p,s}), && (3c)\\
g^{\text{pv}}_{k,p,s} &\leq NORM^{\text{PV}}_{p,s} \times INT^{\text{PV}}_{k},\ \forall p,s,\ (\mu^{3}_{k,p,s}), && (3d)\\
g^{\text{ls}}_{k,p,s} + g^{\text{micro}}_{k,p,s} + g^{\text{pv}}_{k,p,s} &\leq D^{\text{REF}}_{k,p},\ \forall p,s,\ (\mu^{4}_{k,p,s}). && (3e)
\end{aligned}
$$

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

$$
\begin{aligned}
C^{\text{LS}}_{k,p}(x) &= A^{\text{LS}}_{k,p} + B^{\text{LS}}_{k,p}x, && (4)\\
C^{\text{MICRO}}_{k,p}(x) &= A^{\text{MICRO}}_{k,p} + B^{\text{MICRO}}_{k,p}x. && (5)
\end{aligned}
$$

Constraint (3b) limits the amount of electricity consumer group k can shed while constraints (3c) and (3d) limit the amount of electricity consumer group k can self-generate from micro- and PV generation, respectively. Constraint (3e) 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 (3e) 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 presented in Appendix A.2.

2.3. Market clearing conditions

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

$$
\sum_{f,t} gen_{f,t,p,s} = \sum_{f} (1/EFF) \times gen^{\text{P2G}}_{f,p,s} + \sum_{k} \left(D^{\text{REF}}_{k,p} - g^{\text{LS}}_{k,p,s} - g^{\text{MICRO}}_{k,p,s} - g^{\text{PV}}_{k,p,s} \right),\ \forall p,s,\ (\gamma_{p,s}) \qquad (6a)
$$

$$
\sum_{f,t} DR_t \times cap^{\text{bid}}_{f,t} = TARGET,\ (\kappa). \qquad (6b)
$$

Equation (6a) ensures that the electricity generated equals the electricity consumed. Equation (6b) ensures that the sum of capacity bids from firms, times a derating factor[1], must equal the capacity target. The variable$gen^{\text{P2G}}_{f,p,s}$ reflects the increased electricity demand from power-to-gas operation.

As 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.

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

2.4. Solving the problem

The solution approach involves a two step procedure which utilises a Benders Decomposition algorithm to reduce the computational cost of the model:

1. The MCP is initially solved for a selection of 24 days in hourly resolution. These days represent 8-day periods in winter, spring/autumn and summer, resulting in a total of $24 \times 8 \times 3 = 576$ hourly time steps. The objective function of each player are multiplied by weighting factors of 11.625, 22.750 or 11.375 depending on whether that hour represents a day in summer, spring/autumn or winter, respectively. This ensures that a full year of 8784 hours is represented by the 576 hourly time steps. The weighting factors are determined by the number of days in each season. Spring and autumn are represented by the same week explaining the higher weighting factor of the time steps representing these seasons.

   For this first step, a Benders Decomposition algorithm is used to solve the MCP. Benders Decomposition is a solution algorithm that has been shown to solve stochastic MCPs in a computationally efficient manner (Egging, 2013; Gabriel and Fuller, 2010). The Benders Decomposition pseudo-code is the same as that described in the appendix of Bertsch et al. (2018) while the master problem and convergence metric are similar to those presented in Bertsch et al. (2018) but, in this work, incorporate power-to-gas parameters and variables. Appendix B details the differences. The Benders Decomposition sub-problems of this paper can be described by the MCP presented in this section. For Benders Decomposition sub-problems, the first-stage decision variables (in this case, all investment and capacity bids variables) are fixed at the values obtained from the master problem of the same iteration.

2. The optimal investment (in both power-to-gas and electricity generation), de-commissioning and capacity bid variables from the first step are fixed as parameters in the second step. The MCP is then solved 93 times, each time representing a different 48-hour period in a 366-day year. As there are no inter-temporal constraints, splitting the model into smaller problems is equivalent to solving a single model with 8784 timesteps, assuming investment and exit decisions are fixed. Splitting the problem up into multiple smaller problems is however more computationally efficient (Devine et al., 2016). Furthermore, we believe it is reasonable to assume that investment/exit decisions and operational decisions are not made simultaneously.

The outputs of the model are the optimal investment, de-commissioning and capacity bid decisions from the first step and the optimal operational decisions and resulting prices from the second step. From these outputs, consumer costs, generator profits, power-to-gas revenues, CO_2 emissions and RES curtailment can be easily calculated.

3. Input data

We apply the model described in section 2 to a case study based on the future Irish power system. For this purpose, we mainly use data for 2025 from EirGrid (2016). Demand side data are described in section

3.1. Subsequently, we describe input data related to the conventional supply side and power-to-gas in section 3.2 and data related to renewable generation in section 3.3.

3.1. Demand side data

The consumer groups we consider on the demand side include commercial/industrial as well as residential consumers. Figure 1 illustrates the reference demand of the industrial and residential consumer groups on a typical day. This figure shows that the residential demand profile is less flat (the peak is more pronounced) than the industrial one. Based on EirGrid (2016), we assume total annual electricity demand of 33.6 TWh and peak demand of 5655 MW. In terms of the quantity target for the capacity market, we calculate this as 1.2 times the system peak demand similar to Nolan et al. (2017), i.e. $TARGET = 1.2 \times 5655$ MW $= 6786$ MW.

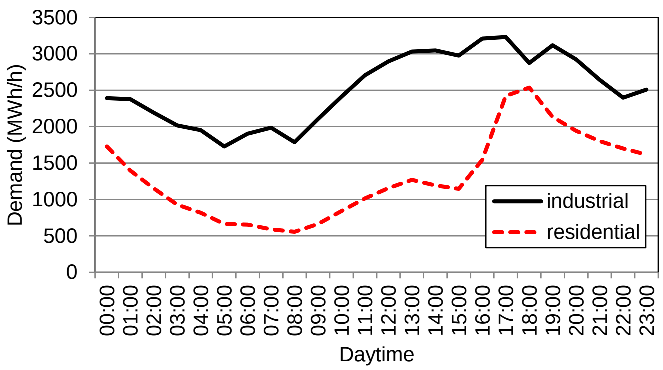

Figure 1: Reference demand of industrial and residential consumers on a typical day

3.2. Conventional power generation and power-to-gas 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 as well as an integrated firm with generation capacity across all of these technologies. The maximum capacity values for each technology are broadly based on EirGrid (2016). The initially installed capacity by technology and firm is presented in Table 5. Note that no firm has power-to-gas in their initial portfolio. Beyond power-to-gas investments, we look at the firms' investment decisions in new conventional generation. In their initial portfolio, however, the firms do not have any of the new technologies.

Our model considers quadratic cost functions for the conventional generators as described in section 2.1, i.e. the marginal costs at the intercept increase with the power output of each generator according to the marginal cost slope $B_t^{\mathrm{GEN}} = 0.000213$ (see Grigg, 1996). Table 6 shows the marginal power generation costs at the intercept, for further details see Bertsch et al. (2018).

There are large variations in the literature for investment costs and operational expenditures of power-to-gas units. For the electrolysis, these range from €300/kW (Breyer et al., 2011) to €1000/kW (Taljan et al., 2008) or even higher. Similarly, assumptions around the efficiency vary between 65% (Breyer et al., 2015b)

Table 5: Initial portfolio by firm ($CAP_{f,t}$).

Technology	firm 1	firm 2	firm 3	firm 4	firm 5
Existing baseload (MW)	1947	1940	-	-	-
Existing mid merit (MW)	512	-	404	-	-
Existing peakload (MW)	270	-	-	234	-
New baseload (MW)	0	0	0	0	0
New mid merit (MW)	0	0	0	0	0
New peakload (MW)	0	0	0	0	0
Wind (MW)	2400-3840	0	0	0	2400-3840
Power-to-gas (MW)	0	0	0	0	0

and 90% (Yildiz and Kazimi, 2006). In this paper, we focus on electrolysis only and assume investment costs of €600/kW and operational expenditures of around 2% of the specific investment per year. These values translate into annualised specific investment costs of €43,589/MW y and fixed O& M costs of €10,897/MW y (Table 6). Moreover, we assume an efficiency of 70% and a gas price of €18.00/MWh$_{th}$, which is relevant for the revenue side and operational decisions of the power-to-gas units.

Table 6: Techno-economic input data of supply side and power-to-gas technologies.

Technology	Annuity of specific invest (IC_t^{GEN}) (€/MW y)	Fixed O& M costs (MTC_t) (€/MW y)	Marginal power gen. costs at intercept (A_t^{GEN}) (€/MWh$_{el}$)	Spec. CO_2 emissions - (t CO_2/MWh$_{el}$)
Existing baseload	-	41,667	48.87	1.17
Existing mid merit	-	27,778	41.10	0.36
Existing peakload	-	23,148	63.38	0.56
New baseload	110,769	41,667	31.58	0.78
New mid merit	67,268	27,778	34.00	0.30
New peakload	40,363	23,148	50.50	0.45
Power-to-gas	43,589	10,897	0	0

3.3. Renewable power generation data

The variable sources of renewable electricity generation we consider in this paper are wind and solar PV. 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. It is therefore important to take these correlations into account when providing input data for the stochastic MCP.

The analysis is based on hourly MERRA2 data on surface incoming shortwave flux, air temperature and wind speed for the years 1981 to 2015 inclusive. This data was transformed to wind and solar capacity factors. For wind, the transformation 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 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 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). The chosen years and probabilities of occurrence are summarised in Table 7. Using these historical wind and PV data as a basis for our analysis ensures that the spatial and temporal correlations between wind and PV are preserved.

Table 7: 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

Our assumptions in relation to the installed RES-E capacity are based on EirGrid (2016). The system we study includes 50 MW of solar PV capacity, which are installed on the demand side in this study. Moreover, the power system described by EirGrid (2016) includes 4800 MW of installed wind capacity, which we assume are installed and operated on the supply side. In order to meet the long-term RES-E and decarbonisation targets beyond 2025, the installed wind capacity will need to be further increased (Slednev et al., 2017). Therefore, in order to analyse how increasing levels of wind capacity affect optimal investment decisions in the power system, in particular in power-to-gas, we run our model several times while exogenously increasing the wind capacity in 10% steps (in relation to the 4800 MW installed, i.e. steps of 480 MW). Consequently, we do not allow for endogenous wind investment decisions. Overall, we consider a range of 4800 MW - 7680 MW of wind on the system corresponding to a capacity of 85% - 136% of the system peak load respectively. Note that we do not vary the installed PV capacity in this paper.

4. Results

Figure 2 shows the total investment in power-to-gas technology under various exogenously-chosen installed wind capacities. There is no investment in power-to-gas at lower levels of wind penetration but once the wind capacity exceeds approximately 5280 MW (corresponding to 93% of the system peak load and a wind penetration of roughly 50% of demand) there is positive investment. This result concurs with previous literature on the topic (Heffels, 2015).

The linear relationship between power-to-gas investment and wind capacity is a consequence of modelling the investment and output decisions of the firms as continuous linear variables. Including discontinuities in the firms' decision variables, such as modelling investment on a per unit basis, or including start costs and no load costs in the dispatch decisions, would most likely alter the linear relationship between installed wind capacity and power-to-gas investment. Altering the investment cost and/or the assumed efficiency of the

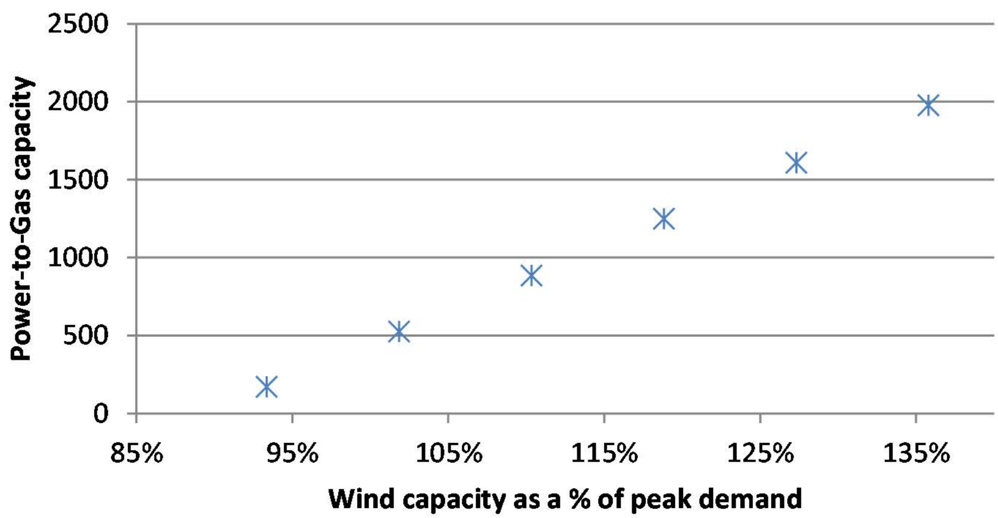

Figure 2: Total investment in power-to-gas technology under various installed wind capacities (MW)

power-to-gas technology would shift the curve up or down in relation to the y-axis but would not change the shape of the curve.

Figure 3 shows the costs and revenues associated with investing in power-to-gas (when considering the technology's profits in isolation) for the scenario where the installed wind capacity on the system equals 127% of the peak demand. Under this scenario, the optimal investment in power-to-gas is approximately 1,600 MW_{el}.

The purchase of electricity to operate the power-to-gas plant yields revenue for the plant as the electricity price becomes negative whenever the amount of wind generation available is greater than the demand. At these times, the marginal cost of production is the marginal cost of wind, which is minus twenty-three euro per megawatt hour (due to wind receiving a FIP over and above the market price). Consumption of electricity during these hours therefore yields revenue for the power-to-gas plant owner.

In spite of this, the sum of the revenue from selling renewable gas at the wholesale price of gas and the revenue from consuming electricity is less than the annual capital costs of investment in power-to-gas, and so power-to-gas is a loss-making technology. Given the positive investment in power-to-gas, market or portfolio effects must render it an efficient investment. This result underlines the importance of examining investment in power-to-gas, and indeed any technology, in the context of the entire portfolio of technologies, rather than restricting focus to the profitability of the technology on a stand-alone basis.

The model was also run without the option of investment in power-to-gas in order to isolate the impact of same. Figure 4 shows the difference in wind curtailment for the cases with and without investment in power-to-gas at each level of installed wind. In the absence of power-to-gas, the level of wind curtailment increases with the level of wind installed on the system. When allowing the players to invest in power-to-gas, however, the level of wind curtailment stays more or less at a constant level.

Figure 5 shows the market price duration curves with and without power-to-gas for levels of installed wind

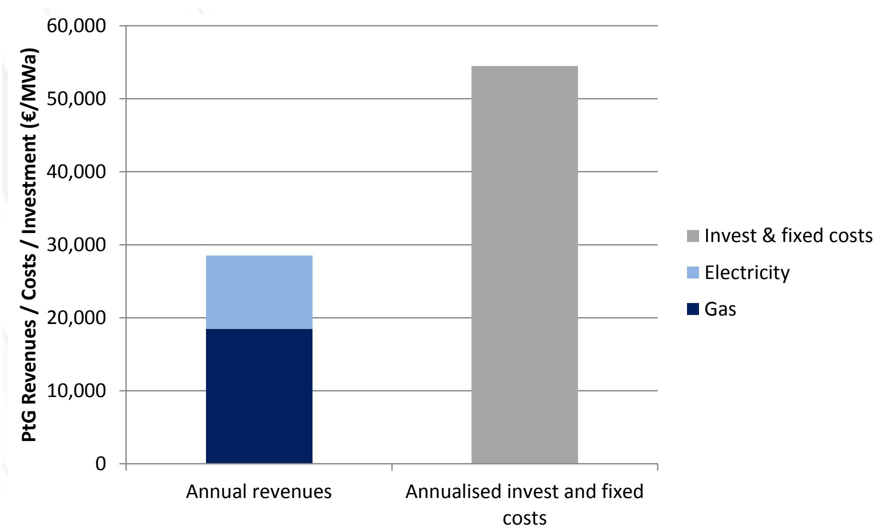

Figure 3: Cost and revenues associated with power-to-gas unit

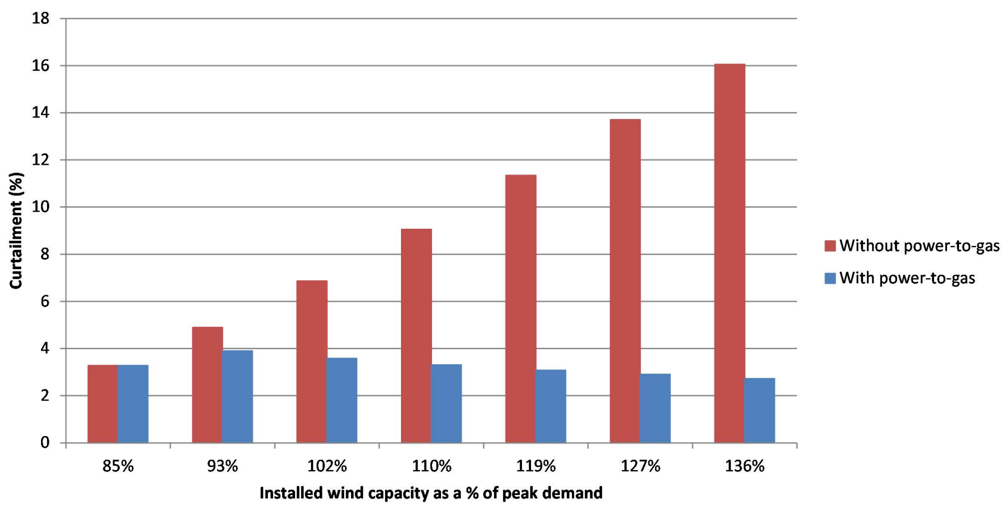

Figure 4: Wind curtailment with and without power-to-gas investment

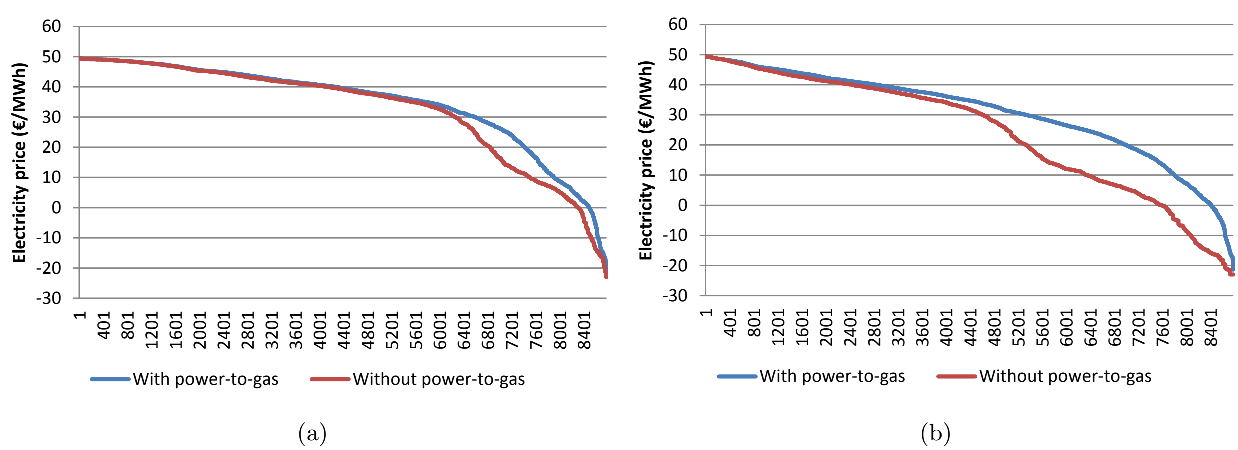

Figure 5: Price duration curves with and without power-to-gas

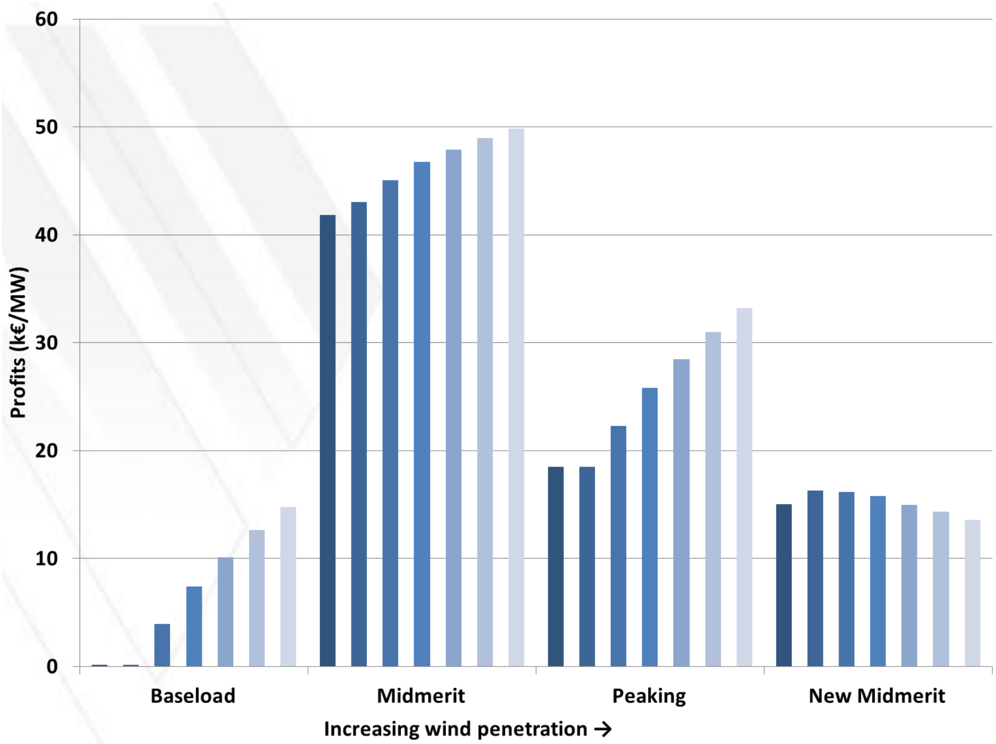

Figure 6: Profitability of each conventional technology per megawatt installed for each wind level

capacity equalling around 100% of the peak load (a) and around 135% of the peak load (b). Unlike storage technologies, which increase off-peak demand and reduce peak demand, power-to-gas only does the former by using electricity for power-to-gas production during periods of low (net) demand. Thus the upper end of the price duration curve is unchanged but off-peak prices increase significantly. This in turn increases the profits of technologies with the lowest marginal costs that generate at times of low net demand, in particular wind generation.

The profitability of each conventional technology type per megawatt installed across all firms is shown in figure 6 for each of the levels of wind penetration considered. The profitability per megawatt installed of the existing technologies increases as wind increases. This is a consequence of retirement decisions. Installed wind capacity crowds out conventional technologies and so the revenues for each technology are distributed over a smaller total installed capacity, boosting the revenues per megawatt installed.

In the case of wind, the profit per megawatt installed decreases as the total amount of wind installed increases. However, the addition of power-to-gas increases the profit per megawatt of wind relative to the case where there is no investment in power-to-gas (figure 7). This is due to the increase in off-peak prices induced by the power-to-gas unit.

Given the results above, it stands to reason that firms that have wind capacity as part of their generation portfolios will benefit the most from the presence of power-to-gas on the system. Figure 8 shows the profits per megawatt of installed capacity that accrue to each firm assuming each firm was the firm to invest in

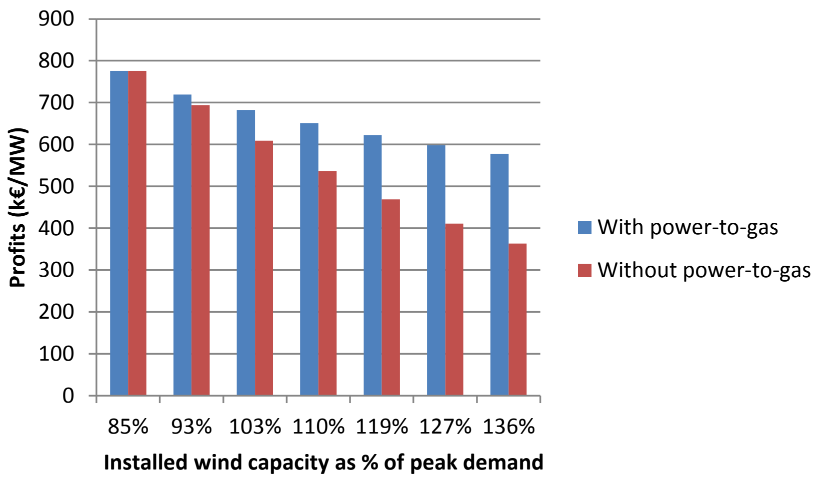

Figure 7: Profitability of wind per megawatt installed for each wind level

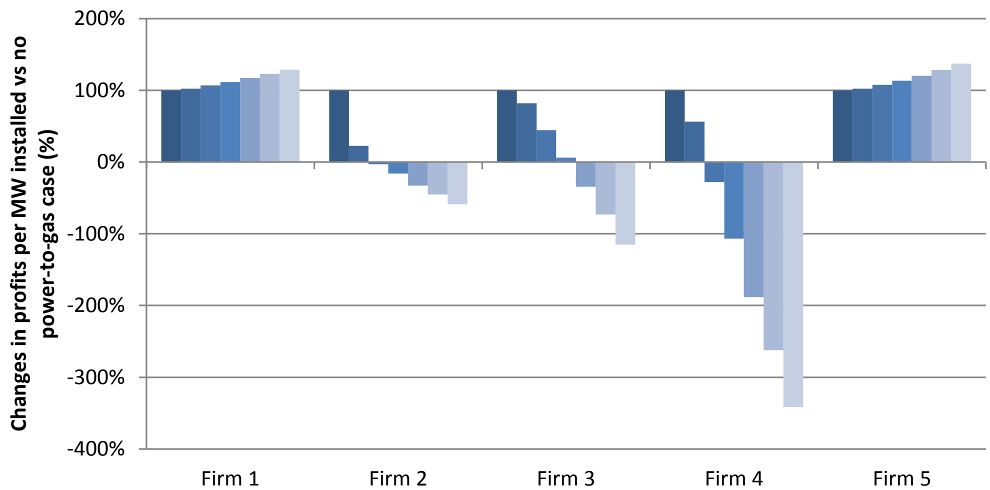

Figure 8: Profitability of each firm relative to the case with no power-to-gas

power-to-gas, thus incurring the capital cost and earning the revenues from electricity consumption and gas production.

As expected, firms one and five, which have wind capacity in their portfolios, see higher profits per megawatt installed for all levels of wind and power-to-gas capacity. The increase in their wind generation's profitability more than offsets the loss-making power-to-gas investment. The firms that have only conventional generation in their portfolios, however, see lower profits relative to the case where there is no investment in power-to-gas.

Figure 9 shows the total cost incurred by consumers at each level of installed wind capacity, both with and without power-to-gas. These costs include energy and capacity payments paid by consumers in each market along with any subsidy payments to wind generation. Any savings from self-consumption of solar generation are also accounted for in the calculation. Consumer costs decrease with increasing levels of wind

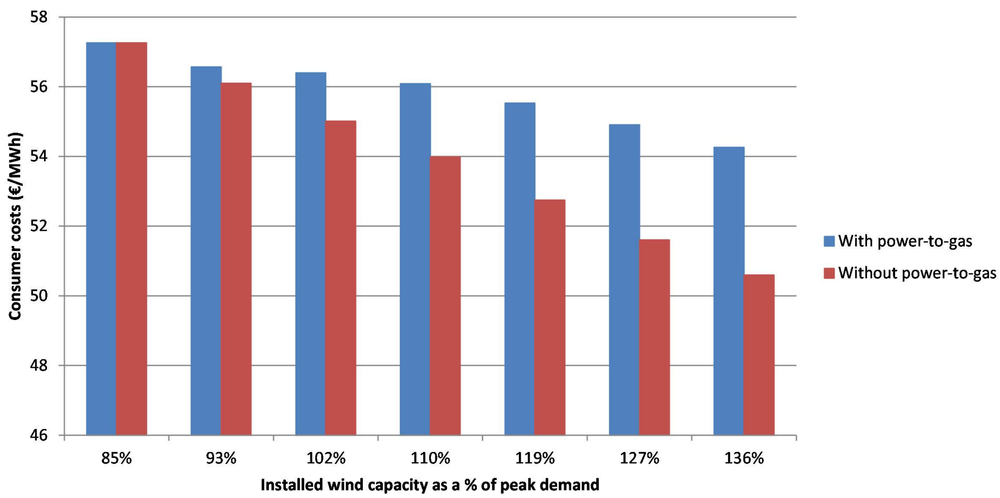

Figure 9: Total cost incurred by consumers at each level of installed wind capacity

generation due to the lower electricity prices induced by wind. However, power-to-gas increases off-peak electricity prices and so increases consumer costs. Thus power-to-gas investments facilitate a transfer from electricity consumers to wind capacity owners over and above the FIP payments wind generators receive from consumers.

5. Discussion

There are several new contributions that the results above make to the literature. The importance of considering the impact of a particular technology on the generation portfolio, rather than considering the costs and benefits of the technology in isolation, is highlighted by this work. This holds both in relation to firm portfolios and market portfolios. Metrics such as Levelised Cost of Electricity (LCOE) exhibit significant weaknesses as a means of determining the relative strengths and weaknesses of generation technology investments. In spite of this, such metrics are still widely used, with Musi et al. (2017); Lai and McCulloch (2017); Clauser and Ewert (2017) and Geissmann (2017) providing only recent examples. The use of net present value to determine whether to invest in a particular technology is also a poor metric as it does not consider the potential for one technology to impact on the profitability of another technology held by a given firm.

The fact that negative prices arise in our model drives the results, at least to some extent. These negative prices incentivise investment in power-to-gas, which in turn raises market prices and thus consumer costs (figure 9). Thus the subsidy paid by consumers to wind generators leads to them paying yet higher electricity prices, and there is a greater total transfer from consumers to wind power producers in the presence of power-to-gas compared to a scenario with no power-to-gas. This is in addition to the carbon cost already incurred by consumers. Our model does not include a carbon credit for the production of renewable gas; however the inclusion of same would increase investment in power-to-gas, and thus electricity prices, even further.

Therefore the total transfer from consumers to wind power producers depends not only on the subsidy level but also on the electricity generation portfolio. This has important implications for policy-makers considering optimal renewable subsidisation and carbon taxation.

There is of course potential for competing technologies to crowd out the investment opportunities for power-to-gas. For example, storage technologies that, like power-to-gas, increase off-peak electricity generation, but also reduce on-peak generation, reduce the potential impact of power-to-gas on wind owners' profits. In particular, consumers may have an incentive to invest in storage technologies, as they can reduce their exposure to peak prices as well as increasing their off-peak price exposure, and so may incur lower costs than those incurred with power-to-gas investment. The trade-offs between power-to-gas versus other potential generation investments should therefore be further explored.

This paper considered optimal investments in a one-period framework. However expanding this work to a repeated game may yield further insights as the timing of investments is important. Given that investments in power-to-gas may render potential storage investments by consumers and other firms less profitable and vice versa, there may be an optimal time to invest in each technology. Similarly, the presence of power-to-gas on the system benefits all players that own wind generation, with the greatest net benefit going to firms that own wind but do not own power-to-gas, and so do not incur the cost of the power-to-gas investment. There is thus an option value of waiting inherent in power-to-gas investment, as a firm's optimal strategy would be to invest in wind given that a rival firm invests in power-to-gas. Future work may explore these possibilities. Moreover, this work modelled all firms as price-takers; however in reality electricity markets are characterised by oligopoly. The presence of price-makers in the market may change the optimal level of investment in each technology, including power-to-gas, as price-making behaviour in the energy market would raise prices, rendering all generation investments more profitable. The divergence of power-to-gas investment, if any, when price making behaviour is introduced may also inform discussion on whether there is an external cost or benefit to power-to-gas investment, and therefore whether a tax or a subsidy is justified. Further work will consider the implications of price-making behaviour on the results presented here.

6. Conclusion

The variability of electricity systems increases with the level of penetration of variable renewable generation. This development calls for an increased flexibility of other parts of the systems, including the supply and demand side. Power-to-gas is one technology that can provide flexibility to the electricity system and has the potential to enhance the system integration of renewable generation.

We present a stochastic mixed complementarity model to understand what level of power-to-gas is optimal, what determines this level, and which market player(s), if any, have an incentive to invest in this technology. In the model, we consider consumers that minimise the costs of their electricity usage and generation firms that maximise their profits from an energy market, a quantity-based capacity market and an additional feed-in premium (FIP) for renewable generation. For each firm, the model endogenously determines optimal investment decisions, including power-to-gas, optimal retirement decisions and optimal operational decisions. We use this model to analyse the market and portfolio effects of investment in power-to-gas, i.e. the potential for power-to-gas to make another technology more or less profitable, which is a significant contribution to the existing literature.

We find that, while we do not observe any investment in power-to-gas at low levels of wind penetration, there is positive investment once the wind penetration exceeds roughly 50% of electricity demand. Moreover, the optimal level of power-to-gas investment increases with the wind penetration in the system. This is interesting because power-to-gas itself is a loss-making technology given the underlying techno-economic parameters in this study. However, firms with renewable generation in their portfolio have an incentive to invest in power-to-gas. This is because power-to-gas increases the electricity demand in hours of low net demand and, hence, increases electricity prices in those hours which is beneficial for their renewable generation. The increase in profits from renewables outweighs the losses the firms make from the power-to-gas investment. These findings underline the importance of considering portfolio and market effects of technology investments rather than considering the profitability of investments in isolation.

In addition, we find that the level of renewable curtailment stays more or less constant in the presence of power-to-gas, whereas it increases with the level of wind capacity on the system when firms do not have the option to invest in power-to-gas. This demonstrates the capability of power-to-gas to accommodate renewable generation. However, it is important to understand that these wider benefits are paid for by the consumers whose costs increase in the presence of power-to-gas. Future research should therefore include competing technologies (e.g., distributed storage technologies) as possible investments on the demand side.

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Appendix 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 (6), 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 $a.b = 0$.

Appendix A.1. Firms' KKT conditions

The firms' KKT conditions include all those from Appendix A.1 of Bertsch et al. (2018) in addition to:

$$0 \leq gen^{\mathrm{P2G}}_{f,p,s} \quad \perp \quad -PR_s\big(C^{\mathrm{GAS}} - \gamma_{p,s} \times (1/EFF)\big) + \lambda^3_{f,t,p,s} \geq 0, \;\; \forall f, p, s, \tag{A.1}$$

$$0 \leq inv^{\mathrm{P2G}}_{f} \quad \perp \quad IC^{\mathrm{P2G}} - \sum_{p,s} EFF \times \lambda^4_{f,p,s} + \lambda^5 \geq 0, \;\; \forall f, \tag{A.2}$$

$$0 \leq \lambda^3_{f,p,s} \quad \perp \quad -gen^{\mathrm{P2G}}_{f,p,s} + EFF \times (CAP^{\mathrm{P2G}}_f + inv^{\mathrm{P2G}}_f) \geq 0, \;\; \forall f, p, s. \tag{A.3}$$

Appendix A.2. Consumers' KKT conditions

The consumers' KKT conditions are

$$0 \leq g^{\mathrm{ls}}_{k,p,s} \quad \perp \quad -PR_s\big(\gamma_{p,s} - \frac{\partial C^{\mathrm{LS}}_{k,p}}{\partial g^{\mathrm{ls}}_{k,p,s}}\big) + \mu^1_{k,p,s} + \mu^8_{k,p,s} \geq 0, \;\; \forall k, p, s, \tag{A.4}$$

$$0 \leq g^{\mathrm{micro}}_{k,p,s} \quad \perp \quad -PR_s\big(\gamma_{p,s} - \frac{\partial C^{\mathrm{MICRO}}_{k,p}}{\partial g^{\mathrm{micro}}_{k,p,s}}\big) + \mu^4_{k,p,s} + \mu^8_{k,p,s} \geq 0, \;\; \forall k, p, s, \tag{A.5}$$

$$0 \leq g^{\mathrm{pv}}_{k,p,s} \quad \perp \quad -PR_s\big(\gamma_{p,s} + X^{\mathrm{PV}} - C^{\mathrm{PV}}_{k,p}\big) + \mu^5_{k,p,s} + \mu^8_{k,p,s} \geq 0, \;\; \forall k, p, s, \tag{A.6}$$

$$0 \leq \mu^1_{k,p,s} \quad \perp \quad -g^{\mathrm{ls}}_{k,p,s} + G^{\mathrm{LS,MAX}}_k \geq 0 \;\; \forall k, p, s, \tag{A.7}$$

$$0 \leq \mu^2_{k,p,s} \quad \perp \quad -g^{\mathrm{micro}}_{k,p,s} + INT^{\mathrm{MICRO}}_k \geq 0 \;\; \forall k, p, s, \tag{A.8}$$

$$0 \leq \mu^3_{k,p,s} \quad \perp \quad -g^{\mathrm{pv}}_{k,p,s} + INT^{\mathrm{PV}}_k \times NORM^{\mathrm{PV}}_{p,s} \geq 0 \;\; \forall k, p, s, \tag{A.9}$$

$$0 \leq \mu^4_{k,p,s} \quad \perp \quad -g^{\mathrm{ls}}_{k,p,s} - g^{\mathrm{micro}}_{k,p,s} - g^{\mathrm{pv}}_{k,p,s} + D^{\mathrm{REF}}_{k,p} \geq 0 \;\; \forall k, p, s. \tag{A.10}$$

Appendix B. Benders Decomposition

In this appendix we describe the differences between the Benders Decomposition algorithms used in Bertsch et al. (2018) and in this work. In particular we consider the differences for the master problems and the convergence metrics.

Appendix B.1. KKT conditions for master problem of ith iteration

The KKT conditions for the MCP master problem of this work includes all the KKT conditions from Appendix B.2 in Bertsch et al. (2018) except the Benders cut KKT conditions which are updated to include power-to-gas parameters and variables as follows:

$$
\begin{aligned}
0 \leq \theta^{\hat{\imath}} \quad \perp \quad & \alpha + \sum_{f,t,p,s} \left(PR_s \big(2B_t^{\mathrm{GEN}} \times gen_{f,t,p,s}^{\hat{\imath}}\big) \times \sum_{\bar{\imath} \leq i} \big(\theta^{\bar{\imath}} \times gen_{f,t,p,s}^{\bar{\imath}}\big) \right) \\
& + \sum_{f,t,p,s} \lambda_{f,t,p,s}^{1,\hat{\imath}} \times (CAP_{f,t} + inv_{f,t} - exit_{f,t}) \times NORM_{f,t,p,s}^{\mathrm{G}} \\
& + \sum_{f,p,s} \lambda_{f,p,s}^{4,\hat{\imath}} \times EFF \times (CAP_f^{\mathrm{P2G}} + inv_f^{\mathrm{P2G}}) \\
& + \sum_{k,p,s} \left(PR_s \times 2B_{k,p}^{\mathrm{LS}} \times g_{k,p,s}^{\mathrm{LS},\hat{\imath}} \right) \times \sum_{\bar{\imath} \leq i} \big(\theta^{\bar{\imath}} \times g_{k,p,s}^{\mathrm{LS},\bar{\imath}}\big) \\
& + \sum_{k,p,s} \left(PR_s \times 2B_{k,p}^{\mathrm{MICRO}} \times g_{k,p,s}^{\mathrm{MICRO},\hat{\imath}} \right) \times \sum_{\bar{\imath} \leq i} \big(\theta^{\bar{\imath}} \times g_{k,p,s}^{\mathrm{MICRO},\bar{\imath}}\big) \\
& + \sum_{k,p,s} \Big(\mu_{k,p,s}^{1,\hat{\imath}} \times G_k^{\mathrm{LS,MAX}} + \mu_{k,p,s}^{2,\hat{\imath}} \times INT_k^{\mathrm{MICRO}} + \mu_{k,p,s}^{3,\hat{\imath}} \times NORM_{p,s}^{\mathrm{PV}} \times INT_k^{\mathrm{PV}} \\
& + \big(\mu_{k,p,s}^{4,\hat{\imath}} + \gamma_{p,s}^{\hat{\imath}}\big) \times D_{k,p}^{\mathrm{REF}} \Big) \geq 0, \quad \forall \hat{\imath} \leq i.
\end{aligned}
\tag{B.1}
$$

The KKT conditions for the MCP master problem of this work also include

$$
0 \leq inv_f^{\mathrm{P2G}} \quad \perp \quad IC^{\mathrm{P2G}} - \sum_{\hat{\imath} \leq i} \theta^{\hat{\imath}} \left(\sum_{p,s} EFF \times \lambda_{f,p,s}^{4,\hat{\imath}} \right) \geq 0, \ \forall f. \tag{B.2}
$$

Appendix B.2. Convergence metric

In this appendix the convergence metric for the Benders Decomposition algorithm used in this work is presented. It is similar to that of Bertsch et al. (2018) but is updated to include the power-to-gas parameters and variables as follows:

$$
\begin{aligned}
TOL^i \quad = \quad & \sum_{f,t,p,s} PR_s \left(2B_t^{\mathrm{GEN}} \times \big(gen_{f,t,p,s}^{i} - gen_{f,t,p,s}^{M,i}\big) \right) \times gen_{f,t,p,s}^{M,i} \\
& + \sum_{f,t,p,s} \big(\lambda_{f,t,p,s}^{1,i} - \lambda_{f,t,p,s}^{1,M,i}\big) \times (CAP_{f,t} + inv_{f,t} - exit_{f,t}) \times NORM_{f,t,p,s}^{\mathrm{G}} \\
& + \sum_{f,p,s} \big(\lambda_{f,p,s}^{3,i} - \lambda_{f,p,s}^{3,M,i}\big) \times EFF \times (CAP_f^{\mathrm{P2G}} + inv_f^{\mathrm{P2G}}) \\
& + \sum_{k,p,s} \left(PR_s \times 2B_{k,p}^{\mathrm{LS}} \times \big(g_{k,p,s}^{\mathrm{LS},i} - g_{k,p,s}^{\mathrm{LS},M,i}\big) \right) \times g_{k,p,s}^{\mathrm{LS},M,i} \\
& + \sum_{k,p,s} \left(PR_s \times 2B_{k,p}^{\mathrm{MICRO}} \times \big(g_{k,p,s}^{\mathrm{MICRO},i} - g_{k,p,s}^{\mathrm{MICRO},M,i}\big) \right) \times g_{k,p,s}^{\mathrm{MICRO},M,i} \\
& + \sum_{k,p,s} \Big(\big(\mu_{k,p,s}^{1,i} - \mu_{k,p,s}^{1,M,i}\big) \times G_k^{\mathrm{LS,MAX}} + \big(\mu_{k,p,s}^{2,i} - \mu_{k,p,s}^{2,M,i}\big) \times INT_k^{\mathrm{MICRO}} \\
& + \big(\mu_{k,p,s}^{3,i} - \mu_{k,p,s}^{3,M,i}\big) \times NORM_{p,s}^{\mathrm{PV}} \times INT_k^{\mathrm{PV}} + \big(\mu_{k,p,s}^{4,i} - \mu_{k,p,s}^{4,M,i} + \gamma_{p,s}^{i} - \gamma_{p,s}^{M,i}\big) \times D_{k,p}^{\mathrm{REF}} \Big).
\end{aligned}
\tag{B.3}
$$

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