The ACEWEM framework: An integrated agent-based and statistical modelling laboratory for repeated power auctions

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Abstract

We propose a novel framework for experimental designs of liberalised wholesale power markets, namely the Agent-based Computational Economics of the Wholesale Electricity Market (ACEWEM) framework. Here, we describe a detailed market simulation whereby the strategies of power generators emerge as a result of a stochastic profit maximisation learning algorithm based upon the GAMLSS (Generalized Additive Models for Location Scale and Shape) statistical framework. The ACEWEM framework, which integrates the agent-based modelling paradigm with formal statistical methods to represent better real-world decision rules, is designed to be the foundation for large custom-purpose experimental studies inspired by computational learning. The paper therefore makes a methodological contribution in the development of an expert model of repeated auctions with capacity and physical constraints. It also makes an applied contribution by providing a more realistic basis for identifying whether high market prices can be ascribed to problems of market structure or exercise of market power.

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1. Introduction

Liberalised wholesale power markets tend to be characterised by: (a) an oligopoly of heterogeneous power generators; (b) short term inelastic demand (Borenstein, Bushnell, & Knittel, 1999); and (c) complex (but not necessarily complicated) market mechanisms, which are designed to facilitate both financial and physical trading (see Fig. 1). Potentially, these characteristics in conjunction allow the principal market players to manipulate spot market prices upwards. Does this happen? Or, is the process of balancing supply and demand in real time by means of daily repeat auctions, conducted within a framework of known technical constraints, sufficient to ensure that competitive outcomes prevail? From an expert systems perspective, power markets rank among the most complex of all markets operated at present – supply and demand have to be balanced in real time, considering transmission limits and power unit commitment constraints.

Three major approaches to power auctions can be distinguished: (cost-based) optimisation models, equilibrium models, and (top–down or bottom–up) simulation models (Ventosa, Ballo, Ramos, & Rivier, 2005). A common application of optimisation models in power markets is the capacity expansion planning of public utilities (Simoglou, Biskas, Vagropoulos, & Bakirtzis, 2014). A limitation of such models is that they do not adequately capture strategic interactions between market participants. In contrast, equilibrium models, which may be viewed as generalizations of cost-based models (Weron, 2014), present generators as entities engaged in a rational bidding game for which both the rules of the game and information about rivals are shared among incumbents (Guerci, Rastegar, & Cincotti, 2010; Weidlich & Veit, 2008). In most cases both these top–down-type models involve high levels of aggregation and over simplification: they are not designed to analyse power markets that are heavily influenced by technical details (e.g., transmission network) and strategic player interactions (Sensfuß, Ragwitz, Genoese, & Möst, 2007). Taken together, by ignoring strategic player interactions and/or the environment (transmission grid) these models disregard the consequences of learning effects that result from daily repeated auctions conducted within a framework of known technical constraints (Rothkopf, 1999).

While analytical models provide a reasonable representation of power markets under stationary or strong periodicity of dynamic disturbances (Kannan & Zavala, 2011), they struggle representing short-term behaviour (e.g. hourly bids/offers) observed in power markets (Bunn & Day, 2009). Asymmetric information, imperfect competition, strategic interaction, collective learning, and the possibility of multiple equilibria all point to the complexity inherent in power markets. It is not surprising therefore that the complexities...
of the power markets drive most analytical modelling methods to their limits.

Agent-based Computational Economics (ACE) – a bottom–up simulation-based modelling approach – is a methodology that has the potential to overcome the shortcomings of traditional analytical methods to model complex (power) markets (Tesfatsion (2006) and references therein). In a nutshell, ACE models are computational models of micro-agents (e.g., power generating companies) operating in an environment (e.g., transmission grid), in which they interact repeatedly with other agents over a period of time, thereby permitting the computational study of phenomena as complex adaptive systems (CASs). For Tesfatsion (2006), CAS is a complex system that includes planner units, i.e., units that are goal-directed and that attempt to exert some degree of control over their environment to facilitate achievements of their goals. Voudouris (2011) argues that the development of realistically rendered ACE models offers a better way for the representation and scientific investigation of complex, dynamic phenomena such as energy markets (see Section 2 for details of the ACE methodology).

The work presented here addresses the difficulty of developing models capable of capturing emergent phenomena that are caused by decentralized heterogeneous profit-maximisation decisions (macro-behaviours caused by micro-motives) observed in power markets. It is thus of significant practical importance for agents that participate in daily repeated auctions of wholesale power markets with the aim of maximising their profits. Furthermore, ACE models can be used to explore whether high market prices can be ascribed to problems of market structure or exercise of market power − an important policy question.

To represent better the characteristics of wholesale power market, we introduce the Agent-based Computational Economics of the Wholesale Electricity Market (ACEWEM) framework. Based on the work of Sun and Tesfatsion (2007) and Rigby and Stasinopoulos (2005), the ACEWEM framework can simulate a wide range of power markets. It contains a variety of key agents (system operator, power generators and wholesale electricity consumers) and other supporting environmental elements (e.g., transmission grid). Thus, the ACEWEM framework can represent real-world agents operating over realistically abstracted power grids, in which both economic and physical aspects are taken into account. Specifically, the paper adds to the literature by:

(a) Suggesting a new decision rule for the strategic offers/bids of the agents competing in repeated power auctions. The agents learn both from past performance of their strategies as well as endogenously estimating a statistical model in order to optimise their strategic bids/offers (see Section 3.2). Here, it is important to note that the statistical model is developed by selecting the structure of the GAMLSS-based model developed by Rigby and Stasinopoulos (2005) using the reinforcement-learning algorithm of Erev and Roth (1998). This is a distinguishing feature of our approach towards realistically rendered ACE models.

(b) Incorporating Day-ahead and Real-time spot markets – see Fig. 1. This is important because agents might strategically submit bids/offers across different markets as a way of optimising total profit. Furthermore, physical constraints might not necessarily be taken into consideration in the Day-ahead market. In fact, there are market designs where the physical constraints are resolved during the operation of the Real-time market.

(c) Implementing two congestion management schemes, namely a Locational Marginal Pricing (LMP) scheme (Hogan, 1992) and a Power Re-dispatch scheme (De Vries, 2001) to test the effect of the different congestion management schemes on market dynamics (see experiment 1 and 3).

(d) As a result of (b) and (c), developing a least-cost constrained optimal power flow (COPF) algorithm so to estimate power outputs from different generators operating in two spot markets under different congestion management schemes.

(e) Implementing two alternative auction designs, namely uniform and discriminatory (pay-as-bid) pricing rules (Klemperer, 2004).

The paper is structured as follows. In the next section the ACE approach to wholesale power market modelling is described, followed in Section 3 by a presentation of the ACEWEM computational framework. Here particular attention is given to the optimisation algorithm used by the Independent System Operator (ISO) as well as the statistically driven decision rule of the power generating agents. Following this a number of experiments are conducted to test the behavioural assumptions of bounded rationality (e.g., by estimating the probability density function of power price and commitment of the Day-ahead or Real-time markets) and profit seeking, based on strategic learning under different power market designs.

From this, we advance some comments on the evidence for identifying whether high market prices can be ascribed to problems of market structure or exercise of market power in liberalised wholesale power markets. The latter is particularly important for market participants when they develop their daily strategies (bids/offers of power). Concluding remarks are given in Section 6.

2. The ACE approach to wholesale power market modelling

2.1. Main concepts and why ACE?

An important new development in social and economic science is the adoption of bottom–up models for the representation of complex phenomena. Historically, economists have addressed questions about how decisions are made with aggregated models, assuming perfect information and a rational behaviour. In recent years, a disaggregated modelling approach in social and economic science has advanced, namely the ACE paradigm (Voudouris, 2011). Significant in the context of this paper, the ACE paradigm, using as a basic tool an agent-based model (ABM), has become a
widely accepted approach to solving both theoretical and practical problems in energy economics (Weron, 2014).

The key distinction between ACE models (specific models developed within the ACE paradigm) and other types of economic modelling is that of agent autonomy and interactions between them (see Fig. 2). Agents in ACE models are decision-making entities capable of reactivity, social communication, goal-directed learning, and, most important of all, self-determinism on the basis of private internal processes such as profit maximisation. Thus, the agent is modelled as an independent entity that makes decisions and takes actions using the limited share of influence and/or uncertain information (bounded rationality) available to it, similar to how organizations and individuals operate in the real world. A main feature of ACE models is the repetitive and competitive interactions between the agents – an agent makes publicly available to other interacting agents only a subset of their private information and actions (see Fig. 2).

The other important building block in the ACE paradigm is the representation of the physical and social environment or space within which agents operate – see the different layers of Fig. 2 and Voudouris (2011). Each agent may observe only a subset of the multilayer environment (representing bounded rationality).

ACE models define the initial state of the market by specifying the attributes and methods of each agent and the characteristics of the environment using observational micro-data. The initial attributes of any particular agent might include type characteristics (e.g., power generator), structural characteristics (e.g., cost function), and initial information about other agents (e.g., location on transmissions grids, maximum production capacity). The initial methods might include market protocols (e.g., bidding rules), learning modes (e.g., reinforcement learning), trading rules (e.g., profit maximisation), and rules for changing rules (e.g., strategy updating of forecasting models based on past performance). The market then evolves over time without further intervention. All events that subsequently occur arise from the historical evolution of agents’ interactions (Jennings, 2000; Tesfatsion, 2006).

ACE models offer three main benefits over other modelling techniques for the representation of wholesale power markets. They:

- Capture emergent phenomena, which result from the interaction of the individual entities.
- Provide a natural description of a complex adaptive system. If the system is composed of behavioural entities (as is the case with power markets), agent-based models better capture the reality of these systems.
- Are flexible. The flexibility comes in different dimensions. More agents for instance can be added, and the complexity of their behaviour – in the form of their degree of rationality, ability to learn and evolve – can be fine-tuned. This is important when different market designs need to be integrated in the model (see Section 3).

![Fig. 2. Agents, organisation, environment, and interactions (adopted from Jennings (2000)).](image)
ACE models are useful when:

- The interaction between the agents is complex (see Fig. 2).
- The agents exhibit complex behaviour, including learning (see Fig. 3).
- The representation of physical space (e.g., transmission grid) is crucial.
- The aim is to reveal and explain the complex and aggregate market behaviours that emerge from the interactions of the heterogeneous agents (Koritarov, 2004).

However, ACE models are not appropriate when:

- The dynamics of the systems are linear.
- The representation of physical space is of limited importance.
- The interactions between the constituent components of the system is limited.
- Micro-data is not available.
- Forecasting is the primary focus of the study – although the ACEWEM framework presented here is an important step in addressing this short-coming by integrating ACE models with formal statistical techniques.

2.2. Related work

Below we briefly discuss two set of publications of wholesale power markets that motivated the development of the ACEWEM framework. These models demonstrate the potential of ACE models for the representation of the complexity of power markets [for comprehensive reviews, the reader is directed to the work of Weidlich and Veit (2008), Weron (2014)].

One of the earliest applications of the ACE paradigm to model the strategic behaviour observed in power markets can be found in by Bower and Bunn (2000), which was followed by Bower and Bunn (2001). These authors developed an ACE model for the England and Wales power market with particular focus on the operations of uniform and discriminatory price auctions. Their model simulates a daily repeated power market with two combinations of trading (daily and hourly bidding) and two combinations of settlement arrangements (uniform and discriminatory pricing). Each autonomous adaptive agent represents a generating firm that owns a number of electricity plants characterised by capacity, fuel type, efficiency, marginal production costs and availability. The load-serving agents are modelled as price takers with no ability to influence the market through strategic behaviour. There is no transmission grid (a key limitation of their model). This means that their ACE model does not account for physical transmission constraints and the cost of transmission is assumed to be zero.

One of the most popular open-source ACE models for power markets (agent-based modelling of electricity systems (AMES)) was developed by Sun and Tesfatsion (2007) and Li and Tesfatsion (2012). AMES explicitly represents the transmission grid and three main types of market participants, namely (a) the system operator (who oversees the security of electricity supply and clears the market), (b) the load-serving entities (commonly referred as utilities) and (c) power generators (electricity producers). The AMES employs the Locational Marginal Pricing (LMP) congestion management method with uniform pricing auction (discussed in Section 3). In AMES the trading and congestion constraints are solved during the Day-ahead market without the need to rebalance the market (no use of Real-time markets). Power producers submit their strategic bids using a reinforcement learning algorithm. The aim of the strategic bids/offers is to explore the strategy that maximises profit. The strategic bids/offers are based upon the characteristics of the generating agent; namely marginal production cost, generating capacity, learning capabilities and initial wealth. In AMES power producers do not incur start-up, shut-down and no-load costs and also do not face ramping constants. The load-serving agents are modelled as price takers.

Several other power market ACE tools have been constructed, including those created by Petrov and Sheble (2000), Lai, Motshegwa, Susanghe, Rajkumar, and Blach (2000), Bunn and Oliveira (2001), Skoulidas, Vournas, and Papavassilopoulos (2002), North et al. (2002), Visudhiphan and Ilic (2003), Conzelmann, Boyd, Koritarov, and Veselka (2005), Guerci et al. (2010), Sousa, Pinto, Vale, Praça, and Morais (2012), van der Veen, Abbasy, and Hakvoort (2012), Kowalska-Pyzalska, Maciejowska, Suszczynski, Sznajd-Weron, and Weron (2014) and Young, Poletti, and Browne (2014).

A key design feature of any ACE model is the decision rule of the agents. Fig. 3 summarises the different components of the decision rules used by existing ACE models. Usually, ACE models for wholesale power markets select their bids/offers based either upon past performance (e.g., Li & Tesfatsion, 2012) or by developing exogenous point forecasts as input variables to the ACE models (e.g., Gao, Bompard, Napoli, & Zhou, 2008). Rarely, the decision rules of the agents truly integrate past performance of strategies (looking backward) with endogenous price and load probabilistic forecasts (looking forward) for the selection of the optimal strategy. In ACEWEM framework integrates both looking backward and looking forward features, enabling the agents to endogenously build flexible probabilistic forecasts (decision making under uncertainty). In ACEWEM, each agent develops different probabilistic forecasts based upon a reinforcement learning algorithm, which allows the agent to select a theoretical distribution, which is one of the components of the GAMISS-based statistical model developed endogenously by the agents (Section 3 discusses the process in details). This is a distinguishing feature of our approach. It allows the agents to dynamically calibrate the GAMISS-based model with real-world observational data in order to explore the best strategy given agent-specific and uncertain information [see also points (b) to (e) in Section 1]. Thus, we address one of the key limitations of the existing ACE models for power markets discussed by Weron (2014).

As this brief discussion indicates, ACE models offer a number of possible advantages for the quantitative modelling of wholesale
power markets, in which key market participants can be modelled as cognitive self-activated agents, strategically aware of both competitive and cooperative possibilities with other agents. Moreover, the learning representations used for these agents can be calibrated to empirical data (as discussed in Section 3). Realistically detailed institutional and structural market features can be incorporated with relative ease into the represented wholesale power market. Consequently, the ACE models support simulation-based studies of market dynamics reflecting the repeated attempts by profit maximising agents to exploit the features of the market for their own advantage.

3. The ACEWEM framework

The ACEWEM framework can simulate different wholesale power markets and operate over a high-voltage alternating current grid starting from hour 0 of day 1 to a user-specified maximum daily operation (for example 365 days). The ACEWEM framework includes a variety of key power market participants (agents), namely:

- The Independent System Operator (ISO), which oversees the security of electricity supply
- The Power Plants (GenCos), which produce and sell electricity (sellers)
- The Load-Serving Entities (LSEs), which are the wholesale electricity consumers (buyers).

These market participants, whose key operations are discussed below, operate within different power markers such as the Day-ahead (DA) market and Real-time (RT) market. Thus, the ACEWEM framework explicitly models the DA and RT markets.

Within the ACEWEM framework, the bids and offers accepted at the RT market are only used to resolve the transmission grid congestion under the Re-dispatch congestion management scheme. Under the Re-dispatch congestion management scheme, the DA market is cleared without taking into account transmission grid congestions. Therefore, during the RT market, transmission constraints are taken into account by accepting electricity bids (for power decrement) and offers (for power increment) in order to respect transmission grid congestions.

The ACEWEM framework also employs the Locational Marginal Pricing (LMP) congestion management scheme. Based upon the LMP congestion management scheme, the overall transmission grid congestion is resolved at the DA market by solving a least cost optimisation problem, as discussed below.

3.1. ACEWEM Independent System Operator

With objective of minimising the aggregate power generating cost, the ISO operates the DA and RT market. The ISO solves a least-cost constrained optimal power flow (CPF) problem to determine the power output from different power generators in order to satisfy the system power demand. The standard alternating current (AC) CPF problem involves the minimisation of total variable generation costs subject to nonlinear balance, branch flow, and production constraints for real and reactive power. In practice, AC CPF problems are typically approximated by a more tractable direct current (DC) CPF problem that focuses exclusively on real power constraints in linearised form (e.g., Wood & Wollenberg (1996) and Sun & Tesfatsion (2006)).

Within the ACEWEM framework, the formulation of DC CPF differs with respect to the selected congestion management method. Therefore when an ACEWEM model is launched with the LMP congestion management scheme, the ISO solves the following DC CPF problem during the DA market:

Minimise the total variable cost reported by GenCos:

$$
\sum_{i=1}^{I} \left[ a_i^{DA} P_i^{DA} + b_i^{DA} (P_i^{DA})^2 \right] + \eta \left[ \sum_{m=1}^{M} (\varphi_m - \varphi_{m0})^2 \right]
$$

subject to:

(a) Real power balance constraint for each node $n = 1, \ldots, N$:

$$
P_{nm} - \sum_{i \in \Delta n} P_i^{DA} + \sum_{m \in m \in M} P_{nm} = 0
$$

where

$$
P_{nm} = \frac{V_n^2 (\varphi_m - \varphi_{m0})}{R_{nm}}
$$

(b) Real power thermal constraints for each branch $nm \in \Omega$:

$$
|P_{nm}| \leq \frac{P_{\mu}^{\Omega}}{}
$$

(c) Reported energy generation constraints for each GenCo $i = 1, \ldots, I$:

$$
Cap_{RI}^{DA} \leq P_i^{DA} \leq Cap_{RI}^{DA}
$$

(d) Voltage angle setting at reference node 1:

$$
\varphi_1 = 0
$$

where, $a_i^{DA}$ and $b_i^{DA}$ are the reported to DA market marginal cost curve coefficients of the Generator $i$, $\eta$ is a soft penalty weight ($\eta > 0$), $\varphi_i$ is a voltage angle at node $n \in \Omega$ – set of all distinct branches $nm$, $P_{i}$ is a power withdrawn by LSE $k, k \in K_n$ – total number of LSEs at node $n$, $V_n$ is a base voltage (kV), $R_{nm}$ is a reactance (Ohm) for $nm$, $R_{\mu}^{\Omega}$, $\varphi_m$ are the upper and lower reported generating capacities of the GenCo $i$.

When the Re-dispatch congestion management scheme is selected, the DC CPF problem for DA market is the same as above but without the thermal constraints – implying a transmission grid with infinite capacities. When the DA market is cleared, the ISO accepts bids (to determine power decrement) and offers (to determine power increment) in order to resolve the transmission grid congestion at the RT market. Thus, the ISO solves the following DC CPF problem (note the constrained $c$):

Minimise the total variable cost reported by GenCos:

$$
\sum_{i=1}^{I} \left[ VariableCost_{i}^{INC} + VariableCost_{i}^{DEC} \right] + \eta \left[ \sum_{m=1}^{M} (\varphi_m - \varphi_{m0})^2 \right]
$$

where

$$
VariableCost_{i}^{INC} = a_i^{INC} P_i^{INC} + b_i^{INC} (P_i^{INC})^2
$$

$$
VariableCost_{i}^{DEC} = (a_i^{DA} - a_i^{DEC}) P_i^{INC} + (b_i^{DA} - b_i^{DEC}) (P_i^{INC})^2
$$

subject to:

(a) Real power balance constraint for each node $n = 1, \ldots, N$:

$$
P_{nm} - \sum_{i \in \Delta n} P_i^{DA} + \sum_{m \in m \in M} P_{nm} = 0
$$

where

$$
P_{nm} = \frac{V_n^2 (\varphi_m - \varphi_{m0})}{R_{nm}}
$$

(b) Real power thermal constraints for each branch $nm \in \Omega$:

$$
|P_{nm}| \leq \frac{P_{\mu}^{\Omega}}{}
$$

(c) Power increments and decrements constraints for each GenCo $i = 1, \ldots, I$:...
\[Cap_{RL}^i \leq P_{INC}^i \leq Cap_{RU}^i - P_{DA}^i \]  \tag{11}

\[0 \leq P_{DEC}^i \leq P_{DA}^i \]  \tag{12}

(d) Voltage angle setting at reference node 1:

\[\phi_1 = 0 \]  \tag{13}

Here, \(P_{INC}^i\) and \(P_{DEC}^i\) is a power increment and decrement of GenCo \(i\) at RT market; \(a_{INC}^i\), \(b_{INC}^i\), \(a_{DEC}^i\) and \(b_{DEC}^i\) are the marginal cost curve coefficients reported for power increment (index INC) or power decrement (index DEC) by GenCo \(i\).

The decision rule of ISO is illustrated by Fig. 4 below. In particular, at the beginning of each repeated daily auction, generating and load agents submit to the ISO the offers to sell power (generating agents) and the demand profiles (load agents). Then, the ISO solves the DC COPF problem for the DA market and returns the power commitments and the nodal prices (when LMP congestion management scheme is used) or pay-as-bid price (when the Power Re-dispatch congestion management is used). Clearly, if the Power Re-dispatch congestion management scheme is used, the ISO also accepts bids and offers for increments/decrements to manage the transmission grid congestions.

3.2. ACEWEM generating agent

Within the ACEWEM framework, each generating agent (GenCo) represents an individual power plant with the objective of maximising the daily profit. The overall decision rule of the GenCo within the ACEWEM framework is illustrated in Fig. 5.

The different building blocks [e.g., estimation of reported marginal cost curves \(MC\), estimation of the forecasted probability density function (\(D\)), use of the reinforcement learning algorithm to select the most profitable probability density function] of the decision rule are detailed below.

At the beginning of each day, GenCos submit a supply offer to ISO in the form of a linear marginal cost curve:

\[MC_{DA}^i = a_i + 2b_i Cap_i \]  \tag{14}

![Fig. 4. Decision rule of ISO.](image-url)
Stochastic Profit Optimisation algorithm proposed here.

The reported marginal cost curve coefficients are the commitments of the generating agent. For each generating agent is able to submit the "true" marginal cost curve coefficients (e.g., \(a_i^T, b_i^T\)) or "higher" marginal cost curve coefficients in strategic attempt to increase its daily profit:

\[
MC_{DA}^{i} = a_{i}^{DA} + b_{i}^{DA} Cap_{i}^{T}
\]

where \(a_i\) and \(b_i\) are the marginal cost curve coefficients and \(Cap_{i}\) is a generating capacity of GenCo \(i\) available for the DA market. Each generating agent is able to submit the "true" marginal cost curve coefficients (e.g., \(a_i^T, b_i^T\)) or "higher" marginal cost curve coefficients in strategic attempt to increase its daily profit:

\[
MC_{DA}^{i} = a_{i}^{DA} + 2b_{i}^{DA} Cap_{i}^{T}
\]

where \(a_i^{DA}\) and \(b_i^{DA}\) (\(d_i^{DA} \geq a_i^{DA} \geq b_i^{DA} \geq b_i^{T}\)) are the reported marginal cost curve coefficients. The reported marginal cost curve coefficients are not chosen randomly but are selected as a result of the Stochastic Profit Optimisation algorithm proposed here.

Specifically, the Stochastic Profit Optimisation algorithm (e.g., Eq. (21)) estimates the expected profit given the predictive probability density function (PDF) of the wholesale power price and power commitment. Each agent estimates the predictive PDF of the wholesale power price and power commitment by building a statistical model using the GAMLSS framework first proposed by Rigby and Stasinopoulos (2005).

In particular, each agent assumes that, for \(i = 1, 2, \ldots, n\) observations the response variable \(Y_i\) (wholesale electricity price/power commitment) has probability density function \(f_{Y_i}(y_i|\theta)\) conditional on \(\theta = (\theta_1, \theta_2, \theta_3, \theta_4) = (\mu_i, \sigma_i, V_i, \tau_i)\), which is a vector of four distribution parameters, each of which can be a function of explanatory variables. This is denoted by:

\[
Y_i|\theta \sim D(\theta)\]

i.e. \(Y_i|\theta = (\mu_i, \sigma_i, V_i, \tau_i) \sim D(\mu_i, \sigma_i, V_i, \tau_i)\) independently for \(i = 1, 2, \ldots, n\), where \(D\) represents the distribution of \(Y_i\). Let \(Y = (Y_1, Y_2, \ldots, Y_n)\) be the \(n\) length vector of wholesale electricity prices/power commitments of the generating agent. For \(k = 1, 2, 3, 4\), let \(g_k(\cdot)\) be a known monotonic link function relating the distribution parameter \(\theta_k\) to predictor \(\eta_k:\)

\[
g_k(\theta_k) = \eta_k = X_i \beta_k
\]

i.e.

\[
\begin{align*}
\mu_1(\mu) &= \eta_1 = X_i \beta_1 \\
\sigma_1(\sigma) &= \eta_2 = X_i \beta_2 \\
V_1(v) &= \eta_3 = X_i \beta_3 \\
\tau_1(\tau) &= \eta_4 = X_i \beta_4
\end{align*}
\]

where \(\mu, \sigma, V\) and \(\tau\) are the distribution parameters – vectors of length \(n\); \(X_1, X_2, X_3\) and \(X_4\) are design matrices of independent variables for each one of distribution parameters; \(\beta_1, \beta_2, \beta_3\) and \(\beta_4\) are the unknown parameters to be estimated.

The particular model for wholesale power prices implemented by each generating agents is as follows:

\[
M_i|\theta_i^{DA}, \theta_i^{M}, \theta_i^{V}, \theta_i^{t} \sim D_{DA}(\mu_i^{M}, \sigma_i^{M}, \nu_i^{M}, \tau_i^{M})
\]

\[
\begin{align*}
g_1(\mu_1^{M}) &= \eta_1^{M} = \beta_1^{M} + \mu_1^{M} + \mu_{i-1}^{M} \\
g_2(\sigma_1^{M}) &= \eta_2^{M} = \beta_2^{M} + \mu_2^{M} + \mu_{i-1}^{M} \\
g_3(V_1^{M}) &= \eta_3^{M} = \beta_3^{M} + \mu_3^{M} + \mu_{i-1}^{M} \\
g_4(\tau_1^{M}) &= \eta_4^{M} = \beta_4^{M} + \mu_4^{M} + \mu_{i-1}^{M}
\end{align*}
\]

Effectively, each distribution parameter (\(\mu, \sigma, V\) and \(\tau\)) at time \(t\) is a linear function of the wholesale power prices at time \(t-1\). Here \(g_1(\cdot), g_2(\cdot), g_3(\cdot)\) and \(g_4(\cdot)\) are the link function appropriately selected for \(D_{DA}\) distribution.

Similarly, the model for power commitment is defined as follows:
of flexible distributions which are selected by the reinforcement agent at time for spillover effects (see propensities over time. The experimentation parameter distribution makes use of propensity values in determining its choice probabilistically selects a strategy of the action domain (strategies repository).

The GAMLSS algorithm, which has been implemented within the ACEWEM framework, estimates the distribution parameters (given the information set available to each agents) in order to be used by the agents when they select their offers to sell power in the DA and RT markets. Thus, each agent not only develops regression-type of models for the distribution parameters $\mu$, $\sigma$, $v$ and $\tau$ but also selects the appropriate distribution $D(\theta)$ for the regression model based upon a reinforcement learning algorithm (discussed below). Thus, the agents might have different forecasting models (used by the Stochastic Profit Optimisation algorithm) to better represent their own information sets – allowing for a high degree of heterogeneity.

The reinforcement learning is a learning algorithm that probabilistically selects a strategy $m$ (i.e. a distribution in our case), while the full set of strategies define the action domain $AD$ of the GenCo ($m \in AD$). Specifically the GAMLSS framework incorporates a set of flexible distributions which are selected by the reinforcement learning algorithm using the realised daily profit as the key criterion. This is to say that the probability $p_m(t)$ of choosing a particular distribution $m$ depends on the realised profit obtained by using the distribution $m$ within the Stochastic Profit Optimisation algorithm.

Mathematically, the reinforcement learning algorithm for the selection of the agent-specific model to be used for the selection of the optimal offer/bid to sell/buy electricity is given by:

$$p_m(t) = \frac{\exp\left(\frac{\text{TotalCost} - MC_{DEC} - P_F^{INC}}{\text{DEC}MC}\right)}{\sum_m \exp\left(\frac{\text{TotalCost} - MC_{DEC} - P_F^{INC}}{\text{DEC}MC}\right)}$$

with

$$q_m(t) = \begin{cases} 1 - r q_m(t-1) + R_m(t-1) \\ \frac{[1 - e] \times Z_m(t - 1), \text{ if } m = m^*} {e \times q_m(t - 1) / AD_{m^*}, \text{ if } m \neq m^*} \end{cases}$$

and

$$E(P_{DEC}^t) = \text{TotalCost}_i - MC_{DEC}^i \times P_F^{INC} - D_0[MC_{DEC}^i]$$

where $P_{DA}^t$, $P_{F}^{INC}$ and $P_{DEC}^{INC}$ are the forecast power commitments at DA and RT for INC and DEC (mean parameters of corresponding power commitment distributions). $D_0[MC_{DEC}^i]$ and $D_0[MC_{INC}^i]$ are the PDFs of the GAMLSS-based models discussed above. These PDFs are used to estimate the profit-maximising reported marginal costs $MC_{DA}^i$ and $MC_{INC}^i$ at the DA and RT market. Similarly, $D_0[MC_{INC}^i]$ is used to estimate the profit-maximising reported marginal cost curve $MC_{INC}^i$ at RT market. Note that $D$ subscripts $U$ and $L$ stand for the Upper (right) and Lower (left) distribution tails.

To summarise, given the PDFs of the wholesale power prices and power commitments, each generating agent estimate the probability of acceptance of different MCs. It is important to note that at the DA and RT (for INC) markets the lower reported MC, which might lead to lower profits, has a higher probability of acceptance. For power decrement at RT market, the lower reported MC corresponds to a lower probability of acceptance. Effectively, the optimisation algorithm maximises the expected profit $E(P_{DA}^t), E(P_{INC}^t)$ and $E(P_{DEC}^t)$ as a function of the reported marginal cost curve coefficients $\{a^{INC}, b^{INC}\}$ and $\{a^{DA}, b^{DA}\}$ by taking into account the GAMLSS-based models (e.g., $D_0[MC_{INC}^i]$). The PDF to be used by the GAMLSS-based model is selected based upon the reinforcement learning algorithm discussed above.

### 3.3. ACEWEM load agents

The load agents purchase wholesale power to serve end users in retail power markets. It is assumed that the load agents do not engage in production. The load agents only purchase electricity from the generating agents. The overall decision rule of load agents is illustrated by Fig. 6.

It is important to note that the current implementation of the ACEWEM framework assumes that the load agents bid their ‘true’ load profiles – they do not engage in strategic bidding. One justification for this is that empirical evidence suggests that electricity demand does not fall in response to a short-term price increase (Yusta & Dominguez, 2002; Faruqui & George, 2002). Having said that daily stochastic demand shocks are allowed in order to test the dynamics of the market. The load agents also do not enter the RT market regardless of the congestion management scheme used.1

### 3.4. ACEWEM Transmission Grid

The ACEWEM Transmission Grid (TG) is an altering current grid designed as a balanced three-phase network composed of minimum one branch and two nodes. It incorporates several key assumptions:

- Transformer phase angle shifts are assumed to be 0
- Transformer tap ratios are assumed to be 1
- Charging capacitances of transmission lines are assumed to be 0
- Temperature is assumed to remain constant over time

It is also assumed that the transmission grid has no isolated nodes or branches. All current flows within ACEWEM TG comply with Kirchhoff's Current Law implying that actual and reactive power must be in balance at each node. In other words, the power

1 Future developments of the ACEWEM framework will also incorporate strategic bidding with respect to the decision rule of the load agent.
withdrawn at each node plus transmission losses must be compensated by power injection into the system.

Overall, the ACEWEM framework:

- Does not neglect transmission grid constraints while the large majority of ACE models neglect transmission grid constraints
- Makes use of an integrated flexible statistical framework for decision making
- Implements different market structures and market mechanisms in order to better represent different wholesale power markets

4. Abstract six-node electricity market

The ACEWEM framework presented above can be initialised with real-world data to explore plausible offer strategies by competing electricity generators in repeated auctions of wholesale electricity markets. In practice, the daily strategies of the electric utilities also depend on daily strategies of their competitors (not just their own marginal cost of production). Clearly, the ‘collective’ strategies are reflected in the ‘emergent’ price (the price that emerges from the individual profit maximising offers/bids) of the wholesale power market.

To get an insight into the plausible strategies of competing market participants, the ACEWEM framework is used to simulate a realistically-rendered abstract wholesale power market with six electricity generating agents and four load agents with known features/properties. For example, the “true” marginal cost curve coefficients and generating capacity (see Table 1) for each generating agent are assumed to be known so that conclusions can be drawn.

The agents of the wholesale power market are distributed across six-node transmission grid (as illustrated by Fig. 7). Specifically the locations of agents are as follows: GenCo1 is located at Node1, LSE1 and LSE2 at Node2, GenCo2 and LSE3 at Node3, GenCo3 at Node4, GenCo4 and LSE4 at Node5, GenCo5 and GenCo6 at Node6. All the nodes are sequentially jointed by branches. The ISO agent at the centre of modelled transmission grid operates the wholesale power market.

The transmission grid base values and physical parameters for the branches are presented in Tables 2 and 3 accordingly. Base apparent power is three-phase apparent power common to the entire transmission grid and is a product of its base voltage and current, without reference to phase angle. Base voltage is a nominal rated voltage of the entire transmission grid, set to 10 kV.

Daily load profiles for all load agents follow a typical winter day (see Fig. 8) reaching a minimum in electricity demand from 3 till 6 o'clock and maximum from 16 till 19 o'clock.

Having specified the settings for the realistically-rendered abstract market, we conduct experiments for different congestion management schemes (Locational Marginal Pricing and Power Re-dispatch). This will enable us to explore the plausible daily strategies of the market participants and the price dynamics of wholesale power markets – important building blocks for electric utilities operating in real-world power markets.

4.1. Benchmark

In the “benchmark” experiment, the agents (GenCos) do not exercise market power. In particular the agents do not optimise their strategies and thus report only true marginal costs and true production capacities (see Table 1). The results reported here are based upon: (a) the LMP congestion management scheme (see Table 4) and (b) the Power Re-dispatch congestion management scheme (see Table 5).

Table 4 shows that on the “benchmark market” (absence of strategic bidding by generating agents) cleared under LMP congestion management scheme all the GenCos are allocated daily the power commitments by the ISO. GenCo1 and GenCo2 sell all their generating capacity at every hour. While GenCo3, GenCo4, GenCo5 and GenCo6 sell (on average) 41%, 38%, 74% and 29% of generating capacity accordingly. Overall all generating agents accumulate non-zero daily profits calculated by:

![Decision rule of LSE.](image-url)
where \( N_i \) is the nodal price at GenCo’s node at hour \( h \); \( a_i^T \) and \( b_i^T \) are the true marginal cost curve coefficients and \( P_i \) is the power commitment for hour \( h \).

Noteworthy that the average nodal prices differ across the nodes. This points out the presence of transmission grid congestion. This suggests that it is not always possible to dispatch the cheapest generator due to branch thermal constrains even when the generating agents offer true marginal costs.

Table 5 shows that under the Re-dispatch congestion management scheme GenCo1 and GenCo2 sell all their generating capacity at every hour. GenCo4 sells zero MWs and GenCo5, GenCo6 and GenCo3 sell 95%, 66% and 2% of generating capacity. Note that the power commitments of GenCo3, GenCo4, GenCo5 and GenCo6 differ under LMP congestion management scheme (see Table 4). This is because under Re-dispatch congestion management scheme, electricity congestion does not affect the order of least-cost power dispatch (see Section 3.1). The DA market clearing price at hour \( h \) equals the marginal cost of the last generating agent scheduled for power dispatch to balance electricity demand and supply. However, profits are calculated based upon the pay-as-bid price method:

\[
\Pi_i^{DM} = \sum_{h=0}^{23} \left[ N_i P_i - (a_i^T + b_i^T P_i) P_i \right] P_i^{DA_i} 
\]

(24)

where \( N_i \) is the nodal price at GenCo’s node at hour \( h \); \( a_i^T \) and \( b_i^T \) are the true marginal cost curve coefficients and \( P_i \) is the power commitment for hour \( h \).

The daily profits (for GenCo3 and GenCo4) at RT market are calculated according to:

\[
\Pi_i^{INC} = \sum_{h=0}^{23} [PAB^{INC} P_i^{INC} - (a_i^T + b_i^T P_i^{INC}) P_i^{INC}] 
\]

(25)

where \( PAB^{INC} \) is pay-as-bid price.

After the DA market is cleared, the ISO operates the RT market. At RT market, the ISO estimates the transmission grid congestions by solving COPF problem with added branch thermal constrains (see Section 3.1). The ISO estimates the least-cost optimal dispatch per hour. The daily profits (for GenCo3 and GenCo4) at RT market are calculated according to:

\[
\Pi_i^{INC} = \sum_{h=0}^{23} [PAB^{INC} P_i^{INC} - (a_i^T + b_i^T P_i^{INC}) P_i^{INC}] 
\]

(26)

where \( PAB^{INC} \) is the pay-as-bid price. This price is equal to marginal cost reported by GenCo to the RT market for power increment. The daily profits (for GenCo5 and GenCo6) at RT market are calculated according to:
\[
\Pi_i^{\text{DEC}} = \sum_{h=0}^{23} \left( a_i^h + b_i^h \cdot p_i^{\text{DEC}, h} + P_{\text{AB}, i}^{\text{DEC}, h} - P_{\text{AB}, i}^{\text{DEC}, h} \right)
\]  

(27)

where \( P_{\text{AB}, i}^{\text{DEC}} \) is the pay-as-bid price. This price is equal to marginal cost reported by GenCo \( i \) to the RT market for power decrement. Note that in order to avoid negative profits at RT market for power decrement, the slope parameter of reported marginal cost curve by GenCo \( i \) equals to \( b_i^h = 2 \) only in this experiment. The market clearing price at hour \( h \) for Real-time power increment/decrement is equal to the marginal cost of the last generating agent scheduled for power dispatch.

Moving away from the idealised Benchmark market reported above, the experiments reported below assume that the agents build a GAMLSS-based forecasting model in order to strategically develop their bids/offers. Thus, the agents are not forced to submit their bids and offers based upon their true costs of production. In particular, each GAMLSS model is used by the agents to estimate the forward-looking PDF of the price and power commitment given the information at time \( t \). For this particular reason we have simulated the price and power commitment process for the first 365 days based upon the Normal (NO) distribution in order to ‘control’ for the best forecasting model that the agents can use to develop their strategic bids/offers. This will also enable us to con-

---

**Table 4**

Benchmark case results for LMP congestion management scheme.

<table>
<thead>
<tr>
<th>Power generating agent</th>
<th>Marginal cost curve intercept</th>
<th>Marginal cost curve slope</th>
<th>Average nodal price (Unit/MWh)</th>
<th>Average power commitment (MW/h)</th>
<th>Daily profit (Unit/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GenCo1</td>
<td>14</td>
<td>0.005</td>
<td>22.50</td>
<td>110</td>
<td>20992.10</td>
</tr>
<tr>
<td>GenCo2</td>
<td>15</td>
<td>0.006</td>
<td>28.55</td>
<td>100</td>
<td>31084.46</td>
</tr>
<tr>
<td>GenCo3</td>
<td>25</td>
<td>0.01</td>
<td>29.30</td>
<td>215</td>
<td>13390.78</td>
</tr>
<tr>
<td>GenCo4</td>
<td>30</td>
<td>0.012</td>
<td>31.37</td>
<td>75</td>
<td>2456.53</td>
</tr>
<tr>
<td>GenCo5</td>
<td>10</td>
<td>0.007</td>
<td>16.22</td>
<td>444</td>
<td>33162.12</td>
</tr>
<tr>
<td>GenCo6</td>
<td>12</td>
<td>0.017</td>
<td>16.22</td>
<td>124</td>
<td>6287.94</td>
</tr>
</tbody>
</table>

**Table 5**

Benchmark case results for Re-dispatch congestion management scheme.

<table>
<thead>
<tr>
<th>Power generating agent</th>
<th>Market</th>
<th>Marginal cost curve intercept</th>
<th>Marginal cost curve slope</th>
<th>Average power commitment (MW/h)</th>
<th>Average market clearing price (Unit/MW)</th>
<th>Daily profit (Unit/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GenCo1</td>
<td>DA</td>
<td>14</td>
<td>0.005</td>
<td>110</td>
<td>21.64</td>
<td>1452</td>
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<tr>
<td>GenCo2</td>
<td></td>
<td>15</td>
<td>0.006</td>
<td>100</td>
<td>1.40</td>
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<tr>
<td>GenCo3</td>
<td></td>
<td>25</td>
<td>0.01</td>
<td>8</td>
<td>0</td>
<td>89</td>
</tr>
<tr>
<td>GenCo4</td>
<td></td>
<td>30</td>
<td>0.012</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>GenCo5</td>
<td></td>
<td>10</td>
<td>0.007</td>
<td>567</td>
<td>54,536</td>
<td>8907</td>
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<tr>
<td>GenCo6</td>
<td></td>
<td>12</td>
<td>0.017</td>
<td>284</td>
<td>37,473</td>
<td>4191</td>
</tr>
<tr>
<td>GenCo1</td>
<td>RT INC</td>
<td>14</td>
<td>0.005</td>
<td>0</td>
<td>32.58</td>
<td>0</td>
</tr>
<tr>
<td>GenCo2</td>
<td></td>
<td>15</td>
<td>0.006</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>GenCo3</td>
<td></td>
<td>25</td>
<td>0.01</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>GenCo4</td>
<td></td>
<td>30</td>
<td>0.012</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>GenCo5</td>
<td></td>
<td>10</td>
<td>0.007</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>GenCo6</td>
<td></td>
<td>12</td>
<td>0.017</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>GenCo1</td>
<td>RT DEC</td>
<td>14</td>
<td>0.0025</td>
<td>0</td>
<td>11.37</td>
<td>0</td>
</tr>
<tr>
<td>GenCo2</td>
<td></td>
<td>15</td>
<td>0.003</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>GenCo3</td>
<td></td>
<td>25</td>
<td>0.005</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>GenCo4</td>
<td></td>
<td>30</td>
<td>0.006</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>GenCo5</td>
<td></td>
<td>10</td>
<td>0.0035</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>GenCo6</td>
<td></td>
<td>12</td>
<td>0.0085</td>
<td>81</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**Fig. 9.** Reported MC, true MC, forecast average NP and actual average NP in experiment 1.
control for information symmetry/asymmetry in the market. Thus, we will be in a position to draw some conclusions with respect to the repeated nature of the daily power auctions.

4.2. Information symmetry under the LMP management scheme: experiment 1

In experiment 1, the generating agents employ the same structural forecasting models for the nodal power price and the power commitment of the DA market.

The structure of the model for the estimation of the predictive PDF of nodal price is given by:

\[
M_{t|1} \sim N \left( \mu_{t|1}, \sigma_{t|1}^2 \right)
\]

\[
\mu_{t|1} = \mu_{t-1} + \beta_1 M_{t-1}
\]

\[
\log(\sigma_{t|1}^2) = \log(\sigma_{t-1}^2) + \beta_2 M_{t-1}
\]

While the structure of the model for the estimation of the predictive PDF of power commitment is given by:

\[
P_{t|1} \sim N \left( \mu_{t|1}, \sigma_{t|1}^2 \right)
\]

\[
\mu_{t|1} = \mu_{t-1} + \beta_1 P_{t-1}
\]

\[
\log(\sigma_{t|1}^2) = \log(\sigma_{t-1}^2) + \beta_2 P_{t-1}
\]

Note that since the same structural model is utilised by every agent, there is no forecasting asymmetry among the agents. In other words, the market dynamics observed in this experiment are not affected by information asymmetry.

Fig. 9 shows that agents with different cost of production exhibit different dynamics with respect to their offers over time. In particular, the two least expensive power plants expect to sell their full capacity. Note that the risk assumed by the agents is characterised by the probability of acceptance for the reported MCs, which is discussed in Section 3.2 and illustrated by Fig. 10. Therefore GenCo1 and GenCo2 effectively select a risk averse strategy by offering marginal costs that have a high (about 90%) probability of acceptance (see Fig. 10). Also note that the marginal costs are higher by factor of 1.4 (for GenCo1) and 1.7 (for GenCo2) compared with their the true marginal production costs. GenCo3, GenCo4, GenCo5 and GenCo6 are the most expensive power plants. They find optimal to take a higher risk and offer their production capacity close to the expected nodal price at about 50% probability of acceptance (see Fig. 10)). In our view, this behaviour confirms the risk-taking strategy of the 'expensive producers', which is also observed in real markets as some power produces tend to make offers with a lower probabilities of acceptance but with higher returns – making strategic offers based upon predicted peak prices during the DA market.

An interesting observation relates to the dynamics of the nodal prices. Fig. 9 clearly shows that the volatility of the average NP decrease over time (each simulation step represents a trading day). This can be explained by examining the daily predictive probability density function of the NP of the Day-ahead market. This is showed by Fig. 11.

Fig. 11 shows that the predictive PDF of the average NP with 500 days interval (from day 500 to day 3500). It is clear from the figure that the predictive pdf of the average NP at day 500 (PDF with the symbol x) is 'fatter' in the middle of the distribution than other PDFs illustrated. This indicates that the first 500 days there is a higher degree of uncertainty compared with uncertainty around the expected NP at the day 3500 (note the predictive PDF of the average NP at the day 3500 – PDF with the symbol h). This indicates that not only there is information symmetry in the market but also the information used to form the offers in the DA market is more precise. Thus, information symmetry and better information over time cause the emergence of competitive markets out of individual profit maximisation actions. This results contradicts the conclusions suggested by Bunn and Day (2009): the repeated nature of the daily power auction with a substantial amount of information in common, give rise to a continuous evolution of learning with no evidence of convergence to a stationary solution.

An interesting question is whether the emergence of competitive markets out of individual profit maximisation actions is also observed when the system is characterised by frequent supply and demand shocks. This is addressed in the experiment below.

4.3. Information symmetry with shocks under the LMP congestion management method: experiment 2

In the experiment 2, the repeated random positive shocks in demand and random negative shocks in supply are introduced. By simulating contingency in the load and generating capacity we aim (a) to test system reliability and (b) to access electricity price variability at certain nodes. Two agents were selected, namely GenCo5 (for shocks in electricity production) and LSE4 (for shocks in electricity demand). The shock mechanism is as follows:

- The upper generating capacity of GenCo5 submitted to ISO is pre-multiplied daily by the random number withdrawn from the set \( X = \{ x : 0.3 \leq x \leq 1.0 ; x \in R \} \). This represent a generation outage up to 70% of agent’s capacity.
- The hourly electricity demands submitted by LSE4 to ISO are pre-multiplied daily by the random number withdrawn from the set \( X = \{ x : 0.3 \leq x \leq 2.0 ; x \in R \} \). This represents a random load increase up to 20% of LSE4 total demand.

![Fig. 10. Probability of acceptance for reported MC in experiment 1.](image_url)
Fig. 12 shows the dynamics of node electricity prices and reported marginal costs by the generating agents. First the focus is on the average electricity price at Node 6 (location of GenCo 5 and GenCo 6), the higher volatility compared with the experiment 1 can be observed. The increased price volatility is reflected by the scale of the PDF modelled by GenCo 6 (see Fig. 13). This suggests that GenCo 6 has a higher probability of acceptance for extreme offers compared with experiment 1. This also explains the enhanced exercise of market power by GenCo 6. Thus the average reported marginal cost by GenCo 6 in experiment 2 is 1.3 times higher compared with the average reported marginal cost in experiment 1.

The results of experiment 2 show that demand/supply shocks can intensify the strategic behaviour of some generating agents (note the different dynamics compared with the nodal price of the reported MCs by GenCo 5 and GenCo 6) by increasing the volatility of the power price under the LMP congestion management scheme. In order to test the effects of the different congestion man-
agement methods, the experiment below reproduce the experiment 1 and 2 under the Re-dispatch congestion management scheme.

4.4. Information symmetry under the re-dispatched congestion management scheme: experiment 3

In the experiment 3, every generating agent employs the GAM-LSS model to forecast the average market clearing price (MCP) and the average daily power commitment. Power congestion, unlike experiments 1 and 2, is resolved here according to Power Re-dispatch congestion management scheme. Therefore each generating agent forecasts the price and commitments both for the DA market and RT market (for power increments and decrements).

Figs. 14–16 illustrate the reported MC, true MC, forecast average MCP and actual average MCP for DA, RT(INC) and RT(DEC) markets. The figures show that agents with different cost of production exhibit different dynamics with respect to their offers and bids over time. In the long run (DA market – see Fig. 14), we observe the MCP falling below true MC for GenCo3 and GenCo4.
This indicates that in order to fulfil total electricity demand in a least-cost manner these power plants are not required for power generation. Note, this is possible since the solution of DA COPF under Re-dispatch congestion management scheme does not account for transmission grid thermal constrains (see Section 3.1). This behaviour also confirms the risk-taking strategy of the more expensive ‘peak producers’, which base their strategic bids/offers upon predicted peak prices during the DA market. On the other hand, less expensive power generators (GenCo1, GenCo2, GenCo5 and GenCo6) maximise their expected profit when offer below the expected MCR with a 90% probability of acceptance. This behaviour confirms the strategy of the ‘base load producers’.

The RT market is cleared accounting for branch thermal constrains (see Section 3.1). Furthermore, the clearing of the RT market takes into account the total generating capacity contracted at DA market. As a result, GenCo3 and GenCo4 are the only power producers that have commitments to produce power. This means that the MCP at RT market for power increment is considerably higher compared with the DA market. It is interesting to observe that the other ‘cheaper’ power plants submit their offers just below the offers of ‘expensive’ producers, namely GenCo3 and GenCo4. This is a clear indication of the emergence of collective learning in repeated auctions with capacity and physical constrains.

At RT market, the ISO also accepts bids from GenCos in order to balance the congested system. We observe that the ISO only schedules GenCo5 and GenCo6 for power decrement to alleviate the electricity congestion. Note that strategic behaviour by each agent here is to bid below its ‘true’ MC. Noteworthy that the other power plants submit their bids close to bids of GenCo5 and GenCo6.

To summarise, information symmetry cause the emergence of competitive markets (cleared according to Power Re-dispatch congestion management method) out of individual profit maximisation actions. It is also interesting to observe how the agents’ competitive behaviour changes when the system is characterised by frequent supply and demand shocks and when the market is cleared based upon the Re-dispatch congestion management scheme. This is addressed in the experiment below.

4.5. Information symmetry under the Power Re-dispatched management scheme: experiment 4

In the experiment 4, random positive shocks in demand (LSE4) and random negative shocks in supply (GenCo5) are introduced for the DA market. The contingency mechanism is described in the Section 4.3.
Fig. 17 illustrates the average MCP dynamics at DA market (left), RT market for INC (middle) and RT market for DEC (right). It suggests that when the system is subject to power shocks, the average MCP undergo a series of frequent peaks with the RT market for power increment expressing higher volatility.

Note that since the generating agents implement identical GAMLSS model (18) to forecast MCP, the predictive PDFs are identical across all agents. Fig. 18 compares the predictive PDF of the MCP between the experiment 3 and experiment 4 at the DA market (left figure), the RT market for power increment (middle figure) and the RT market for power decrement (right figure). It is clear that the scale of the PDFs of the experiment 4 is higher compared with the scale of the PDFs in the experiment 3. This suggest higher market volatility. As argued earlier, a higher market volatility can intensify strategic behaviour since extreme bids/offers have higher probability of acceptance. Indeed, the agents report offers (compared with the experiment 3) at the DA market higher by a factor of 1.2, at the RT market for power increment higher by a factor of 1.9 and bids at the RT market for power decrement lower by a factor of 1.1.

5. Synthesising results

We analyse the extent to which different market designs permit and even contribute to the exercise of market power by generating agents. The results reported are of significant practical value to market participants and regulators alike.

Experiment 1 shows how the repeated nature of daily power auctions involving generators that share a common pool of information (same predictive pdf of power price and commitment), results in competitive markets. We also observe that “expensive” or “peak” power producers tend to exhibit risk-taking behaviour, when compared with that of the less expensive or “base load” power producers. Therefore, a computational approach inspired by the integration of the ACE paradigm with formal statistical models, appears to be useful in reflecting well the type of behaviour observed in real-world liberalised power markets.

However, when the information assumption is relaxed as in experiment 2, the uncertainties and complexities of the daily power auction might cause the emergence of strategic bidding. Thus, in the second experiment, we introduce stochastic (in terms of magnitude) supply and demand shocks. It is clear that the shocks can intensify the strategic behaviour of some agents by increasing power prices under the LMP congestion management scheme, while the average reported marginal cost increases by a factor of 1.3 across the generating agents – quantifying the emergence of market power.

From the experiment 3, it is clear that information symmetry and the gathering of improved information over time cause competitive markets to emerge (cleared according to Power Re-dispatch congestion management method) from individual profit maximising actions. An interesting observation is that the most expensive power producers find it difficult to sell their capacity in the Day-ahead market. However, the most expensive power plants are the main market participants during the operation of the Real-time market. It is also important to note that different congestion management schemes might favour certain generating technologies. For example, Fig. 19 suggests that under the Power Re-dispatch congestion management scheme the most expensive power plants achieve higher profits compared with their profits under the LMP congestion management method. Overall, the average daily profit of the generating agents is higher by a factor of 3.4 compared with corresponding profits observed in experiment 1.

Experiment 4 (Power Re-dispatch congestion management scheme with supply and demand shocks), shows the strong emergence of strategic behaviour. In particular, average offers to sell electricity in the DA market are higher (by a factor of 1.2) when compared with the results of the experiment 3. Using the same comparator, the reported offer in the RT market is higher by factor of 1.9 for power increments and lower by a factor of 1.1 for power decrement. Again, power generators achieve higher profits under the Power Re-dispatch congestion management scheme (see Fig. 20). This reconfirms the importance for the market participants in understanding the rules of the daily repeated auctions of wholesale power markets when they develop their daily strategies to sell power, given capacity and physical constraints.

6. Conclusions

From an expert systems perspective, we propose a detailed computational model for repeated power auctions operating across realistically rendered transmission grids that are subject to congestion.

To get an insight into the plausible strategies of competing market participants, an ACEWEM framework is used, simulating a model wholesale power market with six electricity generating agents and four load servicing agents with known features/properties. In particular, we explore two market designs:

- Market design 1: The wholesale power market is managed according to a LMP (Locational Marginal Price) congestion management scheme.
- Market design 2: The discriminatory price wholesale electricity market is managed according to a Power Re-dispatch congestion management scheme.
The results reported are of significant practical value to market participants and regulators. The key practical insights from the experiments are:

- Enhanced dissemination of information (leading to information symmetry) and either the LMP or Re-dispatch congestion management scheme leads to competition over time, even when market participants are heterogeneous (in terms of production costs, capacity and technology).
- ’Expensive’ power producers tend to exhibit risk-taking behaviour when compared with the behaviour of ‘less expensive’ power producers – reflecting presciently behaviour observed in real-world liberalised power markets.
- Overall, the Re-dispatch congestion management scheme seems to result in higher market prices compared with the LMP congestion management scheme. This points to the importance for the market participants in understanding the rules of the daily repeated auctions.
- Unexpected supply or demand shocks lead to the likelihood of market power being exercised, particularly under the Re-dispatch congestion management. Thus, advanced information about ‘power outages’ will curtail this from happening.
- Incumbent costs of production structures affect their ability to participate in Day-ahead or Real-time markets, with high cost producers more active in Real-time markets.

The ACEWEM framework makes possible an (improved) expert system of market competition of daily repeated power auctions. Its main methodological and applied contributions are:

- Implementation of a new decision rule for the strategic offers/bids of the agents competing in repeated power auctions.
- Integration of Day-ahead and Real-time markets to allow the exploitation of different strategic bids/offers between different markets.
- Implementation of alternative congestion management schemes (experiments 1 and 3) and auction pricing rules.
- Development of a least-cost constrained optimal power flow to estimate power outputs under different congestion management schemes (see Section 3.1).
- Exploration of simulation-based studies of market dynamics in the face of repeated attempts by profit maximising agents to exploit the features of the market for their own advantage. This is particularly important to the liberalisation process of power markets. For example, the EU power markets are being redesigned towards a ‘target model’. The ACEWEM framework can be used to test the opportunities and threats of the ‘target model’ for different EU countries.

We propose the following future research directions for the ACEWEM framework:

- Extend the ACEWEM framework to allow the representation of coupled wholesale power markets. This is particularly important when different market mechanisms and structures need to be integrated (e.g., EU power markets).
- Build a specialised Graphic User Interface (GUI) so that appropriate visualisations can support the design and exploration of alternative experiments of real-world power markets by domain experts – to conduct controlled computational experiments of real-world power markets using the ACEWEM framework.
- Enhance the ecology of the decision rules to include alternative business strategies (e.g., bid to ensure dispatch, bidding based on corporate utilities with different attitudes to risk).
- Develop an endogenous investment strategy for capacity decommissioning/expansion.

Aside from the methodological claims made in this work and the practical insights it yields, the paper draws attention to the conditions under which collusive pricing is observed. This is a finding that has important policy implications. In setting out to provide a computational laboratory that can be used for controlled experimental experiments of wholesale power markets, the approach adopted here provides a fertile basis for evaluating the interactions between policy makers, politicians, business executives and key consumers.

Acknowledgements

We would like to thank the two anonymous reviewers for their suggestions and comments. Furthermore, we want to thank Prof John Sedgwick and Prof Michael Jefferson for suggestions to improve the flow of the paper. Finally, we are indebted to Rob Rome, Glen Steer and James Law of EDF Energy (UK) for the fruitful meetings during the development of the ACEWEM framework. The authors are solely responsible for any remaining errors.

References


