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Modelling and Optimisation Study of DIES Taking into Account IDR (Integrated Demand Response)

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Abstract:- The work presented here collects and synthesises technical requirements, implementation and optimisation methods for modelling grid-level matrix models, with particular reference to renewable energy access and controllable loads. The work presents the controlled connected load modelling approach and places it in the same economic modelling and control framework as the interconnection planning measurement generation facility. The paper uses system parameters to test model performance. The test results are used to illustrate and validate the described approach. This work will improve energy efficiency and minimise energy pollution to the environment, which has become an important issue in the energy sector as energy and environmental issues become more acute. In IDR, energy consumers can respond not only by reducing energy consumption or by choosing off-peak energy consumption, but also by changing the type of energy consumption. Increasing the level of integrated energy use has been a central objective in the optimal design of integrated energy systems (DIES), which requires an accurate assessment of energy efficiency. We introduce a new optimisation model which is compounded in deep learning techniques.

Keywords:- *matrix; IDR; electricity market; model performance; optimization methods.*

I. INTRODUCTION

As energy companies continue to meet the demand for stable electricity, concerns about climate change are driving them to look for ways to reduce greenhouse gas emissions. Chief among these methods is the generation of electricity from renewable sources, a major component of the generation resource mix. In some systems, the growth of renewables has reached a level that has led to existing frequency control resources responding to certain deviations more frequently than in the past (Frangopouos, 2018). In response, some companies have sometimes been forced to plan and deploy more expensive reserve resources and/or reduce their use of cheaper renewables. This response requires other reserve resources to be purchased at a price higher than the marginal cost of intermittent resources, thereby increasing the effective cost of renewable energy (Zhou et al., 2019).

The focus of direct load control is to use the load as a traditional function of load shedding at frequency. Control models for such resources are primarily based on the impulse response of the load to large frequency deviations (Tan et al., 2020). However, with respect to frequency tuning, the load control design must examine the stability of the system's small signals (Husmann et al., 2001). This last approach does not consider the size of the total installed controllable load capacity (Qin et al., 2019; Kalogirou, 2001), but also considers the effect of the total load gain, and the feedback effect of loop control is only designed to use resources for various load states.

The lack of consideration of load factors in the energy market is a major barrier to DR technology (Wang et al., 2019). In addition, the cost, installed capacity and reliability of controllable load communication systems undermine the security of the public sector in load as an alternative to dispatchable generation [security systems (Azaza and Wallin, 2017). Energy markets also exhibit significant instability, including the amount of load available for response, load impact times and the degree of bounce when load is released (Jin et al., 2016). Finally, the option of allocating N1 to contingencies-1 in the allocation of generation resources to other capacities and shifting resources also imposes operational costs.

There is a long history of using load as a resource, starting with demand-side management (DSM) and time-of-use (TOU) programs. DSM programs take advantage of long-term seasonal demand elasticities through energy efficiency measures, and delay capacity growth by curbing peak loads when load growth slows in industrialised countries. TOU programs are an effective strategy for controlling electricity prices based on continuity of maximum load, using Midday demand elasticity. Some generation capacity is converted to short-term elasticity by exploiting the pseudo-energy storage potential of thermostatic loads (Alarcon-Rodriguez et al., 2010). Peak hour discounts, key peak tariffs and real-time tariff signals were used to reveal more directly the short-term elasticity of demand (Lu et al., 2018) .

For real-time price demand response (RTP) systems, market pricing is a major challenge (Zhang et al., 2019), which can be addressed by developing a 'switch control' function. In these two-way systems, information on available resources and their floor prices* is collected from demand resources, which includes the use of supply and demand curves in a two-way auction market to determine the price equilibrium between supply and demand. Such mechanisms are used to address real-time resource capacity allocation in terms of utility scale (Liu et al., 2020), but the issue of adjusting resource allocation has not been carefully examined (Su et al., 2020).

The main objective of this paper is to assess and review the design requirements, implementation considerations and optimisation methods for agent-based simulation to assist in the design of load control strategies. In addition, simulations can help utilities to address the renewable energy access issues they encounter in reducing greenhouse gas emissions from conventional generating units. These simulated environments should reflect all the salient features of energy network electromechanics, dispatchable and renewable generation resources, market design and market participants, the operation of control domains and regulators, and unresponsive and responsive loads. At the same time, these simulations must be computable in order to study the large network areas that are critical for managing inter-institutional exchanges.

The paper is structured as follows. Section 2 presents an agent-based simulation approach for solving quasi-static models of networks, generation resources and markets, with a particular focus on system behaviour over a one-hour period. Section 3 focuses on the modelling of individual loads, total loads and load control on this time scale. Sections 4 and 5 discuss the validation challenges and preliminary results based on the Western Electricity Coordinating Council (WECC) scheme model.

II. SYSTEM MODELLING ILLUSTRATION

Modelling the complex behaviour of more complex networked systems has been a major challenge for engineers since the advent of the first digital simulation devices (Tan et al., 2020). Recent advances in agent-based computing have helped engineers overcome many obstacles in simulation, particularly in finding solutions for various differential equation systems with largely incompatible subsystem models (Turk et al., 2020).GridLAB-D™ is an example of a simulation environment that overcomes these challenges, although its implementation poses verification challenges (Mohammadi et al. 2020). In particular, the lack of analytical solutions and stability proofs continues to hinder the use of agent-based time-domain simulation as a tool for designing control systems. However, agent-based simulation remains highly effective because the simulation environment still allows for experimentation, experience and detail, and demonstration when a particular proposition or strategy does not work as expected. Quickly through negation.

Intermittency bandwidths, short-term demand response and compliance with renewable energy frequency regulations have been observed, as shown in Figure 1. Positioning between major operational response bandwidths The demand and intermittency of wind power generation presents both opportunities and challenges for system planners. The potential for coupling between demand response and intermittent resources means that any feedback mechanisms and delays can lead to instability if controls are not designed properly. However, for the same reason, a well-designed control device will lead to efficient performance from both an economic and performance perspective of the control device.

A. Markets

A generator set cannot be started, stopped or moved within its operating envelope without incurring additional costs. In general, the problem of determining the output power of a unit in real time is based on the system area control feedback, when trying to track and record the load and adjust the output fluctuations of the generator d. The range of possible output power for the next hour depends on the condition of the unit in the last few hours. The financial impact of autocorrelation is handled by a dual settlement system (Perrear et al., 2013). This system separates real-time trading from all futures trading and ensures that the resource is active in real-time, even if no future trading occurs, making it insignificant to errors occurring in the futures market and encouraging the use of the futures market to increase profits in the real-time market and vice versa.

In a standard dual settlement system, under a contract for difference, the load side must pay the producer the difference between the current price and the contract price. This requirement applies if it is profitable to do so without prejudice to the other parties, even if the price differential requires the producer to pay the user and allows the parties to deviate from the price differential in the terms of the contract. The financial transmission right can provide the same guarantee for the transmission price if the transaction takes place on a potentially congested connection line. The dual clearing system ensures that inefficient futures contracts are corrected in real time and without risk to the trader. Ex post pricing situations can lead to differences in spot prices, creating an unavoidable transmission cost risk for the trader. CFDs cannot avoid these inefficiencies and the risk is always present. This issue is an area of research in market design.

The unit matching exercise determines the specified generating unit and demand response capability, and the level of generation or demand that is practical and most economical over a given period of time. Because incentive-compatible market design allows units and loads to automatically and accurately provide the data needed to correctly solve the mix problem, the market influences how the problem is solved. Whereas the combined power system directly addresses the unit-mixing problem, ensuring that incentives are compatible with the market design, power switching ignores the unit-mixing problem, forcing units and loads to address it and avoiding incentive compatibility issues altogether.

Most controlled markets have a generator portfolio plan that changes hourly for each control area one day in advance. The availability of generation resources is specified by the supply offer. A combined supply curve for all dispatchable generation resources is added to the intermittent generation forecast. Each unit or equipment is prioritised in descending order of cost. This process is similar to the demand curve process, except that demand response is prioritised from highest to lowest willingness to pay. Demand responsiveness is described in the form of demand offers. In addition, trunk switching is integrated into the adjustment process from unit pairing (time

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programming) to cost effective scheduling (reprogramming every five minutes).

The combined effect of these processes is shown in Figure 2. The supply and demand curves clearly illustrate the available supply, the reactive power demand Q R and the reactive power demand Q U. Scheduling and optimising the power flow corresponds to the power flow at the network level. The main scheduler is not the subject of this study, but its hourly output power is important for task scheduling and adjustment.

B. Energy efficiency conservation

In cellular networks, user energy efficiency (EE) can be defined as the safe delivery of a few bits of information per unit power of the broadcaster. This is equally beneficial and important for assessing the EE of a system when there are several users. Furthermore, this allows resources to be allocated in such a way as to improve overall energy use. With this aim, we have made significant progress in terms of energy savings.

$$\eta = \frac{\text{Through-put}}{\text{Total consumed energy}} (\text{bits/Joule}). \qquad (1)$$

The energy efficiency equation is therefore Bit.(S.Hz), as depicted by the simulation results of the work. An overall quantity capacity is maximised, as a single supply is now broadcast at maximum power. However, when it comes to energy efficiency, this may not be the maximum option.

In reality, energy is used to power the data computing circuit and to transport the data to its intended destination. It is assumed that during downlink operation, the energy consumption of the circuit is the nominal pa of the transmission as long as U>1. When there is no cellular energy, then there must be no expenditure.

C. Sources with long latency and effective capacity

The chapter describes how bandwidth is determined when the data provided by the UE is sensitive to latency. In the form of a data wait constraint, we propose to use the efficiency rate as a performance metric. Each tail dispersion of the buffer size needs to provide a decreasing rate controlled by an exponential, so that the probability of buffer corruption is expressed as

$$\Pr\{Q_i \geq Q_{max}\} \approx e^{-\theta_i} Q_{max}. \qquad (2)$$

Qi is the overflow limit for static waiting lines and liquids within the Ith consumer shield. Such a buffering constraint limits the ability of this cellular network to tolerate high arrival frequencies. The maximum possible bit rate for data transmission over the transmission medium is determined by the amount of immediately available bandwidth. These are the random arrival time of the Ith consumer and the immediate transmission (or appropriate operation) rate for the nth time period, respectively.

$$C_i^e(\theta_i) = -\frac{1}{T\theta_i} log\left(E\left\{e^{-\theta_i T R_{i[n]}}\right\}\right) \qquad (3)$$

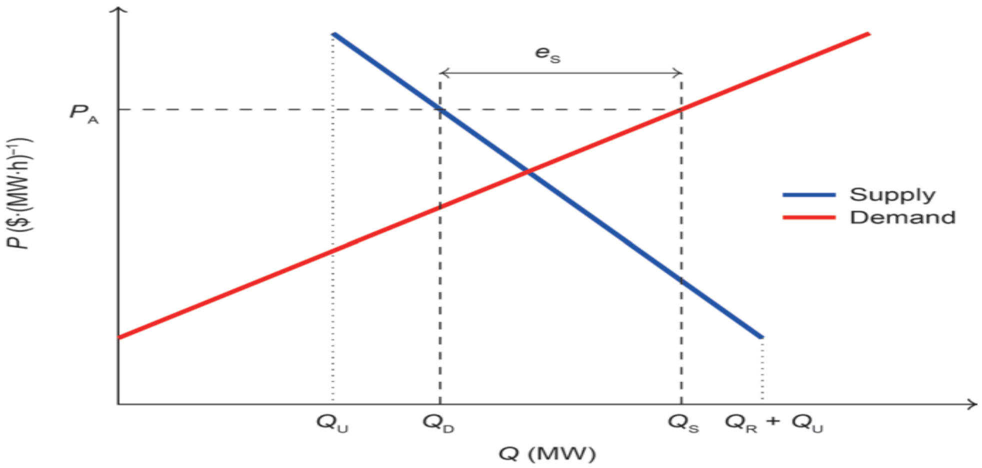

Fig. 1: Current state of the production resource planning market

The harmonisation problem can lead to a loss of the traditional balance in the energy exchange, indicating that the energy system presents an energy distribution system (Perera et al., 2013). This problem is a precursor to problems when including distributed renewable energy generators and when not considering generator start-up costs. Different systems address these upfront centralisation and energy payment costs, including the upfront blending costs of dispatch implementation. Resource reserve market adjustments provide an organised market mechanism to identify these parallel packages independent of the primary energy market.

As one of the main problems in the operation of high capacity generation systems, the control area scheduling problem includes uniformity and scheduling issues. Resource explosion is a predictable operational problem, due to its limited predictability. The optimum value of alternative operating units (the best combination of output units and efficiency levels) varies as they occur, while other variations are substitution and energy efficiency levels needs. Most solutions to these problems are simply combined with supply intermittency methods and use density probability determination methods for load and combination (Wei et al., 2019) and probabilistic statistical methods for cost estimation (Iria, J et al., 2020) . Turbine

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mixing and demand response have been considered as optimisation problems (Zhang et al., 2004) and are relevant to wind power generation (Deb et al., 2002; Guo et al., 2013). Combinations of units have been proposed (Underwood, 2016) and the same effect may occur due to the uncertainty in generation and demand resolution.

Both approaches require simulations in the time domain to solve the scheduling problem explicitly. However, in agent-based simulations, the distributed approach is sufficient to determine the optimal structure and avoid the forecasting and daily CPU combination problems altogether. Market-based approaches address these issues, for example, switching control allows the construction of simulation models that assume that the system maximises the global power surplus problem, and these assumptions are not included in the assumptions tested.

It is useful to establish a dual system for the settlement of energy market transactions, which ensures that the simulation is independent of the existence of a day-to-day market model. Assuming that the market design is incentive compatible and that all resource quotes reflect the cost of the design, any uncertainty arising from the absence of futures prices can be removed by real-time market operations (Perera et al., 2013). Unless an attempt is made to investigate incentive compatibility or strategic pricing, real-time market simulation is sufficient. The same principle can be further applied to all multi-billing methods that adjust resource allocation, i.e. there is no need to simulate a third programming market (e.g. hourly programming) or a second scheduling market (e.g. re-scheduling every five minutes), as only the difference between the cost of the primary adjustment response (e.g. four seconds) and the actual frequency affects direct payments. With this in mind, the author believes that relevant adjustments and controls should be made for market-driven scheduling issues.

D. Adjustments

In most current systems, the energy market discussed above is not relevant to the adjustment process and the ancillary services market can be used to overcome these shortcomings. However, changing this is the goal and it is worth reviewing how it should be adjusted before discussing how it can be linked to the energy market.

Grid frequencies are calculated based on supply and demand balances, inertia and damping. The control zones operate independently when large scale energy markets and multi-period real time adjustments are concentrated at one point. Generator sets under primary frequency control (governor/speed tilting) react to any frequency deviations according to their dead zones, while those under secondary frequency control also react to deviations in the tie lines. The role of the secondary control system is to restore the power flow of the tie line to the recommended value and to eliminate the steady-state frequency deviation using the most economical genset. With this in mind, the authors calculate the Area Control Error (ACE) by selecting generators to adjust their output power. Goods, together with at least one dispatchable market and a forward energy market, constitute a retail energy trading market. The dispatchable market is similar to that shown in the Olympic and Columbus diagrams (Lu et al., 2018; Liu et al., 2020), i.e. a decentralised consumer load and distribution market that imposes power constraints on bulk supply. The system frequency control diagram is shown in Figure 3. When the load responds to frequency, the control area is adjusted by three main components: main protected load (L), voltage drop controlled generation (G D) and ACE controlled generation (GA). The load and voltage drop are only affected by the frequency deviation, while the ACE generation is affected by the mooring line flow error and the frequency deviation.

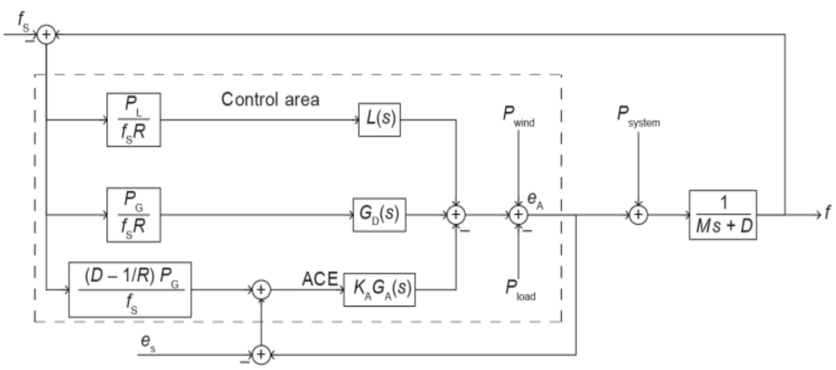

Fig. 2: System frequency and control area output adjustment control diagram.

The regulation control is based on a combination of hourly unit, economic dispatch, frequency deviation and connection line flow in optimal power flow planning, the details of which are beyond the scope of this study. One part of the primary regulation control is used to control generator voltage dips, low-frequency load shedding and so-called main protection loads, while the other part reacts to the ACE signal. In each control zone, the ACE signal is updated approximately every 4 seconds, using the following equation*.

$$ACE = (e\ A - e\ S) + B\ (f - f\ s) \quad (4)$$

In equation (4), (e A - e S) is the deviation between the actual net output sum A of the mooring line and the specified net output sum S; B is the frequency deviation in the control area; and (f - f S) is the grid deviation between the frequency f, and the specified frequency f S. Note that the ACE signal is usually filtered. The filtering is modelled using the transfer function 1/(1 + sTA), where the value of TA is greater than 10s.

E. Based on modelling

In the 1990s, agent-based modelling became increasingly popular as computing power advanced and the complexity of numerical simulations increased. Today, agent-based modelling moves away from traditional simulations by incorporating expected break-even points based on time-domain results into a system of differential equations representing the behaviour of individual elements. Agent-based simulations therefore represent the behaviour of individual elements and subsystems, allowing results to emerge from the interaction of endogenous and exogenous conditions. Agent-based models allow for a more natural 'bottom-up' description, with greater flexibility in the complexities and phenomena observed during the simulation (Wang et al., 2010). In particular, agent-based models take into account different levels of integration and methods employed, making these models particularly suitable for interdisciplinary simulation studies. While these advantages over traditional simulation methods are clear and are the overall motivation for choosing agent-based simulations, model validation of agent-based simulations still faces significant challenges.

In the 20 years since the emergence of agent-based simulation, there have been thousands of publications related to its use in current research, in software usage and in simulation, especially in verification techniques. and standards have provided simulation specifications. In surveying the literature, Heath et al. (Makkeh et al., 2020) summarise six key challenges inherent in the adoption of agent-based modelling tools that exist independently of field research, tools and associated issues.

- Agent-based modelling tools need to be developed independently of the software that implements the simulations, and their results need to be published along with details of the software and numerical methods used to obtain them so that others can replicate them...
- The development of agent-based modelling requires the development of a separate specialism within the simulation profession, using a common language across domains.
- The simulation designer needs to set expectations for the agent-based model, matching these values to the intended use.
- A full description of the simulation must be provided to enable others to independently assess the applicability and validity of the model to support these results.
- The models used must be fully validated and fully documented in the text.
- Statistical and non-statistical validation techniques need to be specifically designed and developed to communicate performance objectives to these constructed models.

As these problems are inherent to agent-based simulations, they present insurmountable challenges. Firstly, we must separate the challenges of obtaining a macroscopic behavioural representation of the system from the microscopic behavioural representation of individual agents. Secondly, agent-based simulations are particularly effective for modelling these highly non-linear transient phenomena, as analytical methods are not always available and are often difficult to generalise. Finally, the amount of data that can be collected from agent-based simulations is often much larger than that obtained from the real systems they simulate, making comparisons difficult even using the most powerful statistical and analytical methods (Sivaneasan et al., 2015). Despite these factors, agent-based simulations are often considered to be the most appropriate approach for solving problems related to electricity dispatch using market mechanisms (Mohamadi et al., 2020).

III. RESOURCE MODELLING

The multi-layer/multi-period supply and demand model sought by the author requires schedule information for wholesale electricity market settlements to be considered every five minutes in the dispatch market offer. Similarly, scheduling market settlement information every five minutes is considered in the adjustment control. In this section, the author examines the supply and demand models for planning, scheduling and adjustment to determine what information needs to be exchanged.

A. Power supply

The behaviour of the supply offer also applies to planning and scheduling, as illustrated in Table 1, using base and marginal prices for different categories of facilities (e.g. renewables, base load, medium load and peak load).

Class	Base price ($\$\cdot(\text{MW}\cdot\text{h})^{-1}$)	Marginal price ($\$\cdot(\text{MW}^2\cdot\text{h})^{-1}$)	Mix (%)
Renewable	0	NA	10
Base-load	15	0.08	40
Mid-load	25	0.32	25
Peak-load	65	1.10	25

Table 1: Scheduling prices and generating unit capacity ratios

The values in the table are used to construct the asymptotic supply curve.

$$P(q) = c_0 + c_1\left(1 - \frac{q - q_{\mathrm{w}}}{q_{\mathrm{m}}}\right)^{-c_2} \tag{2a}$$

In equation (2a), q w is the dispatched wind generation; q m is the maximum available generation, including wind generation* and resource reserves; and the curve parameters for the price and resource ratios shown in Table 1 are.

C 0 =11.0 C 1 =4.0 C 2 =2.6 (2b)

Three types of generator sets - hydraulic, thermal reheat and thermal non-reheat - must be modelled for use in tuned systems. The transfer function (power output as opposed to power control) of the control plant unit, including its governor, is described below.

$$G_h = \underbrace{\left(\frac{1}{1+sT_G}\right)}_{\text{Governor}} \underbrace{\left(\frac{1+sT_R}{1+s\dfrac{R_T T_R}{R_P}}\right)}_{\text{Compensator}} \underbrace{\left(\frac{1-sT_W}{1+0.5sT_W}\right)}_{\text{Turbine}} \quad (3a)$$

Thermal reheating unit.

$$G_s = \underbrace{\left(\frac{1}{1+sT_G}\right)}_{\text{Governor}} \underbrace{\left[\frac{1-sF_{HP}T_{RH}}{(1+sT_{CH})(1+sT_{RH})}\right]}_{\text{Turbine}} \quad (3b)$$

Thermal non-reheating unit.

$$G_c = \underbrace{\left(\frac{1}{1+sT_G}\right)}_{\text{Governor}} \underbrace{\left(\frac{1}{1+sT_{CH}}\right)}_{\text{Turbine}} \quad (3c)$$

It is important to note that the inclusion of progress settlements in the adjustment system has not been specified, as this is an ongoing area of research that must be considered, and there is no agreement in the literature on how to account for it. Indeed, existing models need to be used to support the conduct of such research.

B. Price response to demand

A comprehensive load model was introduced to represent the total load on the feeder, which correctly reflects the effect of changing the end-use load (Jing et al., 2014). While the model is able to replicate many of the load behaviours commonly found in distribution systems, including motor shutdowns and thermal protection, it cannot replicate some of the important behaviours associated with demand response control that can be used when loads are used as trusted resources. bring about dynamic changes in large systems. In particular, the model does not represent the effects of state-based offer feedback in real-time pricing systems, nor the performance of network protection frequency response, as demonstrated in the Olympic project. Unfortunately, many aggregated demand response models are too complex to be modelled using low-level linear models (Zheng et al., 2015), although some alternative load control designs use very low-level load models (Ren et al., 2012) to model demand response aggregation as quickly as possible for as long as possible.

Demand scheduling behaviour can be partially demonstrated using a random utility model (Yu et al., 2012). The model has been applied to study the value of electrical equipment and comparative judgments of electrical equipment (Vahidinasab, 2014). The stochastic utility model appears to be applicable to switching control systems as the model introduces two main assumptions that apply to switching systems.

When the consumer (or the device as a consumer) has to make a yes/no decision (how to turn the air conditioning on or off), the consumer's choice is a discrete event. The consumer (or the device) cannot choose the next interval to operate under partial load.

The attractiveness of a given choice to the consumer is a random variable that changes very slowly over time, in which case it corresponds to the desired level of comfort. For retail, we use the term 'attractiveness', but we could also just use the term 'utility' to satisfy economic theory. In any case, the randomness of the ideal level of comfort is central to the assumption. Furthermore, it is assumed that the device as a consumer will reasonably choose the most efficient outcome based on the optimal comfort level specified by the consumer.

Without knowing the number of consumers required, the total demand curve is statistically derived from the discrete choices of the thermostat, whose temperature is restricted to a limited field. For example, the thermostat must choose an offer when the price of the abandoned demand is lower than the minimum selling price. This is the only option for submitting an offer and is currently required because it needs to be powered at the clearing price. As for the choice of two points, the reason is this. u has benefits for the electrical equipment (utility in economic theory) and taking specific measures to obtain the thermostat can make the electrical equipment better. It can be assumed that the net benefit depends on an invisible eigenvalue α with a logistic distribution and a visible eigenvalue β with a logistic distribution. The net benefit is defined as U = α + βx + ε, where x is the electrical equipment decision and ε is the independent random error. If U > 0, the choice is made with the appropriate action.

The relative probability of taking action is then

ρ {x} = e - (α + βx) (4)

The best electrical equipment offer is one that maximises the benefits while minimising the costs of the positive outcome. This condition is satisfied when the marginal benefit of the positive outcome equals the marginal cost of the negative outcome. In the absence of reliable price forecasts, the probability of this happening is 1/2 when x = -α/β, i.e. 50% of the current condition of the electrical equipment. For thermostats this corresponds to providing a quotation p based on the currently observed temperature T a, the ideal temperature T d, the comfort level K and the average PA and variance P 2 D of the most recent price, written as the equation p = ±K (T d -T a)/PD +PA, where the choice of the comfort signal K depends on whether the global process is heated or cooled. The ideal comfort level of the electrical equipment is the basis item for the selection of the thermostat for the electrical equipment, quantity β. Therefore, the parameter for each electrical equipment must be given by the difference between the actual temperature of the room air and the ideal temperature of the electrical equipment as a function of ΔT = T d -T a .

The utility of an electrical device is

U (ΔT) = α (ΔT) + β[p(ΔT)-p c] + ϵ (5)

In equation (5), pc is the electricity clearing price and independent random errors are assumed to be normal, with a large number of power devices taking ε→0.

The exchange control system used in the demonstration project is in equilibrium when the diversity of equipment states is at its maximum and the total load is stable. A quasi-steady state is formed when the distribution offer and the average price are symmetrically distributed and have the same relative variance. The actual quantity and unresponsive demand Q U of the stochastic system is adjusted according to the price p and the responsive demand Q R. The total demand at price p is (Jiang et al., 2014).

$$Q(p)=Q_U+\frac{Q_R}{1+e^{2\eta\left(1-\frac{p}{P_A}\right)}} \tag{6}$$

This curve does not accurately represent the erratic behaviour of the demand response. In particular, when the diversity of load states is distributed according to price deviations, the curve changes as the load response changes and recovers from the price perturbation, sloping first to the left and then to the right. Modelling the general behaviour of the demand response following diversity perturbations is an ongoing area of research, but the general behaviour removes the effects of perturbations within a time constant of decaying state diversity.

a) Network protection fees

Network protection loads, such as those studied in the Olympic demonstration project, will provide very fast frequency responses. In recent years, researchers have developed a variety of low and over-frequency network protection strategies (Patwal et al. 2020; Ren et al. 2010; Kbari et al. 2014; Zhou et al. 2013). The details of these strategies vary, and for the purposes of this paper, a single model cannot be built. However, in general, I was able to summarise the expected characteristics of any cyber protection countermeasure, as described below.

The initial response is very fast, peaking in about 1 second.

- The peak response is largely proportional to the frequency deviation and can last for more than 10s.
- The response decay corresponding to the zero total error feedback charge recovery delay is typically less than 2 minutes, although longer decay times are possible under certain conditions.

The load transfer function that exhibits these behaviours is

$$L(s)=\frac{s}{T_L s^2+s+K_L} \tag{7}$$

C. Joint resource scheduling

Short to medium term demand response economic dispatch projects are underway in several markets. the expected hourly price of PA electricity is determined by the wholesale electricity market and is used to set the expected market price for 5 minutes of retail capacity. The demand response function uses this average price and the expected value of price fluctuations to determine which offers to make to reduce the dispatch market, which is the adjusted price relative to available supply, as shown in Figure 4.

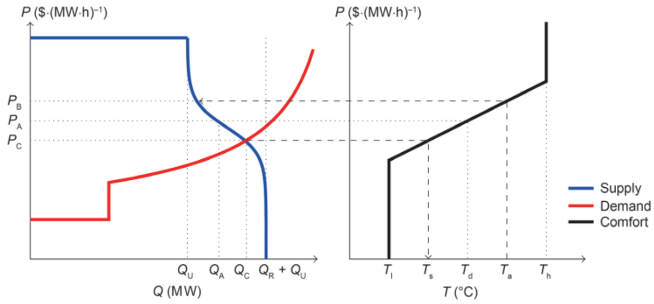

Fig. 3: Bidirectional real-time resource scheduling (5 minutes) bidding (left) and demand resource control (right).

In the control area, dispatch prices are sent to all controllable resources every 5 minutes. While resources respond according to their offer, a purely stepped response to price changes should be avoided. For loads that respond faster than generators, this can be achieved by adding a filter to the dispatch price signal.

$$Q(t-t_C)=Q(t_C)+[Q_C(t_C)-Q(t_C)]e^{-\frac{1}{T_L}(t-t_C)} \tag{8}$$

In equation (8), tC is the market clearing time; QC (t C) is the quantity shipped; and TL is the decay rate, which must not exceed the rate at which the control area changes with load, e.g. about 10 s. 98% of the responses use only generation resources. This suggests a reasonable value of TL ≈ 2.5 s. This value decreases with increasing fast demand resources. In the Olympic demonstration project, the total frequency response was about 0.4s 90%, i.e. TL = 0.2s (Wang et al., 2020) determined by the time constant of the local frequency measurement filter and used in section 4.

It is worth noting that I have not used a constant slope, as the response may create unwanted marginal stability problems in the local control system when using a stepped signal input. While the pitch signal input or the slope input would introduce one or two poles respectively, the attenuation input would introduce a true negative pole at s=-1/TL without introducing stability problems.

D. Adjustment costs

The price control uses a 'network protection' load adjustment based on marginal prices for demand (R D) and energy supply (R S) in US$-(MW -2-h)-1.

$$R_D=\frac{Q_R P_A}{2\eta(Q_U+Q_R-Q_C)(Q_C-Q_U)} \tag{9a}$$

and

$$R_S=\frac{c_2(P_C-c_0)}{Q_S-Q_C} \tag{9b}$$

These marginal dispatch energy prices provide linear energy prices per megawatt of supply and demand for the next five minutes of allocation and regulatory control respectively. The slope of the supply and demand curve is the basis for the response required to return the system to the planned state, and the response to supply and demand adjusted resources is priced and dependent on magnitude.

Adjust the price to

$$P_R = P_C + \frac{\Delta Q_{reg}}{\frac{1}{R_S} - \frac{1}{R_D}} \tag{10}$$

In equation (10), ΔQreg is the amount of additional energy required to restore the link line frequency and switch to the planned state, and the current value of ACE is a reasonable approximation of this amount. The marginal price of energy is also used to calculate the participation factor used in the adjusted allocation of supply and demand resources.

$$\rho_S = \frac{R_D}{R_D - R_S} \tag{11a}$$

$$\rho_D = \frac{R_S}{R_S - R_D} = 1 - \rho_S \tag{11b}$$

These participation factors are the amount of gain in the supply and demand adjustment control that results in the best economically feasible adjustment. The question of how to incorporate these factors into the adjustment control remains an open area of research. While the adjusted marginal dispatch energy price generally varies depending on the supply and demand resources, for a given frequency deviation, the adjusted energy price is the same for all resources responding to the deviation, regardless of the supply resource. and demand, as shown in Figure 5.5.

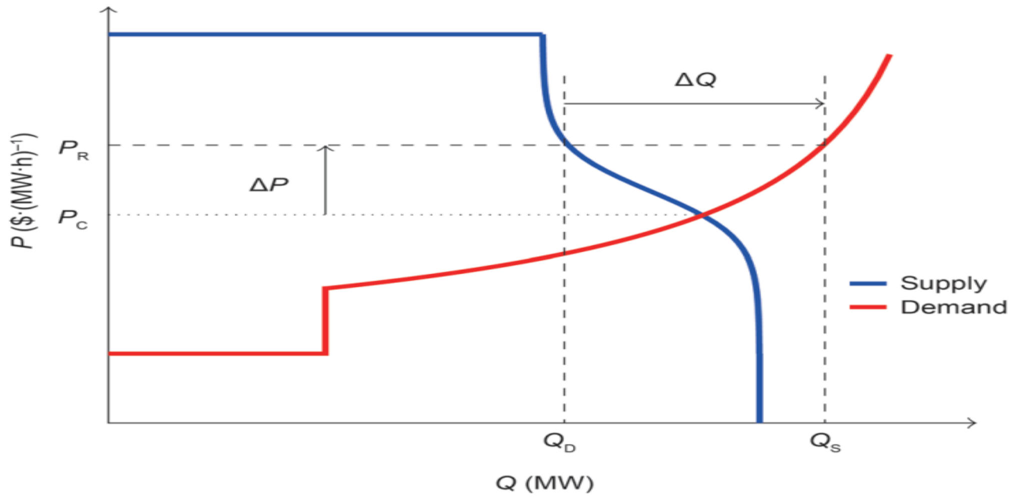

Fig. 4: Adjusted resource response price when e S = 0.

Any change in frequency Δf results in a change in net output of the control area ΔQ, which corresponds to a change in energy price ΔP. The general change in supply and demand due to changes in energy prices is necessary to adjust the output of the control area to provide the expected 5% frequency drop response. All configured resources providing tuning services cannot exceed the total tuning cost of providing tuning services through frequency reduction alone.

$$C_R = P_R \Delta Q + Q_C \Delta P \tag{12a}$$

An adjusted answer is provided at this time.

As the marginal cost of PC QC scheduling is already paid for at the time of scheduling, no further charge is required and only the deviation between the power adjustment cost and the scheduling cost has to be taken into account. In the case of deceleration control, only the actual adjusted performance ΔQ SDC is paid for.

$$C_{SDC} = C_R \frac{\Delta Q_{SDC}}{\Delta Q} \tag{12b}$$

The compensation provided for demand response resources is again calculated based on the actual adjusted control response ΔQDR.

$$C_{DR} = C_R \frac{\Delta Q_{DR}}{\Delta Q} \tag{12c}$$

In the case of supply resources responding to ACE, the calculation must include compensation values to correct for deviations in the connection line. The authors therefore use the actual response value ΔQ ACE of the ACE control device .

$$C_{ACE} = C_R \frac{\Delta Q_{ACE}}{\Delta Q} \tag{12d}$$

Taking these factors into account, for each schedule (0, T), the total adjusted price is

$$C_{REG} = \int_{t=0}^{T} P_R(t) \Delta Q(t) + Q_C \Delta P(t) \mathrm{d}t \tag{13}$$

The engine works in a similar way to a Dutch auction, with the fastest moving asset currently receiving the highest price and the slowest asset being paid based on its lowest price and delayed response. This mechanism is an important basis for reducing the fungibility needed to adjust the market in real time, including programming every 5 minutes and every hour.

Adjustment costs do not need to be captured from the units that generate the adjustment, such as fluctuating loads, intermittent renewables and generators that are not rescheduled. To properly account for these costs, adjustment prices must be charged as a penalty for every 5 minute deviation from schedule and/or rescheduling of indigenous resources. Based on these penalties for deviations, the need to implement a segregated imbalance market is assessed. However, locally adjusted prices cannot simply be applied to link deviations, as these prices may differ at each end of the link. These issues appear to require further research.

The general structure of the adjustment model in the planning and scheduling context is shown in Figure 6. In general, the energy supply and demand, production capacity and the offer of the adjustment resources meet the requirements of the hourly plan, the construction of the supply and demand curves used to determine the average hourly price PA and the eS contact line plan is carried out. For each 5-minute schedule, the average price and the contact line schedule were used to determine the price and quantity to be rescheduled every 5 minutes, as well as the adjusted marginal supply and demand prices RS and RD. Adjustment response measurements were made every second in order to determine (i) the quantity deviation ΔQ required to maintain the tie line schedule and (ii) the adjusted price PR required to obtain that quantity. Any fluctuations in the adjusted price PR are used to estimate the standard deviation of the price PD for the next progress interval, and the quantity deviation ΔQ is used to adjust the next progress and the next progress so that the sequence of progress and progress changes takes into account the jump response in the presence of the system state.

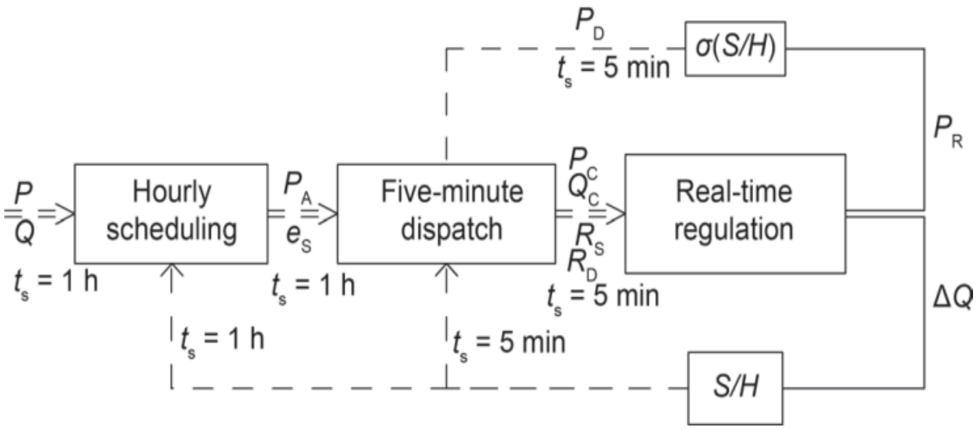

Fig. 5: Information flow diagram for different time periods

IV. OPTIMISATION

Simulation validation is usually considered using Zeigler model validity levels, i.e. repeated validation, predictive validation and structural validation. Such a validation approach exists in the taxonomy, however, for agent-based simulation validation, Klügl suggests that only two levels are used (Sivaneasan et al. ,2015) - surface validation. This model evaluation is divided into the following three steps. (1) the expert assesses whether the simulated macro behaviour replicates the behaviour of the actual system by observing the results of a large number of simulations; (2) in order to assess whether the simulated macro behaviour replicates the behaviour of the actual system, the human an expert observes the simulations; and 3. the human expert assesses the outputs of the simulations to determine whether these outputs are plausible under specific conditions.

Empirical validation. This validation is also carried out in three steps. (1) sensitivity analysis to illustrate the role of different parameters; (2) calibration to determine if the values are applicable; and (3) statistical validation using different data sets to ensure that the model is not only applicable to a specific situation.

Three alternative approaches have been identified in agent-based economics, namely indirect calibration, the Werker-Brenner method and metrological conservation methods, which may be suitable for agent-based engineering design. Indirect calibration has a more microscopic focus, with the method first validating and then indirectly calibrating the model by focusing on parameters that are consistent with the output validation. the Werker-Brenner method is probably the most relevant method for calibrating agent-based engineering design models, as it includes a Bayesian perturbation process that validates the output and allows the specification of each model to be assigned according to its compatibility. In this method, known as 'method induction', the model is not constructed from assumed preconditions; it only considers the common features of the model and the actual system to be employed. The advantage of this approach is that it reduces the number of degrees of freedom and can avoid validation failures based on small historical data sets, providing a more rigorous approach to simulations based on empirical data. Like the Werker-Brenner method, the real-world conservation approach is calibrated first, but is easier to incorporate into a contract or daily knowledge record than the former. However, as with indirect calibration methods, they are more micro-focused.

Windram et al. also point out that there are some important gaps in current research on agent-based model validation. Notably, there is currently no way to overcome the problem of over-parameterisation of agent-based models. Actual assumptions at the individual agent level often lead to the existence of various degrees of freedom at the macro level, leading to arbitrary results when the model is executed, which significantly reduces the original explanatory power of the model itself and makes it only marginally better than random. Studying the causal relationship between assumptions and outcomes becomes difficult. Often, these problems can be solved by reducing the number of degrees of freedom, which gives the model builder many options.

The second open question is the interpretation of the counterfactual output of a model. The probability of observing a given model output is unknown, and in the real world the same output can be observed across all representative outputs, i.e. we are not sure how to assess the explanatory power of a model.

Finally, the availability, quality and bias of the empirical data set are important considerations during model validation. Not all records are kept, usually only 'relevant' events are recorded and 'irrelevant' data are excluded, essentially the empirical data covers possible significant biases.

V. RESULTS AND DISCUSSION

Model validation based on model agents for joint economic energy systems is still an immature discipline. I use the discussion in Section 4 as a general guide to help illustrate the validation methods described in this section. To illustrate these validation methods, the author examines three elements of the model. He first investigates the open-loop response of a single control region to frequency disturbances and the bondline switching due to fluctuations in the output of renewable energy generation during the grid process. The closed-loop response of the system to a blackout emergency in another control area is then examined. Finally, the change in system adjustment costs in the presence of demand response is investigated.

A. Response in the control area

The validation of the adjustment plan is carried out in the generation and load models operating in the control area, in an open circuit network environment, i.e. the flow of these frequencies and link lines is influenced by the network as a boundary condition. rather than the network itself. The validation parameters for the control area are shown in Table 2 and the simulation results are shown in Figure 7.

The results show that the model represents an acceptable fitted response at the control area level with reasonable assumptions about rescheduling every 5 minutes, intermittency of renewables and availability of demand response resources. In particular, the energy loss from renewable energy corresponding to the over-speed switching of wind power is significant around 35 minutes after start-up and in the last 20 minutes. The availability of additional demand response shows significantly less amplitude and variation in the ACE signal for the same exogenous frequency and mooring line fluctuations occurring in the control zone, indicating better control system performance at 11% and <1% demand response.

Parameter		**Value**	**Unit**
Generation	Intermittency (1σ)	0.25	$MW \cdot s^{-1}$
	ACE filter T_A	78	s
	ACE gain K_A	0.4	(Unitless)
Demand	Average short-term elasticity η	–4	(Unitless)
	Stdev short-term elasticity σ_η	1	(Unitless)
	Unresponsive load volatility	0.05	$\% \cdot s^{-1}$
	Responsive load volatility	0.05	$\% \cdot s^{-1}$
Interconnection	Tieline volatility (measured)	0.09	$\% \cdot s^{-1}$
	Frequency volatility	0.5	mHz
	Firm reserve requirement	25	%
	Non-rm reserve requirement	85	%

Table 2: Validation parameters for a single control area

B. System response

The low frequency response during peak days was verified by looking at the response of a single control zone to a 1% power loss (system) in another control zone of the grid, indicating that all control zones are networked and that the network has a closed loop response. The network model and control zone parameters are shown in Table 3.

Parameter		Value	Unit
System	Capacity	100	GW
	Inertia	9	s
	Damping	1	(Unitless)
Control area	Capacity	1000	MW
	Renewable	10	%
	Hydro	10	%
	Thermal (reheat)	60	%
	Thermal (non-reheat)	20	%

Table 3: Network and control area model parameters

In terms of the different levels of demand response availability in the matrix, Figures 8 and 9 show the response of the closed loop system for 10s and every 5min respectively. Figure 8(c) shows the increase in rapid load dump response when the demand response (DR) schedule is increased. Figure 9(c) shows the corresponding recovery for the next 2 min. Furthermore, as can be seen in Figure 8(a) and (b), increasing demand response scheduling reduces the displacement and generation required to maintain production. Overall, the total output is consistent across all levels of DR dispatch, indicating that the system-wide impact is relatively indifferent to every 5-minute re-dispatch, as

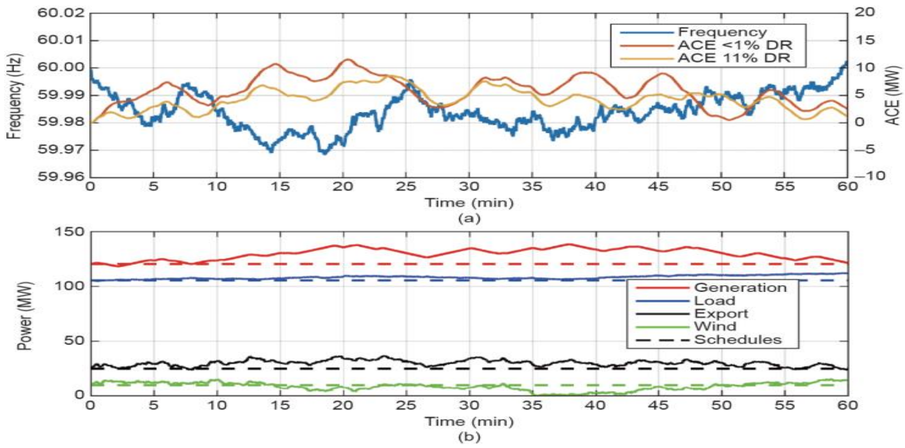

Fig. 6: Open control area test. (a) Frequency and ACE; (b) power adjustment

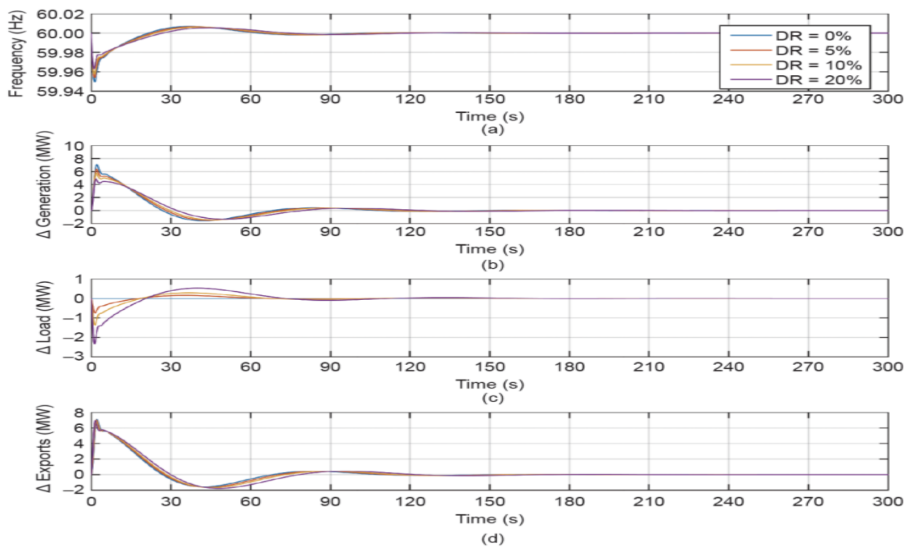

Fig. 7: Low frequency response of the network (5-minute window). (usual; (b) variation in generation; (c) variation in load; (d) variation in exports.

The adjustment costs for the above closed-loop system scenario are shown in Table 4. the introduction of an additional 10% demand response capability had a significant impact on the adjustment costs, with a 65% reduction in total adjustment costs. In addition, the demand response adjustment cost increased significantly, with the total adjustment cost in the control area increasing from 2.4% to 22%.

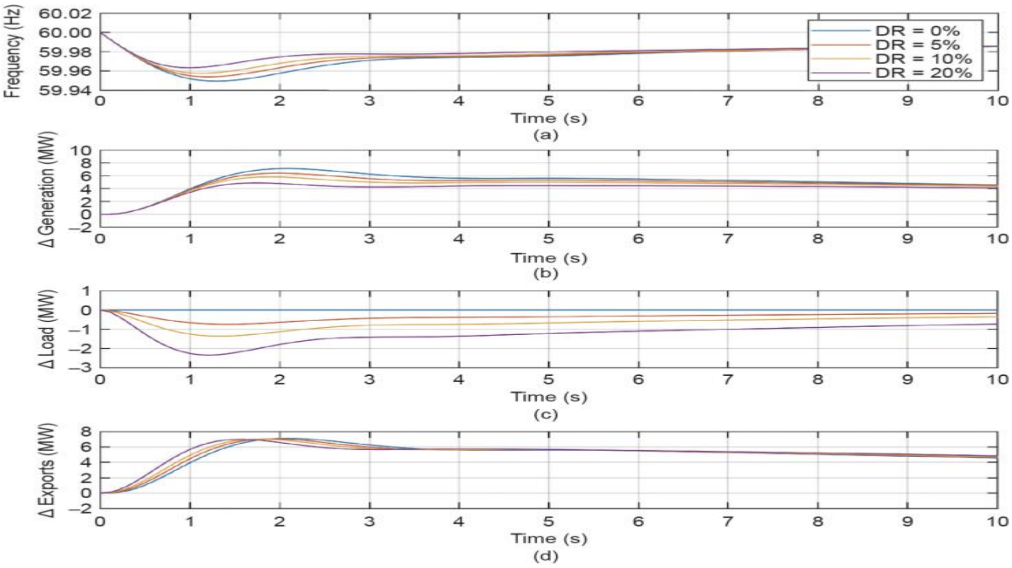

Fig. 8: Underfrequency response of networking (10s window). (a) frequency; (b) generation variation; (c) load variation; (d) output variation

Cost element	DR < 1%	DR = 11%
Generation	58.3	17.1
Droop	52.5	15.4
ACE	5.8	1.7
Demand response	1.2	3.9
Total	59.6	21.0

Table 4: Adjustment of costs by type of resource

Figure 10 shows the dispatch, adjustment and deviation penalty prices for the control areas studied. The landed replacement of resources is clearly visible, and the dispatch price per 5 minutes is lower than the real-time adjusted price. Deviation penalties are essentially in line with the adjusted prices, but are not entirely accurate. This difference is caused by tie-line deviations and cannot be used as a local dispatch deviation penalty collected in the control area. The mechanism used to determine the tie-line deviation penalty requires adjustment of the penalty price in the tie-line connection area, which is not currently supported by the model.

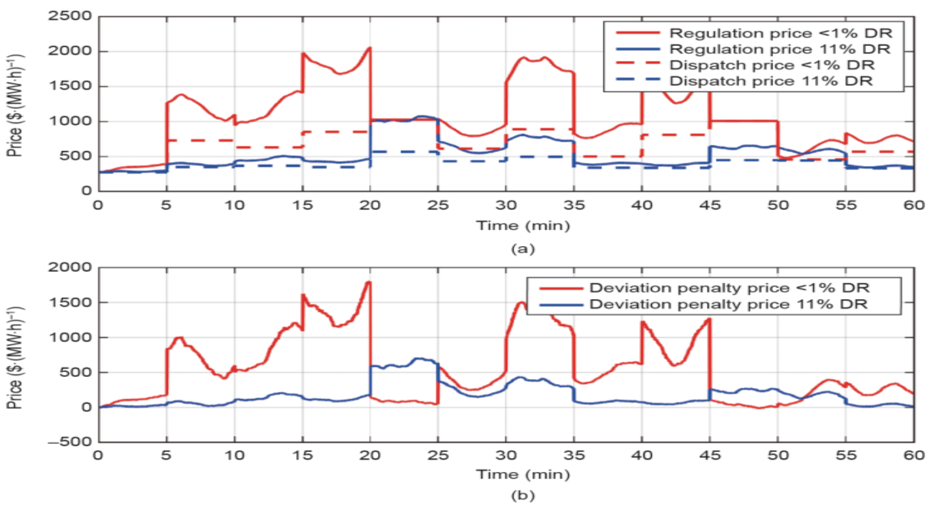

Fig. 9: Impact of demand response on (a) scheduling and adjustment costs and (b) deviation penalty prices

VI. SUMMARY

This paper summarises the engineering modelling requirements, implementation framework and algorithms, and validation techniques required for grid-level model simulations, which are needed for a regulatory response study of interconnected generation and controllable loads using renewable energy sources. For interconnection planning and operation studies using large-scale demand response in the presence of generation sources, an integrated controlled load modelling approach should be used that can be used as a generation resource under the same economic and operational framework. Controlled Modelling. Implementation.

Agent-based simulations should form the basis for a wide range of system studies such as demand response control design, renewable energy access studies, performance optimisation strategies control zones and market studies. Parametric models and systems with such performance are generally close to the scale of the network. The results show that the expected macro-systems and control areas can be trained using an agent-based modelling approach that works regardless of the presence of an unequal number of responses to requests in the matrix.

The model does not currently answer the following open research questions. Firstly, the calculation of the optimal hourly power flow schedule to maximise the overall power process remains an unmodelled process and boundary conditions must be provided. Secondly, the network is currently modelled using microcontrollers, but in reality there are many different control domains associated with different electromechanical and economic forces. Thirdly, anchor line deviation adjustment assumes that only the other end of the anchor line will produce when adjusted for similar productivity and demand responses. Finally, the costs of line pull diversions cannot be fully recovered without imposing dispatch diversion penalties on all participants, including intermittent load and generation.

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