Aggregated Demand Modelling Including Distributed Generation, Storage and Demand Response

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Abstract

It is anticipated that penetration of renewable energy sources (RESs) in power systems will increase further in the next decades mainly due to environmental issues. In the long term of several decades, which we refer to in terms of the future grid (FG), balancing between supply and demand will become dependent on demand actions including demand response (DR) and energy storage. So far, FG feasibility studies have not considered these new demand-side developments for modelling future demand. In Australia, installed rooftop photovoltaic (PV) generation has been increasing significantly in recent years, and this is increasingly influence the nett load profile for FG feasibility studies. This paper proposes an aggregate nett load or demand model to be used at higher voltage levels considering the effect of rooftop PV, energy storage and DR for FG scenarios, which is inspired by the smart home concept. The proposed model is formulated as an optimization problem aiming at minimizing the electricity cost. As a case study, the effect of the load model is studied on the load profile, balancing and loadability of the Australian National Electricity Market in 2020 with the increased penetration of wind and solar generation.

Keywords

Aggregated demand modelling, demand response, future grids, renewable energy sources.

I. INTRODUCTION

Australia’s renewables portfolio target aims at increasing the penetration of renewable energy sources (RESs) to 20% and 50% by 2020 and 2050, respectively [1]. As a result, maintaining the balance between supply and demand will become more dependent on the demand-side to achieve balance with fluctuating renewable power generation. In conventional power systems, the generation is able to follow demand by a combination of dispatch and regulation processes. However, in future grids (FGs) both demand and generation are variable and actions such as demand response (DR) alongside energy storage will be needed to achieve balance. So, the paradigm is changing from generation following demand to demand following generation. This leads to a new modelling question, namely how to represent the aggregated nett demand or load (including distributed generation (DG), storage and DR) for modelling in FG scenarios.

In particular, installed capacity of rooftop photovoltaic (PV) has been increasing considerably in the world, and greater penetration of battery storage is anticipated [2]–[8]. Global installed capacity of PV has increased from approximately 4 GW in 2003 to nearly 128 GW in 2013 [2]. Such a deployment of PV is due to electricity price increases, government incentives and also worldwide drop of PV capital costs [2], [3]. The Electric Power Research Institute (EPRI) has recently shown that users equipped with PV and storage will be integrated into the USA grids, and provide responsive demand in the future [2]. Another study using a copper plate transmission model has demonstrated that users equipped with PV-plus-battery systems will reach retail price parity from 2020 in the USA grids [3]. Also, it can be argued that demand management would accelerate this phenomenon. Until 2013, over 3 GW of PV generation had been installed in Australia mostly by residential and commercial customers [4]. Moreover, installed battery storage capacity has been increasing in the past couple of years [5], [6]. It is predicted that PV and storage penetration in Australia will increase further in the next decades [5]–[7], and, this will greatly influence the load profile and future direction of Australia’s electricity system [7]. The Alternative Technology Association (ATA) in Australia has also suggested that due to high penetration of PV-plus-storage system in the Australian National Electricity Market (NEM), retail price parity appears highly plausible by 2020 [8]. The Australian Energy Market Operator (AEMO) has also noted an increased difficulty of predicting the future demand because of the rapid growth of those sources in the
NEM [5]. Furthermore, it is clear that for studying FG scenarios of uptake of the various demand technologies (DGs, storage, DR), models which can represent different levels of each technology are needed.

The literature review below considers studies which relate directly to meeting new modelling and analysis challenges in FGs [9]–[13]. A preliminary study by the University of Melbourne Energy Research Institute has proposed an electrical grid for Australia in 2020 relying 100% on RESs [9]. However, balancing and performance of the proposed grid was not studied which makes the proposal highly speculative. The University of New South Wales researchers have analysed the feasibility of 100% RES scenarios considering a copper plate transmission model for the NEM [10], [11]. They have demonstrated that the NEM can be powered most of the time entirely on RESs within the specified NEM reliability standard. Also, they have determined the least-cost mix of 100% RESs scenario including wind farms (WFs), utility PV, concentrated solar plants (CSPs) with thermal storage, hydro and biofuelled gas turbines (GTs). Beside national FG feasibility studies, some studies are reported for other electrical grids in the world. USA researchers have proposed a combination of RESs (i.e. onshore and offshore WFs, utility PV and fuel cells) and conventional generation (i.e. GTs) for the future of the PJM network using a copper plate network [12]. They have illustrated that demand in the PJM network can be met 90-99.9% of the time with the suggested mix of RESs, while RESs are predicted to be at price parity in 2030 with the existing PJM generation system. In a similar study by other USA researchers, the least-cost mix of RESs (i.e. WFs, CSPs, utility PV, hydro and geothermal) and conventional generation (i.e. GTs) has determined for California in 2050 [13].

The existing studies have demonstrated that relying on higher penetration of RESs is possible, and fossil fuel use can be limited in the future. However, all of the above studies have used conventional load models and so neglected the influence of newer demand-side technologies for modelling nett future demand. Due to the significant effect of loads on performance and stability of power systems, it can be expected that this will affect the results of FG feasibility studies significantly. The Australian Commonwealth Scientific and Industrial Research Organisation (CSIRO) FG Forum has debated that demand management will play a major role in the FG of Australia [7]. They have also proposed a simple aggregated demand model at state levels in the NEM. However, a generic modelling approach is still required which can be used for any granularity level in the grid (e.g. from a city, a state or even the whole network). Furthermore, all of the reviewed studies have focused on balancing by using a simplified grid models such as the copper plate model. These assumptions can influence the results of power system studies significantly.

In this study, we make a step towards aggregate demand modelling suitable for FG scenarios. The proposed load model considers aggregated demand-side PV and storage, and is inspired by the smart home concept [14]. The load model is formulated as an optimization problem aiming at minimizing the customer electricity costs. The electricity price is predicted by core vector regression (CVR) [15] using a combination of historical market data from the AEMO and simulated market prices for the future. Then, as a case study, the effect of the model on the load profile, balancing and loadability of the NEM in 2020 is studied using a 14-generator model [16]. The electricity market model is built in PLEXOS based on the suitably modified 14-generator model. Five scenarios are analysed with one business as usual (BAU), and four different levels of DR with renewable integration. (i) For the BAU Scenario in 2020, the electricity supply is dominated by coal, gas, hydro and biomass; and (ii) for the Renewable Scenarios, some of the conventional coal generators in Queensland and South Australia are replaced with CSPs with storage and WFs respectively, as suggested in [11], [5], [9] to meet Australia’s RES target. The Renewable Scenarios are analysed with both the conventional and the proposed load models. Simulation results show that demand management can improve balancing and decrease the required energy from the backup supply with the increased intermittent supply in the grid.

The remainder of the paper is organised as follows: Section II proposes the aggregated load model considering demand-side technologies. Section III describes the test-bed and the electric market assumptions and modelling. Section IV describes simulation scenarios, and discusses simulation results. Section V consists of the conclusion of the simulations.

II. AGGREGATED LOAD MODEL CONSIDERING DEMAND-SIDE TECHNOLOGIES

Aggregated load models are commonly used in system studies to reflect the combined effect of numerous physical loads [17], [18]. These can be inspired by a physical devices, e.g. using a large induction motor to represent all the motors connected, or by data-driven approaches. This paper proposes an aggregate load model for studies at higher voltage levels inspired by the smart home concept [13]. A smart home can be thought of as an automated residential building that uses its own DGs for robustly managing energy consumption to reduce electricity costs.
A smart home energy management system (SHEMS) implements an algorithm to schedule DGs and storage, and so achieve demand-side control [14]. The proposed model includes aggregated PV, storage and DR assuming users are price takers, i.e. the effect of their actions is not reflected in the electricity price. This assumption is usually considered when the number of users is large, and the amount of information provided to each user is limited [19].

A. Optimization model

The proposed load model aims at minimizing the electricity cost for end-users by reducing power consumption from the electrical grid. This aim can be achieved by controlling the battery state of charge (SOC) at the beginning of those hours. Each decision horizon for the model (i.e. 24-hour period) is divided into one hour time-steps, giving a total of $H=24$ time-steps; denote a particular time-step by $h$. The objective function of the model, which is solved using the linear programming approach, can be written as:

$$
\text{min} \quad \sum_{h=1}^{H} C_{el}(h)P_g(h),
$$

where, $H$ is the total number of those hours. Each decision horizon for the model (i.e. 24-hour period) is divided into one hour time-steps, giving a total of $H=24$ time-steps; denote a particular time-step by $h$. The objective function of the model, which is solved using the linear programming approach, can be written as:

$$
\text{min} \quad \sum_{h=1}^{H} C_{el}(h)P_g(h),
$$

(s.t.)

$$
P_{\text{grid}}^{\text{min}} \leq P_g(h) \leq P_{\text{grid}}^{\text{max}}, \quad \forall h \leq 24$$

$$
B_{\text{dis}}^{\text{rate}} \leq P_b(h) \leq B_{\text{cha}}^{\text{rate}}, \quad \forall h \leq 24$$

$$
B_{\text{SOC}}(1) = B_{\text{SOC}}^{\text{min}}, \quad \forall h \leq 24$$

$$
B_{\text{SOC}}(h) = B_{\text{SOC}}(h-1) + P_b(h-1) \forall h \geq 2, \quad \forall h \leq 24$$

$$
B_{\text{SOC}}^{\text{min}} \leq B_{\text{SOC}}(h) \leq B_{\text{SOC}}^{\text{max}}, \quad \forall h \leq 24$$

$$
P_g(h) = P_L(h) + \eta P_b(h) - P_{\text{pv}}(h), \quad \forall h \leq 24$$

where, $C_{el}$ and $P_g$ are the electricity price and the grid power, respectively. In the (1b), the grid power is constrained by the maximum, $P_{\text{grid}}^{\text{max}}$, and the minimum, $P_{\text{grid}}^{\text{min}}$, electrical grid power. If, $P_g(h) \geq 0$ the power is flowing from the grid to the demand. Otherwise, the power is flowing back to the grid. Constraints (1c) to (1f) represent battery storage power, $P_b$, and its SOC limit, where, $B_{\text{cha}}^{\text{rate}}, B_{\text{dis}}^{\text{rate}}, B_{\text{SOC}}^{\text{max}}$, and $B_{\text{SOC}}^{\text{min}}$ are charging and discharging rate, SOC, maximum and minimum SOC, respectively. If $P_b(h) \geq 0$, battery stores energy, and if $P_b(h) \leq 0$, it discharges the stored energy. The last constraint (1g) is the balance equation for the load model, where, $P_{\text{pv}}, P_L$ and $\eta$, are the aggregated PV and demand power, and the battery efficiency, respectively.

The model in (1a)-(1g) augments a conventional balancing load model by the aggregated effect of numerous price taker entities is a realistic assumption for a large number of users [19]. However, high penetration of those users might affect power system performance, as discussed in more detail in Section IV. To solve the above optimization problem, the electricity price, aggregated demand and PV power are required for each time-step. The next subsections describe how these variables are obtained for the model.

B. Electricity price prediction

In the model (1a)-(1g), the electricity price, $C_{el}$, plays a key role. Amongst different techniques, we chose intelligent methods that have been used successfully in the past for electricity price prediction [20]–[22]. In this study, we used CVR [15] for the electricity price prediction which requires a short training time and small memory requirement for a large training dataset. The modelling algorithm and inputs for the CVR were inspired by the models reported in [20], [21]. So, the interstate line limits, predicted demand, time factor, capacity, type and area of generators are chosen as the inputs and the electricity price is selected as the output for the CVR. The electricity price predictor has been trained using a combination of historical data from the AEMO and simulated market prices for the future (For the future, the electricity prices have been simulated in PLEXOS to cater for situations where part of the generation bids in to the market at zero cost). Using the trained CVR, the electricity price is predicted for 2020, and is given to users.
TABLE I. THE AGGREGATED STORAGE AND PV CAPACITIES FOR EACH REGION OF THE NEM FOR DIFFERENT UPTAKE SCENARIOS

| Region | Scenario | $P_{SOC}^{min}$-$P_{SOC}^{max}$ (GWh) | PV capacity (GW) |
|--------|----------|--------------------------------------|------------------|
| QLD    | Low      | 0.4-4.3                              | 1.3              |
|        | Medium   | 0.6-6.4                              | 1.9              |
|        | High     | 0.9-8.5                              | 2.6              |
| NSW    | Low      | 0.7-6.7                              | 2.0              |
|        | Medium   | 1.0-10.1                             | 3.0              |
|        | High     | 1.4-13.5                             | 4.1              |
| VIC    | Low      | 0.5-5.0                              | 1.5              |
|        | Medium   | 0.8-7.5                              | 2.3              |
|        | High     | 1.0-10.0                             | 3.0              |
| SA     | Low      | 0.1-1.2                              | 0.3              |
|        | Medium   | 0.2-1.7                              | 0.5              |
|        | High     | 0.2-2.3                              | 0.7              |
| NEM    | Low      | 1.7-17.0                             | 5.0              |
|        | Medium   | 2.5-25.0                             | 7.5              |
|        | High     | 3.4-34.0                             | 10.5             |

C. PV and battery storage

The aggregated demand ($P_L$) and PV ($P_{pv}$) power are uncertain variables in a particular time-step of the load model. The AEMO has proposed 16 zones for the NEM to capture differences in generation technology capabilities, costs, weather and so on in the future [5]. In this study, hourly demand and PV power are obtained from the AEMO predictions for 2020. The PV output power is reported for 16 zones, however, the reported demand data is aggregated across each region of the NEM (i.e. Queensland (QLD), New South Wales (NSW), Victoria (VIC) and South Australia (SA)). The predicted demand data is divided between the zones based on the available loads of the 14-generator model in each zone and their default values. The 14-generator model of the NEM and the match between 14-generator model and the AEMO zones are described in Section III.

According to the AEMO, the percentage of the residential and commercial customers with PV will be 23%, 28% and 36% for low, moderate and high uptake scenarios in 2020, respectively [6]. In this paper, price-responsive users are chosen from the residential and commercial customers, which are considered to account for 60% of the total system load in the NEM in 2020 [5]. The industrial customers are left unaffected. Also, the percentage of the residential and commercial customers with PV are considered 20%, 30% and 40% for low, medium and high uptake scenarios, respectively. Table I shows the aggregated storage and PV capacities for each region of the NEM for different uptake scenarios. The chosen PV capacities for each region of the NEM for different uptake scenarios are inspired by the AEMO study [6]. Also, the chosen battery storage capacities roughly correspond with a typical PV and storage capacity for a household in Australia (i.e. 3kW PV and 10kWh battery storage).

III. THE AUSTRALIAN NEM MODEL

The main contribution of this paper is to propose the load or demand model considering new technologies (DG, storage and DR). In Section IV, the effect of the model will be illustrated on the load profile and performance of the NEM in 2020. A 14-generator model of the NEM, which was originally proposed for small-signal stability studies [16] is used as the test-bed, where market effects and constraints are also taken into account.

A. Test-bed assumptions and modelling

The schematic diagram of the 14-generator model of the NEM is shown in Figure 1. Areas 1 to 5 represent Snowy Hydro (SH), NSW, VIC, QLD and SA, respectively. In order to extract data for the load model and generators in 2020, the 14-generator model of the NEM is matched with the 16 zones according to the AEMO’s planning document [5], as shown in Figure 1. The modified 14-generator model of the NEM is then modelled in PLEXOS and MATLAB (MATPOWER) for the market simulations, balancing and loadability studies, respectively.
B. Electricity market assumptions and modelling

The market simulations of this paper are done in PLEXOS, following the dispatch process used by the AEMO. The resolution of the market simulations is taken as one hour. Combinations of coal, GT, hydro and biomass are considered for the NEM to supply the load in 2020 in the BAU Scenario. The generator technologies in this study are assumed as: pulverized supercritical coal generators based on black and brown coal, combined cycle GT based on natural gas, solar parabolic trough CSP with solar multiple of 2 and 12 hours thermal storage, biomass based on landfill gas (LFG) and WFs. The coal power plant in NSW and QLD are assumed to be black coal-based, and in VIC and SA are assumed to be brown coal-based [1], [5]. For each hour of the year, the mixed integer linear solver dispatches the generation, in merit order, to meet demand for that hour. In market simulations, the fossil-fuel generators were assumed to bid at their respective short-run marginal costs (SRMC), calculated using the predicted fuel price, thermal efficiency and variable O&M [5], [23], while the SRMC of renewable generation is assumed to be zero. Table II lists the SRMC of the generators in 2020. The maximum and the minimum interstate line flow between NSW/QLD, NSW/VIC and VIC/SA are considered to be (600, -1000), (500, -1500) and (500, -500) MW, respectively. The interstate line flows roughly correspond with the NEM limits [5]. The market model also considers
TABLE II. THE SRMC OF THE GENERATORS IN 2020

| Generator | Type       | AEMO zone | SRMC ($/MWh) |
|-----------|------------|-----------|--------------|
| BPS_2     | Black coal | NNS       | 28.45        |
| EPS_2     | GT         | CAN       | 69.20        |
| MPS_2     | Black coal | SWNSW     | 27.43        |
| VPS_2     | Black coal | NCEN      | 26.40        |
| LPS_3     | Biomass    | MEL       | 39.50        |
| YPS_3     | Black coal | LV        | 21.88        |
| CPS_4     | Black coal | CQ        | 26.14        |
| GPS_4     | Black coal | CQ        | 26.14        |
| SPS_4     | Black coal | NQ        | 32.74        |
| TPS_4     | GT         | SWQ       | 73.84        |
| NPS_5     | Brown coal | NSA       | 30.89        |
| PPS_5     | Brown coal | SESA      | 30.89        |
| TPS_5     | GT         | ADE       | 69.20        |

Fig. 2: The relation between the electricity price, demand and the electricity market

the minimum stable level of generators reported in [5].

Figure 2 illustrates the relation between the electricity price, demand and the electricity market. The CVR-based model predicts the electricity price signal for each hour, and price-responsive users respond to the signal. The demand data is then communicated to the electricity market to be used for the dispatch process. If supply cannot meet the demand, the hour is recorded as the unserved hour. However, if available generation exceeds demand (i.e. due to high generation of intermittent RESs), the surplus power is recorded as dumped energy and that hour is marked as a dumped hour. Finally, the dispatch results are used as input for the MATPOWER for balancing and loadability studies.
IV. SIMULATION SCENARIOS AND RESULTS

The following subsections describe simulation scenarios, and demonstrate the effect of the proposed model on the load profile, balancing and loadability of the NEM in 2020 with increased penetration of WFs and CSPs.

A. Simulation scenarios

Five scenarios will be analysed with one BAU and four different levels of DR with renewable integration. For the BAU Scenario, a combination of coal, gas, hydro and biomass are considered to supply the load in 2020 (i.e. Scenario 1). Then, some of the conventional coal generators in QLD and SA are replaced with CSPs together with storage and WFs respectively to meet Australia’s RES target. Displacement of the conventional generators in the Renewable Scenarios and the chosen capacity for the RESs are inspired by the studies in [5], [9]. NPS_5 in SA is replaced with a WF with the capacity of 3 GW using NSA data. Also, SPS_4 and GPS_4 in QLD are replaced with two CSPs with the capacity of 4.5 GW each and using NQ and CQ data, respectively. The operating strategy for CSPs has been determined using PLEXOS. It was found that delaying CSP output by 12 hours minimizes the unserved and dumped energy. The RESs serve about 20% of the total demand energy in the Renewable Scenarios. The Renewable Scenarios are evaluated with the conventional and the proposed load to study the effect of demand-side technologies on the system performance with the increased penetration of RESs. In the rest of the paper, the Renewable Scenarios with conventional load, low, medium and high uptake of demand-side technologies are called Scenarios 2 to 5, respectively.

B. Load profile

The load in Section II is modelled using the predicted electricity price and the aggregated demand and PV power. Figure 3(b) shows the effect of different PV-plus-storage uptake scenarios on the load profile resulting from solving the proposed model in NSW during the 14th and 15th of May 2020. The electricity price signal (Figure 3(a)) is predicted by the CVR using demand data, RESs generation (Figure 3(c)), conventional generation availability in the grid, and line flow limits. As it can be seen in Figure 3(a), when generation from RESs decreases, electricity price mainly increases because conventional generators need to compensate for the lack of generation in the grid. Price-responsive users respond to the electricity price signal and shift their consumption from expensive time-slots to cheaper ones (i.e. using their PV-plus-storage system) to utilize zero cost electricity produced by RESs more, as it can be seen in Figure 3(b). This clearly shows that DR can help balance intermittent RESs power and demand in FGs. However, as users are price takers, they may shift their consumption to cheaper time-slots all together which can result in secondary peaks for the system under high penetration of demand-side sources and storage, as shown in Figure 3(b). Furthermore, management of price-responsive users using this electricity price signal might result in less smooth load profile in comparison with the conventional load profile because the effect of users’ action is not reflected in the electricity price signal. To address this, demand response aggregators will likely emerge in the future, which will require the loads to be treated as price anticipator entities, necessitating game-theoretic approaches for the electricity price signal designing [19], [24].

In the following subsection, both conventional load and the proposed load are used to study the effect of demand-side resources and storage on the balancing and loadability of the NEM with the increased penetration of RESs in 2020.

C. Balancing and loadability results

1) BAU Scenario: Figure 4 shows balancing results for the BAU Scenario in one of the critical summer peaks from the 19th to the 22nd of January 2020. A big portion of the demand is supplied by coal-fired power plants and the peak loads are met with GTs. The results for supplied electrical energy from GTs and average loadability are summarized in Table 3. It is noteworthy to mention that for loadability calculation, all loads in QLD are assumed to increase uniformly in small steps with constant power factor until power flow fails to converge. Also, it is assumed that all the generators in QLD are scheduled with the same participation factor to pick up the system loads. The loadability is computed for each hour until a step before power flow divergence.
Fig. 3. (a) Electricity price, (b) demand profile, (c) total RESs generation, and (d) aggregated PV generation for Scenarios 2 to 5 in NSW during the 14th and the 15th of May 2020.

Fig. 4. Balancing results for the BAU scenario from the 19th to the 22nd of January 2020.
TABLE III. BALANCING AND LOADABILITY RESULTS FOR SCENARIOS 1 TO 5

| Scenarios | Spilled energy (TWh) | Spilled hrs (%) | GT energy (TWh) | Loadability (GW) |
|-----------|----------------------|-----------------|-----------------|------------------|
| 1         | -                    | -               | 18.73           | 27.13            |
| 2         | 0.71                 | 13.65           | 18.77           | 22.17            |
| 3         | 0.66                 | 13.03           | 18.33           | 23.78            |
| 4         | 0.61                 | 12.67           | 17.85           | 25.53            |
| 5         | 0.54                 | 11.71           | 17.28           | 24.41            |

2) Renewable Scenarios: Four different PV-plus-storage and DR uptake scenarios were considered for 2020: zero, low, medium and high, denoted Scenarios 2, 3, 4, and 5, respectively in Table III. Unserved hours for all scenarios are zero. Comparing the BAU Scenario and the Renewable Scenario with the conventional load (Scenario 2), it can be seen that with the increased penetration of RESs, the loadability is reduced from 27.13 GW to 22.17 GW. Also, the required electrical energy from the backup generation (i.e. GTs) is increased from 18.73 to 18.77 TWh.

Compared to Scenario 2, a larger penetration of PV-plus-storage (Scenarios 3 to 5) improves the balancing and loadability, and reduces the required energy from backup supply. The high uptake scenario has the lowest spilled energy and hours followed by medium and low uptake scenarios. The medium uptake scenario (Scenario 4) has, however, the highest loadability. The loadability is increased from 22.17 GW for the Scenario 2 to 25.53 GW for the Scenario 4, which implies a considerable improvement in loadability. Surprisingly, increasing the penetration of PV-plus-storage system beyond a certain point (from medium to high), fails to improve loadability further. This is due to the price-taking assumption of users, so for the high uptake scenario (Scenario 5), secondary load peaks are created as all the users shift consumption to the cheaper time slots. This deteriorates loadability compared to lower uptake scenarios.

V. Conclusion

In this paper, an aggregate load model considering demand-side technologies is proposed for FG scenarios. The load model is intended to be used for system studies at transmission levels. The model is inspired by the smart home concept and formulated as an optimization problem aiming at minimizing the electricity cost. The users are assumed to be price takers. Also, the effect of the load model on the load profile, balancing and loadability of the NEM with the increased penetration of RESs is studied using a modified 14-generator model of the NEM.

Simulation results show that with the increased penetration of RESs and no price-responsive users the loadability is reduced. With price-responsive users, however, the loadability is improved and the required backup supply is reduced with increasing uptake of PV-plus-storage and DR. Interestingly, increasing the penetration of demand-side technologies beyond a certain point does not necessarily improve the performance further and might even deteriorate the system loadability. This depends on the price taking assumption of the loads, when secondary peaks are created.
due to load synchronization. The proposed model is the first step made towards demand modelling (including DG, storage and DR) for FG scenarios. A more realistic analysis of high penetration of demand-side sources and storage will require an implicit modelling of demand response aggregators using game-theoretic approaches, which will be the focus of future research. Also, the effect of the proposed modelling approach will be studied on power system stability.

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