Demand Response and Ancillary Service Management Using Fractional-Order Integral Indicator and Dynamic Game Model for an Aggregator Program in Smart Grids

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Abstract To avoid penalties on over-contract demand, electricity customers can adopt a demand response strategy to shift or reduce demands from main grid during peak periods or partial peak periods. The direct or indirect load control is a common strategy used to change operational conditions

with or without incentive / contractual strategies. The time-of-use and real-time pricing in addition to incentive services can encourage customers to change their preferences, further reducing demands during contractual periods. Therefore, ancillary services can manage and dispatch ancillary power, such as renewable energy, stored energy, and onsite generation, to reduce expensive power generation from main grid and to meet the customers' extra demands in smart grids. The fractional-order integral operation is used to calculate the area under the curve for evaluating power consumption at a scheduled timing interval of 15min / 1hour and identify demand levels. The dynamic game model is employed to dispatch the available distributed generations to meet the customers' extra demands. For an aggregator program, results will show that the proposed method can reduce the demand from the main grid and increase system flexibility to activate the active-duty distributed generations. Benefits for billing charges may arise.

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Introduction

Demand response is a management strategy employed to make changes in customer usages and coordinates with power utilities or electricity market conditions. Its strategy allows the consumptions to reduce by direct load controls (DLCs), indirect load controls (ILCs), or incentive controls [1, 2]. In a DLC strategy, utilities directly send command signals to switch off the lower priority loads.

An ILC strategy, including incentive and contractual controls, uses incentive payments to reduce customer demands. Hence, customers can obtain pricing information to control power consumption, such as time-of-use (TOU), real-time (RT), and peak time prices. These conventional methods are performed by power utilities and independent system operators, which can reduce peak period (PP) demands or shift demands to the off-peak period (OPP). In this operating scheme, lower priority loads need to switch off, and distributed generations (DGs), such as photovoltaic energy and wind power, are not fully utilized to meet the local demands. In an innovative electricity market model, an aggregator business model integrates a demand response aggregator and a generation aggregator into a single purchasing unit with DG pools [3], as seen in Fig. 1. This model offers demand responses and ancillary services provide available incentives to use the DG resources. This leads to reduce high energy costs, high-carbon power generation, and transmission loss. In addition, a generation aggregator meets the demands to satisfy the electricity customers [4, 5], and dispatches available power for customers or integrates the exported electricity. Hence, DG pools as a virtual power plant (VPP) can also reduce demands from the main grid, such as small scaled power plant (<150kW), rooftop photovoltaic system, and small-scaled wind farm. The VPP provides power supply to alleviate the extra power demands in PP hours, and provides back-up powers while uncertain outage event occurrences [6, 7]. A virtual net metering (VNM) network [8, 9] can monitor DG information to dispatch available powers for onsite customers or exports rest to other customers and power utility.

The ancillary power capacity should be at least 50% of the maximum demands. A VPP is employed to supply back-up power during peak load and to avoid the load shedding. Onsite generations, such as Eq. 1 renewable energy and stored energy, and Eq. 2 AC generators: microgenerators, small scaled co-generation systems, and diesel-generators [10–12], can be employed temporarily instead of using electricity from the main grid during peak demand, and

renewable energy can synchronously store into the storage devices by using power converters (DC-DC or AC-DC) [11, 13, 14]. Droop controllers regulate the voltage and frequency at the connection point of common coupling (PCC) [7] by using power inverters. To activate DG resources, onsite generations are employed to support net changes in smart grids [11, 15, 16]. Advanced metering / grid infrastructure (AMI/AGI) and VNM [8, 9, 17, 18] provide a smart grid platform to perform the consumption modifications and to dispatch the available DGs with smart meters, bidirectional communication, intelligent computations and controls to achieve the demand response and ancillary service tasks [19]. In this electricity market, an aggregator program acts as a mediator between end users and power utilities to (1) perform the demand response during PP or contractual hours, (2) activate the available DGs for PP demands, (3) promote energy and load managements, and (4) avoid exceeding the contract demands.

Based on day-ahead or hour-ahead scheduling [20, 21], the capacity of demand responses and the customer load profile can be predicted, while electricity prices, active power, and reactive power can also be determined. In this situation, AMI / AGI can monitor the load profiles, voltages, and currents, while the customers' consumptions can be monitored in the timing sector from 15min to 1hour. VNM can monitor the exported electricity generation within its local load area and resell it to nearby customers. However, extra electricity demands, such as air conditioners and refrigerators, might cause over the contractual demands in summer season. A better strategy can reduce the electricity bills for unpredicted demand variations. In addition, an aggregator should also provide sustainable ancillary power to reduce the risk for outage event occurrences. According to forecasting demand and DG information, the energy management offers available DGs and achieves adequate electricity compensations. Therefore, this study proposes a management strategy to reduce peak demand from the main grid and reduce retail energy costs. The fractional-order integral (FOI) based indicator is designed as an index

Fig. 1 An aggregator program includes demand response and ancillary service in an electricity market

to determine the ratio of customer demand and contractual demand. Discrete FOI computation [22–24] is used to calculate the area under the curve (AUC) at each 15-min or 1-h time interval. The AUC ratio (AUCR) is carried out to identify the changes in customer demand, including the ranges within $\pm 10\%$ of contractual demand and over 10% contractual demand. The AUCR index is employed to determine the constraints of the demand, referring to the threshold values, < 0.90 , $0.90 \sim 1.10$, and > 1.10 . Electricity customers can be incentive to reduce demand from the main grid through dynamic electricity prices, while the DG resources are available during the PP or partial peak period (PPP). Then, the proposed dynamic game model (DGM) [25, 26] is carried out to dispatch the onsite DG resources for meeting the customers' extra demands or incentive demand response. The flexibility strategy is given a contract duration to balance supply and demand in time, with the aim to (1) restrain PP demands, (2) reduce high-price demand from the main grid, (3) to avoid exceeding the contract demands, and (4) to activate the active-duty DGs. For the proposed integrating AUCR indicator with FOI and DGM, energy managements and ancillary services can be achieved for an aggregator program in smart grids.

The remainder of this paper is organized as follows: “Demand Response Strategy” describes the demand response strategy in microdistribution systems, “Methodology” addresses the methodology involved in this study, and “Simulation Results” and “Conclusion” present simulation results and conclusions to demonstrate the efficiency of the proposed model.

Demand Response Strategy

Based on advanced controls and dynamic managements, DGs can both reduce power losses and improve higher energy efficiency, as shown in Fig. 2. For electricity customers, a capacity based demand response can reduce payments in a peak period under contractual demand. For power utilities, DGs can reduce the requirement of expensive power plants and electricity facilities in meeting peak demands. In addition, depending on contractual demand, electricity customers can obtain credit on their billing charges. After determining the contractual demands, the demand response strategy may include [27–29]:

- reserve capacity ($> 50\%$ of the maximum demands): renewable energy and ac generators provide for electricity consumption during critical peak or peak demands.
- storage capacity: battery banks store renewable energy during OPP hours and provide electricity consumption during critical peak or peak demands,

To achieve demand response, active information management provides two-way communication to and from power utilities, such as pricing, billing charges, predicted demands for day-ahead / hour-ahead scheduling [20, 21], and reserve capacity can be sold back to the grid for time-of-day scheduling. VNM network provides DG information and allows customers in a residential, commercial, or industrial multitenant group to participate in a common renewable source, such as solar energy or wind energy

Fig. 2 The concept of peak-period dynamic demand from the distributed generations

system. An AMI consists of smart meters, a data integration unit, computers, and the use of telecommunication/power line carrier techniques, as seen in Fig. 2, which can provide predicted usage profiles, daily usage profiles, and real time usage data. Electricity customers then have smart meters to track power consumption with options to change the measuring frequency from 15 to 60 minutes, using the following functions:

- monitor the usage of load profiles, voltage, and current,
- detect the abnormality electricity consumption or service without a billing charge,
- detect outages and verify online restoration.

Ensuring reliability, quality, and continuity of service is an important issue in a smart-grid environment. The AMI can provide available information for electricity customers and system operators. In this innovative electricity market, demand response aggregators join a group of customers and pool DG resources, while forecast loads and DG capacity to meet the demand. By combining the FOI based AUCR indicator and the DGM, the aim of proposed model is to reduce desired demands from the main grid. Hence, high-priced power demand can be reduced. DG resources can fully utilize to meet the customer demands, and also resell power to the power utility or other customers.

Methodology

Customer Monthly Charges

In Taiwan, an electricity customer determines contractual demand for a specified capacity, $\geq 50\text{kW}$, and three-phase rated low level voltages, 220V/380V, sufficient to meet normal maximum demand. Customers use less than contractual demands they will be charged the contract requirements (\$/kW). If any reading of the demand meter in any month exceeds the contractual demand, the maximum reading becomes the new contractual demand. The customer monthly charge covers the cost of electricity equipment, maintenance expenses, and generation of fuel costs, including the seasonal rate (SR), non SR, TOU rate, and non TOU rate. For example, the SR is from 1 June to 30 September (in summer) per year, and the peak periods are from 10:00–12:00 a.m. and 13:00–17:00 p.m. daily, as seen in Fig. 3. Thus, the monthly charges for SR are divided into the base charge, C_b , and the penalty, C_p , and are defined as

$$C_b = S_{pp} \times M_{pp} + S_{ppp} \times M_{ppp} + S_{opp} \times M_{opp} \quad (1)$$

where S_{pp} , S_{ppp} , and S_{opp} are the contractual demands (kW) at peak period (PP), partial peak period (PPP), and off-

Fig. 3 Billing charges for contract demand in Taiwan. **a** Contract demand schedule, **b** TOU rate and non TOU rate schedule (capacity $\geq 50\text{kW}$, three-phase rated voltage levels, 220V/380V)

peak period (OPP) hours, respectively, as seen in Fig. 3a; and parameters, M_{pp} , M_{ppp} , and M_{opp} are the TOU rates (\$/kW) at the three time periods, as seen in Fig. 3b. In addition, the demand charge of the excess within 10 % of the contractual demand is charged at twice the rate of the con-

tractual demand, and the excess over 10 % of the contractual demand is charged at three times the rate. For TOU rates, the penalty in the three periods is defined as

(a) PP hours

$$\Delta S_{pp} = S_m - S_{pp}, \Delta S_{pp} > 0 \quad (2)$$

$$C_{p,pp} = \begin{cases} 0, \Delta S_{pp} \leq 0 \\ 2 \times M_{pp} \times \Delta S_{pp}, 0 < \Delta S_{pp} \leq 0.1 \times S_{pp} \\ M_{pp} \times (3 \times \Delta S_{pp} - 0.1 \times S_{pp}), \Delta S_{pp} > 0.1 \times S_{pp} \end{cases} \quad (3)$$

where S_m is the metering maximum demand (kW); ΔS_{pp} is the difference (kW) in PP, while $\Delta S_{pp} > 0$ is the over the contractual demand; M_{pp} is the TOU rates at PP hours, where $M_{pp} = 236.2$ (\$/kW) for summer season and $M_{pp} = 173.2$ (\$/kW) for non-summer

season. Figure 3b shows the power service's billing charges and rates (\$/kW) for contractual demands in Taiwan, including the non-TOU rate and the TOU rate.

(b) PPP hours:

$$\Delta S_{ppp} = S_m - (S_{pp} + S_{ppp}) \quad (4)$$

$$C_{p,ppp} = \begin{cases} 0, \Delta S_{ppp} < \Delta S_{pp} \\ 1.15 \times M_{ppp} \times (\Delta S_{ppp} - \Delta S_{pp}), (\Delta S_{ppp} - \Delta S_{pp}) \leq 0.1 \times S_{ppp} \\ M_{ppp} \times [3 \times (\Delta S_{ppp} - \Delta S_{pp}) - 0.1 \times S_{ppp}] \times 1.15, (\Delta S_{ppp} - \Delta S_{pp}) > 0.1 \times S_{ppp} \end{cases} \quad (5)$$

where ΔS_{ppp} is the difference (kW) in PPP; M_{ppp} is the TOU rates at PPP hours, where $M_{ppp} = 47.2$ (\$/kW) for summer

season and $M_{ppp} = 34.6$ (\$/kW) for non-summer season.

(c) OPP hours:

$$\Delta S_{opp} = S_m - (S_{pp} + S_{ppp} + S_{opp}) \quad (6)$$

$$C_{p,opp} = \begin{cases} 0, \Delta S_{opp} < (\Delta S_{pp} + \Delta S_{ppp}) \\ 2 \times M_{opp} \times [\Delta S_{opp} - (\Delta S_{pp} + \Delta S_{ppp})] \times 1.15, \Delta S_{opp} - (\Delta S_{pp} + \Delta S_{ppp}) \leq 0.1 \times S_{opp} \\ M_{opp} \times \{3 \times [\Delta S_{opp} - (\Delta S_{pp} + \Delta S_{ppp})] - 0.1 \times S_{opp}\} \times 1.15, \Delta S_{opp} - (\Delta S_{pp} + \Delta S_{ppp}) > 0.1 \times S_{opp} \end{cases} \quad (7)$$

where ΔS_{opp} is the difference (kW) in OPP; M_{opp} is the TOU rates at OPP hours, where $M_{opp} = 47.2$ (\$/kW) for summer season and $M_{opp} = 34.6$ (\$/kW) for non-summer season.

In addition, the power factor (PF) is used to indicate the efficiency level of electrical usage. An electric rate also includes surcharges, while the customer has PF less than the threshold value, 80 %. Surcharge and reward, C_S , are defined as

$$PF = \frac{kWH}{\sqrt{kWH^2 + kVARH^2}} \times 100 \% \geq 80 \% \quad (8)$$

$$C_S = \begin{cases} C_{S,S}, PF < 80 \% \\ C_{S,R}, PF \geq 80 \% \end{cases} = \begin{cases} C_b \times 0.003 \times (0.8 - PF), PF < 80 \% \\ C_b \times 0.015 \times (0.8 - PF), PF \geq 80 \% \end{cases} \quad (9)$$

where C_b is the base charge for TOU rate; $PF = 80 \%$ is the threshold value, while $PF < 80 \%$, surcharge, $S_{S,S}$, can be computed, otherwise, electricity customers will obtain the reward, $S_{S,R}$. The monthly charge amount for contract demand is

$$C = C_b + C_S \quad (10)$$

Discrete Fractional Order Integral (FOI)

Fractional-order differentiation and integration were conducted using fractional calculus with non-integer orders; when operations are conducted with integer order, "value change per time" or "AUC" can be obtained [24, 30]. Fractional-order calculus was employed to describe

dynamic behaviors in both time and frequency domains. For signal processing, the FOI employs all non-integer numbers to deal with signals, and the summation is computed using ratios of the Gamma function, $\Gamma(\alpha)$, incorporating the number of sampling data points in the range $[t_0, t_1]$, and the fractional-order parameters, α . Parameters, α and t , are the limits of operation. The original continuous FOI, the α th FOI of function $P(t)$, $0 < \alpha < 1$, $\alpha \in R$, is given by [22]

$$D^{-\alpha} P(t) \approx \frac{1}{\Gamma(\alpha)} \int_{t_0}^{t_1} (t - \tau)^{\alpha-1} P(\tau) d\tau \quad (11)$$

where numerical integration is computed using the Riemann sum over the variable t at time step τ . The two definitions, such as Riemann-Liouville (R-L) or Grünwald-Letnikov (G-L) fractional approximations, [22–24] are carried out as the basis for discrete formulations and computations, and were derived from the iterated derivative formula. Therefore, Eq. 11 can be represented as the discrete fractional-order operator using the G-L definition as [22–24]

$$D^{-\alpha} P(t) \approx \lim_{\Delta\tau \rightarrow 0} (\Delta\tau)^\alpha \sum_{i=0}^{n-1} |(-1)^i \binom{-\alpha}{i}| P(t - i \cdot \Delta\tau) \quad (12)$$

where $0 < \alpha < 1$ for the FOI process, $\alpha \in R$; $-1 < \alpha < 0$ for the fractional derivative process; integer, $\alpha = +1$, for integer-order differentiation; α as integer is the integer-order differentiation or integration process; $i = 1, 2, 3, \dots, n$, n is the number of sampling points; and the binomial coefficients are given as

$$\binom{\alpha}{0} = 1, \quad \binom{-\alpha}{i} = \begin{cases} 1, & i = 0, -1 < \alpha < 0 \\ \frac{\Gamma(-\alpha-1)}{\Gamma(i+1)\Gamma(-\alpha-i+1)}, & i > 0 \end{cases}, \quad (13)$$

timing step for FOI process:

$$\Delta\tau = \frac{t_1 - t_0}{n} \quad (14)$$

Time parameters, t_0 and t_1 , are the limits of FOI at the time interval $[t_0, t_1]$. AUC is defined using integral computations as a positive area between the continuous function and the transverse-axis. In this study, we can compute the AUC of contractual demand, $P_{cd}[i]$, and the tracking energy consumption, $P_{tec}[i]$, as shown in Fig. 4. The fractional-order AUCs during the tracking time are

$$AUC_{cd} \approx \lim_{\Delta\tau \rightarrow 0} (\Delta\tau)^\alpha \sum_{i=0}^{n-1} |(-1)^i \binom{-\alpha}{i}| P_{cd}[i] \quad (15)$$

$$AUC_{mec} \approx \lim_{\Delta\tau \rightarrow 0} (\Delta\tau)^\alpha \sum_{i=0}^{n-1} |(-1)^i \binom{-\alpha}{i}| P_{tec}[i] \quad (16)$$

Fig. 4 Customer demand (kW) versus tracking time (min)

each tracking time:

$$\Delta\tau = \left(\frac{15 \text{ min}}{n}\right) \text{ or } \Delta\tau = \left(\frac{60 \text{ min}}{n}\right) \quad (17)$$

where the tracking energy consumption be obtained via metering measurement, referring to $P_{mec}[i]$; the contractual demand is referred to as $P_{cd}[i]$, $i \in [0, n-1]$. Therefore, the AUC ratio (AUCR) is defined as [28]

$$AUCR = \frac{AUC_{mec}}{AUC_{cd}} = \begin{cases} < 0.90 \\ 0.90 \sim 1.10 \\ \geq 1.10 \end{cases} \quad (18)$$

where the AUCR should be less than 1.00 when the customer's demand is less than the contractual demand, as seen the white region in Fig. 5. In this study, we have three conditions for performing the demand response strategy, as follows:

- $AUCR < 0.90$ (white region in Fig. 5) refers to $< 90\%$ of contractual demand: customer demand is less than the contractual demand, that is power consumption from the main grid and renewable energy,

Fig. 5 Customer demand and ancillary capacities

- $0.90 \leq AUCR < 1.10$ (yellow region in Fig. 5) refers to 90 % ~ 110 % of contractual demand: customer demand approaches to the contractual demand (-10%) or excesses within $+10\%$ of the contract demand, while provides the extra demand using the renewable energy and storage units,
- $AUCR \geq 1.10$ (light blue region in Fig. 5) refers to $>110\%$ of contractual demand: customer demand excesses over 10 % of the contractual demand, while provides the extra demand using the ac generators, such as micro-generator and diesel-generator.

Ancillary Power Sources' Dispatch

Solar and wind generation systems produce renewable energy that can be synchronously stored into the storage devices on a microgrid. The charging percentage of a storage battery can be measured, a microcontroller can determine its supply loads, and its capacity can be 100 % charged. In addition, AC generators are ancillary power sources integrated into a large power hybrid system to supply AC loads. These available ancillary power sources are installed near electricity customers and work to reduce power losses on transmission lines. Safety and reliable operations are important criteria, and the frequency and voltage must accommodate the loads required. All generators must respond in a coordinated manner to variable loads, and the frequency and voltage must be controlled to ensure the power balance in real time. A droop characteristic control performs the coordination of the generator with the frequency (f) versus real power (P) droop characteristic and the voltage (V) versus reactive power (Q) droop characteristic, to adjust demands for real and reactive power [7, 13, 14]. Depending on the loading conditions, they are selected to control the frequency within ranges of ± 0.5 Hz at a setting of 60 Hz, with variations, 59.7–60.2 Hz. At the connection PCC, the system frequency of the DBs can be determined so that real power is shared appropriately. The ancillary capacity can be 50 % of the micro-distribution system's capacity, with a permissible 3 %–5 % voltage imbalance [11].

For each electricity customer, we have three operation conditions in the utility-connected mode and the ancillary power sources' dispatch as follows:

- $AUCR < 0.90$: customer demand is from both main grid and renewable energy; and adequate capacity is stored into the storage devices for local load balancing,
- $0.90 \leq AUCR < 1.10$: customer demand and extra demand are from main grid and renewable energy, and interconnects with storage units during the PP, PPP, or OPP hours and DG's outage,
- $AUCR \geq 1.10$: customer demand is also from main grid and renewable energy, and exceeding over $+10\%$ of

the contract demand is supplied by ac generators and other DGs at the local levels.

Different DGs offer various activation times or active-duty times, while DGs are available to serve in short-term operations. They are service for outage events occur or demand over expected values. Renewable energy usually relies on local weather conditions, with a typical forecast error of 5 %–15 % of installed capacity. The AC generators, such as a microgenerator and a diesel generator, have a stable ancillary capacity to supply PP demands with the specific contract. Figure 6 shows overall ancillary power source dispatch during PP, PPP, or OPP hours. The desired DG capacity, S_{DG} , is estimated by

$$S_{DG,h} \approx \begin{cases} 0.1 \times S_{\max} + S_{Loss}, & AUCR_h < 0.9 \\ 0.2 \times S_{\max} + S_{Loss}, & 0.9 \leq AUCR_h \leq 1.1 \\ 0.3 \times S_{\max} + S_{Loss}, & AUCR_h > 1.1 \end{cases} \quad (19)$$

$S_{Loss} \leq 0.01 \times S_{\max} = 0.01 \times (S_{pp} + S_{ppp} + S_{opp})$ (20) where index, $h = 1, 2, \dots, 96$, is the timing slot (15min slot in this study); PP durations are from 10:00 a.m. to 12:00 a.m. and 13:00 p.m. to 17:00 p.m. daily, PPP duration from 07:30 a.m. to 10:00 a.m., 12:00 p.m. to 13:00 p.m., and 17:00 p.m. to 22:30 p.m. daily, and OPP are the rest of durations. The dispatches of these ancillary power sources can be determined by the customer demands and capacities of the selected DG. Their quantities are parameterized with certainty factors (CFs) as shown in Figs. 7a and b, where the probability value is between "0" and "1" for presenting possible operation states, as follows

- for customer demand:

$$CF_{1,h} = \begin{cases} 1, & AUCR_h \leq 0.90 \\ \exp(-0.5 \times (\frac{AUCR_h - 0.90}{0.10})^2), & AUCR_h > 0.90 \end{cases} \quad (21)$$

$$CF_{2,h} = \begin{cases} 1, & AUCR_h \geq 1.00 \\ \exp(-0.5 \times (\frac{AUCR_h - 1.00}{0.10})^2), & AUCR_h < 1.00 \end{cases} \quad (22)$$

- for desired DG's capacity:

$$CF_{3,h} = \begin{cases} 1, & S_{DG,h} < 0.1 \times S_{\max} \\ \frac{S_{DG,h}}{0.1 \times S_{\max}}, & S_{DG,h} \geq 0.1 \times S_{\max} \end{cases}, \quad S_{\max} = 50kW \quad (23)$$

$$CF_{4,h} = \begin{cases} 0, & S_{DG,h} < 0.1 \times S_{\max} \\ \frac{S_{DG,h}}{0.1 \times S_{\max}} - 1, & 0.1 \times S_{\max} \leq S_{DG,h} < 0.2 \times S_{\max} \\ 1, & S_{DG,h} \geq 0.2 \times S_{\max} \end{cases} \quad (24)$$

We have four dispatch strategies in a DGM [25, 26, 29]; these are described in a strategic form in Table 1, with rows representing the operational states of the capacity of selected DGs and columns representing customer demand. Four operational states have strategy combinations, $(CF_{1,h}, CF_{3,h})$, $(CF_{2,h}, CF_{3,h})$, $(CF_{1,h},$

Fig. 6 Ancillary power sources' dispatch

$CF_{4,h}$), and $(CF_{2,h}, CF_{4,h})$. Their states are independent if, and only if, their joint probabilities follow a multiplication rule. The outcomes of joint probabilities are given by

$$S = \begin{bmatrix} CF_{1,h} \times CF_{3,h} & CF_{2,h} \times CF_{3,h} \\ CF_{1,h} \times CF_{4,h} & CF_{2,h} \times CF_{4,h} \end{bmatrix} = \begin{bmatrix} s_{1,h} & s_{2,h} \\ s_{3,h} & s_{4,h} \end{bmatrix} \quad (25)$$

Hence, the dispatch of a selected DB can be determine as

$$S^+ = \max[(s_{1,h} + s_{3,h}), (s_{2,h} + s_{4,h})] \quad (26)$$

- desired capacity of renewable energy, S_{renew} :

$$(s_{1,h} + s_{3,h}) \geq (s_{2,h} + s_{4,h}) : S_{renew} = S_{DG,h} \times \left(\frac{s_{1,h}}{s_{1,h} + s_{3,h}} \right) \\ \text{or} \\ (s_{1,h} + s_{3,h}) \leq (s_{2,h} + s_{4,h}) : S_{renew} = S_{DG,h} \times \left(\frac{s_{2,h}}{s_{2,h} + s_{4,h}} \right) \quad (27)$$

- desired capacity of ac generator, S_{ac} :

$$(s_{1,h} + s_{3,h}) \geq (s_{2,h} + s_{4,h}) : S_{ac} = S_{DG,h} \times \left(\frac{s_{3,h}}{s_{1,h} + s_{3,h}} \right) \\ \text{or} \\ (s_{1,h} + s_{3,h}) \leq (s_{2,h} + s_{4,h}) : S_{ac} = S_{DG,h} \times \left(\frac{s_{4,h}}{s_{2,h} + s_{4,h}} \right) \quad (28)$$

Fig. 7 Certainty factors for presenting the possible operation states. **a** Certainty factors versus AUCR index, **b** Certainty factors versus desired DG's capacities

$$\frac{1}{2} \times S_{ac,max} \leq S_{ac} \leq S_{ac,max}, \quad S_{storage} \leq 0.5 \times S_{renew} \quad (29)$$

where $S_{ac,max}$ is the maximum capacity of AC generators; and S_{renew} and $S_{storage}$ represent solar energy and storage energy, respectively, during 08:00 and 17:00, otherwise for wind energy. At any time, an AC generator should be within its lower and upper rated capacities as Eq. 29. The start-up time depends on the size of the genset, but they can deliver electrical power loads from within 10 seconds to a few minutes after accelerating to the rated speed, warming-up, and synchronizing with the system. Thus, the desired capacity of renewable energy and AC generators can be determined using the Eqs. 27 and 28, respectively.

Simulation Results

A group of residential customers with a contract demand of 50 kW, and a voltage level of 220V/380V, is conducted

Table 1 Strategic form of dynamic game model

DGs	$AUCR$	$AUCR < 0.90$, $CF_{1,h}$	$AUCR \geq 0.90$, $CF_{2,h}$
Renewable Energy, $CF_{3,h}$		$s_{1,h} = CF_{1,h} CF_{3,h}$	$s_{2,h} = CF_{2,h} \times CF_{3,h}$
AC Generator, $CF_{4,h}$		$s_{3,h} = CF_{1,h} CF_{4,h}$	$s_{4,h} = CF_{2,h} CF_{4,h}$
Mixed Operation		$s_{1,h} + s_{3,h}$	$s_{2,h} + s_{4,h}$

to validate the proposed methods using practical load patterns (red line), as shown in Fig. 8a. Contract demands, S_{pp} , S_{ppp} , and S_{opp} , at PP, PPP, and OPP time durations are 10 kW, 15 kW, and 25 kW, respectively. The three different time durations and TOU rates used in the summer are shown in Fig. 3. We consider ancillary power capacity to be at least 50 % of the maximum contract demand. The DGs additionally have renewable energy and ac generators with 10–15kW and 10kW ancillary capacities and rated 5kW of energy storage, respectively. We assume that the renewable energy is obtained from a small-scale wind farm (5 wind-turbine generators) and 15 photovoltaic (PV) panels, where each one has about rated power of 1 kW, the DGs will be capable of reducing the peak demand by about 15 kW. However, the efficiency of PV and wind energy conversions are influenced by environmental conditions such as solar radiation, temperature, wind speed, and weather conditions. A maximum power point tracking algorithm [17] is used to increase the conversion efficiency and account for environmental changes. Hence, an average rated capacity of 66 % is estimated to be obtained from solar radiation and temperature that varies from 0.2 kW/m² to 1.0 kW/m² and from 25° C to 45° C in summer season, respectively. Wind speed ranges vary from 5 m/sec to 10 m/sec during the night or in the winter season.

The AC generators, including a micro-generator and a diesel-generator, have a stable ancillary capacity of 10 kW and can supply 10 % of peak demand under specific contract levels. In addition, they have the capability to start-up and reach full load in about 15 minutes. Regular demands from the main grid allow 90 % of day-ahead scheduled demands, while the remaining desired demands are obtained from the DGs, which reduce usages of permanent electricity provision by 10 %. Depending on contract demands, customers are promised credit on their billing charges, and the **demand response** needs to facilitate ancillary power for peak loads to avoid penalties from over-the-contract demand. The following procedures are used: (1) to identify the AUCR change at each time slot using fractional-order integrators; (2) determine the strategic operation combinations using the DGM; (3) to dispatch ancillary power.

Based on day-ahead scheduling, one day can be divided into 96 time slots; the forecasted demands in each time

slot (15-min interval) are shown in Fig. 8a. Case study is made for a working day in a group of residential customers in a building, tariff ranges and demands have been addressed. To identify AUCR changes, fractional-order integrators, with $\alpha = 0.10 - 0.20$, and sampling points $n = 15$ (1-min tracking time), are employed to calculate AUCs using Eqs. 12 and 13. The overall AUCR can be seen to change, as shown in Fig. 8b, while their values exceed 1.0 as the excess + 10 % of the contract demand or over 10 % contract demand. Four time-slots are highlighted, 06:30–07:00, 08:15–09:45, 12:15–12:45, and 17:15–20:00. For example, during the time-slot of 09:30–09:45 (PPP), an AUCR = 1.25 determined that the microdistribution system was operating as over the contract demand, and the **demand response** is detailed according to the following procedure:

- Step 1) give the AUCR = 1.25 to estimate the desired DG's capacity using the Eqs. 19 and 20, and $S_{DG} = 15.5\text{kW}$,
- Step 2) compute the operation states using the Eqs. 21 to 24, $[CF_1, CF_2, CF_3, CF_4] = [0.6065, 1.0000, 1.0000, 1.0000]$,
- Step 3) compute the outcome of strategic combinations, $S = [s_1, s_2, s_3, s_4] = [0.0022, 1.0000, 0.0022, 1.0000]$, and the desired DG's dispatch can be determined using Eq. 26, $S^+ = \max[0.0044, 2.0000] = 2.0000$,
- Step 4) dispatch the DG's capacities, $S_{renew} = 7.75\text{kW}$ and $S_{ac} = 7.75\text{kW}$, using the Eqs. 27 to 29, as seen in Fig. 8c.

The simulation results from 09:00 a.m. – 10:15a.m. were also shown in Table 2. During OPP hours, 05:45–06:30, AUCRs have a value of less than 1.00, while the electricity demand approach that of the OPP's contract demand, as seen in Fig. 8b. For example, from 05:45a.m. – 06:00a.m., the demand response also provides an operational strategy, as $S = [s_1, s_2, s_3, s_4] = [0.8352, 0.9231, 0.8352, 0.9231]$ and $S^+ = \max[1.6704, 1.8462] = 1.8462$. The capacity of selected DGs can be determined as $S_{renew} = 5.25\text{kW}$ and $S_{ac} = 5.25\text{kW}$ ($S_{ac} > \text{lower capacity}$), and their dispatches of 96 time slots are shown in Fig. 8c.

In Fig. 8a, the blue line represents electricity demand from the main grid. The total customer consumptions are

Fig. 8 Demand response results from each tracking time. **a** Day-ahead scheduled demand and demands from the main grid and DGs, **b** AUCR indexes, **c** Ancillary power sources' dispatch

Table 2 The simulation results of demand responses and ancillary services from 05:45a.m. to 06:30a.m. and 09:00 a.m. to 10:15 p.m.

Time	Demand	$CF_{1,h}$	$CF_{2,h}$	$CF_{3,h}$	$CF_{4,h}$	Dynamic Game Model (DGM)				Renewable	AC
						$s_{1,h}$	$s_{3,h}$	$s_{2,h}$	$s_{4,h}$		
a.m.	(kW)									Energy (kW)	Generator (kW)
05:45	23.0	0.9802	0.7261	1.0000	1.0000	0.9802	0.9802	0.7261	0.7261	5.25	5.25
06:00	24.0	0.8352	0.9231	1.0000	1.0000	0.8352	0.8352	0.9231	0.9231	5.25	5.25
06:15	24.5	0.7261	0.9802	1.0000	1.0000	0.7261	0.7261	0.9801	0.9801	5.25	5.25
06:30	25.0	0.6065	1.0000	1.0000	1.0000	0.6065	0.6065	1.0000	1.0000	5.25	5.25
09:00	50.0	0.0022	1.0000	1.0000	1.0000	0.0022	0.0022	1.0000	1.0000	7.75	7.75
09:15	50.0	0.0022	1.0000	1.0000	1.0000	0.0022	0.0022	1.0000	1.0000	7.75	7.75
09:30	50.0	0.0022	1.0000	1.0000	1.0000	0.0022	0.0022	1.0000	1.0000	7.75	7.75
09:45	50.0	0.0022	1.0000	1.0000	1.0000	0.0022	0.0022	1.0000	1.0000	7.75	7.75
10:00	50.0	0.6065	1.0000	1.0000	1.0000	0.6065	0.6065	1.0000	1.0000	5.25	5.25

Table 3 Benefit comparisons

Strategy	Contract Demand (kW)			Excess <10 %, (kW)	Excess >10 %, (kW)	Billing Charge, \$		
	Time	S	ΔS			Base Charge	Penalty	Sum
Day Ahead Schedule	PP	10	0	0.0	0.0	2,362.0	0.0	2,362.0
	PPP	15	10	4.0	6.0	708.0	1227.2	1,935.2
	OPP	25	5	2.5	2.5	1,180.0	590.0	1,770.0
	Sum	50	15	6.5	8.5	4,250.0	1,817.2	6,067.2
Demand Response	PP	10	0	0.0	0.0	2,362.0	0.0	2,362.0
	PPP	15	0	0.0	0.0	708.0	0.0	708.0
	OPP	25	0	0.0	0.0	1,180.0	0.0	1,180.0
	Sum	50	0	0.0	0.0	4,250.0	0.0	4,250.0

Billing charge for day-ahead: 6067.2\$, Penalty: 1817.2\$

Billing charge for demand response: 4250.0\$, Penalty: 0.0\$

Genset fuel and maintenance cost: 113.18\$,

PF > 90 %, reward: $C_S \leq 4250.0\$ \times 0.015 \times (0.8-0.9 \sim 0.95) = -6.375\$ \sim -9.563\$$,

Charge reduction: $6067.2\$ - (4250.0\$ + 113.18\$) + (-6.375\$) = 1697.65\$$

seen to decrease from 807.10 kWh to 613.73 kWh per day, and the consumption charges are thus lowered for fuel generation costs. The flexibility ranges for integrating 10%–25 % of DGs were achieved. The renewable and storage energy has a priority curtailment strategy to avoid expensive energy sources. Genset fuel and maintenance costs are about 10.14 \$/kWh–15.46 \$/kWh at 50 % to 75 % of the maximum capacity. The total cost of AC ancillary power is 113.18 \$ per day, and thus when compared with the day-ahead scheduled demand, the demand response can reduce billing charges 1697.65\$ per day in relation to the cost of electricity equipment, as seen in the benefit comparison of Table 3. In addition, the OPF was used to verify the demand response strategy in each time-slot. The PF can rise to $\geq 90\%$ –95 %, with a reward of $C_S \leq -6.375\$ \sim -9.563\$$ per day. It is therefore concluded that use of the demand response will be of considerable benefit to the electricity customer.

Conclusion

This study presents the fractional-order integrator and DGM for a peak-period dynamic demand response strategy in smart grids. Based on the forecasted scheduled loads, the fractional-order integral based indicator was employed to identify customer demand quantity, and the demand response strategy was then performed in relation to dispatching ancillary power, when demands exceeded contract quantity. The DGM represented outcomes in a strategic form and determined the capacity of selected DGs. Use of the demand response can reduce 23.96 % of an electricity

customer's power consumption, and can also avoid a penalty charge of 1817.2\$. Although the billing charges slightly increased for genset fuel and maintenance costs, the total charge reduction can be reduced by 27.98 % per day. The proposed methods can handle dynamic demand response programs to facilitate demand and dispatch DGs. In a smart grid, AMI can provide predicted usage profiles, daily usage profiles, and real time usage data. demand response aggregators and electricity customers can track power consumptions and DG information via AMI and VNM. The timing slot for demand response program can range 1 hour in an electricity market to 1 day for day-ahead forecast. In the electricity market, announcement addressed demand response schedules and DG information, thus an aggregator program carried out match the requirements according to schedule by available DGs. Therefore, DG resources were requested to be available for customers' demand during each timing slot. For these support methods, a smart grid integrating energy management, load management, and ancillary services can operate to supply electricity customers, in order to reduce dependence on the main grid. The algorithms and demand response programs are also easily to implement in an embedded system and to further integrate into the AMI/AGI. However, key policies required are to: (1) perform dynamic demand response programs using the active-duty DGs during PP hours or contract hours; (2) promote an innovating business model for energy management, load management and ancillary services as demand response aggregators and generation aggregators; (3) encourage green financial loans for constructing onsite generation and energy pools, such as rooftop photovoltaic system, small scaled co-generation plants, and

storage devices; and (3) increase flexibility for integrating DGs and storage devices in Taiwan. Hence, the proposed model for an aggregator program is a promising solution to provide an increase of 10 %–25 % flexibility and reliability of customer dynamic demands during PP hours in the summer season.

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References

- Wang Z, Paranjape R, Sadanand A, Chen Z (2013) Residential demand response: an overview of recent simulation and modeling applications, 26th Annual IEEE Canadian Conference on Electrical and Computer Engineering, May 5–8
- Lu N (2012) An evaluation of the HVAC load potential for providing load balancing services. *IEEE Trans on Smart Grid* 3(3):1263–1270
- Pacific Gas and Electric Company (2013) Aggregator programs, Demand Response Fact sheet
- Rodriguez-Molina J, Martinez-Nunez M, Martinez J-F, Perez-Aguar W (2014) Business models in the smart grid: challenges, opportunities and proposals for prosumer profitability. *Energies* 7:6142–6171
- Gulich O (2010) Technological and business challenges of smart grids-aggregator's role in current electricity market, Master's thesis, Lappeenranta University of Technology Faculty of Technology and Electrical Engineering
- Anderson RN, Boulanger A, Powell WB, Scott W (2011) Adaptive stochastic control for the smart grid. *Proceeding of the IEEE* 99(6):1098–1115
- Bai H, Miao S, Ran X, Ye C (2015) Optimal dispatch strategy of a virtual power plant containing battery switch stations in a unified electricity market. *Energies* 8:2268–2289
- (2015). Virtual net metering policy background and tariff summary report, Center for sustainable energy, california solar energy industries, and association, interstate renewable energy council
- Langham E, Cooper C, Ison N (2013) Virtual net metering in Australia: opportunities & barriers Report prepared for Total Environment Centre
- Guo Y, Pan M, Fang Y (2012) Optimal power management of residential customers in the smart grid. *IEEE Trans on Parallel and Distributed Systems* 23(9):1593–1606
- Reddy KS, Madhusudan Kumar TK, Mallick H, Sharon S (2014) Lokeswaran, a review of integration, control, communication and metering of renewable energy based smart grid. *Renew Sust Energ Rev* 38:180–192
- Che L, Shahidehpour M (2014) DC Microgrid: economic operation and enhancement of resilience by hierarchical control. *IEEE Trans Smart Grid* 5(5):2517–2526
- Nguyen K-L, Won D-J, Ahn S-J, Chung II-Y (2012) Power sharing method for a grid connected microgrid with multiple distributed generators. *J Electr Eng Technol* 17(4):459–467
- Abegaz BW, Mahajan SM (2015) Optimal real-time integration control of a virtual power plant, 2014 North American Power Symposium, pp 1–6
- Brusco G, Burgio A, Menniti D, Pinnarelli A, Sorrentino N (2014) Energy management for an energy district with demand response availability. *IEEE Trans Smart Grid* 5(5):2385–2393
- Lin C-H, Huang C-H, Yi-Chun D, Chen J-L (2011) Maximum photovoltaic power tracking for the PV array using the fractional-order incremental conductance method. *Appl Energy* 88(12):4840–4847
- Li F, Qiao W, Sun H, Wan H, Zhang P (2010) Smart transmission grid: vision and framework. *IEEE Trans Smart Grid* 1(2):168–177
- Sakis Meliopoulos AP, Cokkinides G, Huang R, Farantatos E, Choi S, Lee Y, Yu X (2011) Smart grid technologies for autonomous operation and control. *IEEE Trans Smart Grid* 2(1):1–10
- Aalami HA, Parsa Moghaddam M, Yousefi GR (2010) Demand response modeling considering interruptible / curtailable loads and capacity market programs. *Appl Energy* 87:243–250
- Yang P, Chavali P, Gilboa E, Nehorai A (2013) Parallel load schedule optimization with renewable distributed generators in smart grids. *IEEE Trans Smart Grid* 4(3):1431–1441
- Golshannavaz S, Afsharnia S, Aminifar F (2014) Smart distribution grid: optimal day-ahead scheduling with reconfigurable topology. *IEEE Trans Smart Grid* 5(5):2402–2411
- Krishna BT (2011) Studies on fractional order differentiators and integrators: a survey. *Signal Process* 91(3):386–426
- Petras I (2011) Fractional-order nonlinear systems: modeling, analysis and simulation, *Nonlinear Physical Science*, Springer, ISSN 1867–8440
- Jian-Xing W, Li C-M, Ho Y-R, Ming-Jui W, Huang P-T, Lin C-H (2016) Bilateral photoplethysmography analysis for peripheral arterial stenosis screening with a fractional-order integrator and info-gap decision-making. *IEEE Sensor J* 16(8):2691–2700
- Doebeli M, Hauert C (2005) Models of cooperation based on the Prisoner's Dilemma and Snowdrift game. *Ecol Lett* 8:748–766
- Nowak MA (2006) Five rules for the evolution of cooperation. *Science* 314(8):1560–1563
- Siemens (2010) Smart energy consumption and the smart grid. <https://www.usa.siemens.com/buildingtechnologies>
- Aalami HA, Parsa Moghaddam M, Yousefi GR (2010) Demand response modeling considering interruptible/curtailable loads and capacity market programs. *Appl Energy* 87(1):243250
- Sofana Reka S, Ramesh V (2016) A demand response modeling for residential consumers in smart grid environment using game theory based energy scheduling algorithm *Ain Shams Engineering Journal* Article in Press. doi:10.1016/j.asej.2015.12.004
- Krishna BT (2011) Studies on fractional order differentiators and integrators: a survey. *Signal Process* 91(3):386–426