Sustainable Computing: Informatics and Systems 36 (2022) 100786

Contents lists available at ScienceDirect

Sustainable Computing: Informatics and Systems

journal homepage: www.elsevier.com/locate/suscom

Call Auction-Based Energy Management System with Adaptive Subsidy and Dynamic Operating Reserve

Jia-Hao Syu [a], Jerry Chun-Wei Lin [b,*], Gautam Srivastava [c,d,*]

[a] Department of Computer Science and Information Engineering, National Taiwan University, Taiwan
[b] Department of Computer Science, Electrical Engineering and Mathematical Sciences, Western Norway University of Applied Sciences, Bergen, Norway
[c] Department of Mathematics and Computer Science, Brandon University, Brandon, Canada
[d] Research Centre for Interneural Computing, China Medical University, Taichung, Taiwan

ARTICLE INFO

Keywords:
Call auction
Energy management
Subsidy
Operating reserve

ABSTRACT

According to the Paris agreement and the European climate law, carbon neutrality should be achieved by 2050. Therefore, the long-term planning of energy production and the development of green energy have become indispensable research topics in recent years. Due to the unstable production and high cost of green energy, the mechanisms of operating reserve and subsidy should be included in the energy management system. In this paper, we proposed a Call Auction-based Energy Management System (CAEMS) that manages energy using economic theories and dynamic control mechanisms. We use production theory to determine the amount of energy produced, which takes into account the market equilibrium price of supply and demand curves. Then, a dynamic operating reserve rate is designed and embedded in the demand curve to ensure energy stability. An adaptive and self-financing subsidy is proposed to gradually achieve the target energy distribution. Simulation results show that the CAEMS has outstanding improvements in convergence day (42% reduction), mean absolute error (MAE) of supply distribution (1.2% in each type), and extremely low MAE of operating reserve rate (3.2%) and failure rate (0.03%).

1. Introduction

Energy generation is not only a matter of livelihood but also has to do with industry and national development. According to the Paris agreement[1] and the European climate law,[2] all countries should achieve carbon neutrality by 2050. Therefore, long-term energy planning and green energy development are indispensable and thought-provoking research topics in recent years. Green energy, also known as renewable green energy, is an environmentally friendly and ideal solution for energy production and generation [1,2]. Common green energies include hydropower, wind power, and solar energy [3–5], which harness the kinetic energy of water and wind as well as the photovoltaic energy of the sun [6,7].

Due to the unstable production of green energy, it is necessary to attach great importance to the reliability of the power grid, which is ensured by the mechanism of operating reserve [8]. Some energy is reserved to prevent unforeseen shortages, but determining the ratio is not a trivial task [9]. An insufficient reserve ratio can cause the power supply to fail and cause circuit breakers to trip on the grid. Too high a reserve ratio reduces energy efficiency and causes many costs and wastes. Therefore, the operating reserve ratio refers to the trade-off between grid stability and energy efficiency. In addition, to achieve carbon neutrality, the government can set a target supply distribution for its energy market (distribution for each type of energy generation). The energy management system should also efficiently promote energy supply for target distribution. Therefore, a sustainable energy management system with stability and reliability is urgently needed in each country.

To solve these problems, various economic theories are incorporated into the smart grid system. Mondal et al. [10] formulated a game-theoretic approach with household storage, which has a lower energy price while ensuring the profit of microgrids. Zhang et al. [11] studied the market equilibrium mechanisms for thousands of electricity consumers and obtained a higher payoff while maintaining secure dispatch. Khorasany et al. [12] proposed a platform for peer-to-peer energy trading and compared different auction mechanisms that saved costs for both sellers and buyers. Existing literature uses economic theories to lower equilibrium prices and increase agent payoffs. However, lower

* Corresponding authors.
E-mail addresses: f08922011@ntu.edu.tw (J.-H. Syu), jerrylin@ieee.org (J.C.-W. Lin), SRIVASTAVAG@brandonu.ca (G. Srivastava).

[1] https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement
[2] https://ec.europa.eu/clima/eu-action/european-green-deal/european-climate-law_en

https://doi.org/10.1016/j.suscom.2022.100786
Received 30 December 2021; Received in revised form 5 May 2022; Accepted 13 August 2022
Available online 24 August 2022
2210-5379/

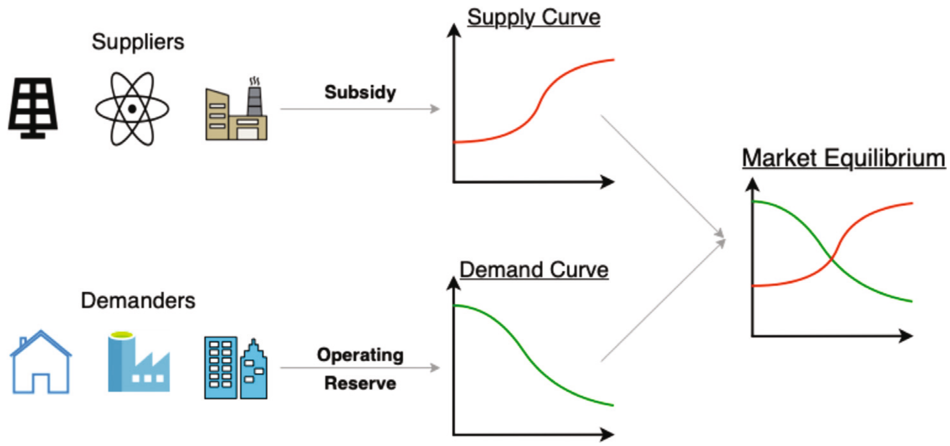


Fig. 1. The flowchart of the designed CAEMS.

energy prices increase energy consumption and negatively impact energy efficiency and carbon neutrality. In addition, green energy is not price competitive. Therefore, subsidies and long-term energy distribution planning should be included in the energy management system to internalize the external costs of non-renewable energy and the revenues from green energy. However, the operating reserve rate and subsidies are often fixed in the current energy market, which could not reflect the long-term planning of energy distribution or the real-time demand (supply) of millions of end-users (suppliers).

In response to the above problems, we proposed a Call Auction-based Energy Management System (CAEMS) with adaptive subsidy and dynamic operating reserve. The proposed CAEMS manages energy through economic theories and dynamic control mechanisms to achieve stability and reliability. We use production theory [13] to determine the production quantity and cost of energy suppliers, and construct the aggregated supply curve (from suppliers) and demand curve (from demanders) to determine the market-clearing price and quantities, as shown in Fig. 1. In addition, a dynamic operating reserve rate is developed with the Exponential Moving Average (EMA) mechanism embedded in the demand curve to dynamically reserve energy and ensure energy stability. In terms of subsidies, the CAEMS provides positive subsidies to under-supplied suppliers and negative subsidies to oversupplied suppliers. As a self-financing and sustainable system, the CAEMS balances revenues and expenses from negative and positive subsidies. With the proposed CAEMS, suppliers and demanders can intuitively and interactively determine their production or consumption based on the market equilibrium, and the market can gradually achieve the targeted energy distribution with stability through the efficient operating reserve. The contributions can be summarized as follows:

1. We adopt economic theories and dynamic control mechanisms for the proposed CAEMS.
2. A dynamic operating reserve rate is developed for energy efficiency and stability.
3. An adaptive and self-financing subsidy is proposed to achieve the targeted energy distribution.
4. CAEMS achieves efficient convergence, low MAE of supply distribution and operating reserve rate, and extremely low failure rate, and significantly outperforms the benchmarks.

The simulation results show that the proposed CAEMS has significant improvements in average convergence days (42% reduction) and MAE of supply distribution (average MAE of 1.2% for each supply type), indicating the effectiveness of the CAEMS in promoting energy supply to the target distribution. In addition, the CAEMS achieves extremely low MAE operating reserve ratio (3.2%) and failure rate (0.03%), demonstrating the energy stability and efficiency of the proposed CAEMS.

We organize this paper as follows. Section 2 reviews the literature on energy management systems, call auction, and production theory. Section 3 presents the proposed CAEMS, and Section 4 presents the designed dynamic operating reserve rate and the proposed adaptive subsidy. Section 5 first sets the simulation conditions and then presents and discusses the simulation results. Section 6 summarizes the results of the designed system.

2. Literature review

2.1. Energy management system

Modern energy management systems include the emerging themes of smart homes and buildings, smart grids, and smart cities. Smart homes and smart buildings focus on energy consumption scheduling [14,15] with communication between IoT devices [16,17] and smart metering [18]. Numerous studies have looked not only at the price of electricity, but also at green power generators in the home (e.g., solar panels) and energy storage devices [19,20].

On a larger scale, there is much discussion of the smart grid, which includes distributed energy management systems [21], load forecasting [22], energy transaction and efficiency [23,24], and economic theory [10,11]. Distributed energy management systems focus on moving load and energy between microgrids through IoT techniques [25] and edge cloud computing [21]. However, a critical issue is energy efficiency, including energy transmission [26] and operating reserve [23]. To address this issue, various economic theories are incorporated into the smart grid system. Mondal et al. [10] formulated a game-theoretic approach with multiple leaders and multiple followers and household storage, which has a lower energy price while ensuring the profit of microgrids. Zhang et al. [11] studied the market-clearing mechanisms based on game theory for thousands of electricity consumers and obtained a higher payoff for most agents while maintaining a secure disposition. Khorasany et al. [12] proposed a platform for peer-to-peer energy trading and compared different auction mechanisms that saved costs for both sellers and buyers.

Existing economic literature uses various economic theories to lower equilibrium prices and increase agent payoffs, which is effective for resource allocation. However, lower energy prices increase energy consumption and harm energy efficiency and carbon neutrality. Therefore, long-term energy allocation planning and subsidies (penalties) for different types of energy generation are needed to internalize external costs and improve market efficiency.

2.2. Call auction and market order books

Call auctions bring together the needs of suppliers and demanders, considered as sellers and buyers, and are widely used in financial markets, especially in the large transactions of opening and closing the market.[3] In the call auction, the orders of sellers and buyers are first combined within a period. The orders from sellers are called "ask" and contain information about the quantity to sell and the minimum price the seller is willing to sell. Buyers' orders are called bids, containing information about the quantity to buy and the maximum price the buyer is willing to buy. At the auction, orders with the same price as the order book [27] are then collected and bundled. This order book records the total quantity bid (buying) and demanded (selling) for each price, collecting bids and demands separately. Finally, find a mutually acceptable price (p') that has the most matches. The matched quantity is the minimum of the bid set with willing prices greater than p' and asking quantity with willing prices less than p'. All matched orders trade at a single price of p', called the equilibrium price and the market-clearing price [28].

The benefits of call auctions include increasing liquidity and transparency. On the other hand, call auctions can also reduce price volatility and opportunities for price manipulation [29]. In addition, the market mechanism will eliminate suppliers with outdated technology and uncompetitive prices. However, the price of matched orders in a call auction may not be optimal, i.e., suppliers may sell at a price higher than their minimum price, and demanders may buy at a price lower than their maximum price. In summary, the call auction is an efficient mechanism with the largest transaction quantity and would leave a positive surplus (difference between the equilibrium price and the willing price [28]) for both suppliers and demanders.

After the order book is created, the supply and demand curves can also be created. The demand curve represents the relationship between price and quantity demanded. More specifically, for any price p, the demand curve represents the summation quantity of bids with a maximum willing price less than p and is a decreasing function. Similarly, the supply curve represents the relationship between price and quantity supplied. More specifically, for any price p, the supply curve represents the sum of bids with a minimum price greater than p and is an increasing function.

2.3. Production theory

The theory of production is one of the fundamental principles of economics, which involves the determination of the quantity of supply and the equilibrium price (of factors and commodities) [13]. The prices of factors of production are relevant to the cost of production, which can be further divided into fixed and variable costs. Fixed costs refer to factor costs that do not change with the quantity of production, and variable costs refer to costs proportional to the quantity of production. The sum of fixed and variable costs is the total cost of production.

Using production theory [28], suppliers can then determine the quantity produced according to the market equilibrium price of the commodity ($p*$) and their costs of production. The following three conditions apply to production theory:

1. If a supplier with an average total cost is less than $p*$, it makes profits and survives for a long time.
2. If a supplier with an average total cost greater than $p*$ but with an average variable cost less than p^*, the supplier suffers losses but continues to produce in the short run to avoid wasting fixed costs (also known as sunk cost [30]).
3. If a supplier's average total variable is greater than $p*$, the supplier suffers losses in both the short and long run and should be shut down immediately. Note that the average variable cost equals $p*$ is called the shutdown point.

Production theory explains well the behavior of suppliers under different equilibrium prices and production costs in the proposed system.

Table 1
Notations.

Notation	Description
NTS	Number of types of energy suppliers
NS and ND	Number of energy suppliers and demanders
$AO_{is,d}$	The ask order from the is-th supplier on the dth day
$SP_{is,d}$	The minimum willing price of the is-th supplier on the dth day
$SQ_{is,d}$	The supply quantity of the is-th supplier on the dth day
$MaxSQ_{is}$	Maximum supply quantity of the is-th supplier
FC_{is} and VC_{is}	Fixed and variable costs of the is-th supplier
$SUB_{its,d}$	The subsidy for the its-th type suppliers on the dth day
$EquP_d$ and $EquQ_d$	The equilibrium price and quantity of the dth day
$TarSD_{its}$	Target supply distribution of the its-th type suppliers
$TarORR$	Target operating reserve rate
ORR_d	The operating reserve rate on the dth day
$DMOR_d$	The dynamic multiplier for operating reserve on the dth day
its	The its-th type of energy suppliers with maximum value of NTS
is	The is-th energy supplier with maximum value of NS
d	The dth day

3. Designation of call auction system

Fig. 1 shows the flowchart of the designed CAEMS, which includes the three modules of the supply curve, the demand curve, and the market equilibrium, described respectively in Sections 3.2 to 3.4. The supply curve indicates the planning quantity and production costs of the energy suppliers, which includes a discussion of subsidies and production strategies. The demand curve indicates the energy consumption at different prices, in which the designed CAEMS also embeds the operating reserve mechanism. After obtaining the supply and demand curves, the equilibrium price (market-clearing price) and quantity are then determined.

3.1. Notations and problem statement

Table 1 lists notations used in this paper and their descriptions. The NTS, NS, and ND represent the information of suppliers and demanders in the simulation. The $AO_{is,d}$, $SP_{is,d}$, $SQ_{is,d}$, $MaxSQ_{is}$, FC_{is}, and VC_{is} represent the supply in formation of each supplier. The $SUB_{its,d}$, $EquP_d$, and $EquQ_d$ state the information of market equilibrium. The $TarSD_{its}$, $TarORR$, and ORR_d are government objectives for the supply-side of market.

For the problem statement, this paper aims to propose a sustainable power management system that determines subsidies to control the market equilibrium, thereby further affecting the operating reserve rate and supply distribution. Operating reserve rate refers to the trade-off between grid stability and energy efficiency. To achieve carbon neutrality, the government will set a target supply distribution for its energy market (distribution for each type of energy generation). The energy management system should also efficiently promote the energy supply to the target distribution through subsidies. In summary, the problem is defined as determining subsidies to well manage the energy market equilibrium with key indicators of operating reserve rate and supply distribution.

[3] A. Hayes, Call auction (Jul 2021). URL https://www.investopedia.com/terms/c/call-auction.asp

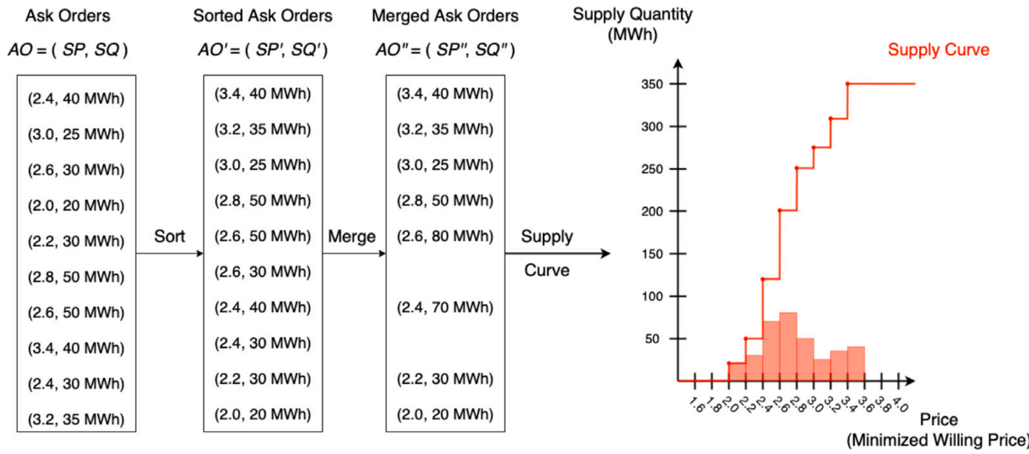


Fig. 2. Ask orders and the supply curve.

3.2. Supply curve

Fig. 2 illustrates the formation of the supply curve in CAEMS. Before each day, each supplier specifies its demand (ask) order (AO, the information about energy production), including the quantity offered (SQ) and the minimum price at which it is willing to sell (SP). The ask order of the is-th supplier on the dth day is denoted as $AO_{is,d} = (SP_{is,d}, SQ_{is,d})$. After collecting ask orders from all NS suppliers $(AO_1, \ldots, AO_{NS})$, CAEMS sorts the ask orders by price and aggregates them. Aggregation of the supply quantities then yields the supply curve shown in the red curve in Fig. 2.

Note that the designed CAEMS is based on the assumption of Pareto optimality [31] and all suppliers honestly ask for the minimum willing prices equal to their average total cost minus subsidies (determined in Section 4.2). One supplier may lower the minimum willing price to increase the quantity sold, but this will negatively affect others and violate Pareto optimality. The vicious competition of price wars will hurt the market and each supplier in the long run. We, therefore, assume that the supplier's minimum willing price is equal to the average total cost minus the subsidy. The average total cost of the is-th supplier (the its-th type of supplier) is called $ATCost_{is}$ and is defined as:

$$ATCost_{is} = \frac{FC_{is} + VC_{is} \times SQ_{is}}{SQ_{is}}, \tag{1}$$

and the minimum willing price is denoted and defined as:

$$MWP_{is} = ATCost_{is} - SUB_{its,d} \tag{2}$$

According to production theory, suppliers whose average variable cost is higher than the equilibrium price should not produce. Thus, in CAEMS, if the equilibrium price of the previous day ($EquP_{d-1}$) is less than a supplier's average variable cost (with subsidy), the supplier will not produce on the dth day; otherwise, it will produce the maximum quantity. The supply quantity of the is-th supplier on the dth day is denoted as $SQ_{is,d}$ and is defined as:

$$SQ_{is,d} = \begin{cases} 0 & EquP_{d-1} < VC_{is} - SUB_{its,d} \\ MaxSQ_{is} & \text{else} \end{cases} \tag{3}$$

3.3. Demand curve

In the CAEMS, the expected demand curve of a consumer is assumed to be constant and can be determined from historical data. However, there is still uncertainty (variance) on any given day. The CAEMS can then capture the expected demand curve of all ND consumers.

Then, the CAEMS considers the operating reserve and embeds it into the demand curve. In other words, for each unit of energy demand in the demand curve, a specific energy ratio is reserved to prevent accidental shortages. Finally, CAEMS multiplies all demands by one plus the dynamic operating reserve multiplier ($1 + DMOR_d$, defined in Section 4.1). Then aggregate the adjusted demand curves of all ND consumers to obtain the final demand curve, as shown in Fig. 3.

3.4. Market equilibrium

For each dth day, the CAEMS collects the ask orders from NS suppliers (before the day) to create the supply curve of the dth day. The aggregated (adjusted) demand curve of ND consumers can also be obtained from historical data. The CAEMS then determines the equilibrium price (also known as the market-clearing price) and the equilibrium quantities, i.e., $EquP_d$ and $EquQ_d$, as the intersection of the supply and demand curves. The intersection point indicates that the supply and demand quantities are exactly equal at that price, which is called the market equilibrium point.

Since the prices in the supply and demand curves are discrete, the intersection may not lie exactly on an available price. Also, the supply and demand curves are (not necessarily strictly) increasing and decreasing functions, so there would be multiple intersections. Therefore, the CAEMS sets the equilibrium price ($EquP_d$) to the maximum price at which demand is greater than or equal to supply, and sets the equilibrium quantity ($EquQ_d$) to the quantity demanded.

Furthermore, since the demand curve is adjusted by the dynamic multiplier of the operating reserve, a specific energy ratio is reversed and should be paid by the demand side. For example, a demander who consumes C units of energy should pay:

$$C \times (1 + DMOR_d) \times EquP_d \tag{4}$$

In other words, the price charged to consumers for each unit of power is:

$$\frac{C \times (1 + DMOR_d) \times EquP_d}{C} = EquP_d \times (1 + DMOR_d) \tag{5}$$

Moreover, the dth day operating reserve rate, ORR_d, is the actual energy consumption (below the equilibrium price) divided by the total energy supply (of all suppliers), which is denoted and defined as follows:

$$ORR_d = 1 - \frac{\frac{EquQ_d}{1+DMOR_d}}{\sum_{is=1}^{NS} SQ_{is,d}} \tag{6}$$

4. Dynamic operating reserve rate and adaptive subsidy

4.1. Dynamic operating reserve rate

In CAEMS, the operating reserve is embedded in the demand curve described in Section 3.3, and the dynamic multiplier of the operating

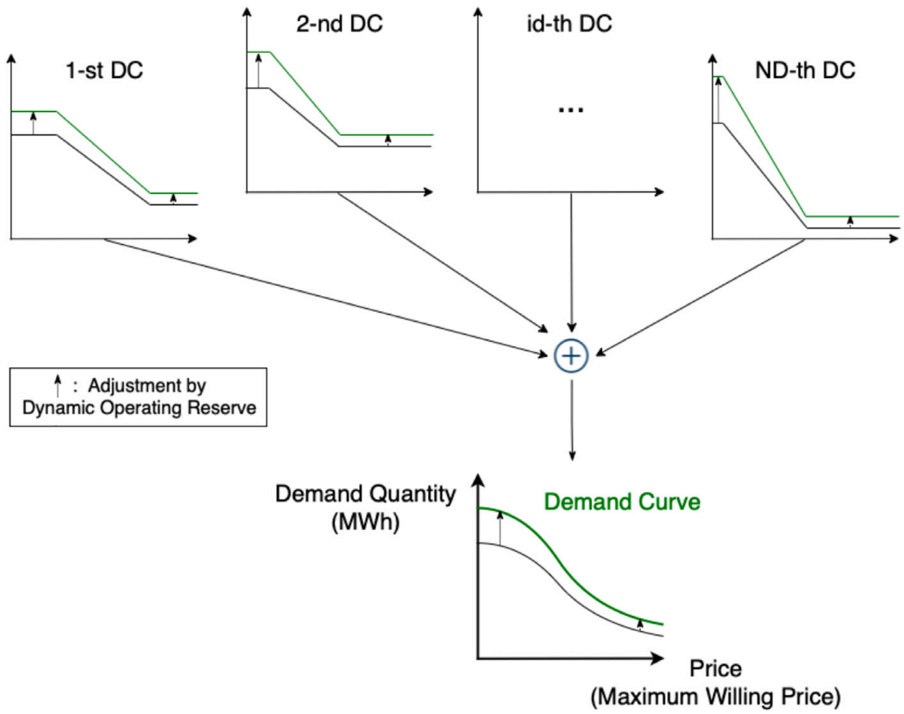


Fig. 3. Aggregated demand curve.

reserve on the dth day ($DMOR_d$) is defined as:

$$DMOR_d = \alpha \times DMOR_{d-1} + (1-\alpha) \times NM_d \tag{7}$$

The α is the multiplier of the EMA to smooth the $DMOR_d$, and the NM_d is the new multiplier of the dth day, defined as:

$$NM_d = DMOR_{d-1} + (TarORR - ORR_{d-1}) \tag{8}$$

The NM_d is the previous $DMOR$ plus the difference between the target and previous operating reserve rates ($TarORR$ and ORR_{d-1}). The CAEMS assumes that the previous day's $DMOR_{d-1}$ results in the difference in the reserve rate of $TarORR - ORR_{d-1}$; therefore, the new multiplier should be increased by $TarORR - ORR_{d-1}$. The designed $DMOR$ will gradually move the operating reserve rate towards the target.

However, in addition to the $DMOR$, random shortages in energy generation and unexpected fluctuations in energy consumption also affect the operating reserve. Therefore, the proposed $DMOR$ takes these aspects into account as well. The CAEMS captures the failure quantity of energy generation of all suppliers, denoted as $FailS$, and the unexpected energy consumption of all demanders, denoted as $FailD$, i.e., the actual values minus the expected values. The average unexpected shortage, AUS_d, is defined as:

$$AUS_d = \text{Mean}(\ [FailS_{d-30} + FailD_{d-30}, \ldots, FailS_{d-1} + FailD_{d-1}]\ ), \tag{9}$$

which is the average summation of $FailS$ and $FailD$ over the past 30 days. Then, the $DMOR_d$ is adjusted to:

$$DMOR_d = \text{Max}(DMOR_d, \frac{AUS_d}{EquQ_{d-1}}) \tag{10}$$

In other words, if the rate of unexpected shortage is larger, the $DMOR_d$ will be changed to $\frac{AUS_d}{EquQ_{d-1}}$.

4.2. Adaptive subsidy

To support the development of green energy and achieve the target energy distribution, an adaptive subsidy mechanism is proposed. We first calculate the target quantity and price for each type of energy supply. For the its-th type supplier, the target quantity is denoted and defined as follows:

$$TarQ_{its} = TarSD_{its} \times EquQ_d \tag{11}$$

The target price, $TarP_{its}$, is defined as the minimum price in which the supply quantity (of the its-th type of supply) is greater than $TarQ_{its}$.

A naive subsidy for its-th type suppliers is $TarP_{its} - EquP_{d-1}$, which would provide sufficient supply to meet the target distribution. There will be positive subsidies for the under-supply type of suppliers and negative subsidies for the over-supply type of suppliers as a penalty. However, the subsidies may require large amounts of money. As a self-financing and sustainable energy management system, the CAEMS balances the total subsidy revenues and expenditures through Algorithm 1.

For every dth day, Algorithm 1 first calculates subsidy income, expenditures, and balance, expressed as $Income$, $Expend$, and $Balance$ (lines 3 to 5). When $Balance$ is greater than zero, the algorithm calculates less of the revenue (it only calculates the demand), and the shrinking revenue multiplier, MSI, is defined as line 7. For each type of supplier with a negative subsidy, the algorithm defines the subsidy that collects only the adjusted income, $AdjIncome$, from the suppliers (lines 9 to 11). For each type of supplier with a positive subsidy, the algorithm sets the subsidy to the naive subsidy (lines 12 to 13). On the other hand, if $Balance$ is less than zero, the algorithm will spend less on the expenditure (only spend as they have), and the shrinking expenditure multiplier, MSE, is defined as line 15. For each type of supplier with a positive subsidy, the algorithm determines the subsidy that just spends the adjusted expenditure, $AdjExpend$, on the suppliers (lines 17 to 19). For each type of supplier with a negative subsidy, the algorithm sets the subsidy to the naive one (lines 20 to 21).

Note that the $Income$ and $Expend$ in Algorithm 1 are the expected values for determining the subsidy. The actual values, $Income^*$ and $Expend^*$, should be calculated by the subsidy and the equilibrium quantity of the following day. In addition, the difference between payments received from consumers and payments to suppliers is also added to the remainings of the subsidy. Furthermore, the exponential moving average technique is also applied to stabilize the adaptive subsidy (line 22, the same α as Eq. (7)).

Algorithm 1 Self-financing algorithm for adaptive subsidy

$Remains = 0$;
for each d-th day **do**
  $Income = \text{Sum}(\ \{(EquP_{d-1} - TarP_{its}) \times TarQ_{its} \ \mid \ EquP_{d-1} > TarP_{its}\}\ )$;
  $Expend = \text{Sum}(\ \{(TarP_{its} - EquP_{d-1}) \times TarQ_{its} \ \mid \ TarP_{its} > EquP_{d-1}\}\ )$;
  $Balance = Income - Expend + Remains$;
  if $Balance > 0$ **then**
    $MSI = \frac{Remains - Expend}{Income}$;
    for each its-th type suppliers **do**
      if $TarP_{its} < EquP_{d-1}$ (negative subsidy) **then**
        $AdjIncome = (EquP_{d-1} - TarP_{its}) \times TarQ_{its} \times MSI$;
        $SUB_{its,d}$ = subsidy that just charge $AdjIncome$ from its-th type suppliers;
      if $TarP_{its} >= EquP_{d-1}$ (positive subsidy) **then**
        $SUB_{its,d} = TarP_{its} - EquP_{d-1}$;
  else
    $MSE = \frac{Remains + Income}{Expend}$;
    for each its-th type suppliers **do**
      if $TarP_{its} > EquP_{d-1}$ (positive subsidy) **then**
        $AdjExpend = (TarP_{its} - EquP_{d-1}) \times TarQ_{its} \times MSE$;
        $SUB_{its,d}$ = subsidy that just spend $AdjExpend$ on its-th type suppliers;
      if $TarP_{its} <= EquP_{d-1}$ (negative subsidy) **then**
        $SUB_{its,d} = TarP_{its} - EquP_{d-1}$;
  $SUB_d = \alpha \times SUB_{d-1} + (1-\alpha) \times SUB_d$;
  $Remains = Remains + Income^* - Expend^*$.

5. Experimental evaluation

In this section, we evaluate the performance of the proposed CAEMS and compare it to benchmarks widely used in real-world implementations of energy management, called traditional and statistical methods. Both the traditional and statistical methods establish subsidies for fair competition that result in equal minimum willing prices (MWP) for all suppliers. Explicitly, SUB_{its} is set to the average total cost of all suppliers minus the cost of the its-th supplier. Note that the subsidies for under-supplied suppliers are non-negative (i.e., the maximum value of SUB_{its} and 0). Similarly, subsidies for over-supplied providers are non-positive (i.e., the minimum value of SUB_{its} and 0). Moreover, both traditional and statistical methods intuitively define the dynamic operating reserve ratio as $TarORR$.

The difference between the traditional and statistical methods is the mechanism to prevent an unexpected shortage of energy production (additional operating reserve). In the traditional method, the demand curve is shifted upward when an unanticipated production shortage occurs on the last day for all suppliers, increasing the operating reserve by the previous shortage. In the statistical method, the demand curve is shifted upward by summing the production variance, adding the operating reserve by the historical statistics of production shortages.

5.1. Environment setting

This paper refers to the Taiwan energy market to simulate the proposed CAEMS, and the reference data (parameters) are from TPC.[4] It is assumed that the energy grid is initialized to supply and consume 50,000 megawatt-hours (MWh) of electricity per day and that the target operating reserve rate ($TarORR$) is set at 10% by the Taiwan government.

Simulation settings of demand-side parameters are listed in Table 2. According to TPC data,[5] energy consumers are divided into three categories, including household, commercial and industrial consumers.

[4] Taiwan Power Company, https://www.taipower.com.tw/en/index.aspx

[5] https://www.taipower.com.tw/tc/page.aspx?mid=96

Table 2
Demand-side simulation settings.

Type of consumers	Household	Commercial	Industrial
Consumption distribution	20%	15%	65%
Mean of MDC (MWh)	20	100	2000
Var of MDC (MWh)	4	20	400
Var of daily consumption	10%	10%	20%
Number of demanders	500	75	16

Table 3
Supply-side simulation settings.

Type of suppliers	Coal	Fuel	Gas	Nuclear	Hydro	Wind	Solar
Supply distribution	29%	3%	36%	8%	9%	2%	13%
Target distribution	20%	5%	25%	15%	10%	10%	15%
Mean of MDP (MWh)	600	200	500	1000	100	100	10
Var. of MDP (MWh)	120	40	100	200	20	20	2
Var. of daily production	5%	5%	5%	5%	30%	30%	30%
Mean of FC (NTD)	600	200	500	1000	250	140	30
Mean of VC (NTD)	0.5	4	0.8	0.3	0	0	0
Number of suppliers	24	8	36	4	45	10	650

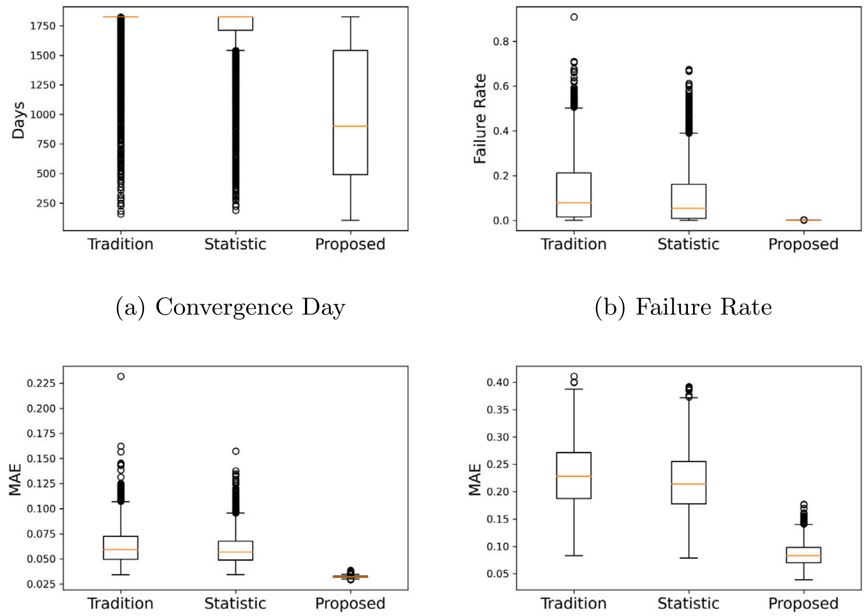
The assumed parameters of energy consumption distribution, mean of maximum daily consumption (MDC), variance (Var) of MDC, and Var of the daily consumption are listed in Table 2. Based on the consumption distribution and the mean of MDC, there are $\frac{50{,}000\times 20\%}{20} = 500$ household consumers in the grid, and the number of demanders of each type is shown in the last row of Table 2. Assume that the consumers' demand curves are Z-shaped continuous functions with left and right breakpoints that are linear inside the breakpoints and constant outside the breakpoints. The x-value of the left and right breakpoints of a consumer are randomly sampled from a normal distribution with the mean of 0 and 5 new Taiwan dollars (NTD) and variance of 0.5 and 0.5 NTD, respectively. The y-value of the left and right breakpoints is set to the maximum daily energy consumption multiplied by 1 and 25%, respectively.

The simulation settings of the supply-side parameters are listed in Table 3. According to the TPC data, energy consumers are divided into seven categories, including coal, fuel, gas, nuclear, hydro, wind, and solar suppliers. The assumed parameters of supply distribution, target distribution, mean of maximum daily production (MDP), Var of MDP, VAR of the daily production, fixed cost (FC), and variable cost (VC) are listed in Table 2. Based on the production distribution and the mean value of MDP, there are $\frac{50{,}000\times 29\%}{600} = 24$ coal suppliers in the grid, and the number of suppliers of each type is shown in the last row of Table 3. In addition, each supplier has capital 100 times its MDP. Suppliers whose accumulated loss is greater than the capital immediately go bankrupt and stop producing.

To simulate the entry of new suppliers into the energy market, we design two ways to establish new suppliers, including government establishment and splitting from old suppliers. For each supplier, if its capital is greater than 1,200 times the mean MDP of the supply type, a new supplier is split out with the 1,000 MDP for the establishment, 100 MDP as the new supplier, and the remaining 100 MDP as the capital of the old supplier. Note that if a type of supply distribution is greater than the target, that type of supplier will not split the new ones. The government only establishes one supplier whose type is the most lower than the target supply distribution, $TarSD$. In addition, the government only establishes a new supplier if the remaining subsidy (as mentioned in Section 4.2) is greater than 1,100 times the mean MDP of the supply type using the 1,000 MDP for the establishment, and 100 MDP is as the capital of the new supplier. Note that newly established suppliers are with randomly sampled parameters.

5.2. Simulation results

We simulated the systems in 3000 iterations over 5 years (1825 days). Simulation results are evaluated using four measurements: the



(a) Convergence Day (b) Failure Rate

(c) MAE of Operating Reserve Rate (d) MAE of Supply Distribution

Fig. 4. Box plot comparison of the proposed CAEMS and benchmarks.

Table 4
Performance evaluation of the systems.

	Tradition	Statistic	Proposed
Average convergence day	1725	1686	**989**
Average failure rate	13.09%	10.12%	**0.03%**
MAE of operating reserve rate	6.3%	6.0%	**3.2%**
MAE of supply distribution	22.9%	21.7%	**8.5%**

Table 5
Performance evaluation of the CAEMS with different EMA parameters.

α	0.75	0.50	0.25	0
Average convergence day	1064	964	887	**804**
Average failure rate	**0.02%**	0.03%	0.04%	0.07%
MAE of operating reserve rate	**3.1%**	3.2%	3.3%	3.4%
MAE of supply distribution	9.9%	8.4%	7.7%	**7.4%**

convergence days, the failure rate, the MAE of the operating reserve rate, and the MAE of the supply distribution. The MAE of the operating reserve rate is the average absolute value of the difference between the daily operating reserve rate and the target value of $TarORR$. Similarly, the MAE of the supply distribution is the average absolute value of the difference between the supply distribution and the target value of $TarSD$. The day of convergence is the first day when the MAE of the supply distribution is less than 10% (and still less than 10% after that day). Note that the non-convergent simulation is recorded as 1825 days (the last day). The failure rate is the probability that energy consumption is greater than production and corresponds to the probability that the operating reserve is less than zero, which may cause the circuit breaker to trip on the entire grid.

Table 4 and Fig. 4 present the performance evaluation of the proposed CAEMS (with α of 0.75) and benchmarks. The simulation results show that the proposed CAEMS has a significant improvement compared to the benchmarks. The traditional and statistical methods obtain convergence days of 1725 and 1686, which are 4.73 and 4.62 years, respectively. With the proposed adaptive subsidy, the proposed CAEMS shortens the average convergence day to 989 days, a reduction of about 42%, which means the CAEMS achieves the target supply distribution within 3 years on average. Note that the actual convergence day should be larger, especially for benchmarks, since numerous simulations of traditional and statistical methods did not converge on the last day. As shown in Fig. 4(a), all quartiles of the traditional method (the median of the statistical method) are 1825, which means that only a few (less than half) simulations converge.

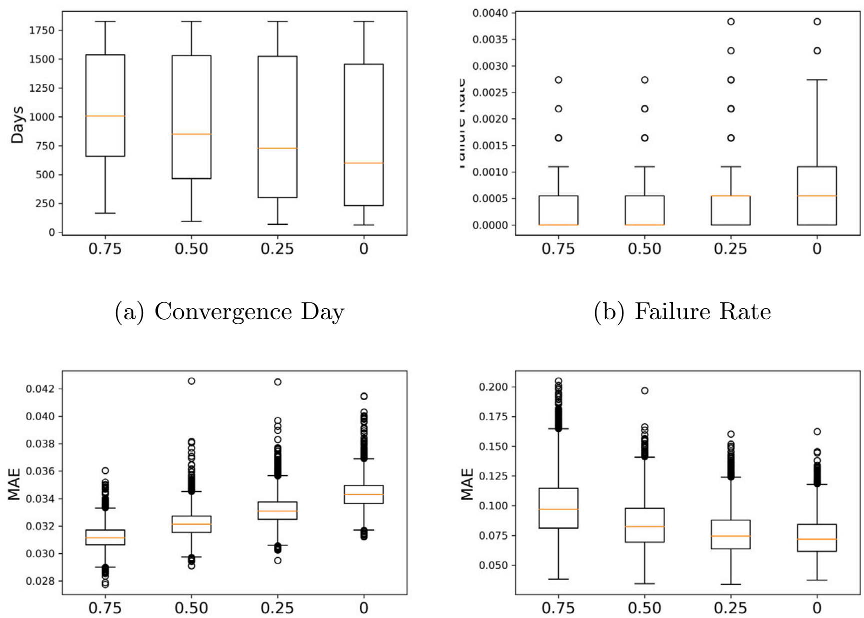
For the supply distribution, the traditional and statistical methods obtain a large tracking error of 22.9% and 21.7%. The CAEMS has a tiny tracking error with an MAE of 8.5% in 7-type of supply distribution (the average MAE of each type is only 1.2%), even if 45% (hydro, wind, and solar) of energy production has a daily variance (uncertainty) of 30%. In conclusion, CAEMS rapidly moves supply towards the target distribution with tiny errors.

For operating reserves, CAEMS achieves an extremely low MAE of 3.2% through the designed dynamic operating reserve rate, almost half that of the benchmark methods. In addition, all MAEs of CAEMS are lower than 5%, as shown in Fig. 4(c). The excellent results mentioned above are also reflected in the extremely low failure rate of 0.03%, which is significantly lower than that of the benchmarks (13.09% and 10.12%). As can be seen in Fig. 4(b), all quartiles of the CAEMS are close to zero.

5.3. Influence of EMA parameter

In this section, we examine the influence of the EMA parameter (α, in dynamic operating reserve and adaptive subsidy), which is respectively set to 0.75, 0.50, 0.25, and 0. The larger α is the greater impact of the previous value. When α is 0, it means that the EMA is deprecated, and the value is not influenced by the previous one.

Table 5 and Fig. 5 present the performance of the CAEMS with different α. The simulation results show that as α decreases, the average convergence day and the MAE of the supply distribution gradually decrease. The smaller α leads to faster subsidy adjustments, faster convergence, and the MAE for the supply allocation. However, the



(a) Convergence Day (b) Failure Rate

(c) MAE of Operating Reserve Rate (d) MAE of Supply Distribution

Fig. 5. Box plot comparison of the EMA parameters.

decreasing α also leads to a progressive increase in the average failure ratio and the MAE of operating reserve ratio due to the large fluctuations in the energy market (equilibrium price and quantity). The same phenomenon is also found in the broader distribution of failure ratio and MAE of operating reserve ratio under the smaller α in Fig. 5. In conclusion, we recommend the use of CAEMS with a α of 0.5, which maintains an excellent balance of α with an extremely low failure rate and a tiny MAE of supply distribution.

6. Conclusion

Due to the unstable production and high cost of green energy, the operating reserve and subsidy mechanisms should be included in the energy management system. The operating reserve rate and subsidy are often fixed in the current energy market and do not reflect energy distribution planning or real-time supply and demand. In response to the issues, we proposed a Call Auction-based Energy Management System (CAEMS) with adaptive subsidy and dynamic operating reserve that manages energy using economic theories and dynamic control mechanisms. We use the production theory to determine the energy suppliers' production and generate the supply and demand curves to determine the market-clearing price. In addition, a dynamic operating reserve rate is designed and embedded in the demand curve to reserve energy dynamically, and an adaptive subsidy is proposed for self-financing. With the proposed CAEMS, the market gradually achieves the target energy distribution through the efficient operating reserve. Simulation results show that the proposed CAEMS has outstanding improvements in average convergence day (42% reduction), MAE of supply distribution (1.2% average MAE in each supply type), and has extremely low MAE of operating reserve rate (3.2%) and failure rate (0.03%). Furthermore, CAEMS can achieve the targeted energy distribution in 3 years on average. In studying the effect of EMA, we found that as α decreases, the average convergence day and MAE of supply distribution gradually decrease, and the average failure rate and MAE of operating reserve progressively increase.

In the future, we will attempt to forecast the demand curve for precisely managing the energy market and further optimizing supply. We will also explore the mechanism of carbon credits and carbon tax that will be introduced globally soon.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is partially supported by the National Centre for Research and Development under the project Automated Guided Vehicles integrated with Collaborative Robots for Smart Industry Perspective and the Project Contract no. is: NOR/POLNOR/CoBotAGV/0027/2019 -00. All authors approved the version of the manuscript to be published.

References

[1] O. Ellabban, H. Abu Rub, F. Blaabjerg, Renewable energy resources: Current status, future prospects and their enabling technology, Renew. Sustain. Energy Rev. 39 (2014) 748–764.
[2] J.H. Syu, M.E. Wu, G. Srivastava, C.F. Chao, J.C.-W. Lin, An IoT-based hedge system for solar power generation, IEEE Internet Things J. (2021).
[3] E.F. Moran, M.C. Lopez, N. Moore, N. Müller, D.W. Hyndman, Sustainable hydropower in the 21st century, Proc. Natl. Acad. Sci. 115 (47) (2018) 11891–11898.
[4] S.A. Vargas, G.R.T. Esteves, P.M. Maçaira, B.Q. Bastos, F.L.C. Oliveira, R.C. Souza, Wind power generation: A review and a research agenda, J. Cleaner Prod. 218 (2019) 850–870.
[5] M.H. Ahmadi, M. Ghazvini, M. Sadeghzadeh, M. Alhuyi Nazari, R. Kumar, A. Naeimi, T. Ming, Solar power technology for electricity generation: A critical review, Energy Sci. Eng. 6 (5) (2018) 340–361.
[6] T.J. Kazmierski, S. Beeby, Energy Harvesting Systems, Springer, 2014.
[7] G.K. Singh, Solar power generation by PV (photovoltaic) technology: A review, Energy 53 (2013) 1–13.
[8] J. Wang, X. Wang, Y. Wu, Operating reserve model in the power market, IEEE Trans. Power Syst. 20 (1) (2005) 223–229.
[9] M. Quashie, C. Marnay, F. Bouffard, G. Joós, Optimal planning of microgrid power and operating reserve capacity, Appl. Energy 210 (2018) 1229–1236.
[10] A. Mondal, S. Misra, M.S. Obaidat, Distributed home energy management system with storage in smart grid using game theory, IEEE Syst. J. 11 (3) (2015) 1857–1866.
[11] N. Zhang, Y. Yan, S. Xu, W. Su, Game-theory-based electricity market clearing mechanisms for an open and transactive distribution grid, in: 2015 IEEE Power & Energy Society General Meeting, IEEE, 2015, pp. 1–5.

[12] M. Khorasany, Y. Mishra, G. Ledwich, Design of auction-based approach for market clearing in peer-to-peer market platform, J. Eng. 2019 (18) (2019) 4813–4818.
[13] R.W. Shephard, Theory of Cost and Production Functions, Princeton University Press, 2015.
[14] B. Zhou, W. Li, K.W. Chan, Y. Cao, Y. Kuang, X. Liu, X. Wang, Smart home energy management systems: Concept, configurations, and scheduling strategies, Renew. Sustain. Energy Rev. 61 (2016) 30–40.
[15] Q. Zhou, J. Lou, Y. Jiang, Optimization of energy consumption of green data center in e-commerce, Sustain. Comput.: Inform. Syst. 23 (2019) 103–110.
[16] M. Alaa, A.A. Zaidan, B.B. Zaidan, M. Talal, M.L.M. Kiah, A review of smart home applications based on Internet of Things, J. Netw. Comput. Appl. 97 (2017) 48–65.
[17] C. Stergiou, K.E. Psannis, B.B. Gupta, Y. Ishibashi, Security, privacy & efficiency of sustainable cloud computing for big data & IoT, Sustain. Comput.: Inform. Syst. 19 (2018) 174–184.
[18] W. Anupong, R. Azhagumurugan, K.B. Sahay, D. Dhabliya, R. Kumar, D.V. Babu, Towards a high precision in AMI-based smart meters and new technologies in the smart grid, Sustain. Comput.: Inform. Syst. (2022) 100690.
[19] M. Rahmani Andebili, H. Shen, Price-controlled energy management of smart homes for maximizing profit of a GENCO, IEEE Trans. Syst. Man Cybern. 49 (4) (2017) 697–709.
[20] X. Wu, X. Hu, S. Moura, X. Yin, V. Pickert, Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array, J. Power Sources 333 (2016) 203–212.
[21] H. Golpîra, S. Bahramara, Internet-of-things-based optimal smart city energy management considering shiftable loads and energy storage, J. Cleaner Prod. 264 (2020) 121620.
[22] A. Mukherjee, P. Mukherjee, N. Dey, D. De, B.K. Panigrahi, Lightweight sustainable intelligent load forecasting platform for smart grid applications, Sustain. Comput.: Inform. Syst. 25 (2020) 100356.
[23] M. Quashie, C. Marnay, F. Bouffard, G. Joós, Optimal planning of microgrid power and operating reserve capacity, Appl. Energy 210 (2018) 1229–1236.
[24] A. Kumari, S. Tanwar, Secure data analytics for smart grid systems in a sustainable smart city: Challenges, solutions, and future directions, Sustain. Comput.: Inform. Syst. 28 (2020) 100427.
[25] A. Ghasempour, Internet of things in smart grid: Architecture, applications, services, key technologies, and challenges, Inventions 4 (1) (2019) 22.
[26] Z. Li, J. Wang, H. Sun, Q. Guo, Transmission contingency analysis based on integrated transmission and distribution power flow in smart grid, IEEE Trans. Power Syst. 30 (6) (2015) 3356–3367.
[27] C. Cao, O. Hansch, X. Wang, The information content of an open limit-order book, J. Futures Mark.: Futures Options Other Deriv. Prod. 29 (1) (2009) 16–41.
[28] N.G. Mankiw, Principles of Economics, Cengage Learning, 2014.
[29] C. Comerton Forde, J. Rydge, Call auction algorithm design and market manipulation, J. Multinatl. Final. Manag. 16 (2) (2006) 184–198.
[30] H.R. Arkes, P. Ayton, The sunk cost and Concorde effects: Are humans less rational than lower animals? Psychol. Bull. 125 (5) (1999) 591.
[31] P.M. Pardalos, A. Migdalas, L. Pitsoulis, Pareto Optimality, Game Theory and Equilibria, vol. 17, Springer Science & Business Media, 2008.