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Simultaneous sizing and energy management of multi-energy Virtual Power Plants operating in regulated energy markets

Ahmed Hany Elgamal [*], Mehdi Shahrestani, Maria Vahdati

School of the Built Environment, University of Reading, Reading RG6 6DF, UK

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ABSTRACT

This research analyses the case of a Virtual Power Plant (VPP) in regulated electricity markets, trading energy with the consumers and the grid under a Power Purchase Agreement (PPA). The VPP propagates the deployment of solar PVs while balancing its intermittency with a dispatchable power plant, which is assumed in this research to be a CCHP, supplying cooling, heating, and power. The VPP also integrates energy storage systems for a comprehensive assessment. Traditionally, the VPP concept has not been introduced in regulated markets, but it is widely researched in deregulated markets where VPPs trade energy with the electricity grid for profit maximisation. In regulated markets, a special architecture is proposed for a VPP that mediates between residential compounds and electricity grids for profit maximization and energy demand coverage, thus converting the compound into a power generator with minimum dependence on the grid for its energy demand. In the literature on aggregated energy systems in regulated markets, it is usually overlooked to perform detailed energy modelling and optimisation on an hourly level. Only basic rule-based frameworks for energy management are proposed. In this research, it is initially assumed that since the VPP integrates multi-energy components supplying heating, cooling and electricity, optimization of the output of each component for a common profit maximization, is necessary. However, in VPP-related literature, the capacity of each component, which is a main input for energy modelling, is traditionally assumed and not assessed. Therefore, the research aims to explore how to find the optimal capacity configuration of the residential VPP that achieves optimal profit. The paper analyses an iterative exhaustive search framework, integrating the 2-levels of energy optimisation (hourly profit maximisation objective) and capacities optimisation (Life cycle CAPEX & OPEX minimisation). Compared to baseline cases, where only energy optimisation is performed, and capacities are assumed and not assessed in terms of capital investment, the proposed framework achieved a higher annual profit by 3.1 % and a payback period of 11 years. The results also provide comprehensive 3D charts drawing the relations between the achieved profit against capacities configurations, thus allowing high-level decision-making. The results also prove the hypothesis that hourly energy optimisation should not be performed without investment cost assessment and that targeting the minimization of investment costs will indirectly benefit the achieved profit.

1. Introduction

Renewable energy resources are becoming a focus for overcoming climate change threats. However, they impose an economic challenge because they are intermittent generators with a relatively higher investment cost than conventional power plants [1]. To overcome the intermittency problem, different power technologies were aggregated and formed, so-called “Virtual Power Plants” (VPPs), which proved to be technically and economically viable [2]. VPPs help provide a self-balanced power supply and improve the overall profit from energy trading. Although they may resemble Microgrids in aggregating different power plant technologies, they mainly differ in their ability to aggregate geographically segregated plants and in being constantly connected to the grid to trade energy with the wholesale energy market [3]. The main objective of VPPs is to ensure coordinated operation between the aggregated energy systems for efficient operation and for maximisation of revenues from energy exchange between DERs [4]. VPPs are addressed intensively in deregulated-market-related studies, markets which enable power generators to trade energy with the market where prices are settled by the bids of the generators and energy retailers or buyers [5].

* Corresponding author.
E-mail address: a.h.elgamal@pgr.reading.ac.uk (A.H. Elgamal).

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Nomenclature

Acronyms

BSS	Battery Storage System
CCHP	Combined Cooling Heat and Power
PPA	Power Purchase Agreement
COP	Coefficient of Performance
TES	Thermal Energy Storage
COE	Cost of Energy
LCOE	Levelized Cost of Energy
DER	Distributed Energy Resources
GA	Genetic Algorithm
AC	Absorption Chiller
EC	Electric Chiller
SOC	State of Charge
CAPEX	Capital Expenditures
OPEX	Operational expenditures
LCC	Life Cycle Cost
LCP	Life Cycle Profit
CHW	Chilled Water
HW	Heating Water

Variables

P_{CCHP}	CCHP output power, kW
$\dot{m}_f$	CCHP fuel flow rate, m^3/h
u_{grid}	Binary for energy trading with grid (Buying:1; selling: 0)
$P_{gridbuy}$	Purchased power from the grid, kW
$P_{gridsell}$	Sold power to the grid, kW
$P_{gridbuy\_max,t}$	Upper bound for energy purchased from the grid
$P_{gridsell\_max,t}$	Upper bound for energy sold to the grid
P_{PV}	Solar PV Power, kW
u_{TES_CHW}	Binary for CHW TES
u_{TES_HW}	Binary for HW TES
u_{BSS}	Binary for BSS
P_{ch}	BSS charging power, kW
P_{disch}	BSS discharging power, kW
P_{demand}	Electricity demand, kW
E_{CHW-TS}	State of charge of cooling water storage, kWh
E_{HW-TS}	State of charge of heating water storage, kWh
$E_{BSS,t}$	State of charge of BSS, kWh
η_{BSS}	BSS roundtrip efficiency, %
η_{PV}	Solar PV module overall efficiency, %
η_{PV}	TES roundtrip efficiency, %
η_{CCHPe}	CCHP electrical efficiency, %
$\eta_{CCHPe\_nominal}$	CCHP nominal electrical efficiency, %
γ	Power-to-heat ratio
Q_{CHW}	Cooling energy output from AC, kW_{th}
Q_{HW}	Heating energy supply converted from waste heat, kW_{th}
$Q_{HW\_TES\_ch}$	Heating water TES charging energy,kW_{th}
$Q_{HW\_TES\_disch}$	Heating water TES discharging energy, kW_{th}
$Q_{CHW\_TES\_ch}$	Cooling water TES charging thermal power, kW_{th}
$Q_{CHW\_TES\_disch}$	Cooling water TES discharging thermal power, kW_{th}
$Q_{th\_imbalance}$	Thermal imbalance (non-satisfied thermal demand) (kW_{th})
Q_{EC}	Electric chiller thermal energy output (kW_{th})
F	CO2 emissions, kg

Subscripts

t	Current time step
T	Time duration
k	Lifetime counter from year 1 to year 25

Input parameters

A_{PV}	Solar PV module installed area, m^2
T_o	Ambient Temperature, K
η_r	Solar PV module reference efficiency
G	Solar irradiation, kW/m^2
T_c	Solar PV cell temperature, K
$NOCT$	Nominal operating cell temperature, K
β	PV panel tilt angle
T_{ref}	Solar PV cell reference temperature (25 K)
COP	Coefficient of Performance
μ_{CO2}	CO2 emission factor, kg/kWh
LHV_f	Lower heating value of fuel, kWh/m^3
HHV_f	Higher heating value of fuel, kWh/m^3
r	Discount rate %

Focusing on regulated markets, VPPs would be very beneficial for governments holding the burden of deploying renewables and diversifying the energy mix without relying on the private sector. VPPs, in this exact terminology, are not usually present in regulated markets due to the government's price dictation and the obstacles to energy trading with the grid. This research takes advantage of the developed policies of "Independent Power Plant" concept [6], that enables a power generator to sell energy to the government at a pre-agreed price under a Power Purchase Agreement (PPA) scheme [7,8]. This concept would allow to construct an energy exchange framework between power producers and the electricity grid and would also allow IPPs to sell energy directly to consumers at energy service agreements but at the dictated national electricity tariffs. Accordingly, several IPPs could be aggregated to form a VPP to interact with consumers and the grid. From that concept. a VPP model has been developed in a previous study by [9] fitting the rules of regulated markets and operate under their dictated prices. However, that study requires further work from investment costs and energy management perspectives. The current research aims to address the sizing of power plants along with detailed energy management.

As shown in the literature review, VPPs, Microgrids, or Energy Hub-related studies could be categorised by the market type governing the energy systems. Studies on systems in regulated markets usually aim to minimise investment costs (i.e., capital expenditures (CAPEX) and operational expenditures (OPEX)) and simplify energy management with assumed rule-based approaches. The rule-based approach refers to the conditional rules defining the operational sequence of each power plant (e.g. in case of surplus power > stored in batteries). However, rule-based methods cannot guarantee the system's optimal output. On the other hand, studies on energy systems in deregulated markets usually used VPP as a terminology for system trading energy with the grid, focusing only on energy management and economic dispatch of power plants. These studies assumed power plant sizes and considered them to be existing. The current research will use the model developed by [9] and apply a newly proposed exhaustive search method to implement investment cost minimisation. Energy trading profit maximisation ensures optimal profit and that investment costs related to power plants' sizes are feasible. Although the proposed method is simple and computationally expensive, it is reliable in presenting insightful results, showing the relations between all possible power plants' sizes and the resulting profit, CAPEX and OPEX, and payback period.

2. Literature review

The literature overlooked the simultaneous sizing of aggregated energy systems and energy management optimisation. In sizing problems, energy management used to be solved with a designed set of rules. The sizing problem used to be solved through optimisation to find the minimum cost of energy (COE) integrating investment costs, which are functions of the energy system's capacity (i.e. decision variables) [10]. On the other hand, operation management or dispatch optimisation is employed to find an energy system's optimal output power or thermal energy profile that would enable it to maximise profit from selling and exchanging energy. The resolution requirements of the two methods (COE & Profit maximisation) are different; the COE, for example, could be solved annually. However, profit maximisation should be solved at least hourly or sub-hourly. However, the total energy produced by a system, the COE function's denominator for a system combining aggregated technologies, should be optimally obtained from the energy management solution. Many researchers ruled out energy management in the COE approach or simplified it by overlooking many sources of profits, and this method still has the drawback of ignoring the actual tariff conditions of the case being researched.

2.1. Investment costs minimisation objective

The literature on investment cost minimisation of aggregated power systems mainly studied Microgrids and Energy Hubs, not VPPs. Therefore, it did not include energy trading with the grid as a significant source of profit. The studies commonly aimed to find the power plant sizes that mutually achieve the minimum COE. Mahmoud, et al. [11] attempted to find the optimal sizing of an off-grid Microgrid consisting of wind turbines, solar PVs, battery storage systems and diesel generators to achieve the minimum COE. Mahmoud, et al. [11] used Salp swarm algorithms (SSA), grey wolf optimiser (GWO), and improved GWO (IGWO), and achieved 0.2182 $/kWh with the IGWO algorithm. However, this value is still higher than the electricity tariff in Egypt, which means that the proposed system cannot be practically implemented. According to Mahmoud, et al. [11], the COE is a function of capital, replacement, and annual operation and maintenance (O&M) costs. In both studies, estimating diesel generators' fuel cost is very important and ideally obtained from proper energy management of the system. However, a rule-based approach defining the operation of each system on a conditional flow chart is followed. Elkadeem, et al. [12] used the Tunicate Swarm Algorithm (TSA) to estimate the size and configuration of an off-grid Microgrid consisting of solar PV wind turbines, battery storage and a diesel generator. The achieved COE is 0.33 $/kWh, higher than the electricity tariff. Attempting to explore more algorithms, El-Sattar, et al. [13] compared in another study 4 different optimisation algorithms, namely the Slime Mold Algorithm (SMA), Seagull optimisation algorithm (SOA), grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and Sine Cosine Algorithm (SCA), to find the optimal configuration of a hybrid system to minimise the COE. The study aggregated solar PV, Wind turbines, biomass generators, and battery systems. It achieved a COE of 0.11 $/kWh with SMA, which is higher than the electricity tariff currently at 0.046 $/kWh. Similarly, detailed energy management or dispatch optimisation is not considered in these studies; only a rule-based approach, an assumed operation management strategy, is applied.

An off-grid Microgrid was presented by Elkadeem, et al. [12] Also, the aim is to find the sizes of the hybrid system components that would achieve the minimum energy cost, which is a function of the investment costs. The system consisted of a wind turbine, solar PV, diesel generator, fuel cell, batteries, and gas-fired boiler. The model is solved with HOMER software [14], and achieves 0.15 $/kWh, which is higher than the electricity tariff in Egypt. Ramli, et al. [15] used a multi-objective self-adaptive differential evolution algorithm to configure an off-grid Microgrid in KSA consisting of solar PVs, wind turbines, diesel generators and battery storage systems and achieved a minimum COE of 0.081 $/kWh, which is double the current electricity tariff in KSA standing at 0.048 $/kWh. Mandal, et al. [16] used HOMER to optimise the sizing of an off-grid Microgrid in Bangladesh, consisting of solar PVs, diesel generators and battery storage systems and achieved a minimum COE of 0.37 $/kWh, which is higher than the current electricity tariff, which is at 0.052 $/kWh. Cano, et al. [17] also used HOMER to configure an off-grid microgrid in Ecuador, which consisted of a biomass power plant, solar PVs, battery storage systems, and hydrokinetic turbines, and achieved a minimum COE of 0.118 $/kWh. The obtained COE value by Cano, et al. [17] is slightly higher than the electricity tariff in Ecuador, which is currently at 0.096 $/kWh. All the previous studies assumed operation management with conditional rules and did not implement an optimisation method. Such a rule-based method would not guarantee that the optimal profit is achieved and the system is efficiently operated. In addition, several studies included thermal plants (e.g. diesel or biomass plants) and overlooked how to utilise their waste heat for thermal demand coverage. Detailed energy management is necessary when both heat and power are being optimised.

2.2. Profit maximisation objective

This section reviews the VPPs' related literature, mainly focusing on developing energy management or dispatch optimisation methods for profit maximisation from energy trading in the market. This category lacks the proper definition of power plant sizes; most studies assumed the plants' sizes as an initial input for their research. In VPP-related literature, the rules of deregulated markets' trading platforms are used as the boundary of hourly dispatch optimisation for profit maximisation. [18–20]. The reviewed studies vary regarding the aggregated technologies, optimisation algorithms and consideration of simultaneous heat and power operation management. They all share the trading in deregulated electricity markets such as day-ahead markets, balancing (real-time) markets, ancillary services or spinning reserve markets. In that case, the objective functions used for the relevant studies are tailored to maximise the profit from trading on a time-series basis (hourly or sub-hourly). However, these studies assume that the systems sizes are known and not a matter of optimisation; therefore, minimisation of their investment costs, hence, capacities optimisation, are not considered.

Basu [21] presented a bottlenose dolphin optimiser (BDO) to solve the day-ahead scheduling of VPP that covers electrical, thermal and cooling demand and consists of micro-biomass plants, wind turbines, solar thermal plants, batteries, thermal storage systems, electric vehicles, electric chillers and absorption chillers. Basu [21] The study only aimed to demonstrate that BDO is superior to other algorithms and found that it earns 5.25 % and 9.82 % higher profits than a modified PSO and GWO. However, the system's investment costs are not addressed. Aghdam, et al. [22] presented a MINLP to maximise day-ahead profit for a VPP model combining diesel generators, CHPs, solar and wind power plants, batteries, and thermal storage systems. For modelling the uncertainty of wind and solar power, Aghdam, et al. [22] used chance-constrained programming, which is a probabilistic method for modelling uncertain parameters. Aghdam, et al. [22] also did not consider the investment costs and treated the plants' sizes as predefined or assumed. Another probabilistic scenario-based approach was presented by Rahimi, et al. [23], to consider the uncertainty of wind speed and market prices for a VPP consisting of conventional plants, solar PVs, solar thermal plants, wind turbines, CHPs, and batteries. MILP solves the optimisation, simplifying the conventional plant's and the CHP's part-load non-linear functions. Like the previous studies, investment costs and sizing are not addressed.

Ju, et al. [24] attempted to introduce MINLP to solve a VPP model aggregating Power to Gas units, gas storage tanks, wind turbines, solar PVs, Gas Turbines, Electric Vehicles, and controllable loads, considering the quadratic function of the CGT efficiency. Ju, et al. [24] found that MINLP is complex to solve, time-consuming and complicated to obtain an optimal solution, and switched to MILP instead by linearising the non-linear functions by piecewise approximation. On the other hand, other studies used heuristic methods for easier and faster computation of non-linear models, such as Particle Swarm optimisation (PSO) [25] and Genetic algorithm (GA) [26]. Maleki, et al. [27] compared both GA and PSO algorithms to maximise the energy trading profit of a VPP aggregating solar PVs, wind turbine, a fuel cell that operates for heat and power supply and a thermal storage tank. It was found that PSO is superior to GA by 0.7 % only for this VPP model.

[28] presented a bi-objective optimization for an Energy Hub, aggregating wind farms, CHPs, and energy storage systems, supplying power and thermal energy. The optimization in the upper level aims to maximize the profit from trading with the energy exchange platforms, while in the lower level aims to minimize the operational costs. The study presents a different approach for energy management compared to others, however, it also overlooked to include the systems' sizing and investment costs assessment. Similarly, [29] attempted to minimize the cost of energy purchased from the grid for an Energy hub consisting of wind turbines, solar PVs, CHPs and energy storage units. [29] also did not consider investment costs optimization and assumed the systems' sizes. [30] attempted to minimize the capital and operation & maintenance (O&M) costs of an islanded aggregated system (i.e. resembling a Microgrid) integrating wind turbines, CHPs, Electric Vehicles, thermal energy storage units and compressed air energy storage (CAES). The study highlights the economic benefit of the CAES compared to battery and hydrogen storage. However, by including only capital and O&M costs as an objective function, [30] did not model the profit/revenues achievement by the system and also did not report the payback period of the system, hence, the feasibility of the system is unknown. In addition, the study did not model the interaction with the grid, since the system is assumed to be islanded. [31] attempted to minimize the operational costs and power loss penalty for an aggregation of renewables and hydrogen storage system. However, the focus of the study was concentrated on the reliability and the network flexibility side and did not include the source of profits from energy trading nor the investment costs (CAPEX & OPEX) minimization. [32] presented an optimization study for a energy hub consisting of renewables, CHPs, Electric Vehicles, boiler and energy storage systems. The optimization aims at maximizing the profit from energy trading in the day-ahead market, however, it also did not include optimization of investment costs, yet the economic feasibility of the system is unknown. [33]attempted to maximize the profit of energy trading with day-ahead and reserve market, for a VPP consisting of wind turbines, energy storage systems and demand response program. The study presents insightful comparisons between different stochastic and robust optimization methods and their corresponding calculation time, however, it did not include investment costs optimization nor discussed economic feasibility of the analyzed system.

Table 1 depicts the literature review summary and the positioning of the current research within the literature:

2.3. Literature gaps and contributions

The previously reviewed studies aimed only at energy management and attempted to develop methods to achieve higher profit. However, if not assessed against the investment costs of the energy systems, the achieved profit might not be enough to reach the break-even point of the system's lifetime. By overlooking the investment costs, the economic feasibility of the system might not be guaranteed. The literature has overlooked to consider both objective functions to design and plan the energy management of a VPP. In addition, the literature has not yet applied the exact strict rules of energy trading between a privately owned aggregated energy system (i.e. VPP or Microgrid) and the grid, in a regulated electricity market. That means that the actual energy prices of the regulated markets were not considered in the relevant studies. Instead, studies aimed to find the energy systems' sizes to achieve a minimum Cost of Energy (COE) that mostly resulted higher than the actual existing electricity prices of the market being analyzed. Finally, the literature has overlooked the consideration of thermal energy sales as a source of profit for VPPs in regulated markets.

This research attempts to advance the state-of-the-art by further developing the concept of VPPs in regulated markets as follows:

– This work is the first to approach the capacity planning of an aggregated energy system with detailed hourly energy optimisation for a whole working year period. The presented method is iterative, based on preparing permutations of all possible sizes configurations that would cover the energy demand of the case study, and for each permutation, energy management is performed on hourly resolution. The sizes configuration that achieves the highest life cycle profit is decided to be optimal, and the whole space of solutions is reported for better insight. The proposed method enables an economically feasible Virtual Power Plant considering the regulated electricity market's existing tariffs and energy prices. This will advance the state-of-the-art system, which solves similar systems with minimum COE methods and usually yields higher values than the existing prices.
– The presented method advances state-of-the-art by exploring and graphically representing the whole feasible space of solutions of a VPP, which is necessary for developers and decision-makers. In contrast, the state-of-the-art presented alternative bi-objective functions, which usually report a single optimal solution.
– This work is one of the few to address the challenge of different levels of energy modelling resolutions where the investment cost minimisation is done on annual resolution, and the dispatch optimisation is done on hourly resolution.
– This work provides residential heating, cooling and electricity demand profiles in Egypt that could be used in case studies with similar weather conditions. Such a vital input has mostly been overlooked in regulated markets' related literature or Microgrid-related literature, where energy demand was assumed or obtained as a monthly average. The energy demand profiles constructed in this paper will improve the quality of further work on VPPs or Microgrids in the exact case study location or other countries with similar weather and conditions.

The rest of the paper is organised as follows: section. 3 presents the research problem statement and VPP model. Section 4 explains the methodology, section. 5 presents the case study inputs and energy demand profiles. Section 6 presents the numerical and graphical results, and section 7 presents the conclusion.

3. Problem statement

The VPP model in focus of this research is based on the energy exchange framework concept proposed for regulated markets by Elgamal, et al. [9]. The VPP in this research is assumed to be applied for residential compounds in a regulated energy market-adopting country. The VPP model, as shown in Fig. 1, aggregates rooftop solar PVs, CCHPs, absorption chillers, electric chillers, and energy storage units, and performs energy trading with the grid. The difference between this model and a typical Microgrid is that a Microgrid may or may not be tied to the grid. If grid-connected, it mainly exchanges power with the grid to balance supply and demand and not for profit maximisation. Alternatively, this VPP model must ensure that there is a surplus sold to the grid under a Power Purchase Agreement (PPA) and gain profit from selling this surplus and from selling electricity and thermal energy to consumers.

It is assumed that each building block has a set of solar PV panels, occupying a maximum available area of 60 % of the rooftops, as suggested by Paidipati, et al. [43]. The solar power is backed up by either battery storage systems (BSS) or a combined heating and cooling power plant (CCHP). The concept of selecting a CCHP in this aggregation is to improve the overall energy efficiency and avoid dumping heat into the atmosphere, and from an economic perspective, to attain another source of profit from selling thermal energy to consumers. The plant could be either engine-based (internal combustion engine, Stirling engine, gas turbine) [44] or fuel-cell [45]. However, in this research, a gas engine is used. An absorption chiller is added to the aggregation for cooling

Table 1
Comparison between the achieved results and the literature.

Reference	Objective of the study	Solution Method	Power	Heating	Cooling	Energy management/ Profit maximization considered?	Deregulated/ Regulated Market?	Using market's Energy Prices /Calculating required COE?	Systems Sizing optimization considered?
[10]	Systems Sizing to achieve min. COE	Whale Optimization Water Cycle Optimization Salp Swarm Optimization Grey Wolf Optimization	Yes	No	No	No	Regulated	COE	Yes
Mahmoud, et al. [11]	Systems Sizing to achieve min. COE	Salp Swarm Optimization Grey Wolf Optimization Improved Grey Wolf Optimization	Yes	No	No	No	Regulated	COE	Yes
El-Sattar, et al. [34]	Systems Sizing to achieve min. COE	Tunicate Swarm Algorithm (TSA)	Yes	No	No	No	Regulated	COE	Yes
El-Sattar, et al. [13]	Systems Sizing to achieve min. COE	Slime Mold Algorithm (SMA) Seagull optimization algorithm (SOA) Grey Wolf Optimizer (GWO) Whale Optimization Algorithm (WOA) Sine Cosine Algorithm (SCA)	Yes	No	No	No	Regulated	COE	Yes
[12]	Systems Sizing to achieve min. COE	HOMER	Yes	Yes	No	No	Regulated	COE	Yes
[15]	Systems Sizing to achieve min. COE	Multi-objective Self-Adaptive differential evolution algorithm	Yes	No	No	No	Regulated	COE	Yes
[16]	Systems Sizing to achieve min. COE	HOMER	Yes	No	No	No	Regulated	COE	Yes
[17]	Systems Sizing to achieve min. COE	HOMER	Yes	No	No	No	Regulated	COE	Yes
[18]	Dispatch management to maximize the energy exchange profit	MILP	Yes	No	No	Yes	Deregulated	Market's energy prices	No
[19]	Dispatch management to maximize the energy exchange profit	Probabilistic MILP with – Estimate Method	Yes	Yes	No	Yes	Deregulated	Market's energy prices	No
[35]	Dispatch management to maximize the energy exchange profit	MINLP	Yes	No	No	Yes	Deregulated	Market's energy prices	No
[24]	Dispatch management to maximize the energy exchange profit	MINLP	Yes	No	No	Yes	Deregulated	Market's energy prices	No
[27]	Dispatch management to maximize the energy exchange profit	Metaheuristics (GA & PSO)	Yes	Yes	No	Yes	Deregulated	Market's energy prices	No
[36]	Dispatch management to maximize the energy exchange profit	PSO	Yes	No	No	Yes	Deregulated	Market's energy prices	No
[37]	Dispatch management to maximize the energy exchange profit	MILP	Yes	No	No	Yes	Deregulated	Market's energy prices	No
[21]	Dispatch management to	Bottlenose dolphin optimizer (BDO)	Yes	Yes	Yes	Yes	Deregulated	Market's energy prices	No

(continued on next page)

Table 1 (*continued*)

Reference	Objective of the study	Solution Method	Power	Heating	Cooling	Energy management/ Profit maximization considered?	Deregulated/ Regulated Market?	Using market's Energy Prices /Calculating required COE?	Systems Sizing optimization considered?
	maximize the energy exchange profit								
[22]	Dispatch management to maximize the energy exchange profit	MINLP	Yes	Yes	Yes	Yes	Deregulated	Market's energy prices	No
[23]	Dispatch management to maximize the energy exchange profit	Probabilistic MILP	Yes	Yes	No	Yes	Deregulated	Market's energy prices	No
[38]	Dispatch management to maximize the energy exchange profit	DDPG (Machine-learning Category)	Yes	No	No	Yes	Deregulated	Market's energy prices	No
[39]	Dispatch management to maximize the energy exchange profit	Deep Reinforcement Learning	Yes	No	No	Yes	Deregulated	Market's energy prices	No
[40]	Dispatch management to maximize the energy exchange profit	Deep Reinforcement Learning	Yes	Yes	No	Yes	Deregulated	Market's energy prices	No
Gao and Lin [41]	Dispatch management to maximize the energy exchange profit	Deep Reinforcement Learning	Yes	Yes	No	Yes	Deregulated	Market's energy prices	No
[42]	Dispatch management to maximize the energy exchange profit	Deep Reinforcement Learning	Yes	Yes	No	Yes	Deregulated	Market's energy prices	No
Current Research	Dispatch management to maximize the energy exchange profit + Sizing Optimization according to a Life Cycle Cost Analysis	1-Comparing Optimization (MILP & GA) & Machine Learning (DDPG) Categories for dispatch management for profit maximization 2-Finding the optimal system's sizes that achieves minimum life cycle cost/maximum life cycle profit after performing energy management for each sizes configuration	Yes	Yes	Yes	Yes	Regulated	Market's energy prices (Considering Existing Tariff, Existing PPA Price and assuming thermal tariff)	Yes

energy supply purposes to convert the waste heat to cooling energy. Later, it will be shown that if a shortage of thermal energy supply occurs, an electric chiller will compensate for this shortage, and its required power will be added to the power balance. Therefore, an electric chiller is also integrated into the VPP.

Thermal energy storage systems are included in the VPP to assess their effectiveness and impact on profit and costs. As suggested by Sørensen [46], energy storage is necessary for 100 % renewable energy targets; however, dispatchable power plants could back up renewables for less than 100 % of the target. However, considering the regulated markets' limitations and relatively lower tariffs than deregulated markets, it is questionable whether energy storage or dispatchable plants are economically viable from investment costs and achieved energy trading profit perspectives. A quantification of this statement is needed, and an overall insight into the systems types, sizes and overall achieved profit will be helpful for further research.

To illustrate the energy exchange framework, the VPP aggregates DERs segregated in a residential compound and sells power and thermal energy to consumers attempting to cover their power demand and space cooling & heating demands. The VPP is connected to the grid through a PPA that enables it to sell surplus power (mainly from solar PVs) to the grid at a predefined feed-in tariff price announced by the government for the relevant renewable energy source (which, in this research, is solar power). If there is any shortage in power demand not satisfied by solar power, the shortage could be imported from the grid, covered by the BSS, or covered by ramping up the CCHP and utilising its resulting waste heat by storing it in TES units, selling it as thermal energy to consumers if possible, or evade it to the atmosphere. If power is imported directly from the grid, the VPP will act as a mediator only between the grid and consumers, meaning that it does not make a profit from this import,

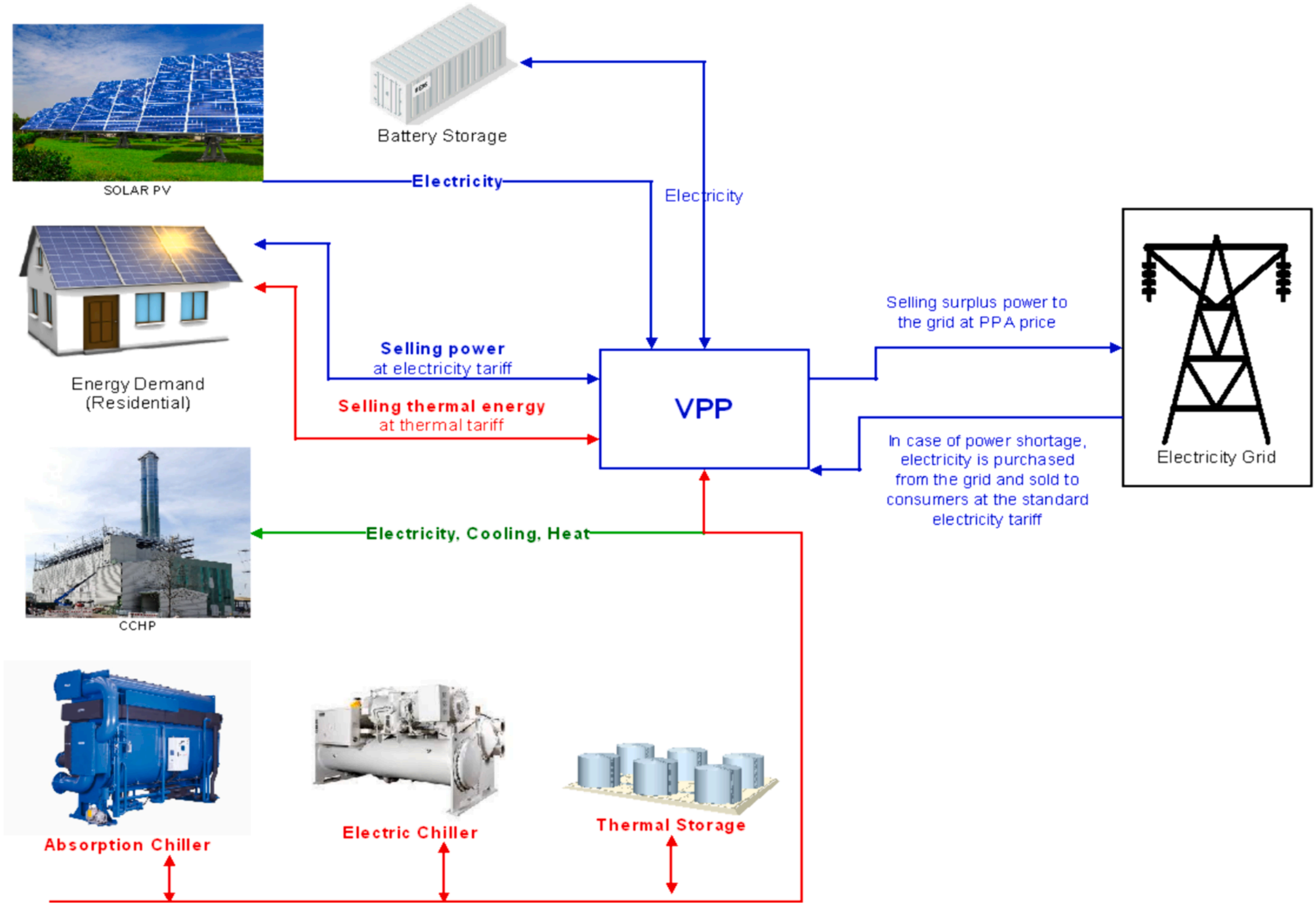

Fig. 1. VPP model framework.

which is a fair concept for the consumers.

The energy management, performed each time step, should be typically driven by the aim of energy exchange profit maximisation. The main problem aimed to be solved by this research is the absence of investment costs of each system in the time-dependent profit maximisation objective. This problem leads to the inability to assess the economic feasibility of a VPP. The research will highlight the importance of the sizing consideration by assessing a VPP with only assumed sizes, not calculated, under a profit maximisation function and compare it with the proposed framework that addresses profit maximisation and sizing. The problem of considering investment costs arises because the profit maximisation function is solved on hourly or sub-hourly resolution. In contrast, investment costs are relevant to the energy systems' capacities, calculated annually. The problem must be solved simultaneously, considering the variation in resolutions.

4. Methodology

4.1. Solution framework

This section will explain the proposed framework for simultaneous sizing and operation management. The proposed method is based on an exhaustive search/iterative framework. The objective function minimises the life cycle cost related to capital costs (CAPEX), operational & maintenance costs (OPEX), and the annual profit from trading energy with consumers and the grid. The main challenge to solving this problem is that the investment costs (CAPEX & OPEX) depend on the components' maximum values and the total annually produced energy from the CCHP; hence, the investment costs are solved on a yearly resolution. On the other hand, the energy trading profit must be solved by energy management solutions, at least on hourly resolution. Accordingly, the proposed framework, as shown in Fig. 2, is based on nested loops, where the sizing will be from the outer loop considering the yearly resolution, and the energy management will be solved as the inner loop considering the hourly resolution. The solution concept in the literature is called the exhaustive search method. [47], also called local search by brute force [48], has the advantage of searching all possible outcomes of the analysis.

The initial step in this framework is to initialise several upper-bound values for each component and produce combinations of these values. The energy management optimisation, fed by each combination representing the upper boundary for the corresponding components, will run for 288 steps (representing a day per month). The energy management runs considering the first combination; the annual profit is extracted and discounted as per the assigned discount rate; after the energy management is finished for that combination, it is followed by a computation of the investment costs, plotting of the discounted life cycle cost against the discounted profit and calculation of the payback period. The following combination is fed into the energy management optimisation till all combinations are assessed. Eventually, using this method, the results of each combination are reported, mainly including the discounted profit, discounted life cycle costs, payback period, grid dependency, and calculated component sizes). The combination that achieved minimum life cycle costs is selected for a refined complete profit maximisation optimisation during 8760 h to obtain reliable results, and the life cycle costs are re-assessed. Although the described method may seem essential and time-consuming, it is beneficial to reach an insightful solution with a clear quantitative result that enables the drawing of statistical relations between the components' sizes and the resulting economic results. This way, high-level graphical results could be extracted to

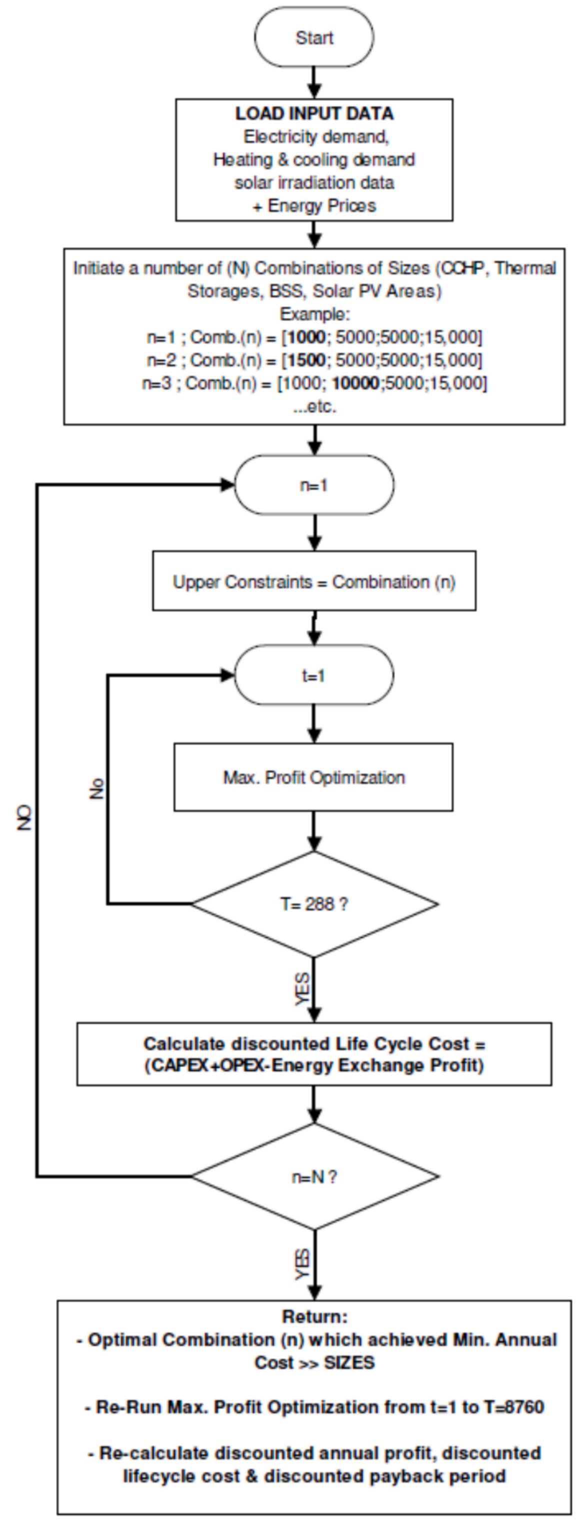

Fig. 2. Exhaustive search framework for simultaneous sizing and energy management.

understand how the optimal sizes are achieved.

Regarding the incorporated energy management method, GA is the most suitable approach for a near-optimal solution. From the literature review, it is noticed that one of the efficient categories of algorithms to solve mixed integer non-linear programming is the metaheuristic methods such as Genetic algorithms (GA), Particle swarm optimisation (PSO), artificial bee colony (ABC) and simulated annealing (SA) [49]. Meta-heuristic algorithms are widely used in literature to solve such complex problems; algorithms such as GA, PSO [36], Ant colony [50], Imperial Competitive algorithm [51], and others. By comparing the most common heuristic algorithms, PSO and GA, it was found that GA achieved better results than others [27]. It is incorporated in this research to solve the profit maximisation objective.

The difference between the steps of this proposed method and the literature is that traditionally, the studies aiming for energy systems sizing consider energy management with rules. This can be clearly shown in many researchers' presented conditional flowcharts precisely defining, for example, power generated from wind or solar as inputs, when to charge/discharge the storage systems, and when to dispatch conventional plants [52,53]. This research eliminates the rule-based approach and aims to find a suitable method for running non-biased optimal calculations for the systems' sizing from the high level (yearly resolution) and for the dispatch of each system from the lower level (hourly resolution). This non-biased calculation also considers renewable plant sizes as a variable to be sized, as it is based purely on the economic objective function. Other technical parameters, such as grid dependency ratio and solar power share, are metrics resulting from the simulation.

As the target of the current process is to size the components, the combination of sizes may encounter times when the supply could be lower than the demand. Thus, the problem requires further consideration of any possible imbalance. Initially, the boundary of this research is that the thermal energy supply from the CCHP waste heat and the thermal storage systems must be consistently higher than the thermal demand. That boundary, by default, enabled the definition of the upper bound of the CCHP in the previously assessed energy management approaches. However, as we explore the possibility of all system sizes, a range of CCHP sizes might not satisfy the thermal demand. In this case, a new variable represents the thermal imbalance (i.e. the non-satisfied thermal demand). As a practical implementation and to reflect that imbalance as a cost, an electric chiller is assumed to cover the thermal imbalance as a backup to the absorption chiller. The profit function reflects the thermal imbalance by subtracting it from the thermal demand part. The thermal imbalance is converted back to the electrical side since it will be covered by the electric chiller, using the corresponding cooling coefficient of performance (COP_{ec}) of 4 [54]. The capital cost of the electric chiller is applied as 108 $/kW [55].

4.2. CCHP modeling

The specific type of the described system suits a "micro-CCHP", also gas-powered, with a relatively lower rating than central CCHP. A study by Martinez, et al. [56] showed different heat-to-power ratios for other

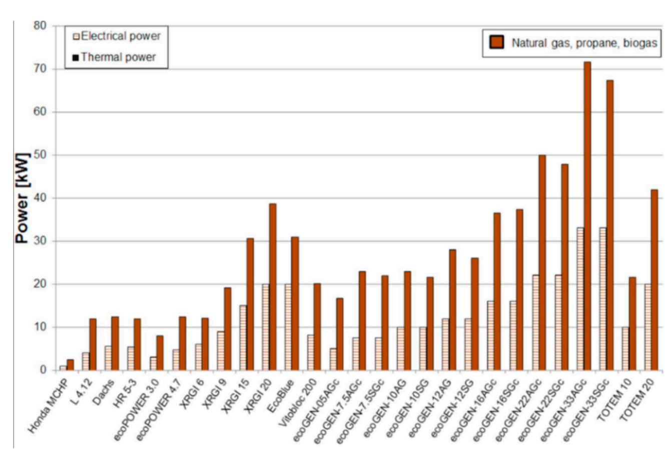

Fig. 3. Electrical and thermal power for different micro-CHP manufacturers [56].

manufacturers as shown in Fig. 3, ranging from 1 kWe and 2.5 kWth to 33 kWe and 71.6 kWth. However, the previous values assume a constant relation between heat and power regardless of the part-load effect. In this research and for accurate modelling, electrical and thermal efficiencies are defined as functions of part load [57]. In the formulas used by [57], the nominal electric efficiency is a function of a logarithm of the rated CCHP power, and this electric efficiency is used later to calculate the thermal efficiency. It should be noted that the variation in electric efficiency is very sensitive and dramatically changes the other parameters. In this research, micro-CHPs are used, and they are characterised by relatively low efficiency. Assuming one micro-CHP has around 50 kW, the nominal electric efficiency ($\eta_{CCHPe\_nominal}$) = 26.5 %. The range between 10 kW and 70 kW shown in Fig. 3 yields 25.1 %–26.7 %. Therefore, the estimated value of 26.5 % could be justified. It is also in the range estimated by Taie and Hagen [58], which varied between 25 % and 27 %. In this case, the thermal efficiency is 59.49 %, and the nominal heat-to-power ratio is 2.24.

It should be noted that the efficiency formula is used to calculate the nominal electric efficiency of 1 unit for accurate modelling of the heat-to-power ratio. However, as the commitment of each unit separately is beyond the scope of this analysis, the remaining efficiency formulas are modelled as functions of the total output power of all CCHP units.

As the CCHP is the only emitting component in this VPP, it should be highlighted that in countries where CO2 emissions are penalised, this penalty should be reflected in the profit formula. However, this does not apply to the electricity market analyzed in this research.

$$\eta_{CCHPe\_nominal} = 0.0194.\, ln(P_{CCHP_{max}}) + 0.2321 \tag{1}$$

$$\eta_{CCHPe,t} = \eta_{CCHPe\_nominal}\left(0.1024\left(\frac{P_{CCHP,t}}{P_{CCHP_{max}}}\right)^3 - 0.7332\left(\frac{P_{CCHP,t}}{P_{CCHP_{max}}}\right)^2 + 1.0155\left(\frac{P_{CCHP,t}}{P_{CCHP_{max}}}\right) + 0.6153\right); \quad t = 1, \cdots, T \tag{2}$$

$$\eta_{CCHPth,t} = \eta_{CCHPth\_nominal}\left(0.2656\left(\frac{P_{CCHP,t}}{P_{CCHP_{max}}}\right)^3 - 0.2972\left(\frac{P_{CCHP,t}}{P_{CCHP_{max}}}\right)^2 + 0.0939\left(\frac{P_{CCHP,t}}{P_{CCHP_{max}}}\right) + 1.1255\right); \quad t = 1, \cdots, T \tag{3}$$

$$\eta_{CCHPth\_nominal} = \eta_{HEX}.(0.926 - \eta_{CCHPe\_nominal}) \tag{4}$$

$$\dot{m}_{f,t} = \frac{P_{CCHP,t}}{\eta_{CCHPe,t}.LHVf}; \quad t = 1, \cdots, T \tag{5}$$

$$Q_{th,t} = \eta_{CCHPth,t}.(\dot{m}_{f,t}.LHVf); \quad t = 1, \cdots, T \tag{6}$$

$$\gamma_t = \frac{Q_{th,t}}{P_{CCHP,t}}; \quad t = 1, \cdots, T \tag{7}$$

4.3. Absorption chillers modeling

The primary sources of heat that could be significantly recovered from ICE engines are low-grade heat from jacket water, which cools the engine, and high-grade heat from exhaust from the combustion process [59]. A double-effect absorption chiller will provide chilled water output to utilise both heat sources. The most common type of absorption chiller is LiBr-H2O, divided into two types: single effect, which recovers temperatures less than 120 °C with a rated COP of around 0.7, and double effect, which recovers exhaust heat and temperatures more than 120 °C with a typical COP up to 1.4 [60]. In this research, a double effect type Absorption chiller with a rated COPc = 1.4 will be used in the model; however, as COP varies with part load, the non-linear part-load COP function illustrated by Zhou, et al. [61], is employed in this research as shown in equations (8) and (9) for accurate modelling. The rated COP (COPr) is assumed as 1.4, which is in the suitable range of double effect type according to Li, et al. [62]. For space heating purposes, the exhaust heat from the CCHP will pass through a heat exchanger with an assumed efficiency of 90 %.

$$COP = COPr.\left(\frac{\beta_c}{0.015 + 1.24.\beta_c - 0.915.\beta_c^2 + 0.66.\beta_c^3}\right) \tag{8}$$

$$\beta_c = \frac{Q_{cooling}}{Q_{chiller\_rated}} \tag{9}$$

4.4. Solar PV modelling

Solar PV output power is converted from solar irradiation at the location of the case study, assumed available rooftop area and PV panel efficiency. Conversion efficiency depends on the panel temperature, which depends on the ambient temperature; therefore, it is variable with time, which is considered in the model. Online PVGIS application [63], is used to obtain the hourly data for the solar beam direct irradiance (Gb), the diffuse irradiance (Gd), the reflected irradiance (Gr), and the air temperature for 2019, the same year as the demand data. The global irradiance (G) equals the summation of Gb, Gd, and Gr.

The solar PVs are in the form of rooftop units occupying the building roof. The maximum potential area is assumed to be used for solar PVs. Few studies suggested percentages of available regions on flat roofs that solar PVs could occupy. Approximately 60 % of the buildings' rooftops are recommended for flat roofs by Paidipati, et al. [43]. Okutan [64] suggested a solar PV installation area range of 60–70 % of flat roofs and 24 % of pitched roofs. Hong, et al. [65] studied the available area of flat rooftops of buildings with various heights considering the shade areas, and found that at 10 AM, 73 % of the rooftop areas are available. In the case of this research, the buildings have the same heights; therefore, there would be no shading effect. This research assumes that 65 % of the roof will be used for solar PV areas.

The solar power conversion from irradiance, PV areas and panel efficiency is estimated in equations (10), (11) and (12) [66]. Panel efficiency is a function of PV Nominal cell temperature (NOCT), ambient temperature, and the rated efficiency, which depends on the type of the PV panel.

$$P_{PV,t} = \eta_{PV} A_{PV} G_t; \quad t = 1, \cdots, T \tag{10}$$

$$T_{c,t} = T_{o,t} + [\left(\frac{NOCT - 20}{800}\right)].G_t; \quad t = 1, \cdots, T \tag{11}$$

$$\eta_{PV,t} = \eta_r\, x\, [1 - \beta(T_{c,t} - T_{ref})] \quad t = 1, \cdots, T \tag{12}$$

4.5. BSS & TES modelling

Batteries and thermal storage systems are employed to store surplus electrical energy for further reuse when the direct energy supply is not possible. However, when the system is grid-connected, it can be sold to the grid instead of storing the surplus if this is economically advantageous. The decision-making of the storage systems dispatch ideally should oversee the expected peak and low-demand times to select the optimal course of action. The rolling-horizon approach of the simulation in this research is challenging for decision-making. It would make decision-making unaware of the later peak periods, as the solver optimises the variables for each step separately. For that, different energy management solutions will be compared and assessed regarding the optimal use of storage systems. As for the data, roundtrip efficiencies for each BSS and TES system are assumed to be 90 %.

The state of Charge for the hot water and chilled water TES systems and BSS are depicted in equations (13), (14) and (15) respectively [67].

$$E_{CHW\_TES,t} = E_{CHW\_TES,t-1} + \eta_{TES}.Q_{CHW\_TES\_ch,t} - \left(\frac{1}{\eta_{TES}}\right).Q_{CHW\_TES\_disch,t} \leq E_{CHW\_TES\_max,t}; \quad t = 1, \cdots, T \tag{13}$$

$$E_{HW\_TES,t} = E_{HW\_TES,t-1} + \eta_{TES}.Q_{HW\_TES\_ch,t} - \left(\frac{1}{\eta_{TES}}\right).Q_{HW\_TES\_disch,t} \leq E_{HW\_TES\_max,t}; \quad t = 1, \cdots, T \tag{14}$$

$$E_{BSS,t} = E_{BSS,t-1} + \eta_{BSS}.P_{charge,t-1} - \left(\frac{1}{\eta_{BSS}}\right).P_{disch,t-1} \leq E_{BSS\_max,t}; \quad t = 1, \cdots, T \tag{15}$$

4.6. VPP operational constraints

The objective function is stated in equation (16), aiming to minimise the capital and annual operational maintenance costs and maximise the yearly energy exchange profit. The profit maximisation, stated in equation (17) It is modified to quantify and subtract the negative thermal imbalance from the thermal energy sales profit. This imbalance is reflected as an additional power demand, as in equation (18), to reflect the input power of the electric chiller that will be used to cover this imbalance. The thermal balance formulas, as shown in (19) and (20), are also modified to include this thermal imbalance quantity supplied by the electric chiller. Eqs. (21), (22), (23) and (24) represent the ON/OFF binaries to prevent simultaneous import/export from/to the grid, simultaneous charging/discharging of BSSs, and simultaneous charging/discharging of TESs, respectively. Eqs. (25) to (31) represent the lower and upper bounds of the CCHP, grid power purchase, grid power export, TES charging and discharging power.

The solar PV area upper bound is defined as the maximum potential available in the analysed case, so the sizing optimiser must determine the optimal area based on the investment costs.

Minimize:

$$LifeCycleCost = \sum_{k=1}^{K=25}\{CAPEX_k + OPEX_k\}.(1+r)^{-k} - \left\{\sum_{t=1}^{T} Profit\right\}.(1+r)^{-k}$$

$$\begin{aligned} LifeCycleCost = \sum_{k=1}^{K=25}\{[&\boldsymbol{Pcchp_{max}}.CAPEX_{CCHPk} + \boldsymbol{Q_{AC}}.CAPEX_{ACk} \\ &+ \boldsymbol{Q_{EC}}.CAPEX_{ECk} + \boldsymbol{Q_{HEX}}.CAPEX_{HEXk} + Ppv_{max}.CAPEX_{PVk} \\ &+ \boldsymbol{E_{BSS\_max}}.CAPEX_{BSSk} + \boldsymbol{E_{CHWTES\_max}}.CAPEX_{TESk} \\ &+ \boldsymbol{E_{HWTES\_max}}.CAPEX_{TESk}] + [\boldsymbol{Pcchp}.OPEX_{CCHPk} \\ &+ Ppv_{max}.OPEX_{PVk} + \boldsymbol{Q_{AC}}.OPEX_{ACk} + \boldsymbol{Q_{EC}}.OPEX_{ECk} \\ &+ \boldsymbol{Q_{HEX}}.OPEX_{HEXk}]\}.(1+r)^{-k} - \left\{\sum_{t=1}^{T} Profit\right\}.(1+r)^{-k} \end{aligned} \tag{16}$$

$$\begin{aligned} \sum_{t=1}^{T} Profit = \Bigg(&\sum_{t=1}^{T}\left(P_{CCHP,t} + P_{PV,t} + P_{disch,t} - P_{gridsell,t}.(1-u_{grid,t}) - P_{gridbuy,t}.u_{grid,t}\right).\lambda_{el,t} + \left(P_{gridsell,t}.(1-u_{grid,t})\right).\lambda_{PPA,t} + \left(Q_{CHW_{demand},t} + Q_{HW_{demand},t}\right. \\ &\left. - Q_{th\_imbalance,t}\right).\lambda_{DE,t} - \left(\left(\dot{m}_{f,t}\right).C_f\right)\Big)\Bigg) \end{aligned} \tag{17}$$

Subjected to:

$$P_{gridbuy,t} + P_{CCHP,t} + P_{PV,t} + \left(\frac{1}{\eta_{BSS}}\right).P_{disch,t} - \frac{Q_{th_{imbalance},t}}{COP_{ec}} - \eta_{BSS}.P_{ch,t} - P_{gridsell,t} = P_{demand,t}; \quad t = 1, \cdots, T \tag{18}$$

$$COP_c.\left(\gamma_t.P_{CCHP,t}\right) + \left(\frac{1}{\eta_{TES}}\right).Q_{CHW_{TES\_discharge},t} - \eta_{TES}.Q_{CHW_{TES_{charge}},t} + Q_{th_{imbalance},t} = Q_{CHW-demand,t} + Q_{dumped}; \quad t = 1, \cdots, T \tag{19}$$

$$COP_h\left(\gamma_t.P_{CCHP,t}\right) + \left(\frac{1}{\eta_{TES}}\right).Q_{HW\_TES\_discharge,t} - \eta_{TES}.Q_{HW_{TES_{charge}},t} + Q_{th_{imbalance},t} = Q_{HW-demand,t} + Q_{dumped}; \quad t = 1, \cdots, T \tag{20}$$

$$u_{grid} \in \{0,1\}; \quad t = 1, \cdots, T \tag{21}$$

$$u_{bss} \in \{0,1\}; \quad t = 1, \cdots, T \tag{22}$$

$$u_{TES\_CHW,t} \in \{0,1\}; \quad t = 1, \cdots, T \tag{23}$$

$$u_{TES\_HW,t} \in \{0,1\}; \quad t = 1, \cdots, T \tag{24}$$

$$P_{CCHP_{min}} \leq P_{CCHP,t} \leq P_{CCHP_{max}}; \quad t = 1, \cdots, T \tag{25}$$

$$0 < P_{gridbuy,t} < P_{gridbuy\_max,t}.u_{grid,t} \tag{26}$$

$$P_{gridsell,t} < P_{gridsell\_max,t}.(1 - u_{grid,t}) \tag{27}$$

$$0 < Q_{CHW\_TES\_charge,t} < Q_{CHW\_TES\_ch\_max,t}u_{TES\_CHW,t} \tag{28}$$

$$0 < Q_{CHW\_TES\_discharge,t} < Q_{CHW\_TES\_disch\_max,t}(1 - u_{TES\_CHW,t}) \tag{29}$$

$$0 < Q_{HW\_TES\_charge,t} < Q_{HW\_TES\_ch\_max,t}u_{TES\_HW,t} \tag{30}$$

$$0 < Q_{HW\_TES\_discharge,t} < Q_{HW\_TES\_disch\_max,t}(1 - u_{TES\_HW,t}) \tag{31}$$

$$0 < P_{ch,t} < P_{ch\_max,t}u_{BSS,t} \tag{32}$$

Fig. 4. Case Study (Degla Gardens compound) buildings snapshot [68].

$$0 < P_{disch,t} < P_{disch\_max,t}(1 - u_{BSS,t}) \tag{33}$$

5. Case study

5.1. Location

The study is applied to a middle-income housing compound in Cairo, Egypt, representing most new development projects. Middle-income housing is usually characterised by a 6-floor + roof building, each floor having four apartments. The upper middle and high-income housing can vary between large flats but in the context of this research, it is meant to be either townhouses or villas having two floors maximum and a roof available for solar PV installation, usually enclosed in compounds, representing a low-density population. This type of housing has become popular in Egypt, and many developers are rushing to deploy more similar compounds. The case study was selected to be performed in a compound called "Degla Gardens" in the October region of Cairo. A representative snapshot showing the shape of the blocks is shown in Fig. 4. As shown in Fig. 5The compound consists of 285 blocks with an available 200 m^2 roof area. Each block contains 6 floors and 4 × 80 m^2 apartments per floor, making a total of 6840 apartments. The definition of the maximum roof area allows the identification of the maximum possible solar PV panel area occupation.

5.2. Energy demand profiles

The energy demand pattern is the driving input to the VPP. As the energy management basis in this research is hourly optimised, the energy demand profile is essential to represent, as closely as possible, the realistic data regarding values and profile. However, most relevant literature does not provide high-resolution data (e.g. hourly or sub-hourly demand); many studies consider monthly average values, which could be valuable for long-term planning but not suitable for energy management research. In this research, profiles are constructed based on average annual electricity consumption data obtained from Caponigro, et al. [69] and then distributed according to normalised monthly average values from the relatively older study by Hegazy and Moustafa [70]. The daily demand profiles for domestic households in

Fig. 5. Case Study (Degla Gardens compound) map view.

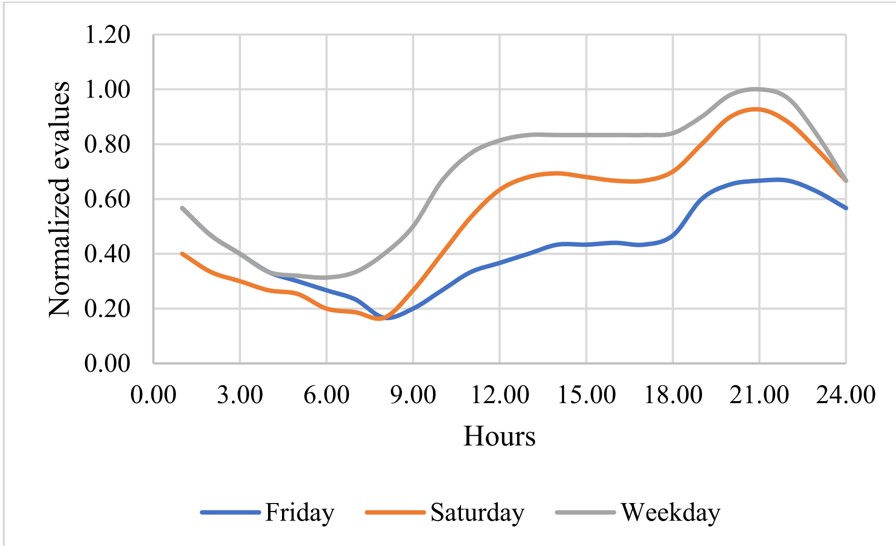

Fig. 6. Normalized hourly electricity demand profile for different types of days.

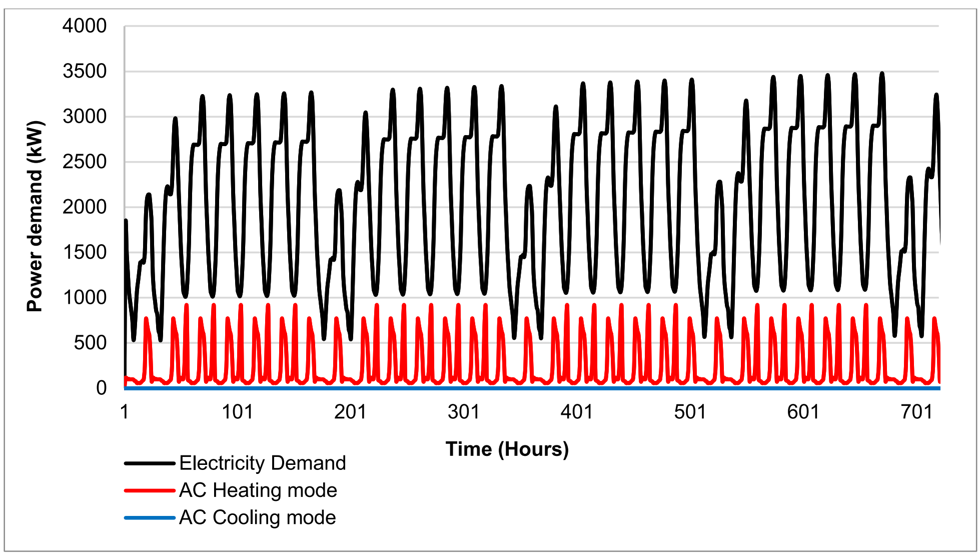

Fig. 7. Power demand, including AC load in heating mode on January 1.

Egypt are obtained from Eljazzar and Hemayed [71], for typical weekend days (Friday and Saturday) and weekdays. These profiles are normalised, as shown in Fig. 6The obtained average consumption values are assigned to the normalised profiles to create 8760 h of annual electricity consumption for the whole residential compound. A typical residential heating demand profile is obtained from Wang and Mancarella [72], while a cooling demand profile is obtained from [73].

The electricity demand, including air-conditioner electric load in cooling and heating mode, is shown in Fig. 7 for January and in Fig. 8 for June, representing winter and summer times. A snapshot of the power demand for 24 h on 1st June is shown in Fig. 9.

5.3. *Energy tariff & PPA pricing*

The pricing in Egypt is divided by monthly consumption categories, as shown in Table 2 for 2023. Prices are converted to USD according to the current rate of May 2023.

The technical parameters of the system based on the previous estimations are summarized in Table 3.

6. Results

6.1. *Baseline case (Energy management with assumed sizes)*

This case is analyzed to establish a better understanding and contrast between the achieved profit and discounted payback period for a VPP with assumed sizes, against the case with researched optimal sizes. This is the case for VPP-related studies that focused on energy exchange profit-maximization objectives without attention to investment costs. In this case, the assumption of the sizes is based on the energy demand profiles. The assumed sizes are reflected on the model, as the upper bounds values of the corresponding decision variables. Regarding the CCHP size, since the air-conditioning load is assumed to be fully replaced by district energy supplied from the VPP model, the system then is supposed to cover the full thermal demand by either the CCHP waste heat or the thermal storage system. Initially, the upper CCHP limit is calculated according to the peak demand which is 11,348 kWth. This peak occurs during cooling demand periods. Assuming heat to power ratio (2.24), as estimated before, and by dividing the peak cooling

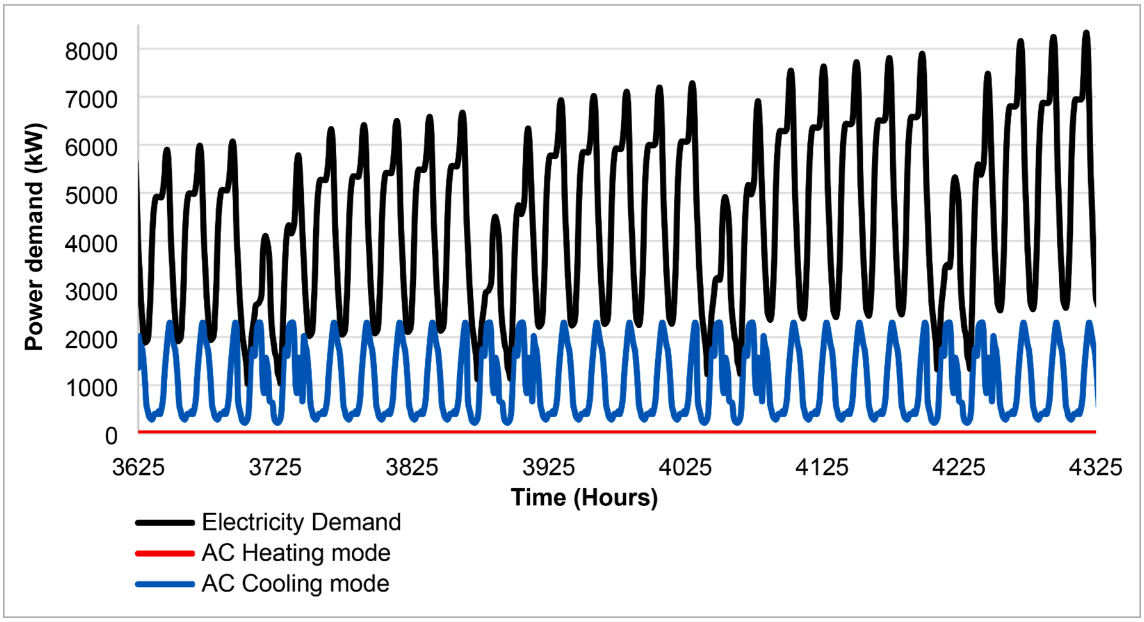

Fig. 8. Power demand including AC load in cooling mode in June.

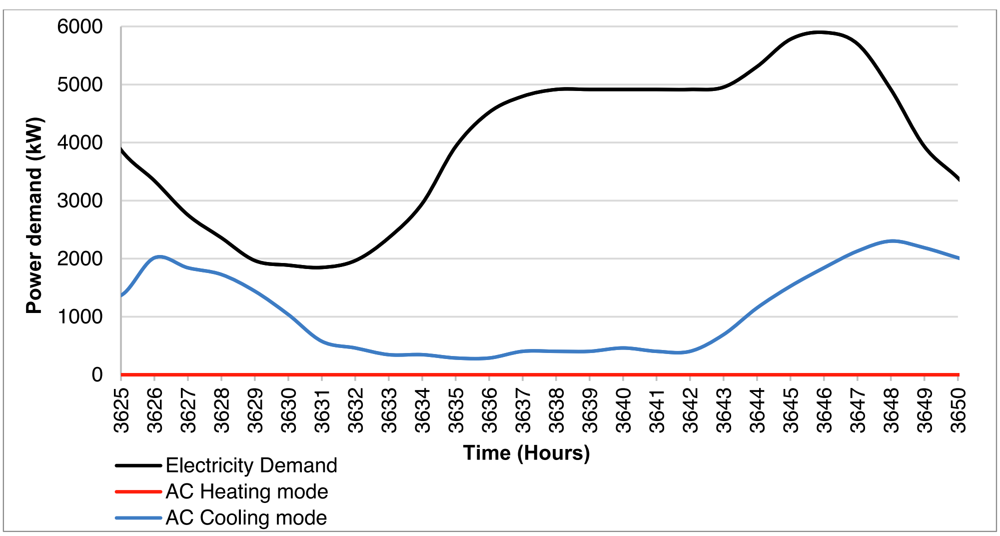

Fig. 9. Power demand for a typical day (24 h) on 1st June.

Table 2
Electricity tariff in Egypt in local currency (EGP) and USD.

Monthly consumption (kWh)	Tariff (EGP)	Tariff (USD)
0–50	0.58	0.019
51–100	0.68	0.022
100–200	0.83	0.027
201–350	1.11	0.036
351–650	1.31	0.042
651–1000	1.4	0.045
>1000	1.45	0.047

demand by the rated COP of the chiller (1.4), the upper limit of the CCHP is taken as 3618 kW.

The solar PV maximum area limit is taken as the maximum available area. Absorption chiller-rated capacity is assumed based on being able to cover the peak space cooling demand, therefore, its upper limit in the model is taken at 11,348 kWth. BSS and TES systems require the definition of the maximum storage capacity (kWh) and the rate of charging and discharging power (kW). According to the Department of Energy SunShot initiative, indicating that TES should maintain energy discharging for a minimum of 6 h [85], it is assumed that the BSS and TES charging and discharging rates equal to 6 times the capacities. The storage capacities are assumed to be equal to the peak demand in order not to overestimate the sizes and consequent investment costs.

Another scenario without BSS is also assessed as a part of the baseline case, given that the BSS investment costs are relatively higher than the other plants, besides requiring replacements every 10 years.

The achieved profit from this case is 26.1 EGP Million and 25.2 EGP Million for the scenarios with and without BSS, respectively. The discounted payback period is more than 25 years for the scenario with BSS, while it reached 13 years for the scenario without BSS. Although the BSSs help to achieve a higher profit and reduce the dependency on the grid, the life cycle costs disqualify them from this market case, as they prove to have very high investment costs and not enough profit to compensate for those costs. The graph result of the life cycle costs is shown in Fig. 10.

Table 3
Technical inputs of the system.

Item	Symbol	Values	Reference
Heat exchanger efficiency	η_{HEX}	90 %	[74]
Absorption chiller-rated COP	COPac_c	1.4	[62]
Heat exchanger efficiency	η_{HEX}	90 %	[62]
Thermal storage systems charging/discharging efficiencies	η_{TES}	90 %	[75]
Li-ion Battery storage system charging/ discharging efficiency	η_{BSS}	90 %	[76]
Temperature of the PV cell at the referenced temperature	Tref	25 °C	[66]
Solar PV panel rated efficiency (Data from local factory)*	η_r	17 %	[77]
CCHP min./max. operating range	$Pcchp_{min}$	10 % of $Pcchp_{max}$	Assumed for gas-powered micro-CHPs knowing that this limit-
CCHP initial upper capacity (kW)	$Pcchp_{max}$	3,618	Estimated according to thermal demand and heat-to-power ratio
Solar PV available area (m^2)	A_{PV}	37,050 m^2	–
Price of selling power to the grid (PPA tariff)**	λ_{PPA}	2.587 EGP/kWh (0.084 USD/kWh)	[78]
Price of selling district energy (thermal energy) to consumers	λ_{th}	0.361 EGP/kWh	Assumed based on consumer energy bill constraint
Nominal electric efficiency of one micro-CCHP unit	η_{CCHPe}	26.5 %	Estimated
Grid carbon intensity	μ_{CO2_grid}	0.923 kg/ kWh	[79]
CO2 emission factor from natural gas	μ_{CO2_NG}	0.220 kg/ kWh	[79]

* Solar PV panels are assumed to be monocrystalline as it has a better efficiency compared to polycrystalline [80].

** The economic parameters of each component are obtained from multiple references, and employed for estimation of the payback period for assessment of the system applicability and further comparison of this study against studies adopting the COE method.

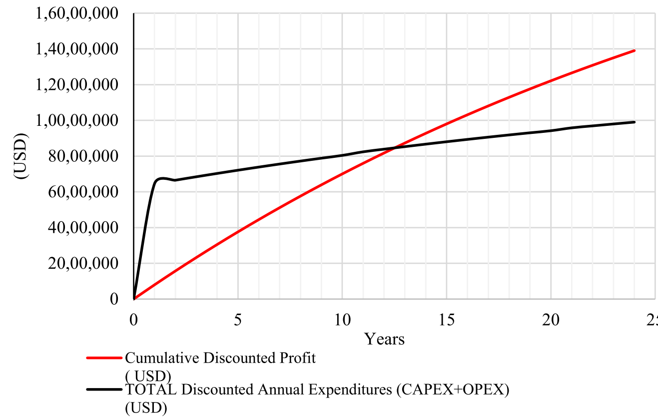

Fig. 10. Life cycle cost, discounted annual profit plot and discounted payback period for the baseline case without BSS.

6.2. *Proposed framework (Sizing & Energy Management) results*

In this framework, as discussed before, a combination of sizes is being economically assessed. The combinations of sizes are automatically generated by assigning values for the CCHP starting from 1500 kW up to the peak power demand, rounded up to 500. 5 values were assigned for the solar PV areas up to the maximum potential area. The storage systems' capacities are divided by 3 values up to the peak power and thermal (heating and cooling) demand with an assumed charging and discharging rate of 1/6 of the capacity if the storage system could contribute during 6 h of the peak day. These splitting results in 3545 combinations. As explained before, each combination is fed into the GA to run its energy management for 288-time steps, thus, the solver runs for the number of combinations multiplied by 288 steps. Higher splitting could be done however, due to computational limitations, the mentioned number of combinations is deemed suitable and was enough to achieve a smooth statistical relations plot as will be shown in the results. To improve the running speed, the initial GA solution is defined with lower parameter (i.e. lower population size), such as 50. After settling on the optimal combination, the energy management is re-simulated again for 8760 h (full year) for a higher population size of 150. This step reduced the running speed per combination to 14 s compared to 30–35 s. The simulation run on MATLAB R2023b, using 4 parallel cores to run the combinations in parallel and combine the results in the end. This renders the total running time to around 192 min

Table 4
CAPEX, OPEX and Lifetime of VPP components.

	CAPEX	OPEX	Lifetime (Years)	Reference
Solar PV [1]	$1635.5.(Ppv_{max})^{-0.104}$USD/kW	10 $/kW/year	25	[81]
BSS	261 USD/kWh	0.004 $/kWh	10	[76]
TES [2]	21 USD/kWh	–	25	[8283]
Absorption chiller	154 USD/kW	1.24 $/kW/year	25	[55]
Electric chiller	108 USD/kW	1.05 $/kW/year	25	[55]
CCHP (Gas Engine) [3]	165 USD/kW	0.01 USD/kWh	25	Contact with a supplier OPEX reference: [84]
Heat Exchanger	31 USD/kW	0.05 USD/kW/year	25	[55]

[1] Solar PV CAPEX is very influential to the sizing of the VPP as it represents the highest CAPEX among all other components. Since the CAPEX & OPEX accurate value depends on the project location and total installed PV capacities, an empirical formula has been proposed by Hamed, et al. [81] for Egypt and different types of PV panels, considering the variability of the CAPEX with the total solar PV capacity. The CAPEX formula includes the costs of structural elements, inverter, labour and wiring [81]. The relevant formula related to monocrystalline panels is used.

[2] Thermal storage tank is assumed to be a standard thermocline system. Investment cost per kW is taken from a detailed analysis by Mostafavi Tehrani, et al. [82], while the lifetime is taken from Cascetta, et al. [83].

[3] Gas Engine operating as the prime mover of the CCHP CAPEX is illustrated in Table 4. The literature presented a lot of different investment costs range for gas-powered CHPs, mostly without presenting references to these costs and using generic and probably old values. For accurate estimation for this research, the price of an 80 kW gas engine is provided by "Weifang Haitai Power Machinery" as 6691 $ including shipping fees. The price is multiplied by 14 % VAT and 15 % customs fees, then multiplied by an assumed value of 150 % to consider installation and contracting fees. OPEX value per kWh is estimated by Mudgal, et al. [84].

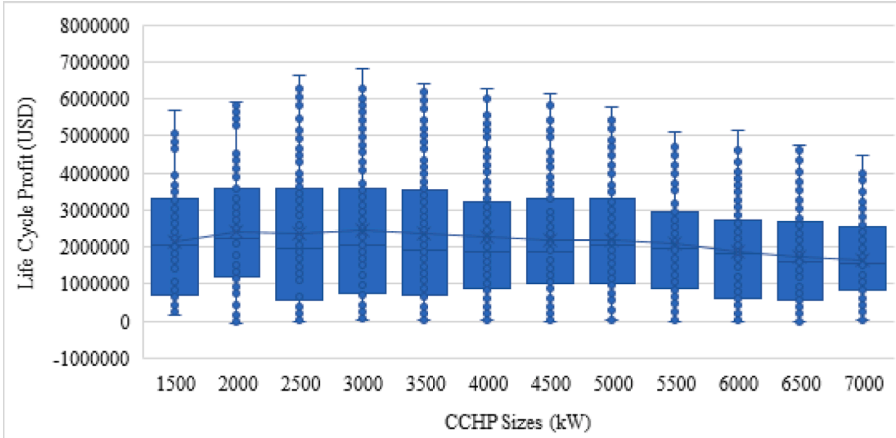

Fig. 11. 2D box plot of the CCHP sizes only vs the total life cycle profit.

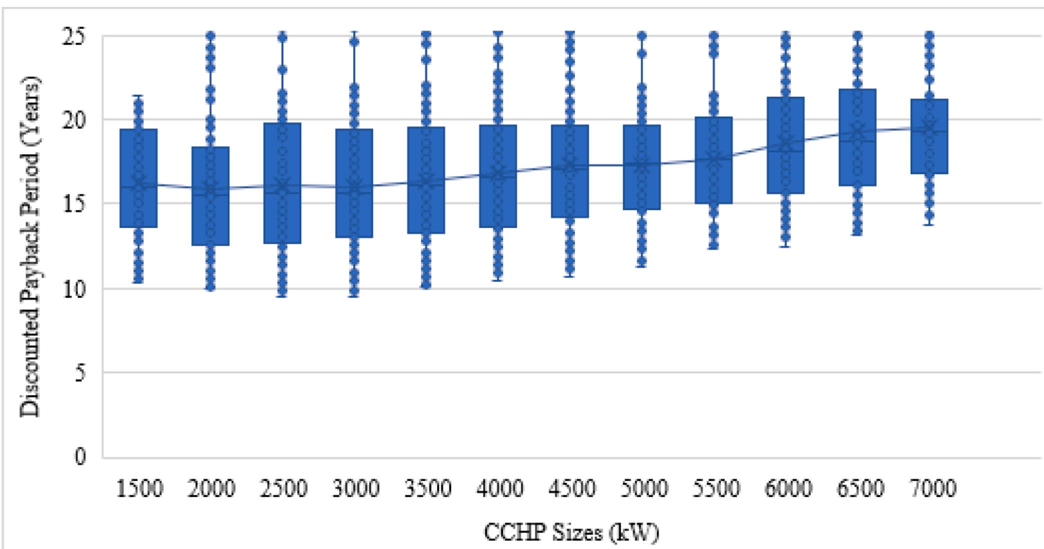

Fig. 12. 2D box plot of the CCHP sizes only vs the discounted payback periods.

(3.2 h).

The life cycle cost, which is the main objective function, is the main criterion for determining the optimal combination, hence, systems' sizes. As can be understood from equation (16), the lowest negative value represents the highest cash flow achieved through the VPP's lifetime. The absolute value of this objective function (i.e. positive value), will be referred to as "Life-cycle-profit" (LCP). The highest LCP achieved by the 288-time steps, which represented 30 days and which could be considered an approximate energy management solution, is 6.8 $ million and the discounted payback period is 9.5 years. After identifying the optimal combination, it is again introduced to the GA to run for 8760 time steps to obtain more refined results, from that run, the total LCP is 5.4 $ million and the discounted payback period is 10.9 years.

Concerning CCHP sizes only, the life cycle cost and payback periods are plotted as 2D box plots against different CCHP sizes as shown in Fig. 11 and Fig. 12, where different points are plotted vertically for each CCHP size. Those points represent different solar PV, TES, and BSS combinations. The solar PV capacities are very significant to both annual profit and investment costs, hence, significantly affecting the life cycle cost. However, It is seen from the listed results that the TES capacities' significance to the life cycle cost can be ignored, and the BSS capacities are raising the CAPEX incredibly in a way to render the payback periods more than 25 years. Therefore, the solar PV, being a third dimension to the results, must be plotted with the CCHP sizes against the life cycle cost/life cycle profit. Therefore, both CCHP and solar PV capacities are plotted against the LCP in a 3D representation in Fig. 13.

In Fig. 13, the TES capacities are represented in the boxes, where the larger the capacities are, the lower the LCP is achieved. The top of the surface plot, shown in red, representing the optimal LCP, is achieved by a range of 2500–3000 kW and the maximum possible defined solar PV area (37,050 m^2). As exact values, the best LCP is achieved by 3000 kW CCHP, 37,050 m^2 solar PV (maximum available rooftop areas), 2997 kW heat exchanger, 5714 kW absorption chiller, 1806 kW electric chiller and no storage units at all. The second-best combination is close to the first one except that it required 2500 kW CCHP instead of 3000 kW, and still no storage systems are required. The third combination is the same as the first but with an Ice storage capacity of 3782 kW (minimum defined capacity). Therefore, it is observed that thermal storage units have a very minimal influence on the profit, therefore they are not preferred by the optimizer. The optimal CCHP sizes range between 2500 and 3000 kW. The battery storage is eliminated and its inclusion is significantly reducing the life cycle cost, to quantify its disadvantage, the combination having the minimum BSS capacity (2612 kW), 3000 kW CCHP, and 37,050 m^2 solar PV area, yielded an LCP lower than the highest achieved LCP by 25 %. This proves that battery storage does not provide an economic advantage in this case. Fig. 14 shows the life cycle

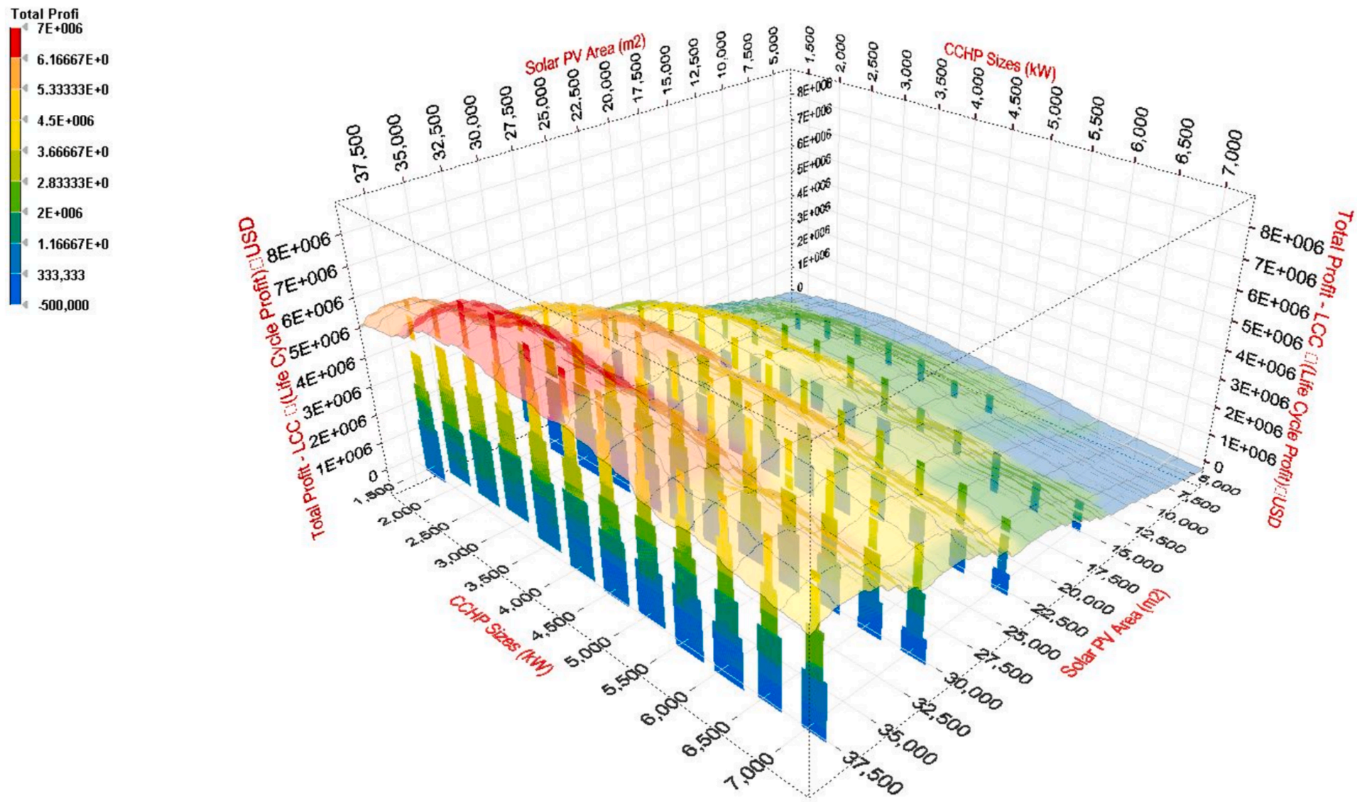

Fig. 13. 3D Plot representation of the CCHP sizes vs Solar PV Area vs thermal storage capacities against the total life cycle profit.

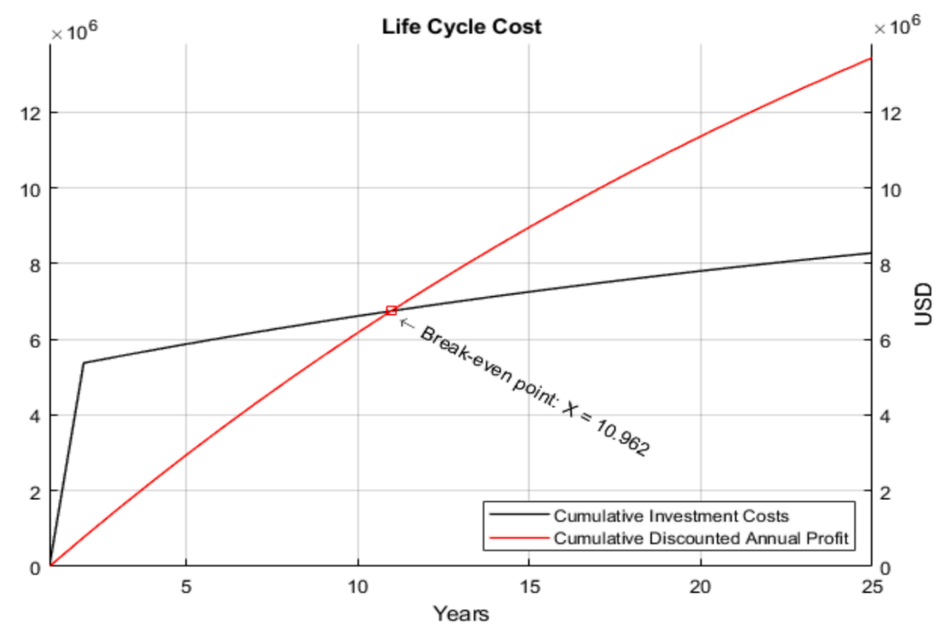

Fig. 14. Life cycle cost, discounted annual profit plot and discounted payback period for the optimally sized system.

cost intersecting with the annual profit yielding the discounted payback period. Fig. 15 shows the cumulative profit through the year, where it is clear that the summer period ramps up the profit quickly compared to wintertime, this is due to higher thermal energy sales. The next paragraph will explain the energy management (i.e. hourly profit maximization) results.

Observing the results, and comparing it with the baseline case, the CCHP size in this method is much lower than the previously estimated 3618 kW CCHP. Fig. 16 and Fig. 17 show the power and thermal balance plots for June and August respectively. As can be clear from the thermal balance, a small portion of the peak is covered by the electric chiller, which is seen as more economical than ramping up the CCHP or selecting a larger size. Fig. 18 presents June results, which clearly show that most of the time the cooling demand is well covered by the absorption chiller and the TES helps to capture the peak periods. The optimal sizes also help to achieve a higher annual profit compared to

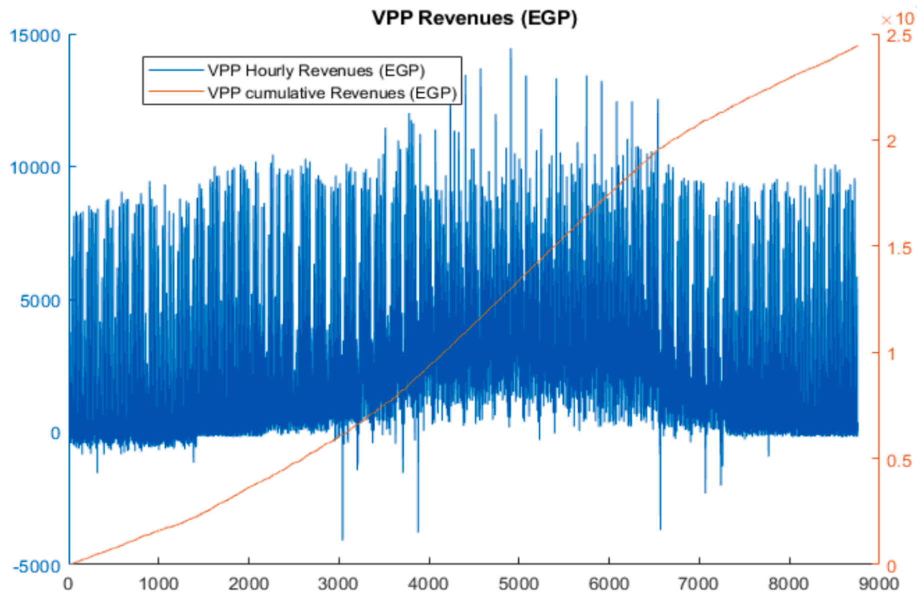

Fig. 15. Hourly profit maximization optimization –cumulative profit for the optimally sized system.

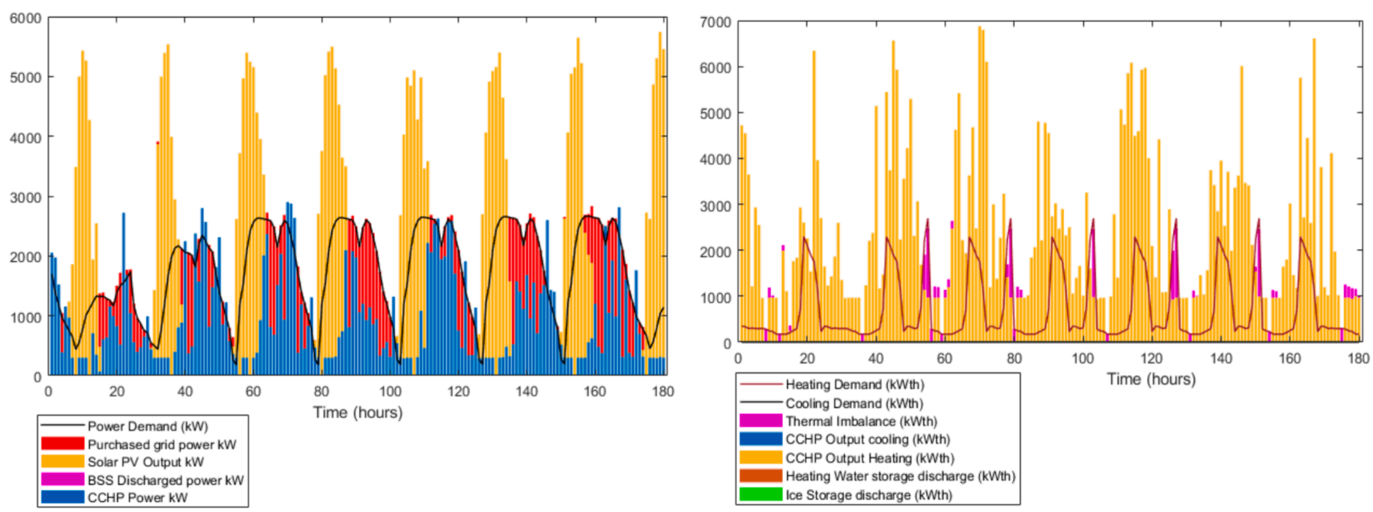

Fig. 16. Sizing & Energy Management model- Power balance (left) and thermal balance (right) for January (Winter).

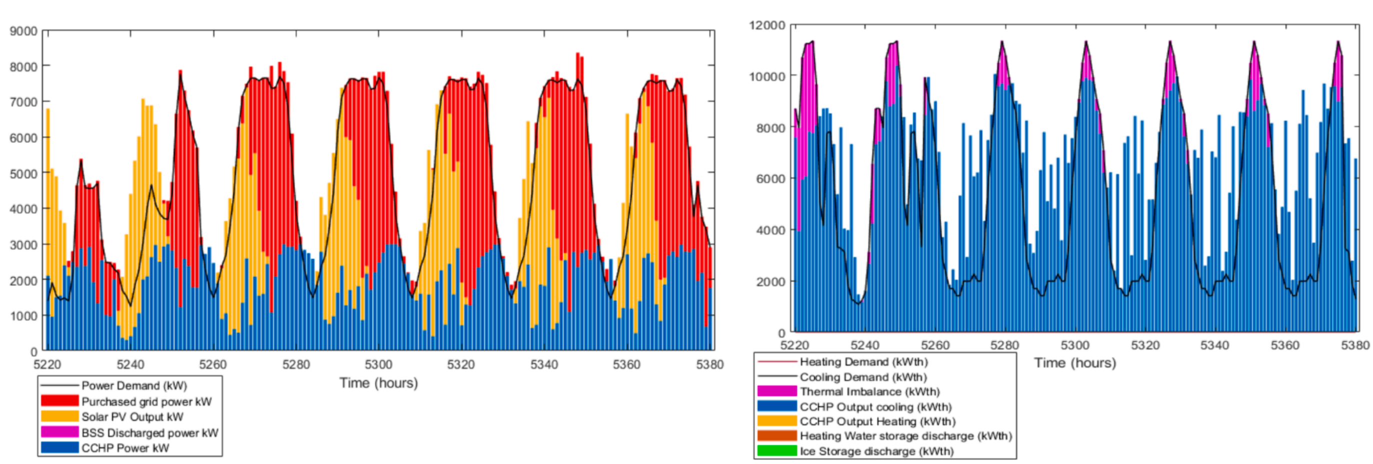

Fig. 17. Sizing & Energy Management model – Power balance (left) and thermal balance (right) for August (Summer).

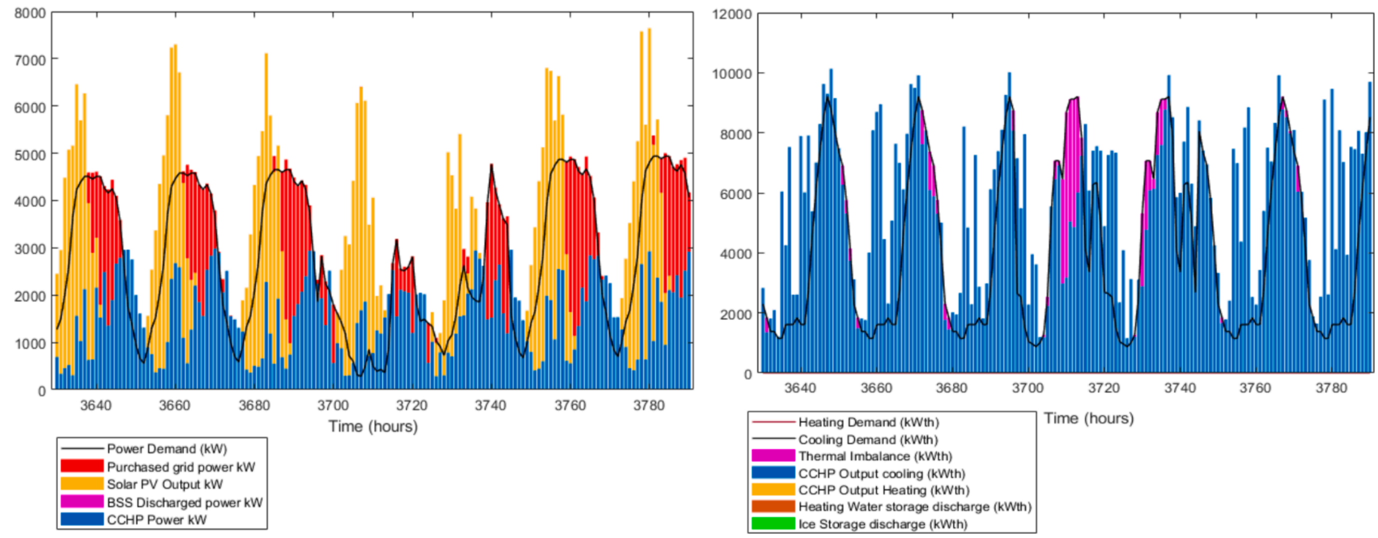

Fig. 18. Sizing & Energy Management model – Power balance (left) and thermal balance (right) for June.

non-optimally sized bounds.

From another perspective, having the objective function purely economic indirectly influenced the technical efficiencies, where the average annual exergy and energy efficiencies resulted as 63 % and 61 % respectively. The grid dependency ratio could be debatable, as it reached 31 %. This may not be the best-anticipated fraction for the grid dependency, however, the system must survive and achieve a suitable return on investment period, to become viable. The relatively high ratio is due to the challenging low tariff, where at some points, the purchase from the grid might be more economical than generating power from the CCHP. It could be also arguable whether the 100 % dependency on an electric chiller is more economically viable than relying on the CCHP. The combinations already analysed a scenario of low CCHP size and no CCHP size at all and the results came in positive in favour of including the CCHP for simultaneous coverage of the power demand, partially, and for the coverage of the majority of thermal demand, while the peak to be covered by the electric chiller.

Table 5
Technical and economic results summary for the case without sizing.

	With assumed sizes		Optimally Sized systems
	GA With BSS	GA Without BSS	GA
CCHP Nominal Size (kW)	3,600	3,600	3000
Solar PV capacity (m^2)	37,050	37,050	37,050
BSS Capacity (kWh)	7,881	186	0
Cooling TES Capacity (kWh)	11,443	11,603	0
Heating TES Size (kWh)	2,725	2,723	0
Electric Chiller Size (kW)	0	0	1806
Absorption Chiller Capacity (kW)	8105	8105	5714
Energy purchased from the grid (kWh)	4,728,533	5,222,538	6,051,744
Energy sold to the grid (kWh)	5,809,749	5,492,488	4,994,715
Average overall energy Efficiency %	63	65	63
Average overall exergy Efficiency %	62	63	61
Total CCHP consumed fuel (m3)	5,199,473	5,009,713	3,586,085
Emitted CO2 from CCHP (kg.CO2)	12,709,832	12,245,974	8,765,993
VPP CO2 Emissions (kg. CO2) (CCHP & Grid)	26,234,579	27,183,696	26,075,443
CO2 Emissions (original case, without VPP) (kg. CO2)	82,685,515	82,685,515	82,685,515
Total VPP profit (EGP)	26,102,928	25,286,125	24,426,243
Total VPP profit (USD)	847,498	820,978	793,317
Discounted Payback Period (Years)	>25 (Infeasible)	13	11

6.3. Results summary

As shown in Table 5, the optimally sized systems showed a significant difference in terms of the CCHP size. The profit of the baseline cases is higher than the sized case, however, the payback period is higher in the case that includes BSS and 13 years in the case without BSS. This proves that the BSSs are not economically viable in this market. It can be concluded that due to the flat prices, the BSSs cannot perform arbitrage (i.e. buying electricity in low-demand periods at low prices and selling it at high prices in peak periods), accordingly, their presence is not economically beneficial compared to directly purchasing and selling from/to the grid. The other thermal storage systems are also insignificant to the annual profit. Since the selected CCHP size is lower than the assumed values in the baseline cases, the annual fuel consumption is lower and naturally the imported power from the grid is higher, however, the overall CO2 emission in the sized case is lower than the baseline cases. Solar PV, as anticipated, proved to be economically viable, therefore, the full available capacity is selected.

7. Sensitivity analysis and energy demand variation

As the objective function of the sizing & energy management is purely based on the economic side, the operation of the selected optimal sizes yielded higher CO2 emissions than the previous method, naturally because of higher grid dependency and consequent higher grid carbon intensity. The proposed framework resulted in a higher grid dependency because it tried to lower the power generated from the CCHP. This decision is obviously because the electricity tariff is very low compared to the equivalent power generation costs from the CCHP. The solar PV output with the available rooftop areas ensures daily that there is a surplus available sold to the grid at a fair rate, however, in terms of investment costs, the BSS inclusion renders the discounted payback period indefinite, therefore, the surplus is directly sold to the grid. There might be a possibility that if the electricity tariff was higher or if the fuel cost was lower, or the opposite, a larger CCHP with a higher output would be more desirable. Accordingly, a sensitivity analysis will be performed to study the increment/decrement.

This section helps to understand the influence of uncertainty of the driving parameters on the performance and sizing variation of the VPP. The experiments are designed to test the influence of the increase and decrease of the energy prices altogether (electricity tariff, district energy tariff, and PPA price), fuel price, and energy demand profile variation. The interest rate variation will directly affect the payback period, so this experiment is eliminated to reduce the number of trials. The parameters' variation is assumed as +/- 20 % as a maximum value, concerning values taken in the relevant literature, such as Reich and Sanchez [86] who performed sensitivity analysis by altering the capacities of a microgrid with variation values up to 20 % with increment 5 %. Also in the microgrid studied by Dash, et al. [87], the affecting parameters, such as fuel price, solar radiation, and wind speed were variated by around 18–20 %. The experiments will be insightful for high-level decision-making in similar VPP planning. The influence of variation in electricity and fuel prices will be assessed by running the previously explained sizing & energy management to report the results of all size combinations and draw statistical relationships between the economic parameters. The next sections will depict the results of each experiment.

7.1. Variation of energy prices and fuel costs

The simulations are performed considering the following scenarios:

a. Increase of electricity prices by 20 %
b. Reduction of electricity prices by 20 %
c. Increase of fuel price by 20 %
d. Reduction of fuel price by 20 %

The initial results, like the original case without variations, show that the BSS inclusion leads to no-break-even points and higher life cycle cost than the life cycle profit, therefore, the permutations containing BSS units are eliminated from the analysis. The influences of the thermal storage systems on the economic results are insignificant. To control the stochasticity of the GA and compensate for its lack of optimality, each permutation runs 5 times and results are reported. The main influenced factors are the CCHP sizes (kW) and solar PV capacities, represented in panel areas (m^2). To represent the data clearly, a 3D plot would be disturbing as the resulting parameters are too much, accordingly, CCHP sizes and solar PV areas are plotted separately against the life cycle profit. As shown in Fig. 19, the optimal CCHP sizes are in the region of 2500–3000 kW. The range from minimum to maximum in each plotted box represents the range from the lowest to the highest solar PV areas, as can be shown in Fig. 20, where the life cycle profit almost linearly increases as the solar PV capacities increase. It can be observed that scenario B, where the prices are reduced by 20 %, has the worst effect on the profit, and the best influence on the profit is obtained from scenario A where the prices are increased by 20 %. The influence of fuel cost variation is less than the influence of the energy prices, however, it has a direct effect on the CCHP size selection, where the peak of the life cycle profit plots is being shifted. Specifically, it can be observed that the increase in the fuel price tends to reduce the CCHP size and the reduction in fuel price tends to increase the size. In terms of solar PV areas, surprisingly, all variated scenarios are in favour of utilizing the maximum full potential of the available areas.

8. Conclusion

A VPP model is proposed for residential compounds, supporting the deployment of rooftop solar PVs backed up with CCHP, BSSs, TESs and electric chiller. The VPP covers the residential electricity, space cooling and space heating demand profiles. The model ensures the energy security of residential clusters' developments, reduces the dependence on the electricity grid, and promotes the growth of decentralized renewable power plants. Approaching this concept from a quantitative perspective, the economic background in which the VPP is operating is essential to the feasibility of the model. This research assessed an iterative framework to assess all possible energy system size combinations by calculating the life cycle investment costs, in which the energy exchange profit is computed by dispatch optimization with GA.

The proposed framework is compared with a baseline case presenting a sole energy management, driven only by profit maximization, without attention to investment costs. This baseline case represents the status of the literature, in which most of the VPPs-related studies did not address the sizing problem of the aggregated systems inside the VPP. The results showed how the results could be very insightful for high-level decision-making by developers, in comparison with approaches that yielded a single sizing solution. The results were more advantageous compared to the profit maximization with non-sized systems (i.e. baseline case). The achieved payback periods with properly sized systems are 11 years, which is lower than the baseline case-with assumed systems' sizes-by 15.3 %. Compared with the literature, as shown in Table 6, the proposed framework enables the system to consider the existing electricity prices as inputs for the model, while the relevant

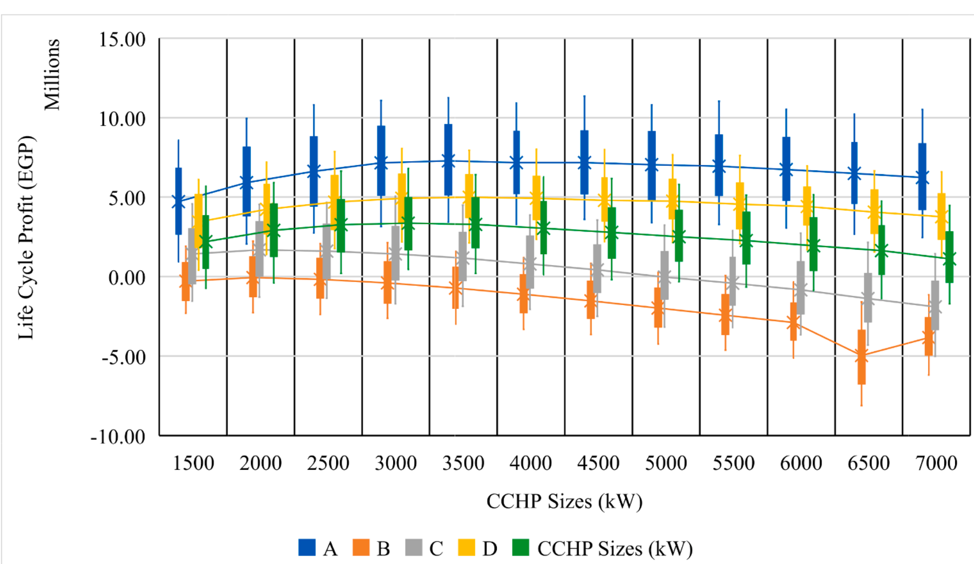

Fig. 19. CCHP Sizes versus the life cycle profit.

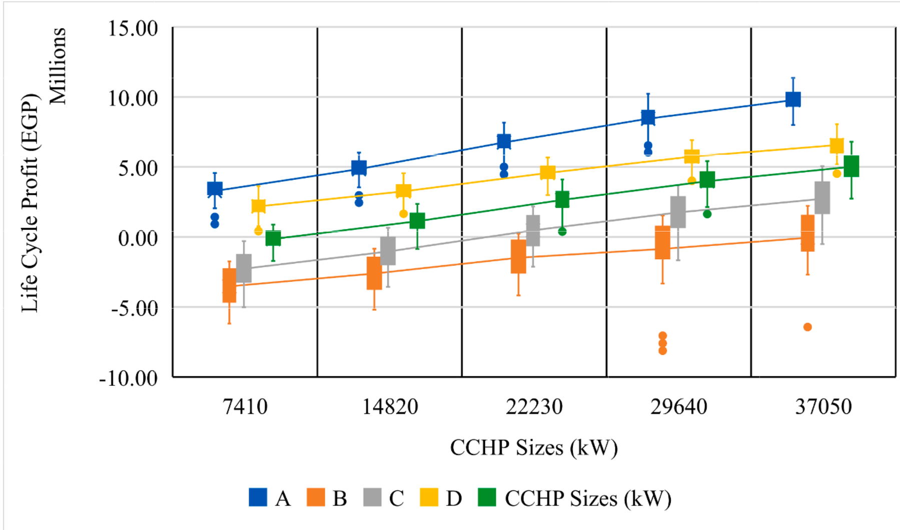

Fig. 20. Solar PV areas (m^2) versus the life cycle profit.

Table 6
Comparison between the achieved results and the literature.

Reference	Achieved COE ($/kWh)	Electricity tariff of the respective market ($/kWh)	Considered electricity tariff in the current research ($/kWh)
Mahmoud, et al. [11]	0.2182	0.046	0.046
El-Sattar, et al. [34]	0.33	0.046	
El-Sattar, et al. [13]	0.11	0.046	
Elkadeem, et al. [12]	0.15	0.046	
Diab, et al. [10]	0.217	0.046	
Ramli, et al. [15]	0.081	0.048	
Mandal, et al. [16]	0.37	0.052	
Cano, et al. [17]	0.118	0.096	

*This is the input tariff value to the VPP model of this research, which is comparable to the COE achieved by the relevant literature.

literature adopting minimum COE method, yielded higher hypothetical COE than the existing market prices which makes their application not feasible until the policy makers of this market increases its price. That signifies that the method applied in this research advanced the literature in achieving a lower cost of energy, and enables the application of a renewable-energy-based VPP model.

Assessing batteries' viability and influence on the profitability, another baseline case with assumed systems' sizes that included batteries was assessed in term of profit maximization objective. This case proved to be infeasible and never achieved a break-even point due to high investment costs compared to the profit advantage that the batteries could provide. This is due to the flat pricing structure of the market which prevents the batteries from taking advantage from price difference, therefore, it was more profitable for the model to sell the surplus directly to the grid. To ensure the robustness of the model, a sensitivity analysis has been performed considering the energy prices, fuel costs. The analysis is done by variation of each parameter while keeping the others constant. The outcome of the sensitivity analysis showed that the electricity prices are much more sensitive to the results compared to fuel prices. The sensitivity analysis also confirms that even with low energy prices and despite its relatively high capital costs, solar power is still favourable for the life cycle profit of the VPP.

The research has the following limitations:

- The energy demand data is a main driving parameter in this study, however, due to lack of accurate data, the current research used constructed energy demand profiles based on the available related literature.
- Solar PV panels and BSSs degradation rate are neglected from the analysis.
- The study is limited to a VPP model backing-up solar PVs, if wind turbines are aggregated, a different simulation might be required due to the higher intermittency level of wind power.

The further work could be summarized as follows:

- The proposed method requires further work to increase the solution speed. Parallelization of the solvers or reduction of sizes combinations could be attempted.
- In context with the solution speed, a machine-learning-based method could replace the GA to improve the solution speed.
- A future work shall include analysing the proposed framework with aggregation of different energy technologies.

CRediT authorship contribution statement

Ahmed Hany Elgamal: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Mehdi Shahrestani:** Writing – review & editing, Supervision, Project administration, Methodology. **Maria Vahdati:** Writing – review & editing, Supervision, Project administration, Methodology.

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.

Data availability

Data will be made available on request.

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