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A three-level model for integration of smart homes, electric vehicle charging stations and hydrogen fuelling stations in reconfigurable microgrids considering vehicle-to-infrastructure (V2I) technology

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ABSTRACT

Smart consumers and prosumers play a key role in the modern power and energy systems; due to significant share of self-consumption, they may reduce the burden on local distribution systems or microgrids; moreover, as a large share of their demand is supplied by their own renewable energy resources, they considerably contribute to the decarbonization targets. Identifying the impact of smart prosumers on microgrids may assist decision makers to find the challenges and make suitable changes. The operation of reconfigurable microgrids with high penetration of green smart homes (SHs), charging stations (CSs) and hydrogen fueling stations (HFSs) has not been addressed in the literature, so, this paper aims to propose a framework for energy management in the mentioned smart consumers/prosumers and investigate their impact on host microgrids. In the proposed framework, firstly, all electric vehicles (EVs) and fuel cell vehicles (FCVs) optimize their own charging schedule using the price signals received through vehicle-to-infrastructure technology; in the second level, each HFS, CS or SH solves its own energy management model and in the third level, the operator of the microgrid solves its day-ahead operational planning model. The solvers of General Algebraic modeling Systems (GAMS) are used to solve all the mentioned models. The results confirm the efficiency of the developed multi-level methodology; according to the results, the studied microgrid enjoys a daily profit of $571.47, meaning that the revenue, earned by selling electricity to CSs, SHs, HFSs and its own demands is considerably higher than sum of the cost of its micro-turbines and the cost of purchased electricity from upstream grid. The results indicate that the batteries decrease the daily cost of smart homes by 4 %; moreover, the results suggest that batteries cause drastic change in operation cost of the microgrid.

Nomenclature

Indices	
BS	Battery storage
CS	Charging station
EL	Electrolyser
EV/ *FCV*	Electric vehicle/Fuel cell vehicle
HFS	Hydrogen fueling station
HS	Hydrogen storage
MT	Microturbine
SH	Smart home
app	Appliance (of home)
br	Branch
dep − *app*	Dependent appliance of *app*
i,*j*	Bus

(*continued on next page*)

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(continued)

pv	PV generator
ref	Reference bus
t	Time
Parameters	
$E_{need,EV}$/ $E_{need,FCV}$	Needed electricity of electric vehicle/fuel cell vehicle
$H_{demand,HFS,t}$	*HFS* demand
$PTR_{e,app,SH}$	End of preferred time range of appliances
$PTR_{s,app,SH}$	Start of preferred time range of appliances
$P_{demand,i,t}$/ $Q_{demand,i,t}$	Real/reactive demand at bus *i*
$P_{fix,demand,SH,t}$	Fixed demand of smart home
$P_{pref,SH,t}$	Preferred consumption of appliances
$RE_{app,SH}$	Required energy of appliances
$UTR_{e,app,SH}$	End of utilization time range of appliances
$UTR_{s,app,SH}$	Start of utilization time range of appliances
$UT_{app,SH}$	utilization time of appliances
$\lambda_{E,t}$	Electricity price
$\lambda_{H,t}$	Price of hydrogen energy
λ_{MT}	Price of electricity purchased from *MT*
Variables	
C_{CS}	CS's operating cost
C_{EV}/ C_{FCV}	EV's/FCV's operating cost
C_{HFS}	HFS's operating cost
CL_{SH}	Comfort level of SH
C_{MG}	MG's operating cost
C_{SH}	SH's operating cost
$H_{EL,HFS,t}$	*EL*'s hydrogen generation
$H_{ch,FCV,t}$	Hydrogen flow rate of FCV
$P_{MT,t}$	Power generation of MT
$P_{app,SH,t}$	Power demand of appliances
$P_{br,t}$/ $Q_{br,t}$	P/Q of branches
$P_{ch,EV,t}$	Charging rate of EV
$P_{demand,CS,t}$	CS demand
$P_{demand,HFS,t}$	HFS demand

1. Introduction

The current power systems heavily rely on active participation of consumers [1]. Nowadays, economic and environmental drivers have caused the addition of renewable power resources in consumer premises in a way that they have been evolved from pure consumers into prosumers which are able to inject electricity into power grid. Indeed, the vision of smart grids is towards decentralized grids in which pure consumers are replaced by prosumers with the capability of bidirectional interaction with smart grid.

With recent drastic advances in information and communications technology and metering systems, traditional grids are being evolved into smart grids and likewise, traditional prosumers are being evolved into smart prosumers. Typically, smart prosumers include renewable energy resources and storage systems. The advantages of smart prosumers may be listed as below.

- ✓ Due to significant share of self-consumption, they alleviate the burden on local distribution systems.
- ✓ As a large portion of their demand is supplied by their own renewable energy resources, they considerably contribute to the global decarbonization targets.
- ✓ Through active participation in electricity and ancillary services markets, smart prosumers enhance the competitiveness of those markets and reduce market clearing prices.
- ✓ They may provide flexibility to power systems; flexibility is an important need of existing power systems.
- ✓ Through participation in demand response programs, smart prosumers not only decrease their own cost, but also fulfil the needs of smart grids.
- ✓ They may enhance the resilience of power systems during extreme events.

Smart homes, smart buildings, smart charging stations and smart hydrogen fuelling stations are examples of smart prosumers [2–4]. The main focus of this paper is on smart homes as they have been researched less than other smart prosumers; Smart homes are crucial prosumers, as a large portion of the global electricity demand is consumed in homes. Today's smart homes mix renewable energy resources, advanced smart technologies and storage systems to evolve from energy-intensive consumers to nearly zero-emission prosumers with the capability to produce, store, consume, sell and purchase electricity [5]. As per energy efficiency and decarbonization targets, the number of homes relying on photovoltaic (PV) energy is expected to increase from 25 million in 2023 to beyond 100 million in 2030; the current global PV capacity in homes is about 130 GW [5].

Smart homes have energy management systems that schedule the resources, storage systems and controllable appliances in a way that the bill of home is minimised and comfort of residents does not fall below a threshold. Smart homes increase energy efficiency and reduce emissions, they may provide ancillary services for host power grids; Additionally, through aggregators, they may participate in electricity and ancillary services markets and spur the competition in those markets.

The research on smart homes may be categorized into two main categories; the researches in the first category only focus on energy management system of smart homes; whereas, those in the second category not only propose strategies for energy management in smart homes, but also assess the impact of smart homes on the operation of power grids. Firstly, we review the researches of the first category; in Ref. [6], a mixed-integer linear programming (MILP)-based model is proposed for energy management of a grid-connected smart home including electric vehicles (EVs), air conditioner, battery, PV, controllable and non-controllable appliances. The energy management system optimises both energy cost and comfort index of home. The smart home may purchase electricity from grid under real-time pricing (RTP) program. The model is solved with CPLEX solver in General algebraic modelling system (GAMS) and the results are compared with well-established metaheuristics such as particle swarm optimisation, genetic algorithm and differential evolution.

In [7], an energy management system is developed for a grid-connected smart home in Madrid, Spain with PV, battery under RTP demand response program. In demand response programs, smart home try to change their consumption pattern according to the needs of the power grid [8,9]. The demands and PV power are forecasted via a sophisticated forecasting model. In Ref. [10], an energy management system is developed for a smart home with PV, battery, EV, controllable and non-controllable appliances to minimise energy cost and flatten demand profile of the home. In Ref. [11], the obstacles and difficulties of responsiveness of smart homes in demand response programs and challenges of their energy management systems are identified and discussed. In Ref. [12], a fuzzy control-based energy management system is developed for an off-grid smart home with hydrogen-driven fuel cell, PV, wind and electrolyser units in order to minimise the hydrogen consumption of fuel cell and maximise comfort index of the home.

In [13], energy management system of a smart home is formulated as a MILP model in which bill and comfort index are optimised and a modified version of particle swarm optimisation (PSO) is used to solve the developed model. In the proposed PSO, five successive mutation operators are applied to the leader, in order to decrease the probability of premature convergence. In Ref. [14], a binary version of PSO is used to solve energy management model of smart homes, formulated as mixed-binary optimisation problem. In the proposed PSO, sigmoid transfer functions are replaced by quadratic transfer functions. The results have been compared for RTP and time-of-use (TOU) tariffs. In Ref. [15], grey wolf optimisation is used for solving energy management model in smart homes with non-interruptible appliances.

Here, the researches which have assessed the impact of smart homes on power grids are reviewed. In Ref. [16], a four-level framework is proposed for market clearing in transactive multi-microgrids, integrated with smart buildings and smart homes. In the first level, the energy

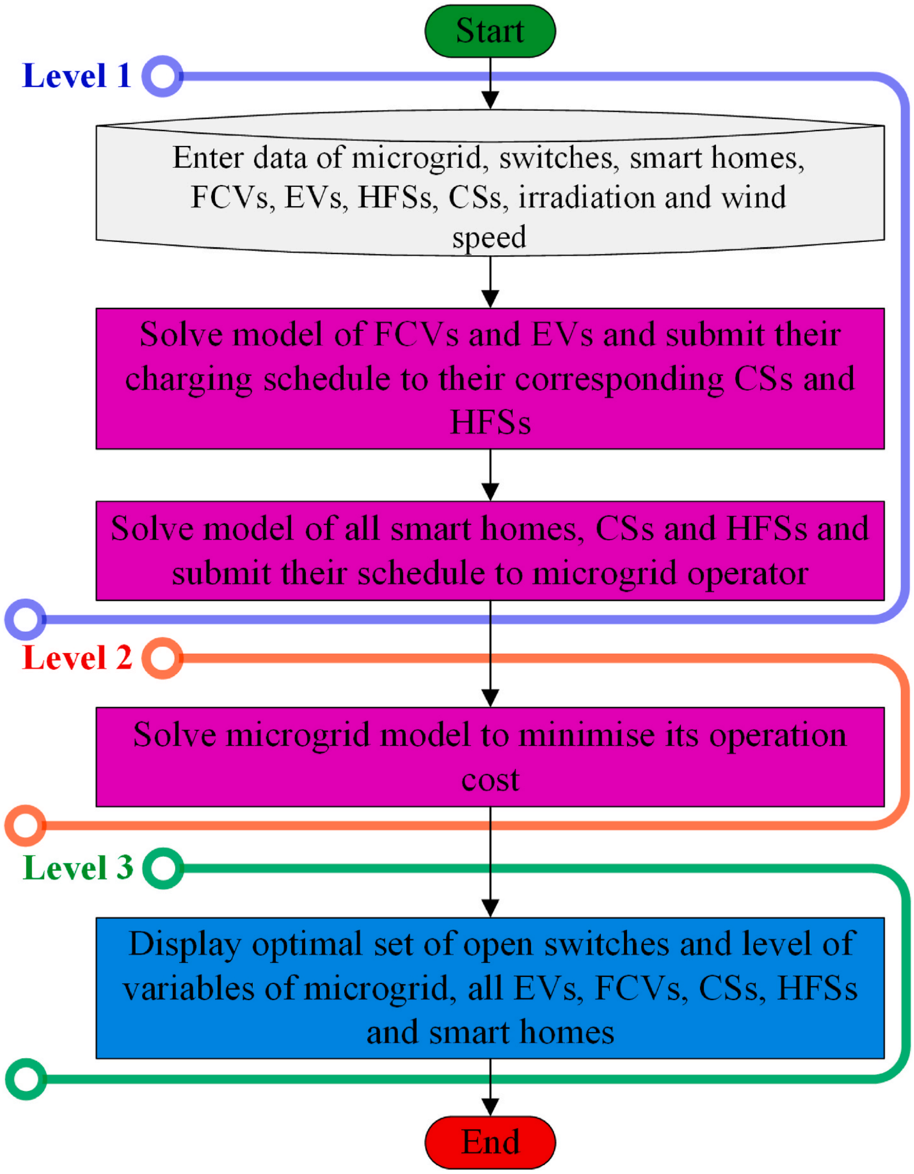

Fig. 1. The Flowchart of the proposed 3-level model.

management system of each smart home schedules its controllable appliances and resources; then schedule of all smart homes are sent to the energy management system of their corresponding smart building; each smart building has PV modules and batteries; in the second level, each smart building schedules its resources and sends its schedule to its corresponding microgrid; in the third level, each microgrid determines its optimal bids or offers and finally in the fourth level, the market is cleared by maximizing social welfare and the accepted offers and bids of microgrids are published. The results show that participation of smart homes in demand response program considerably decreases their energy cost (2.5 % on average), while the comfort of residents is not much affected. The results also indicate that the proposed framework decreases the reliance of smart buildings on microgrids. The impact of size of PV modules and batteries on energy cost of smart buildings has also been assessed.

In [17], a mixed-integer linear model is used for scheduling resources and appliances in a grid-connected smart home with combined heat and power (CHP), boiler, electric and thermal storage systems. Energy cost of home and emissions released from CHP, boiler and grid are used as objectives of the proposed model. The energy cost of the home is given by sum of fuel cost of CHP unit, cost of storage systems and the cost of electricity purchased from grid. The multi-objective optimisation problem is solved by epsilon-constrained method. The case study is a smart building including 30 smart homes with similar living habits. The results approved the efficacy of the proposed method; moreover, the results indicated that inclusion of emissions in the objectives increases energy cost of smart homes.

In [18], smart homes including PV, battery, EV and electric water heater play the role of flexibility providers for power systems. The flexibility provision capacity of each component of smart homes is assessed which signifies that batteries have higher capacity for flexibility provision than thermostatically-controlled components of homes. The results also signify that the flexibility provision capability decreases cost of smart homes. In Ref. [19], the impact of smart homes with PV, battery and electric-heat-cooling demands on operation of a distribution system is investigated. In Ref. [20], a tri-level framework is proposed for energy management of smart home-integrated microgrid clusters in reconfigurable distribution systems. The studied smart homes include solar panels and battery. The results show that batteries, demand response and vehicle-to-grid capability positively impact voltage profile, branches' congestion as well as operation cost of microgrids.

In [21], the peer-to-peer transaction among smart homes is leveraged to decrease the burden on the transformer interfacing smart grid and smart homes. The studied smart homes are under RTP tariff and include EVs, battery, PV and electric water heater. In Ref. [22], a multi-level model is proposed for market management in smart home-integrated multi-microgrids, while microgrids offer RTP tariffs for smart homes. The risk-aware energy management system of smart homes considers both bill and comfort index. The results show that the presence of smart homes lead to a decrease in market clearing prices. The performance of energy management system of the smart home in risk-averse and risk-seeking modes were compared.

In [23], the impact of smart homes on multi-microgrids, market clearing prices and reconfigurable distribution systems has been investigated under a hierarchical decentralized stochastic decision making framework. The energy cost and comfort index of each smart home is optimised by its own energy management system. The results indicate that participation of smart homes in demand response programs not only decreases their own costs (14 % on average), but also decreases market clearing prices. In Ref. [24], smart homes with inverters, battery, EV and thermostatically-controlled systems are leveraged to provide flexibility to smart grids. Due to the presence of inverters, smart homes may also exchange reactive power with grid. A fuzzy-based controller is used to coordinate active and reactive power of smart home.

In [25], energy management in smart homes is formulated as a mixed-integer linear bi-objective optimisation problem to minimise bill and emissions; The smart homes are hosted by some microgrids and epsilon-constrained method is used to solve the developed bi-objective model. The performance of the proposed energy management system was compared under different demand response programs. In Ref. [26], a bi-level model, based on Stackelberg game theory is used for smart homes integrated in a microgrid. In the proposed bi-level model, the microgrid is the leader and smart homes are the followers. Particle swarm optimisation is used to solve the proposed model.

Now, with decentralization of power grids, the increase in the number of microgrids is happening [27–29]; in some cases the smart homes and other smart consumers/prosumers are integrated into microgrids. Identifying the impact of smart prosumers on microgrids may assist decision makers to find the challenges and make necessary changes. By the review of literature, it was found that the operation of microgrids with high penetration of green smart homes (SHs), charging stations (CSs) and hydrogen fueling stations (HFSs) has not been investigated; therefore, this research mainly aims to propose a framework for both energy management in smart homes, charging stations and hydrogen fueling stations and investigation of their impact on host microgrids. The contributions of this paper are as follows:

- A three-level model is developed for integration of smart homes, charging stations and hydrogen fuelling stations in reconfigurable microgrids.
- The resources of all smart homes, charging stations and hydrogen fuelling stations are fully renewable.
- All EVs and fuel cell vehicles (FCVs) optimize their charging schedule using the prices received through vehicle-to-infrastructure (V2I) technology.
- The proposed framework guarantees the acceptable comfort level for home residents.

Note that the field of vehicles is experiencing a drastic advancement and emerging technologies such as deep learning [30,31], internet of things [32], vehicle-to-infrastructure [33] are being used in it. In this research, we use the vehicle-to-infrastructure technology during the charging process of vehicles. The rest of the paper is organized as follows; the second section presents the proposed model for integration of SHs, CSs and HFSs in reconfigurable microgrids. The third section includes the findings of the papers and analysis. Lastly, the conclusions of the paper may be found in section 4.

2. The proposed model

In this section, the developed three-level model for integration of smart homes, electric vehicle charging stations and hydrogen fuelling stations in reconfigurable microgrids is formulated. The whole model is characterized by (1)–(9). The flowchart of the proposed 3-level model may be seen in Fig. 1.

2.1. Level 1: EV and FCV model

In the first level, each EV or FCV schedules itself based on received price signals and its charging demand. The charging scheduling of EVs is characterized by a MILP model, represented as (1a) to (1e). Equation (1b) define the relationship among incoming and outgoing time indicator of EVs and their charging mode in two successive time periods. Constraints (1c) guarantee a non-interruptible charging process for all EVs [34]. Equation (1d) ensure that EVs gain their needed energy from charging process and equations in (1e) give charging cost of EVs. The number of binary variables in this model equals 72 N_{EV} , where N_{EV} denotes the number of EVs. Be noted that binary variable $\phi_{ch,EV,t}$ denotes charging status of EV at time period t.

$$\underline{P_{ch,EV}}\ \phi_{ch,EV,t} \le P_{ch,EV,t} \le \overline{P_{ch,EV}}\ \phi_{ch,EV,t} \quad \forall EV, \forall t \tag{1a}$$

$$\phi_{in,EV,t} - \phi_{out,EV,t} = \phi_{ch,EV,t} - \phi_{ch,EV,t-1} \quad \forall EV, \forall t \tag{1b}$$

$$\sum_t (\phi_{in,EV,t} + \phi_{out,EV,t}) \le 2 \quad \forall EV \tag{1c}$$

$$\sum_t P_{ch,EV,t}\Delta t = E_{need,EV} \quad \forall EV \tag{1d}$$

$$C_{EV} = \sum_t (1.2\lambda_{E,t}) P_{ch,EV,t}\Delta t \quad \forall EV \tag{1e}$$

The charging scheduling of FCVs is mathematically formulated as a MILP model, represented by (2a) to (2e). Equation (2b) define the relationship among incoming and outgoing time indicator of FCVs and their charging mode in two successive time periods. Constraints (2c) guarantee a non-interruptible charging process for all FCVs. Equation (2d) ensure that every FCV absorbs its needed energy during its charging process and equations in (2e) show how charging cost of FCVs is calculated. The number of binary variables in this model equals 72 N_{FCV} , where N_{FCV} denotes the number of FCVs.

$$\underline{H_{ch,FCV}}\phi_{ch,FCV,t} \le H_{ch,FCV,t} \le \overline{H_{ch,FCV}}\phi_{ch,FCV,t} \quad \forall FCV, \forall t \tag{2a}$$

$$\phi_{in,FCV,t} - \phi_{out,FCV,t} = \phi_{ch,FCV,t} - \phi_{ch,FCV,t-1} \quad \forall FCV, \forall t \tag{2b}$$

$$\sum_t (\phi_{in,FCV,t} + \phi_{out,FCV,t}) \le 2 \quad \forall FCV \tag{2c}$$

$$\sum_t H_{ch,FCV,t}\Delta t = E_{need,FCV} \quad \forall FCV \tag{2d}$$

$$C_{FCV} = \sum_t (1.2\lambda_{H,t}) H_{ch,FCV,t}\Delta t \quad \forall FCV \tag{2e}$$

2.2. Level 2: models of smart home (SH), hydrogen fueling station (HFS) and charging station (CS)

The second level of the proposed multi-level model includes the model of SHs, CSs and HFSs. Firstly, SH model, represented by (3a)-(3k), is described [35]. Every SH includes PV, battery storage (BS) and a set of appliances and may exchange electricity with MG. PV and BS models may be found in Ref. [4]. In SH model, $\phi_{app,SH,t}$ denotes the status of appliance *app* owned by smart home *SH*. In the developed SH model, all appliances are of fixed-power type; meaning that when they are ON, they constantly absorb nominal power. Equation (3a) indicate that when an appliance is ON, it absorbs an amount of power equal to its needed energy during its utilization time. Equation (3b) indicate that sum of time periods in which an appliance is ON, equals its utilization time, denoted by $UT_{app,SH}$. In this paper, all appliances are assumed non-interruptible, i.e., once they are turned ON, will not be turned OFF until the end of their utilization time. As per equation (3c), the increase of $\phi_{app,SH,t}$ with respect to $\phi_{app,SH,t-1}$ indicates the start of operation of appliance *app* of smart home *SH* at time. Conversely, the decrease of $\phi_{app,SH,t}$ with respect to $\phi_{app,SH,t-1}$ indicates the end of operation of appliance *app* of smart home *SH* at time. As per (3d), simultaneous start and end of operation of an appliance is not feasible. As per (3e), each appliance may only experience one start and one end; no restart is allowed.

$$P_{app,SH,t} = \frac{RE_{app,SH}\ \phi_{app,SH,t}}{UT_{app,SH}} \quad \forall app, \forall SH, \forall t \tag{3a}$$

$$\sum_{t\in[UTR_{s,app,SH}\quad UTR_{e,app,SH}]} \phi_{app,SH,t} = UT_{app,SH} \quad \forall app, \forall SH \tag{3b}$$

$$\phi_{s,app,SH,t} - \phi_{e,app,SH,t} = \phi_{app,SH,t} - \phi_{app,SH,t-1} \quad \forall app, \forall SH, \forall t \tag{3c}$$

$$\phi_{s,app,SH,t} + \phi_{e,app,SH,t} \le 1 \quad \forall app, \forall SH, \forall t \tag{3d}$$

$$\sum_{t\in[UTR_{s,app,SH}\quad UTR_{e,app,SH}]} (\phi_{s,app,SH,t} + \phi_{e,app,SH,t-1}) = 2 \quad \forall app, \forall SH \tag{3e}$$

In a home, the operation of certain appliances may depend on the operation of another appliance. For instance, the operation of clothes dryer depends on operation of washing machine. Clothes dryer may be turned on only after finishing the operation of washing machine. For appliances *app* and *dep* − *app*, the dependent appliance *dep*− *app* must be started-up at most $\overline{gap_{app,dep-app}}$ time periods after finishing the operation of appliance *app*. This is mathematically formulated as (3f).

$$\sum_t (\phi_{s,dep-app,SH,t}\, ord(t)) - \sum_t (\phi_{e,app,SH,t}\, ord(t)) \le \overline{gap_{app,dep-app}} \quad \forall (app, dep-app)\ \forall SH \tag{3f}$$

Comfort level of any smart home is defined by (3g) which is mainly based on the difference between power of appliances at a time period and their preferred demand at that time. In (3h), comfort level of any SH is forced not to be less than a pre-specified threshold. According to (3i) which establishes the power balance, in any SH and at any time, sum of power exchanged with microgrid (MG), PV power and BS power should be equal to power absorbed by appliances. Inequality constraints (3j) limit power exchange between smart homes and MG and (3k) give the total cost of a smart home, which may be positive or negative depending on the direction of power flow between smart home and MG. Be noted that in (3i), A_{SH}^{pv} and A_{SH}^{BS} respectively represent the set of PV units and batteries owned by smart home *SH* .

$$CL_{SH} = \sum_t \left[1 - W_{SH}\left|P_{fix,demand,SH,t+}\sum_{app} P_{app,SH,t} - P_{pre,SH,t}\right|\right] \forall SH \tag{3g}$$

$$CL_{SH} \ge \underline{CL_{SH}} \quad \forall SH \tag{3h}$$

$$P_{exchange,SH,t} + \sum_{pv\in A_{SH}^{pv}} P_{pv,t} + \sum_{BS\in A_{SH}^{BS}} (P_{dch,BS,t} - P_{ch,BS,t}) = P_{fix,demand,SH,t+}\sum_{app} P_{app,SH,t} \quad \forall SH, \forall t \tag{3i}$$

$$-\overline{P_{exchange,SH}} \le P_{exchange,SH,t} \le \overline{P_{exchange,SH}} \quad \forall SH, \forall t \tag{3j}$$

$$C_{SH} = \sum_t \lambda_{E,t} P_{exchange,SH,t} \Delta t\ \forall SH \tag{3k}$$

The studied CSs include PV and BS units [36]; they are consumers from viewpoint of MG and are modeled as (4a)-(4d) [37]. Equation (4b) indicate that for any CS, at any time, sum of power imported from MG, PV power and discharging power of BSs equals sum of charging power of its BSs and power which CS injects into its EV clients. Inequality constraints (4c) bound the power which CSs import from MG; they also indicate that CSs may not inject power into MG. Equation (4d) imply that operation cost of any CS equals the cost of electricity imported from MG minus the revenue it earns by selling electricity to EVs. To achieve deeper knowledge on the operation of charging stations, refer to Ref. [38].

$$P_{demand,CS,t} = \sum_{EV\in A_{CS}^{EV}} P_{ch,EV,t} \quad \forall CS, \forall t \tag{4a}$$

$$P_{import,CS,t} + \sum_{pv\in A_{CS}^{pv}} P_{pv,t} + \sum_{BS\in A_{CS}^{BS}} P_{dch,BS,t} = P_{demand,CS,t} + \sum_{BS\in A_{CS}^{BS}} P_{ch,BS,t} \quad \forall CS, \forall t \tag{4b}$$

$$0 \le P_{import,CS,t} \le \overline{P_{import,CS}} \quad \forall CS, \forall t \tag{4c}$$

$$C_{CS} = \sum_t \lambda_{E,t} P_{import,CS,t}\ \Delta t - 1.2\sum_t \lambda_{E,t} P_{demand,CS,t} \Delta t \quad \forall CS \tag{4d}$$

Each HFS consists of a PV generator, a hydrogen storage (HS) system and an electrolyser. HFS model can be seen as (5a)-(5e) [39]. The model of hydrogen tank and electrolyser may be found in Refs. [40–44].

$$H_{dch,HS,HFS,t} = H_{demand,HFS,t} \quad \forall HFS, \forall t \tag{5a}$$

$$H_{ch,HS,HFS,t} = H_{EL,HFS,t}\ \forall HFS, \forall t \tag{5b}$$

$$H_{EL,HFS,t} = COP_{EL}\Delta t \left(P_{import,HFS,t} + \sum_{pv\in A_{HFS}^{pv}} P_{pv,t}\right) \quad \forall HFS, \forall t \tag{5c}$$

$$P_{import,HFS,t} \ge 0 \quad \forall HFS, \forall t \tag{5d}$$

$$C_{HFS} = \sum_t \lambda_{E,t} P_{import,HFS,t} \Delta t - \sum_t \lambda_{H,t} H_{demand,HFS,t} \Delta t \quad \forall HFS \tag{5e}$$

2.3. Level 3: Reconfigurable MGs' scheduling

The third level of the proposed multi-level model is the level in which operator of a reconfigurable MG solves its operational planning problem. MG has microturbines (MTs), PVs and BSs. MG operator is committed to satisfy the request of all connected SHs, CSs and HFSs. See the model of MG in (6a) to (6f). Load flow model can be found in Ref. [2]. Constraints (6a) and (6b) respectively ensure balance of real and reactive power at all buses and all times. Constraints (6c) and (6d) respectively bound imported real power and imported reactive power of MG. Constraints (6e) and (6f) respectively limit active and reactive demand shed at buses of MG.

$$P_{import,MG,t}\big|_{i\in ref}+\sum_{MT\in\Lambda_i^{MT}}P_{MT,t}+\sum_{pv\in\Lambda_i^{pv}}P_{pv,t}+\sum_{BS\in\Lambda_i^{BS}}\left(P_{dch,BS,t}-P_{ch,BS,t}\right)+P_{shed,i,t}=\sum_{SH\in\Lambda_i^{SH}}P_{exchange,SH,t}+\sum_{CS\in\Lambda_i^{CS}}P_{demand,CS,t}+\sum_{HFS\in\Lambda_i^{HFS}}P_{demand,HFS,t}+P_{demand,i,t}$$
$$+\sum_{br\in\Lambda_i^{br}}\left(\sigma_{br,i}P_{br,t}+0.5P_{loss,br,t}\right)\quad\forall i,\forall t \tag{6a}$$

$$Q_{import,MG,t}\big|_{i\in ref}++P_{shed,i,t}+\sum_{MT\in\Lambda_i^{MT}}Q_{MT,t}=Q_{demand,i,t}+\sum_{br\in\Lambda_i^{br}}\sigma_{br,i}Q_{br,t}\quad\forall i,\forall t \tag{6b}$$

$$0\le P_{import,MG,t}\le\overline{P_{import,MG}}\quad\forall t \tag{6c}$$

$$0\le Q_{import,MG,t}\le\overline{Q_{import,MG}}\quad\forall t \tag{6d}$$

$$0\le P_{shed,i,t}\le P_{demand,i,t}\quad\forall t \tag{6e}$$

$$0\le Q_{shed,i,t}\le Q_{demand,i,t}\quad\forall t \tag{6f}$$

The reconfiguration possibility in MG is modeled by (7a)-(7c) [45]. Equation (7a) are incorporated to identify parent buses; for branch br , which links buses i and j , the value of 1 for $\phi_{i,j,t}^{parent}$ means that power flow directs from i to j; conversely, the value of 1 for $\phi_{j,i,t}^{parent}$ means that power flow directs from j to i. Constraints (7b) indicate that each bus may be connected at most to a single parent bus. Constraints (7c) indicate that reference bus may not be connected to a parent bus.

$$\phi_{br,t}=\phi_{i,j,t}^{parent}+\phi_{j,i,t}^{parent}\quad\forall br,\forall t \tag{7a}$$

$$\sum_i\phi_{i,j,t}^{parent}\le 1\quad\forall j \tag{7b}$$

$$\sum_j\phi_{j,i,t}^{parent}=0\quad\forall i\in ref \tag{7c}$$

Microturbines (MTs) of MG are simply modeled by (8a) to (8b), which consider their real and reactive power limits.

$$\underline{P_{MT}}\ \phi_{MT,t}\le P_{MT,t}\le\overline{P_{MT}}\ \ \phi_{MT,t}\quad\forall MT,\forall t \tag{8a}$$

$$\underline{Q_{MT}}\ \phi_{MT,t}\le Q_{MT,t}\le\overline{Q_{MT}}\ \ \phi_{MT,t}\quad\forall MT,\forall t \tag{8b}$$

Finally, the operation cost of MG is given by (9).

presented and discussed. In this research, smart homes are considered as prosumers, while HFSs and CSs are consumers. Be noted that due to the absolute function in the comfort index definition, the model of SH is nonlinear. MILP model has been used for EVs, FCVs, HFSs, CSs, while a mixed-integer quadratic programming (MIQCP) model has been used for MG and a mixed-integer nonlinear programming (MINLP) model has been used for smart homes. CPLEX solver is used for MILP models and GUROBI and DICOPT are respectively used for MIQCP and MINLP. The case study may be seen in Fig. 2, which shows a 33-bus grid-connected and reconfigurable MG, including MTs, BSs, PV generators and 5 tie lines which respectively connect buses 8–21, 9–15, 12–22, 18–33 and 25–29.

The six MTs of the studied MG are installed at buses 16, 27, 22, 17, 18 and 32 respectively with capacities 5000 kW, 2000 kW, 1000 kW, 100 kW, 100 kW and 250 kW and prices 0.01 $/kWh, 0.008 $/kWh, 0006 $/kWh, 0.01 $/kWh, 0.01 $/kWh and 0.01 $/kWh. The PV generators of the MG are installed at buses 29, 31, 30, 15 and 10 respectively with capacities 400 kW, 200 kW, 500 kW, 500 kW and 500 kW. The BSs of the MG are installed at buses 10, 20, 30 and 31, respectively with capacities 500 kWh, 100 kWh, 500 kWh and 100 kWh. The maximum active and reactive power which MG may exchange with upstream grid are respectively 200 kWh and 200 kVar. The studied MG hosts some CSs, SHs and HFSs. The branch and demand data of the studied MG have been taken from Ref. [46]. The default units of the paper have been listed in Table 1.

Each HFS includes a hydrogen tank, electrolyzer and PV unit; every CS includes a battery and PV unit and each SH includes a PV, a battery and a set of appliances. The required electricity of each EV is 40 kwh and the required hydrogen of each FCV is 4 kg. In smart homes, washing machine and clothes dryer are dependent appliances with a maximum gap of 2 h. The capacity of PVs in SHs is 5 kW, the acceptable comfort level is 70 %, the maximum power demand of home is 6 kW; the charging and discharging efficiencies of their batteries are 95 % and the capacity of their batteries is 10 kWh. Table 2 includes some specifics of appliances in SHs. To see other data of SHs, refer to Ref. [35]. Fig. 3 illustrates the time factors of demands and solar irradiation and Fig. 4 shows the prices of electricity, reactive power and hydrogen.

$$C_{MG}=\sum_t\lambda_{E,t}P_{import,MG,t}\Delta t+\sum_t\lambda_{Q,t}Q_{import,MG,t}\Delta t+VOLL.\Delta t\sum_i\sum_t\left(P_{shed,i,t}+Q_{shed,i,t}\right)-\sum_{CS}\sum_t\lambda_{E,t}P_{import,CS,t}\Delta t-\sum_{SH}\sum_t\lambda_{E,t}P_{exchange,SH,t}\Delta t$$
$$-\sum_{HFS}\sum_t\lambda_{E,t}P_{import,HFS,t}\Delta t-\sum_i\sum_t\lambda_{E,t}\left(P_{demand,i,t}-P_{shed,i,t}\right)\Delta t-\sum_i\sum_t\lambda_{Q,t}\left(Q_{demand,i,t}-Q_{shed,i,t}\right)\Delta t \tag{9}$$

3. Results and discussion

In this section, the results of the proposed hierarchical strategy for the integration of SHs, CSs and HFSs in reconfigurable MGs are presented and discussed.

The results show that due to similar electricity prices, the schedules of all EVs are the same; likewise, due to similar hydrogen prices, the schedules of all FCVs are the same. The charging cost of EVs which determine their charging program according to the prices received from CSs, is $ 0.549 and the refuelling cost of FCVs which determine their refuelling program, according to the prices received from HFSs, is $ 21.56. Each EV charges itself at hours 7–8 with a charging power of 20

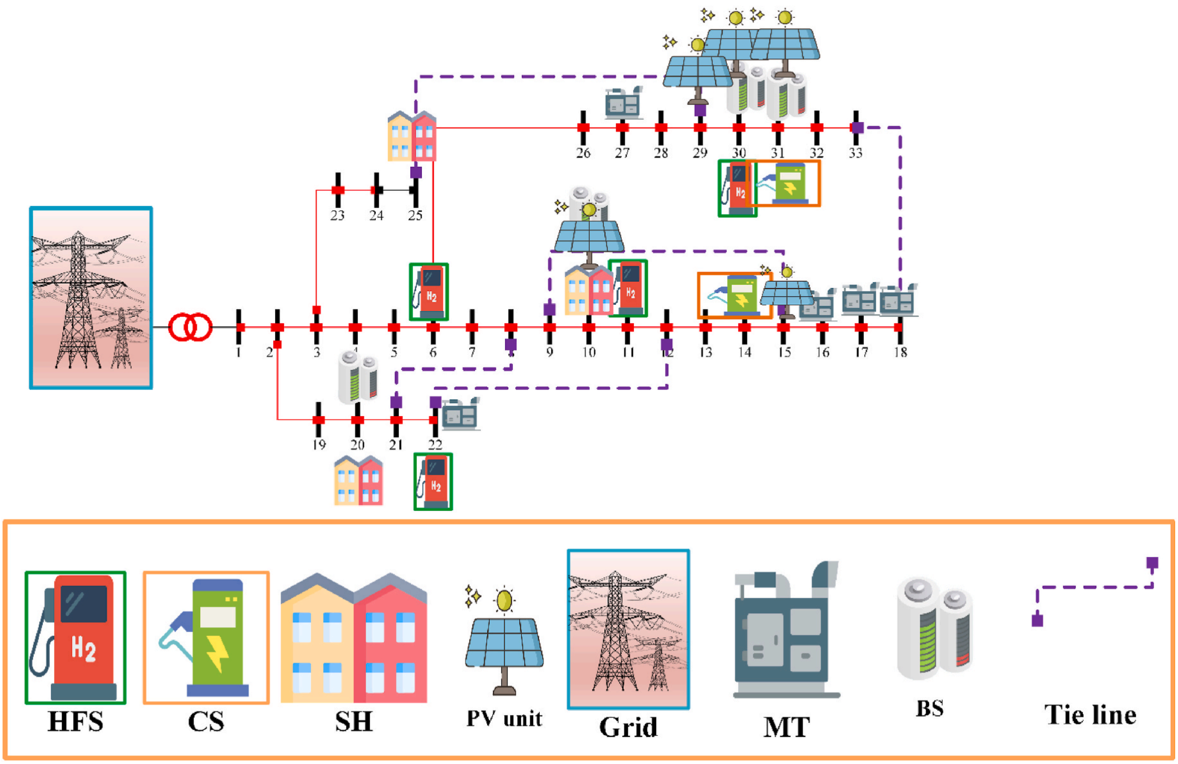

Fig. 2. The studied reconfigurable MG.

kW and each FCV refuels itself at hours 2–5, respectively with 2 kg, 0.2 kg, 0.2 kg and 1.6 kg. If the model of EVs/FCVs are modified in a way that their waiting time is constrained, their schedule and also their charging/refuelling cost would change.

In the second level of the developed tri-level methodology, CSs solve their operational planning model, while know the schedule of all their downstream EVs; similarly, HFSs solve their operational planning model, while know the schedule of their downstream FCVs. The results show that the profits of both CSs are the same and equal to $5.22 and the profit of all HFSs are equal to $431.29. Fig. 5 illustrates the schedule of the components of HFS1, as an example HFS which is installed at bus #6 and Fig. 6 illustrates the schedule of the components of CS1, as an example CS, installed at bus #14. The operator of each CS uses the potential of its PV and BS and also the possibility of purchasing electricity from MG to maximise its profit. The operation cost of any CS is equal to the cost of electricity imported from MG minus the revenue it earns by selling electricity to downstream EVs; similarly, the operation cost of any HFS is equal to the cost of electricity imported from MG minus the revenue it earns by selling hydrogen to downstream FCVs.

The optimal schedule of appliances in smart homes has been tabulated as Table 3. The schedule of appliances confirms that all the associate constraints of the smart home model have been met; the operation of all appliances is non-interruptible and all appliances absorb their required energy. The results confirm that the start of the operation of clothes dryer, as a dependent appliance, occurs at least 2 h after finishing the operation of washing machine. The results show that the optimal cost of each smart home is $1.1. As the prices and appliances are the same for all smart homes, their costs are the same.

Home energy management system in a smart home schedules appliances, PV modules, BS, as well as the exchange with MG in a way that its cost is minimised and its comfort index does not fall below a threshold. The comfort index of a smart home is defined based on the difference between power of appliances at a time period and their preferred demand at that time period. Fig. 7 illustrates the schedule of the components of an example SH, installed at bus #10; the figure shows that thanks to the flexibility added by batteries, the smart home fully utilises the potential of its PV module. As smart homes are prosumers which are able to sell electricity to the MG, expansion of their PV and battery capacities may significantly increase their potential to sell electricity in a way that they not only cover their costs, but also make a considerable profit. As the source of energy, generated by smart homes is renewable and sustainable, awarding governmental incentives to home owners to incentivize the expansion of PV and battery capacities can help to reach the global sustainability and decarbonization targets.

According to the results, the daily operation cost of the MG is $ −571.47; that is, the MG enjoys a daily profit of $571.47; indeed, the revenue that the MG achieves by selling electricity to CSs, SHs, HFSs and

Table 1
Default units of the paper.

Time	*h*
Real power	*kW*
Reactive power	*kVar*
Apparent power	*kVA*
Electric energy	*kWh*
Electricity price	$\$/kWh$
Hydrogen flow	*kg/h*
Hydrogen price	$\$/kg$
Cost/profit	$
Susceptance/conductance	*mho*
Resistance	Ohm

Table 2
The specifics of appliances in smart homes [35].

Appliance	UTR_s	PTR_s	UTR_e	PTR_e	UT	RE
Washing_Machine	9	10	17	11	2	1
Dishwasher	12	15	19	16	2	1.4
Clothes_Dryer	11	12	19	12	1	1.8
Iron	5	6	9	6	1	1.1
Vacum_Cleaner	9	11	19	11	1	0.65
Microwave	11	13	16	13	1	0.9
Rice_Cooker	10	12	15	13	2	0.6
Electric_Kettle	6	7	10	7	1	1
Toaster	6	7	10	7	1	0.8
Air_Conditioner	1	1	20	16	16	38.4
Hairdrayer	16	17	17	17	1	1.2
TV	18	18	24	22	5	1.4
Oven	21	22	24	23	2	2.4

its own demands is significantly higher than sum of the cost of its MTs and the cost of purchased electricity from upstream grid. The MG exploits the reconfiguration possibility to increase its profit. The list of the optimal open switches of MG at different times have been included in Table 4, which shows that MG operator decides to open different sets of switches at different time periods. The list of optimal open switches confirms that the connectivity and radiality of the MG is maintained at all times. The voltage profile of the MG has been depicted as Fig. 8 and testifies that all buses of the studied MG experience a voltage magnitude within the well-established allowed range [0.9, 1.1] Pu. As a direction for future research, using the capability of different demand response programs for increasing the profit of MG is recommended.

In order to assess the impact of batteries on cost of smart homes, HFSs, CSs and MG, we did some experiments which showed that HFSs and CSs would have infeasible models if the batteries are removed, as all constraints of their models would not be satisfied. The results show that the batteries decrease the daily cost of smart homes from \$1.15 to \$1.1, which signifies a 4 % reduction in their cost. The results indicate drastic change in cost of MG by batteries; as they decrease MG cost from \$44326 to \$ −571.47. Without batteries, the MG cannot supply its whole demand at night hours when PV generators do not produce anything and

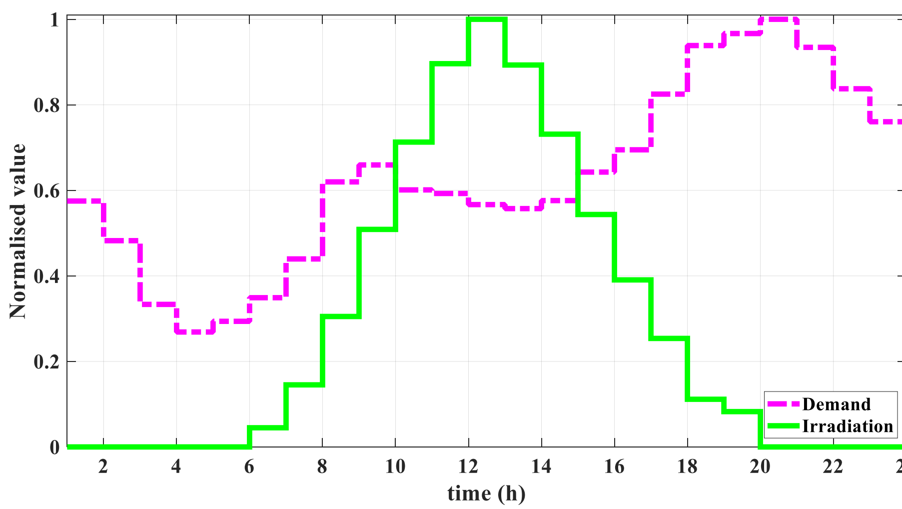

Fig. 3. Time factors of demands and irradiation [47].

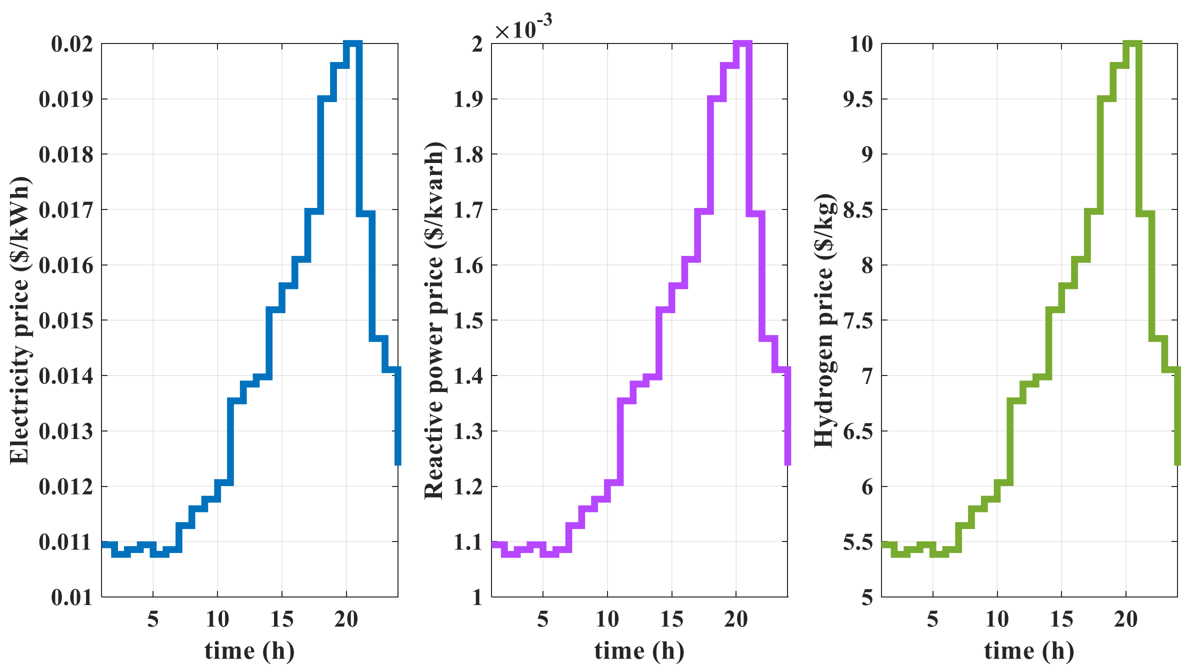

Fig. 4. The prices of Electricity, reactive power and hydrogen [47].

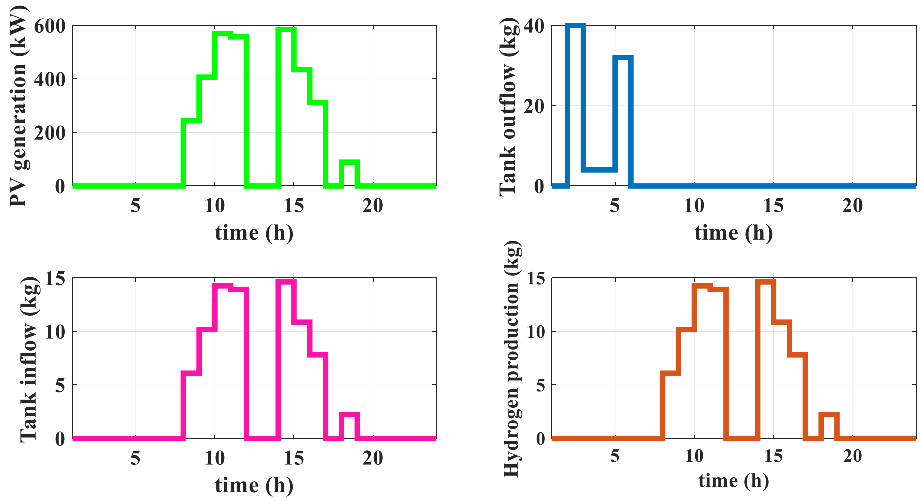

Fig. 5. PV generation, tank inflow/outflow and hydrogen production of HFS #1.

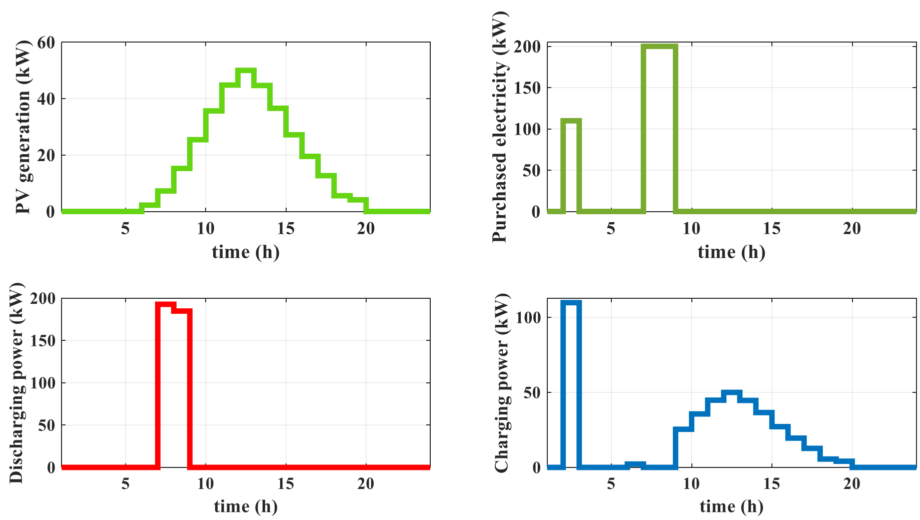

Fig. 6. PV generation, purchased electricity and battery charging/discharging power of CS #1.

microturbines are fully loaded, so a significant portion of MG demand remains unsupplied and the operation cost of MG reaches a very large point. These findings highlight the necessity of batteries for energy systems with high penetration of renewable energy resources; batteries considerably increase the utilization of renewable energy resources and decrease their curtailment.

4. Conclusions

This paper proposed a tri-level framework for energy management in 100 % renewable smart homes (SHs), charging stations (CSs) and hydrogen fueling stations (HFSs) and investigated their impact on the host reconfigurable MG. In the proposed tri-level framework, the charging decisions of EVs and FCVs are considered in energy management model of CSs and HFSs. MILP model has been used for EVs, FCVs, HFSs and CSs, while MIQCP model has been used for MG and MINLP model has been used for smart homes.

The results showed that due to similar electricity prices, the schedules of all EVs are identical; likewise, due to similar hydrogen prices, the schedules of all FCVs are identical. The charging cost of EVs, charging themselves according to the prices received from CSs, is $ 0.549 and the refuelling cost of FCVs, refuelling themselves according to the prices received from HFSs, is $ 21.56. The results show that the profits of all CSs are equal to $5.22 and the profit of all HFSs are the same and equal to $431.29.

Table 3
The optimal schedule of appliances in smart home.

Appliance	Operating hours	Appliance	Operating hours
Washing machine	9–10	Electric kettle	6
Dishwasher	12–13	Toaster	6
Clothes dryer	11	Air conditioner	1–16
Iron	6	Hair dryer	16
Vacuum cleaner	9	TV	17–23
Microwave	11	Oven	22–23
Rice cooker	10–11		

The schedule of smart home appliances show that all the associate

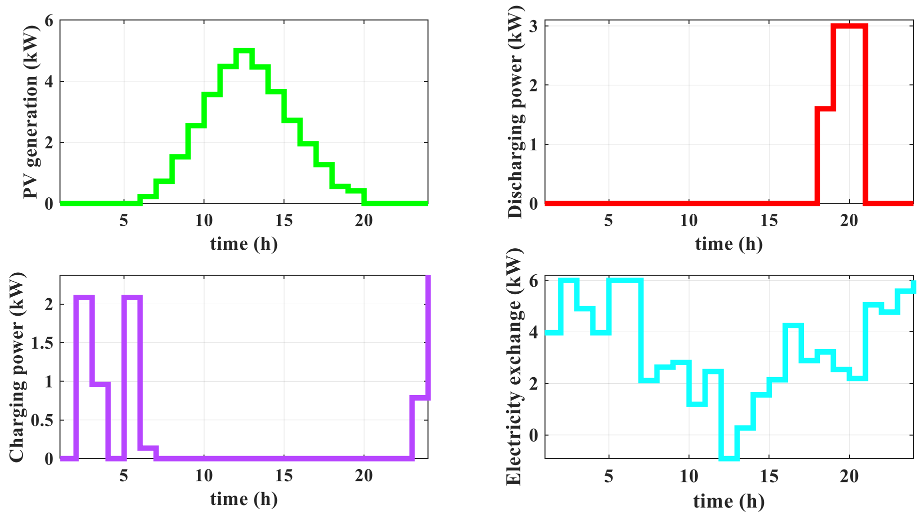

Fig. 7. PV generation, battery charging/discharging power and electricity exchange of SH #1.

Table 4
Optimal MG configuration (list of open switches).

Time period	Open switches	Time period	Open switches
1	[10 15 22 31 33 34 36]	13	[10 15 22 31 33 35 36]
2	[10 15 22 31 33 34 36]	14	[10 15 22 31 33 35 36]
3	[10 15 22 31 33 34 36]	15	[10 15 22 31 33 35 36]
4	[10 15 22 31 33 34]	16	[10 15 22 31 33 34 36]
5	[10 15 22 31 33 34 36]	17	[10 15 22 31 33 34]
6	[10 15 22 31 33 34 36]	18	[10 15 22 31 33 34]
7	[10 15 22 31 33 34 36]	19	[10 15 22 31 33 34]
8	[10 15 22 31 33 34 36]	20	[10 15 22 31 33 34]
9	[10 15 22 31 33 35 36]	21	[10 15 22 31 33 34]
10	[10 15 22 31 33 35]	22	[10 15 22 31 33 34]
11	[10 15 22 31 33 35 36]	23	[10 15 22 31 33 34]
12	[10 15 22 31 33 35]	24	[10 15 22 31 33 35 36]

constraints of their energy management model have been met; the operation of all appliances is non-interruptible and all appliances receive their required energy; moreover, the start of the operation of clothes dryer, as a dependent appliance, occurs at least 2 h after finishing the operation of washing machine. The results show that the optimal cost of each smart home is $1.1. As the prices and appliances are the same for all smart homes, their costs are the same. The results show that the smart homes fully exploit the potential of their PV module. As smart homes are prosumers which are able to sell electricity to the MG, expansion of their PV and battery capacities may significantly increase their potential to sell electricity and make a considerable profit.

According to the results, the MG exploits its reconfiguration possibility to make a daily profit of $571.47. The list of optimal open switches confirms that the connectivity and radiality of the MG is maintained at all times. The voltage profile of the MG testifies that the voltages of all buses of the studied MG are within the range [0.9, 1.1] Pu.

The results show that the batteries decrease the daily cost of smart homes by 4 %. The results show that batteries cause a drastic change in cost of MG; they decrease MG cost from $44326 to $ −571.47. Without batteries, the MG cannot supply its whole demand at night hours when PV generators do not produce anything and microturbines are fully loaded, so a considerable portion of MG demand remains unsupplied and the operation cost of MG reaches a very large point; these findings highlight the necessity of batteries for energy systems with high

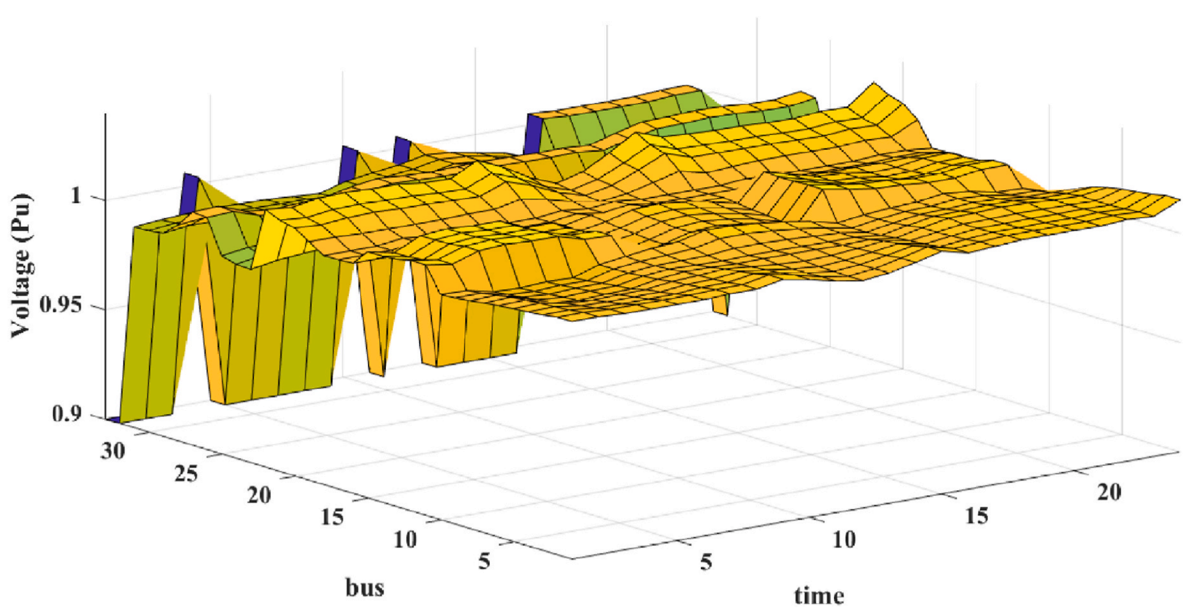

Fig. 8. Voltage profile of MG.

penetration of renewable energy resources. Based on the proposed multi-level model, the participation of microgrids in carbon markets to increase their profitability is recommended as a direction for future research.

CRediT authorship contribution statement

Ahmad Rezaee Jordehi: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Seyed Amir Mansouri:** Formal analysis, Data curation. **Marcos Tostado-Véliz:** Visualization, Formal analysis, Data curation, Conceptualization. **Seyed Mehdi Hakimi:** Resources, Investigation. **Murodbek Safaraliev:** Software, Resources, Data curation. **Mohammad Nasir:** Resources, Formal analysis.

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.

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Data availability

Data will be made available on request.

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