Chapter 12
Modelling the Impact of Uncontrolled Electric Vehicles Charging Demand on the Optimal Operation of Residential Energy Hubs

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12.1 Introduction

Global attention to sustainability in energy use and reduction of greenhouse gas (GHG) emission has become a major driving force for the development and adoption of renewable and low-emission energy technologies. In the on-going development of the existing power grid towards a more sustainable energy future, the adoption of such novel technologies introduces the opportunity to shift towards more advanced energy networks. Under the smart energy network concept, the integration of distributed energy resources (DER) into existing communities provides the potential for more efficient and economic operation. These advantages may be achieved through the optimization of energy flows and through the coordinated operation of various distributed energy technology components within the network. With respect to its applicability to existing communities, there are near-term benefits for adopting smart energy network principles, particularly in consideration of the impacts of DER and mobility electrification on the residential sector.

12.1.1 Literature Review on Energy Hubs

The energy hub framework is an overarching concept for encapsulating the principles of smart energy networks for optimized energy vector dispatch and for the

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coordinated utility of DERs, which have generally been studied via mathematical modelling techniques. Most notably, the formulation of the energy hub model as a mixed integer linear programming (MILP) problem was proposed by Geidl in [1]. This model has been further developed in [2] by Evins et al. to more accurately account for realistic operating characteristics of energy systems. The use of probabilistic considerations to account for uncertainty is presented in [3] by Alipour et al., which is implemented as a mixed integer non-linear programming (MINLP) model. Meanwhile, an iterative approach is discussed in [4] by Batic et al., which was aimed at addressing non-linearity in objective functions for energy vector dispatch within the model. Multi-objective optimization have also been considered, an example of which has been presented in [5] by Beigvand et al. for economic and energy utility criteria. In consideration of the flexibility of the energy hub model, it has been used as the basis for a number of energy hub simulation studies, most of which have been investigative works for unique energy systems or evaluative efforts that applied the energy hub model to examine various operating and optimization strategies. For example in [6], Vahid-Pakdel et al. applies the energy hub model to investigate a multi-energy vector system considering the presence of both thermal and electrical energy storage systems (ESS), demand response programs, and markets, as well as wind-based renewable energy resource (RES) adoption. In a study presented in [7], Moghaddam et al. applies an adaptation of the model using a MINLP approach for a system containing combined heat and power (CHP), electrical heat pump, boiler, absorption chiller, and electrical and thermal ESS technologies. Lastly in [8], Maroufmashat et al. consider an expansion of the energy hub to a network of interconnected hubs, in order to study the potential for more optimized energy vector dispatch resulting from diversity in energy consumption behavior and network size.

While the literature on energy hubs is fairly populated, there are particular topic areas that are of significant relevance to the content of this work. Specifically, the viability of RES integration for adoption into energy systems is critical for their consideration as DER. This characteristic has been investigated in a number of previous works, which have effectively concluded on their emission-reduction and economic potentials within existing energy systems. In [9], a study was conducted by Perera et al. to examine the potential for optimal integration of non-dispatchable renewable resources into electrical energy hubs. The study shows that optimal operation of the electrical energy hub can support RES integration to satisfy more than 60% of the annual electrical demand of the energy hub, under a Sri Lanka context. In another study, Sharma et al. [10] evaluated a centralized energy management system for residential energy hubs considering solar PV availability. The study shows that their energy dispatch strategy can potentially reduce energy consumption and costs by up to 8% and 17%, respectively. In [11], Ha et al. investigated the optimal operation of a residential energy hub implementing solar PV, solar-thermal, and battery ESS under a time-of-use electricity pricing scheme. Zhang et al. [12] present a multi-energy vector energy hub model implementing wind- and solar-based generation with hydrogen as the core energy vector. Both studies investigate the applicability of distributed

RES within the energy hub framework, while noting the need to address the intermittent nature of renewable energy technologies for significant integration into energy hub systems.

Also of significance to this work is the deploy-ability of CHP and ESS technologies, which have been studied in existing literature under the contexts of various unique systems. These studies, however, were aimed at justifying the deployment of such technologies and, as such, did not consider the relevance of EV adoption within complex energy hub systems. In [13], Mohsenzadeh et al. evaluate the operational and cost benefits of CHP implementation within energy hubs. Their study used a simulated energy hub system with electricity and gas energy vectors to demonstrate the potential total and operational cost savings of CHP implementation of up to 9.4% and 10.8%, respectively, as well as improved network reliability and reduced power losses of up to 15.4% and 16.8%, respectively. Similarly, Biglia et al. [14] examined the applicability of CHP implementation in a hospital energy hub based on energy and economic evaluation, under a Sardinia, Italy context. Wang et al. [15] explored the implementation of CHP technology in an integrated energy hub system containing heat pumps and electric boilers. The study investigated the effect of CHP implementation on both heat and electricity networks and the optimal operation of CHP technologies within the energy hub framework. Shams et al. [16] investigated the optimization of a multi-energy vector energy hub model with the presence of CHP technology, distributed renewable generation, and energy storage technologies. The presence of CHP technology in the multi-energy vector system was noted to affect the impact of electricity prices on the demand imposed on the natural gas network.

Meanwhile, the role of ESS technologies in energy hubs have been evaluated in [17] by Thang et al., who notes the advantages of ESS implementation within competitive electricity markets, highlighting the improvement in operational efficiency and flexibility due to inclusion of an energy storage system. Gabrielli et al. [18] discusses the role of both short-term and seasonal ESS technologies in maintaining system efficiency and flexibility in an energy hub subject to significant RES integration. Their study presents an optimized energy hub model incorporating thermal, battery, and hydrogen ESS, along with solar-based generation technologies, heat pumps, and power-to-gas systems. Another study, conducted by Maroufmashat et al. in [19], also considered the potential of hydrogen as a core energy vector in an energy hub containing renewable solar-based generation, hydrogen storage capabilities, and power-to-gas systems. The role of energy storage within a network of interconnected energy hubs has also been explored by Maroufmashat et al. in [20]. Their work illustrates that consideration of energy storage capabilities in combination with a variety of distributed generation technologies in large energy hub networks provides yields lower overall system costs and increased opportunities for integration of distributed generation resources into the network. In [21], Brahman et al. investigates the roles of electrical and thermal ESS within a multi-energy vector energy hub considering demand response programs in the energy vector dispatch optimization problem. Similarly, Javadi et al. [22] presents a study on the optimal operation of a multi-energy vector energy hub with the presence of battery ESS, while accounting for cycling degradation costs of the ESS in the optimization. In [23], Ye et al. incorporates both demand response programs and ESS functionality into an energy hub model and simulated the optimal dispatch of energy vectors within the energy hub based on a cost objective function. The study indicates the cost-cutting benefits of storage technologies in energy hubs that are subject to a time-of-use electricity pricing scheme.

Across these studies, the applicability of various DER technologies have been considered under a number of unique energy systems and conditions, which has established the viability and benefits of different DER technologies within energy hubs. However, recent market trends in electric mobility introduces EVs as another potentially disruptive energy technology that should be considered in the context of smart energy systems.

12.1.2 Plug-in Electric Vehicles in Energy Hubs

As an emerging technology, EVs have been developing at a rapid rate and has been projected to make up to 47% of the total light duty vehicle fleet by 2050 [24]. In comparison to traditional fossil fuel-based vehicles, EVs rely on grid-generated electricity and battery energy storage technologies for fuel. This allows EVs to incur significantly less GHG emissions during operation, particularly in energy systems that can meet their charging demand with electricity derived from renewable or low-emission energy resources. However, significant penetration of EVs into the automotive market will consequently result in tremendous increases in electricity consumption demand due to the charging behavior necessary to fuel EVs. This poses a major challenge to the power grid, which must allocate appropriate generation capacity to accommodate the additional demand. Realistically, much of the charging demand of EV fleets will originate from the residential sector, which provides the context for the adoption of EVs into residential energy systems as manageable components. Most importantly, significant EV charging demands can negatively impact the flexibility of the local energy system and, as such, must be appropriately managed to maintain energy reliability.

Currently, several levels of EV charging rates are available for EV charging, which can affect the shape of the electricity demand imposed on the energy hub by uncontrolled EV charging behavior. In level 1 charging, the low charging rate generally results in long charge durations, as well as in a flat charging profile. This contributes to increasing the base load of the energy hub during EV fleet charging periods. Meanwhile, the relatively higher rate of charging provided by level 2 charging will result in higher peaks in power demand, with a shorter charge period compared to a level 1 charging scenario. Finally, DC fast charging provides a significantly faster charge rate as compared to the other options. Thus, the charging profiles imposed by uncontrolled DC fast charging will be composed of short but significant power peaks during uncontrolled EV charging periods. However, EV charging stations with DC fast charging capabilities are unlikely to be implemented within residential energy hubs due to their high cost, and are therefore not considered in this work.

Within the existing literature, several forecasting efforts have been made to evaluate the relative impact of large-scale EV integration on the power grid. These works are often set in the context of unique power grid systems and broadly estimate the effects of uncontrolled EV fleet charging via total annual and peak charging demand criteria. For example, Clement et al. present in [25] a forecasting study on the impacts of uncontrolled EV charting at the residential level, based upon historic data of EV charging behaviors. A more recent evaluation of these impacts has been conducted by Fischer et al. in [26]. Both studies, however, evaluate scenarios of EV adoption within existing energy system conditions and do not consider how the energy hub concept may be leveraged to mitigate uncontrolled EV charging behaviors. Other notable developments in literature include the work of Dias et al. in [27], who compare impact scenarios between uncontrolled and controlled EV charging strategies within the residential sector. This study, again, is set in the context of conventional power systems and do not account for the role of DERs or for the energy hub concept. Meanwhile, further research has been conducted by Ul-Haq et al. in [28] to provide more realistic estimations of uncontrolled EV loads via stochastic methods. Concisely, there is a gap in the literature in evaluating scenarios of EV adoption into residential energy systems with uncontrolled charging behavior under an energy hub context, which may prove to be the most effective means of regulating volatile EV charging demands under medium to high market penetrations scenarios of EV fleets into the transportation sector.

In response to the significant impacts of uncontrolled EV charging behaviors, several strategies have been proposed to regulate EV charging. In one case, the controlled or smart EV charging mode has been considered for managing EV fleets as flexible loads via advanced communication and information technology. Similarly, the vehicle-to-grid (V2G) charging mode considers the adoption of bi-directional power flow infrastructure and intelligent centralized controls, in order to integrate EV fleets into energy systems as mobile BESS grid components. These two alternative charging modes have been discussed in a number of studies, which have aimed to justify their operational or economic feasibility. For instance, notable contributions to the feasibility evaluation of the V2G concept has been made by Kempton et al. in [29, 30], who concluded that V2G may contribute significantly to battery degradation in EVs and is consequently only economically justified for the provision of high-value services such as peak shaving. In another study, conducted by Locment et al. in [31], the coordinated dispatch of power is studied for an EV charging station system, which aimed to leverage controlled EV charging to improve the energy utility of local solar PV generation components. Anastasiadis et al. proposed a harmony search algorithm in [32] for controlling EV charging behavior in a microgrid containing mixed commercial and residential loads, as well as various DER components. Yao et al. [33] considered a particle swarm optimization approach for economic dispatch of power to a EV fleet with V2G enabled. The energy hub considered for this study contained both renewable and conventional energy technologies. In [34], Moeini-Aghtaei et al. presents a framework for scheduling the charging demands of a EV fleet considering charging patterns. The coordination of EV fleet charging demands is addressed using a particle swarm optimization approach for multi-objective optimization, considering financial factors, RES utilization, and a convenience criterion for EV usage. Alkahafaji et al. [35] considered the optimization of energy vector dispatch within a system containing EV fleets, using a mixed integer quadratic programming approach for the multi-objective optimization of financial and environmental criterion. The study indicates the cost-cutting potential of discharging EV fleets to maintain stability and reliability of the energy hub system. A scheme of integrating EV fleets into smart buildings is simulated and discussed in [36] by Wang et al. In [37], Liu et al. considers the economic and environmental optimization of an energy hub containing a EV fleet operating under both grid-connected and islanded modes. The study presents a comprehensive learning particle swarm optimization model for the coordinated dispatch of energy vectors within the energy hub. Similarly, Khederzadeh et al. [38] investigates the effects of EV fleet penetration in an energy hub operating between grid-connected and islanded modes, with a focus on the roles of the EV fleet, ESS, and responsive loads for maintaining islanded operation of the energy hub. In [39], Munkhammar et al. examine the potential of home-charging of EVs considering solar PV implementation at the household level, using a case study of Westminister London. The study notes the compatibility of solar PV generation and EV charging behavior, both at the single household level as well as at the grid level.

While these advanced charging modes have been considered in detail in research, they have yet to be successfully adopted in a real, large-scale energy system. Meanwhile, current trends of increasing EV penetration into the automotive market are likely to manifest in significant uncontrolled charging demands on existing power grids. As such, there is an immediate research need to evaluate the realistic impacts of uncontrolled EV charging behavior within energy hub systems, particularly for high impact areas such as the residential sector. Furthermore, an understanding of how these uncontrollable charging demands interact with grid components will provide insight into how best to implement available DER and technologies to mitigate their impact on the grid.

12.1.3 Contributions of This Chapter

In this chapter, we aim to address the research need of evaluating the potential of energy hubs for mitigating and regulating probable uncontrolled EV fleet charging demands considering systems with complex DER technology configurations. Specifically, we consider a case study of residential energy networks with solar PV arrays, CHP, electrical and thermal ESS, and conventional boiler heating technologies. This work employs an energy hub model based on [1] to simulate MILP-optimized system operation via a multi-objective approach based on economic and environmental criteria. The novelty of this study is the evaluation of realistic, near-term impacts of EV adoption into residential energy systems under than energy hub context. Furthermore, consideration of various scenarios of DER technology configurations provides insights into the planning and design of DER integration into the residential sector in consideration of disruptive EV integration into existing communities.

The contents of this chapter are structured as follows: the modelling approach and the simulation scenarios are discussed in Sect. 12.2, followed by a description of the examined energy hub system in Sect. 12.3. In Sect. 12.4, the results of the simulated scenarios are shown, and environmental and economic analysis of the results are presented. Lastly, concluding remarks for this work are made in Sect. 12.5.

12.2 EV Fleet Demand and Energy Hub Modelling Approach

12.2.1 Energy Hub Model

The operation of the residential energy hub considered in this work is formulated as a mixed-integer linear programming (MILP) problem and was modelled using the GAMS software, which is a mathematical modelling tool designed for linear, nonlinear, and mixed-integer optimization problems. The formulation of this model is based on the energy balance concept and is as shown in (12.1). In this approach, the operational flows of energy vectors within the residential energy hub is modelled as a process of energy vector transformation, conversion, and storage, beginning with grid feed and ending with consumption at the end-user. A holistic diagram of this energy hub model is as shown in Fig. 12.1.

Using this model, the aim of this work is to simulate the performance of the energy hub system under various energy technology configurations and loads, which is set by specifying the coupling matrix and the outflow energy vector set,

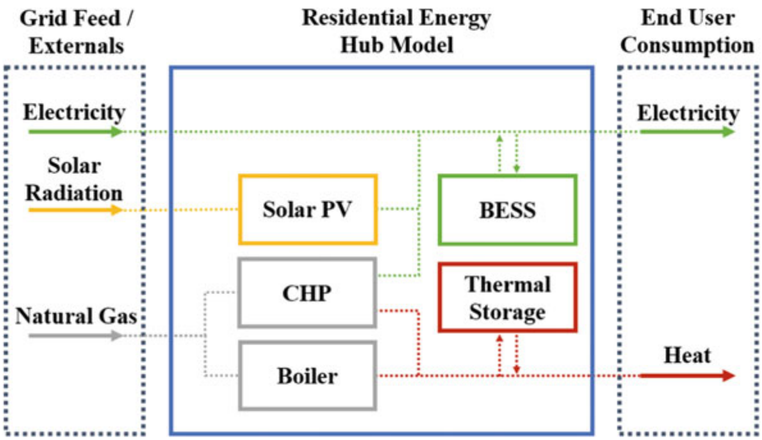


Fig. 12.1 Holistic diagram of the residential energy hub model

respectively. The coupling matrix is representative of conversion efficiencies of implemented energy technologies while the outflow energy vector set represents the various demand loads of end-users within the energy hub system. Furthermore, technology constraints such as flow and capacity constraints, as well as operational constraints, are accounted for by limiting the range of energy vector flows of the inflow energy vectors, as shown in (12.2). Optimization of energy vector flows is done using a weighted multi-objective MILP approach based on economic and environmental criteria, which are evaluated in correlation to the inflow energy vector set. The form of the overall objective function is as shown in (12.3). On the basis of optimizing the objective function, simulation of the energy hub under various scenarios is intended to reflect the optimal performance of the system under the specified conditions of each scenario.

$$O(t) + \frac{Q_{EV}(t)}{\varepsilon_{EV}} = C_{ij} I(t) + \dot{E}(t) \tag{12.1}$$

Where:
$O(t)$ is the energy demand load set of the energy hub
$Q_{EV}(t)$ is the charging required for the EV fleet
ε_{EV} is the efficiency of EV charging
C_{ij} is the coupling matrix for input energy vector i to load j
$I(t)$ is the inflow energy vector set
$\dot{E}(t)$ is the flow of energy into storage system

$$I_{min} \le I(t) \le \mathrm{I}_{max} \tag{12.2}$$

Where:
I_{min} is the set of minimum flow capacities for the inflow energy set
I_{max} is the set of maximum flow capacities for the inflow energy set

$$Z = \mu \cdot Z_1 + (1 - \mu) \cdot Z_2 \tag{12.3}$$

Where:
Z is the overall objective function
Z_1 is the operating cost objective function
Z_2 is the emissions objective function
μ is the weight factor

The individual cost and emission objective functions are evaluated as shown in (12.4) and (12.5).

$$Z_1 = Cost_{fixed} + \sum_t \left(Cost_{oper,conv}(t) + Cost_{fuel}(t) + Cost_{oper,stor}(t) \right) \tag{12.4}$$

Where:

$Cost_{fixed}$ is the fixed cost of the energy technology systems
$Cost_{oper,\ conv}(t)$ is the operating cost of energy conversion systems
$Cost_{fuel}(t)$ is the cost of fuels consumed in the energy hub during operation
$Cost_{oper,stor}(t)$ is the operating cost of energy storage systems

$$Z_2 = \sum_t EF \cdot I(t) \tag{12.5}$$

Where:
EF is the set of emission factors associated with inflow energy vector set $I(t)$.

12.2.2 Energy Storage Model

Energy storage technologies are incorporated into the mathematical model differently as compared to the energy conversion technologies, which are represented by the coupling matrix. Instead, energy storage technologies are constrained not only by their energy conversion efficiencies and power flow limitations, but also by their storage capacities and their temporal state-of-charge, which represents the current amount of energy stored. As such, these technologies are incorporated into the model as discrete temporal systems, where their performance are additionally constrained by a steady-state energy balance, as shown in (12.6). The state-of-charge of the technology is as calculated using a discrete temporal method as shown in (12.7). Further constraints were specified to limit the storage capacity of the energy storage systems, as shown in (12.8). Additionally, due to the bidirectional power flow of energy storage technologies, a further operational constraint is placed such that inflow and outflow of power cannot occur simultaneously.

$$\dot{E}_k(t) = Q_{charge,k}(t) \cdot \varepsilon_{charge,k} - \frac{Q_{discharge,k}(t)}{\varepsilon_{discharge,k}} - \dot{E}_{loss}(t) \tag{12.6}$$

Where:
$\dot{E}_k(t)$ is the flow of energy into storage system for energy vector k
$Q_{charge,k}(t)$, $Q_{discharge,k}(t)$ are the power charged and discharged to storage system k, respectively
$\varepsilon_{charge,k}$, $\varepsilon_{discharge,k}$ are the charge and discharge efficiencies for storage system k, respectively
$E_{loss}(t)$ is the standby loss of energy from the storage system k

$$SoC_k(t) = SoC_k(t-1) + \frac{\dot{E}_k(t)}{E_{max,k}} \tag{12.7}$$

Where:

$SoC_k(t)$ is the state of charge of the storage system k at timestep t
$SoC_k(t-1)$ is the state of charge of the storage system k at timestep $t-1$
$E_{max,\ k}$is the maximum storage capacity of storage system k

$$SoC_{k,min} \leq SoC_k(t) \leq SoC_{k,max} \tag{12.8}$$

Where:
$SoC_{k,\ min}$ is the minimum charge capacity of the storage system k
$SoC_{k,\ max}$ is the maximum charge capacity of the storage system k

12.2.3 Monte Carlo Simulation of EV Fleet Charging Demand

The fleet charging demand of the EV fleet used in this work is derived using a Monte Carlo simulation, which considers stochastic elements affecting individual EV charging behavior including arrival and departure times, daily travelled distance, EV battery capacities, the efficiencies of EV charging nodes, and the non-linear charging characteristics of EV batteries. The use of the Monte Carlo method in this work is for the generation of representative fleet charging behaviors of hypothetical vehicle fleets based upon realistic vehicle use behavior. As the basis of this approach, 2009 National Household Travel Survey (NHTS) data [40] was used to derive the driving requirements of a fleet of light-duty vehicles in a residential context. A flow diagram of the Monte Carlo simulation used in this study is as shown in Fig. 12.2.

Based on this Monte Carlo approach, the following EV fleet charging profiles were derived for an EV fleet composed of 50 vehicles considering both level 1 and level 2 uncontrolled charging behavior. Under the level 1 charging mode, EVs were assumed to be able to charge at a power flow rate of 1.44 kW, whereas the level 2 charging mode was assumed to operate with a power flow rate of 7.2 kW. Under each of these charging level scenarios, the EV charging impact was evaluated and incorporated into the electricity consumption demand of the energy hub system, later described in this chapter. The electricity demand profiles were assumed to be consistent on a daily basis across the annual simulation, which represented the average annual charging requirement of the EV fleet. These profiles are as shown in Fig. 12.3. In the case of the level 1 charging scenario, an aggregate charging demand of 436 kWh was consumed for EV fleet charging, whereas the level 2 charging scenario required 458 kWh.

12.2.4 Model Inputs

In this mathematical formulation, the inputs to the model consist of the end-user energy vector consumption demands of the energy hub system, as represented by the

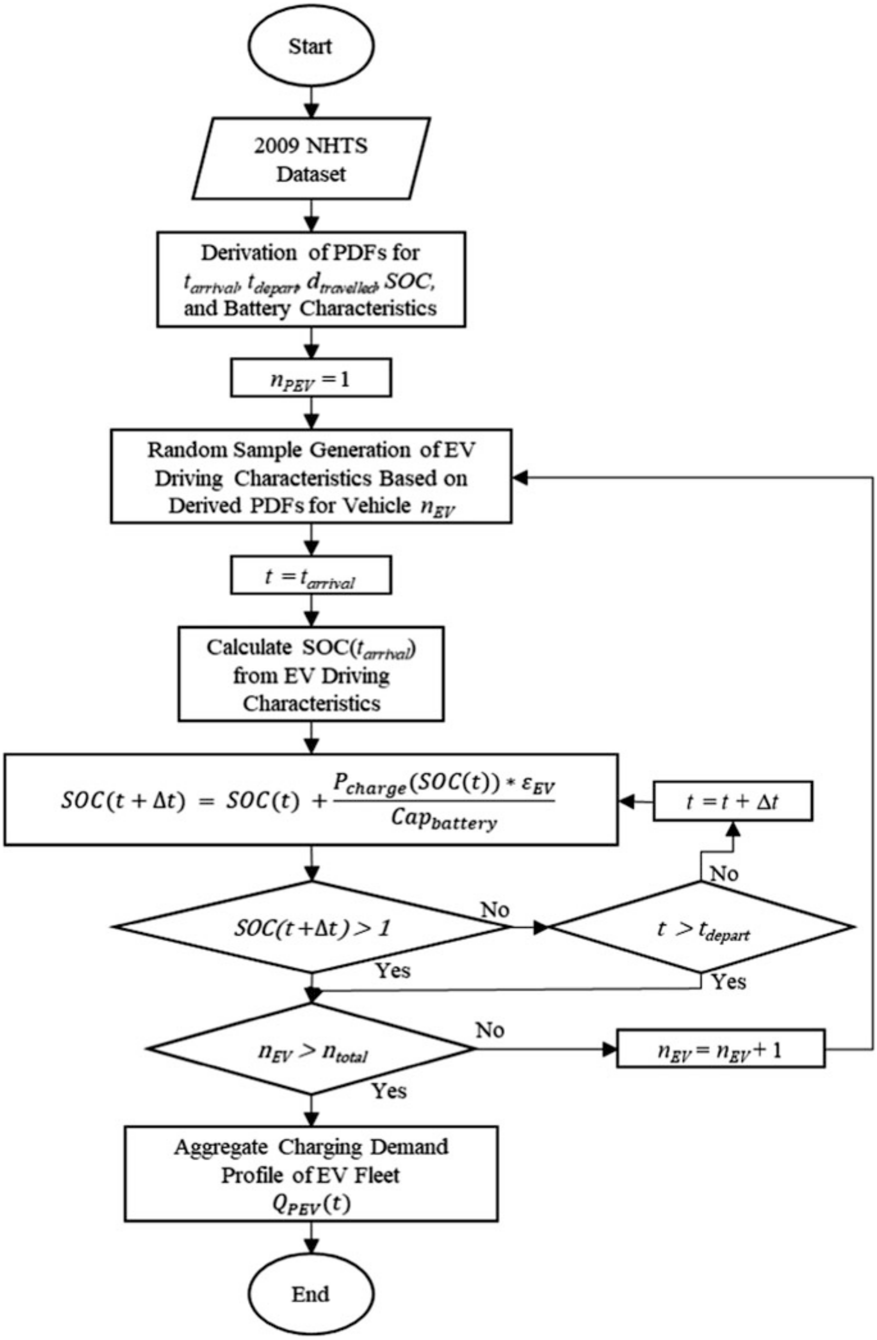


Fig. 12.2 Flow diagram of Monte Carlo simulation for EV fleet charging demand

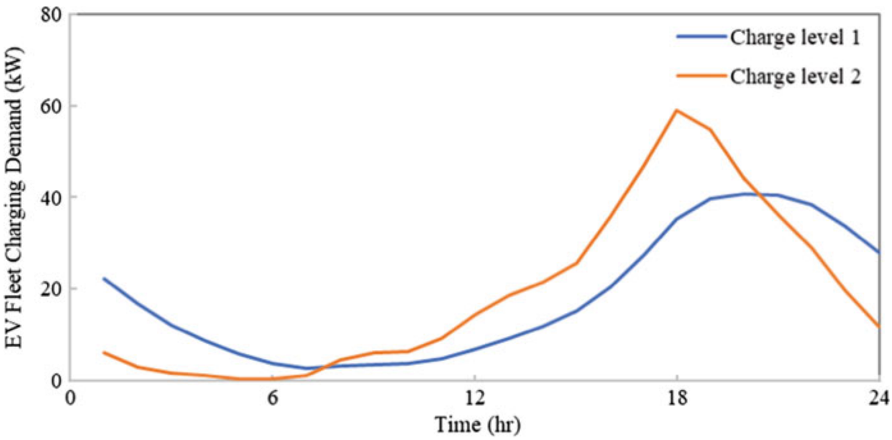


Fig. 12.3 Simulated charging demand of EV fleet for level 1 and level 2 uncontrolled charging

outflow energy vector set. As well, environmental inputs must be specified with respect to the relevant energy technologies, such as solar irradiation data for solar PV arrays. The range of sizes, efficiencies, and operating capacities should also be specified for each of the energy storage and conversion technology components in the energy hub, as well as the operating cost and emission factors associated with the operation of each energy technology. Lastly, relevant grid energy vector pricing schemes and emission factors are also required to reflect the operating cost and emission considerations with respect to grid-purchased energy vector consumed by the energy hub system. These factors contribute to the overall operating costs and emissions of the system and are thus relevant to the objective functions used in this model.

12.2.5 Model Optimization and Solution Methodology

Using a weighted multi-objective optimization, the objective function considered in the GAMS optimization account for both the operating costs and GHG emissions resulting from energy hub operation. The overall model is implemented as a mixed-integer linear programing problem, which is solved using the CPLEX solver. The optimization results in optimized energy vector flows within the system and purchases from the grid. The operating cost and emissions-related implications of these power flows are determined under the economic and environmental factors that were inputted into the model. The optimization is also dependent on the availability of energy transformation and storage technologies, as well as the type of load demand experienced by the energy hub. Thus, different optimized power flows will result under different simulation scenarios due to the conditions that the energy hub is subject to. A diagram illustrating the overall optimization process and optimization criterion, variables, and constraints is as shown in Fig. 12.4.

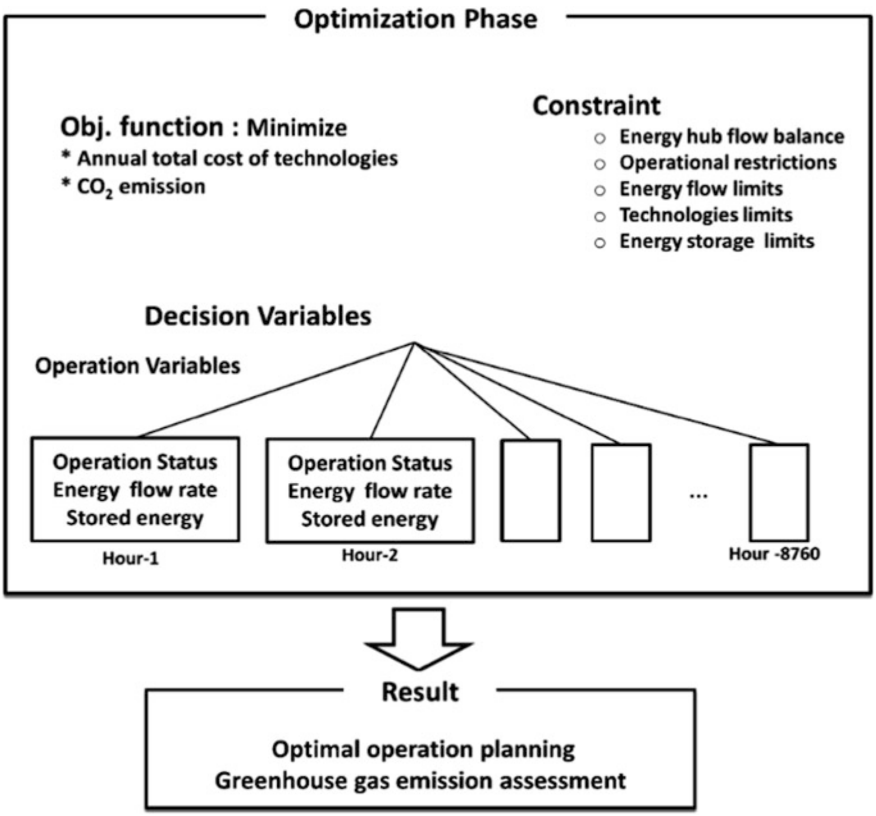


Fig. 12.4 Diagram of optimization process used in energy hub model

12.2.6 Simulation Scenarios

A total of 6 simulation scenarios were considered for the residential energy hub system. These scenarios were selected to evaluate the effect of different EV charging levels and the presence of distributed energy resources on the optimized operation of the energy hub, under the implemented optimization approach. A summary of these simulation scenarios is as shown in Table 12.1.

12.3 Residential Energy Hub System Case Study

In this study, the operational energy loads of a single residential complex were modelled and optimized under various simulated scenarios regarding EV fleet size and DER configurations. Within the energy hub model, the thermal and electrical loads of a 10-story residential complex was considered as the base load of the energy hub. The reference building model consists of 10 floors with a total floor area of

Table 12.1 Summary of simulation scenarios

Scenario	EV charging level	DER adoption
1 (Base Case)	No EV Fleet	Without DER
2	No EV Fleet	CHP and PV
3	Level 1	Without DER
4	Level 1	No CHP, only PV
5	Level 1	CHP and PV
6	Level 2	CHP and PV

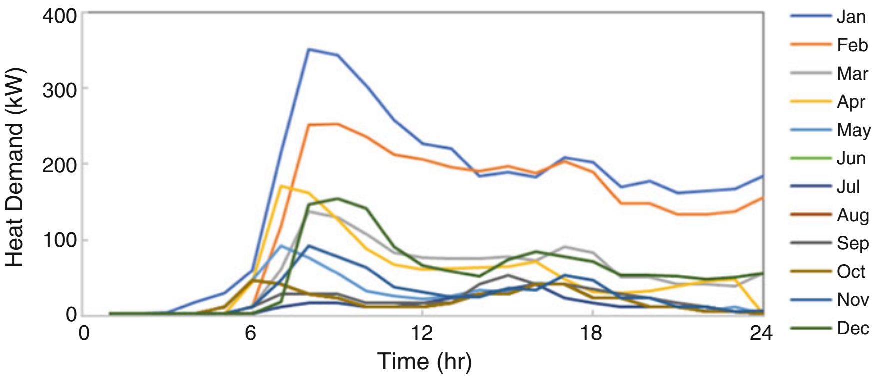


Fig. 12.5 Hourly profiles for heat demand of the residential energy hub system

7765 m^2. The thermal and electrical loads of this building model have been considered to follow hourly profiles, which were assumed to vary monthly. The hourly profiles for the thermal and electrical demands of the building are as shown in Figs. 12.5 and 12.6, respectively.

The costs of grid-purchased electricity are evaluated using a time-of-use pricing scheme, as reflective of Ontario, Canada conditions. Under this scheme, the cost of electricity is evaluated in tiers that consist of off-peak, mid-peak, and on-peak prices, which vary between summer and winter seasons and between weekdays and weekends. The values used for off-peak, mid-peak, and on-peak prices were 0.072 $CDN/kWh, 0.109 $CDN/kWh, and 0.129 $CDN/kWh, respectively. A summary of this pricing scheme for seasonal weekdays is as shown in Fig. 12.7 [41]. The price for weekends is valued consistently at off-peak prices. Meanwhile, the costs of natural gas were evaluated at a rate of 0.22 $CDN/m^3, based on Ontario conditions.

The emission factors used to evaluate the GHG emissions associated with energy hub operation are derived based on the fuels and grid-purchased electricity used to support energy hub operation. For grid-purchased electricity, a time-averaged emission factor of 0.187 kg CO_2/kWh was used to reflect Ontario, Canada conditions, which produces most of its electricity using a grid mix as shown in Fig. 12.8 [42]. Meanwhile, an emission factor of 1.9 kg CO_2/kWh was used for natural gas.

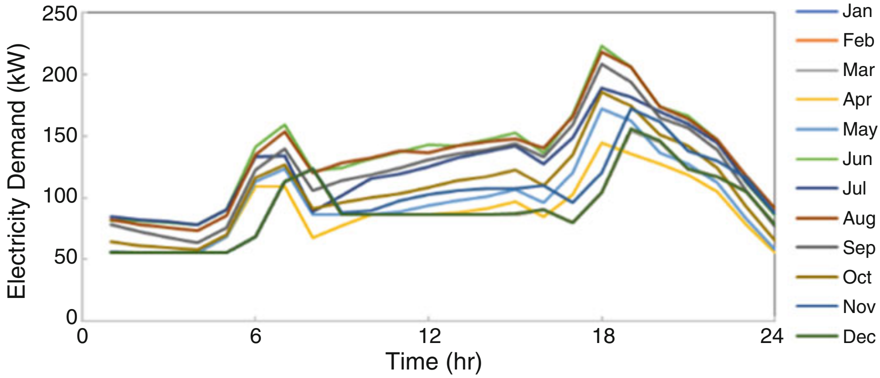
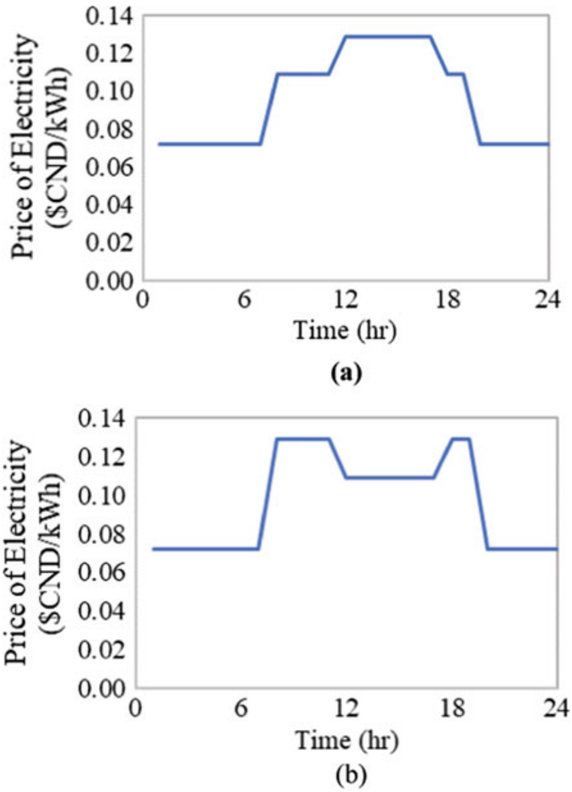


Fig. 12.6 Hourly profiles for electricity demand of the residential energy hub system

Fig. 12.7 Time-of-use pricing scheme for electricity costs in Ontario, Canada for: (**a**) summer weekdays (May 1st–October 31st) and (**b**) winter weekdays (November 1st–April 30th)



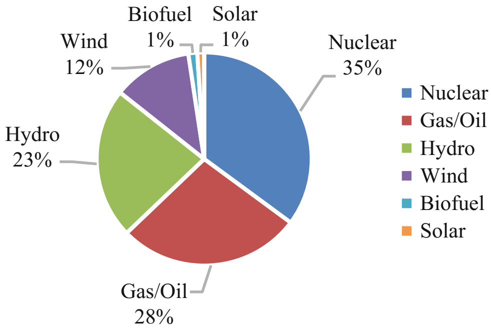


Fig. 12.8 Generation grid mix for Ontario, Canada

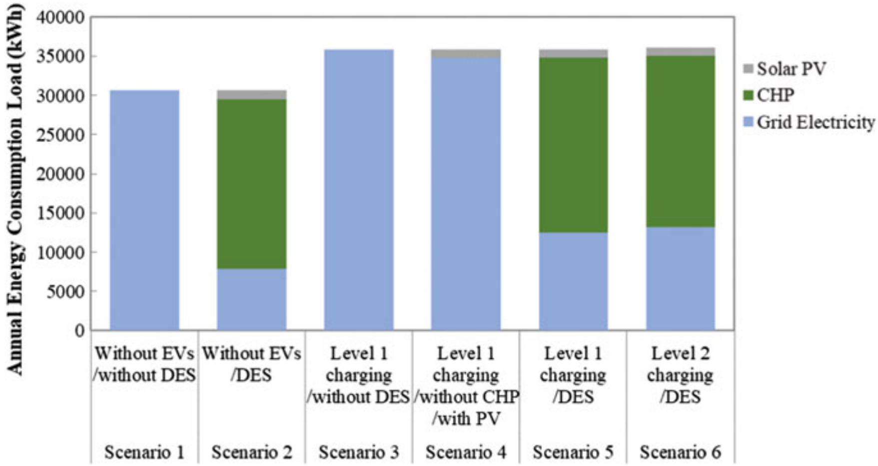


Fig. 12.9 Summary of energy consumption loads from simulated scenarios

12.4 Results and Discussion

A summary of the overall energy consumption behavior of the energy hub system in each of the simulated scenarios is as shown in Fig. 12.9. From these results, it is seen that the presence of uncontrolled EV fleet charging contributes to approximately 17.1% additional electricity consumption in the energy hub in comparison to a scenario in which a EV fleet was not considered. The significant increase in electrical power consumption of the residential energy hub indicates the potential for escalating power demand on the electrical grid as a result of EV penetration into the automotive market. Meanwhile, residential energy hubs must also adapt the necessary charging and power transfer infrastructure to accommodate the integration of EV fleets.

With respect to DER technology options in a residential context, the simulation results also indicate the distributed energy generation potential of CHP implementation in a residential context, which is shown to be able to supply up to 70% of the residential energy hub's overall consumption demand. This indicates the contribution of CHP implementation to improving energy security for residential energy hubs, as the overall system becomes significantly less reliant on grid generation for meeting its operational energy requirements. With respect to scenarios 5 and 6, in which CHP implementation was considered with EV fleet charging behavior, the results indicate the effects of significant DER implementation on alleviating the escalating demand of EV integration into residential energy hubs. This is due to the increased self-efficacy of the residential energy hub system, which in turn reduces the need for additional power transfer infrastructure and spinning reserve capacities at the grid level. PV adoption, however, is seen to play a minor role in meeting the energy hub's consumption demand, meeting only 3% of the total electricity requirements of the energy hub, considering the additional load of EV fleet charging. This is a result of the system's limitations for solar PV implementation in the target residential energy hub. Particularly, the lack of available rooftop surface area for solar PV array installation in residential high-rises limits the overall generation potential of solar PV technology, relative to the consumption needs of the building.

12.4.1 Operating Costs Analysis

A summary of the total operating costs derived for each of the scenarios is as shown in Fig. 12.10. As shown, adoption of fleet charging behavior into the residential energy hub results in an increase in operating costs. This increase in costs results from the additional electrical demand imposed onto grid generation and corresponds to an increase of 12.6% of the total operating costs of a scenario

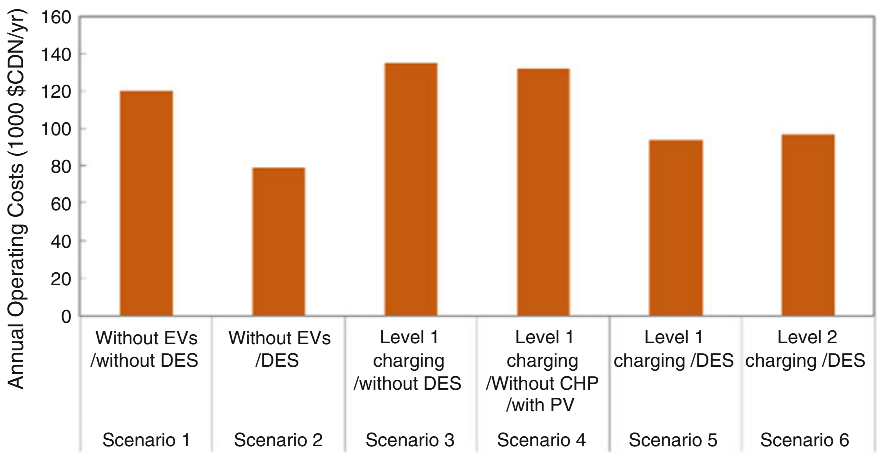


Fig. 12.10 Summary of cost analysis of simulated scenarios

without EV adoption. In comparison to the 17.1% increase in overall electricity demand determined from the energy analysis, the relatively lower increase in total operating costs results from the factoring of space heating costs as well as the time-of-use costs for EV fleet charging. These costs are incurred largely during mid-peak and off-peak periods, thus incurring a lesser impact on the operating costs of the residential energy hub as compared to its overall electricity consumption. A comparison between the two levels of EV fleet charging showed that level 1 charging results in lower operating costs for the system, due to the limitations in the rates of power purchase from the grid. These limitations extend the charging times of the EV fleet, thus constraining a larger portion of uncontrolled EV fleet charging behavior to occur during off-peak hours, thereby incurring lower charging costs during these periods. This indicates the advantages of controlled charging strategies, which can potentially schedule EV fleet charging to low-peak hours to minimize the costs of EV fleet charging, while still meeting the charging needs of the EV fleet.

With respect to DER implementation in the residential energy hub, scenarios considering DER implementation incur significantly lower operating costs. In comparison to scenarios not considering DER implementation, this corresponds to a reduction in operating costs of up to 34%. In particular, a significant portion of this cost reduction potential results from the adoption of CHP technology, due to the relatively cheaper costs of natural gas purchases in comparison to grid electricity costs. In these scenarios, optimization of the objective function for energy hub operation resulted in increased reliance on CHP operation, based on its economic advantage over mid- and on-peak costs of grid generation in Ontario's time-of-use pricing scheme. Based on this comparison, it is evident that significant DER implementation offers an economic advantage for residential energy hub systems, particularly in grids with high peaking prices for electricity. Lastly, a comparison between scenarios 3 and 4 indicates that solar PV implementation within the residential energy hub contributes to reducing the operating costs of the system by 2.5%. Again, the low significance of its contribution to the overall costs of the system highlights the low applicability of PV technology in residential energy hubs with spatial constraints for PV implementation.

12.4.2 GHG Emissions Analysis

As shown in Fig. 12.11, the simulation results indicated that the adoption of a EV fleet increases the operating GHG emissions of the residential energy hub, due to the additional energy consumption of the EV fleet. This represents an increase in annual GHG emissions of 11.3%. Meanwhile, it is also seen that the uncontrolled level 1 charging scenario resulted in higher emissions as compared to the uncontrolled level 2 charging scenario. This was because the optimized energy vector flows in the energy hub for the lower charging rate scenario satisfied more of its energy demand from CHP operation, which has a higher emission factor than compared to

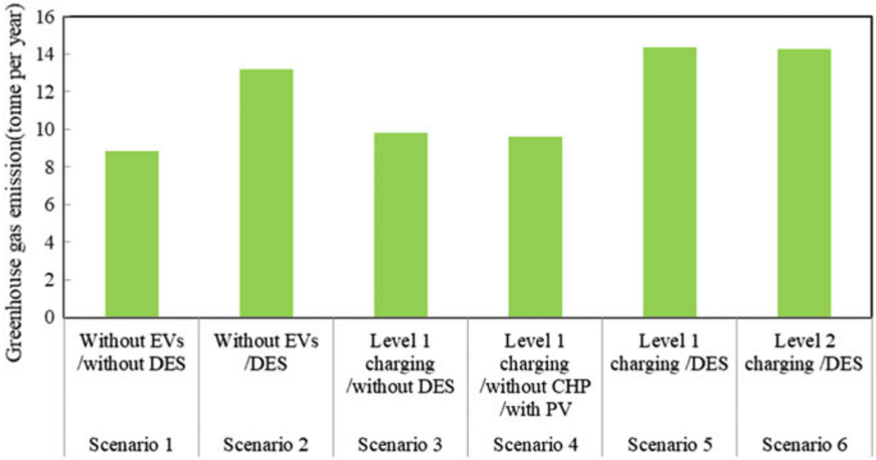


Fig. 12.11 Summary of operating emissions analysis of simulated scenarios

grid-generated electricity. In this case, the charging limitations of the level 1 charging scenario extended the charging demand of the EV fleet into a profile with a longer tail, with a less significant charging demand during on-peak periods. In this comparison, the results highlight the tradeoff between economic incentive offered by CHP operation and the environmental demerit incurred by natural gas consumption, relative to a power grid with a large portion of low emission generation.

Considering the implementation of DER technologies, CHP implementation was found to significantly increase GHG emissions resulting from energy hub operation. This was due to the effect of increased natural gas consumption resulting from CHP implementation, which has a significantly higher emission factor in comparison to Ontario's grid generation, which derives most of its generation capacity from low emission resources. This corresponds an increase in emissions of up to 49% of the scenario where DER implementation was not considered. These results indicate the negative environmental impacts of significant CHP implementation as a DER technology in a low emission power grid. Finally, comparison between scenarios 5 and 6 showed that solar PV implementation reduces the overall emissions of the energy hub system by 2.1%.

12.5 Conclusion

In this study, the following contributions to the literature has been made:

- Primarily, this work addresses the research gap in understanding the impact of realistic EV adoption scenarios into existing residential communities and the potential applicability of the energy hub concept in mitigating the volatile energy consumption behavior of uncontrolled EV fleet charging.

- This work provides insight into the compatibility of different DER technology configurations with uncontrolled EV fleet charging within residential energy hubs, which should aid in the planning and design of DER implementation within such systems.
- A case study of residential systems has been examined under an Ontario, Canada context, in order to evaluate the relevance of the study to real-world systems and conditions.

With respect to the results of the case study, analysis of the results based on energy, operating cost, and emissions criteria showed the impacts of EV adoption in escalating energy consumption, operating costs, and emissions at the residential level. Considering these effects, additional power transmission and distribution infrastructure, as well as spinning reserve capacities, may be necessary at a grid level to accommodate the additional demand. As well, sufficient charging infrastructure must also be adopted within residential energy hubs to accommodate the integration of EV fleets. Results concerning DER technology implementation indicated the benefits of significant DER implementation within residential energy hubs. Particularly, increased self-efficacy due to DER implementation allows the energy hub to address increasing EV fleet charging demand using its own DER generation resources. This could largely reduce the need for additional power transmission and distribution infrastructure, as well as the need for spinning reserve capacities at the grid level. The results also indicated the tradeoff between operating costs and emissions for the two levels of EV charging considered. The differences in EV fleet charging behavior indicate the potential benefits of controlled or scheduled charging behaviors, which could leverage time-of-use pricing schemes to provide economic and environmental benefits for the residential energy hub.

Appendix A

The nomenclature is shown below.

Nomenclature	
BESS	Battery energy storage system
CHP	Combined heat and power
DC	Direct current
DER	Distributed energy resource
GHG	Greenhouse gas
ESS	Energy storage system
MILP	Mixed integer linear programming
MILNP	Mixed integer non-linear programming

(continued)

NHTS	National Household Travel Survey
EV	Electric vehicle
PV	Photovoltaic
SOC	State of charge
V2G	Vehicle-to-grid
Variables	
$\varepsilon_{charge,\ k}$	Charge efficiency for storage system k
$\varepsilon_{discharge,\ k}$	Discharge efficiency for storage system k
ε_{EV}	Efficiency of EV charging
μ	Weight factor
C_{ij}	Coupling matrix
$Cap_{battery}$	Capacity of plug-in electric vehicle battery
$Cost_{fixed}$	Fixed cost of the energy technology systems
$Cost_{fuel}(t)$	Cost of fuels consumed in the energy hub during operation
$Cost_{oper,\ conv}(t)$	Operating cost of energy conversion systems
$Cost_{oper,\ stor}(t)$	Operating cost of energy storage systems
$d_{travelled}$	Distance travelled
$\dot{E}(t)$	Flow of energy into storage system
$\dot{E_k}(t)$	Flow of energy into storage system for energy vector k
$E_{loss}(t)$	Standby loss of energy from the storage system k
$E_{max,\ k}$	Maximum storage capacity of storage system k
EF	Emission factors associated with inflow energy vector set $I(t)$
$I(t)$	Inflow energy vector
I_{min}	Minimum flow capacities for the inflow energy set
I_{max}	Maximum flow capacities for the inflow energy set
i	Index for inflow energy vector set
j	Index for energy demand load set
k	Index for energy storage technologies
n_{PEV}	Index for plug-in electric vehicle in fleet
n_{total}	Total number of plug-in electric vehicles in fleet
$O(t)$	Energy demand load of the energy hub
$Q_{charge,\ k}(t)$	Power charged to storage system k
$Q_{discharge,\ k}(t)$	Power discharged to storage system k
$Q_{EV}(t)$	Charging required for the EV fleet
$SoC_k(t)$	State of charge of the storage system k at timestep t
$SoC_{k,\ min}$	Minimum charge capacity of the storage system k
$SoC_{k,\ max}$	Maximum charge capacity of the storage system k
t	Index for time
$t_{arrival}$	Time of arrival at energy hub
t_{depart}	Time of departure from energy hub
Z	Overall objective function
Z_1	Cost objective function
Z_2	Emissions objective function

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