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Vehicle-to-Grid: quantification of its contribution to security of supply through the F-Factor methodology

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Abstract
The increasing adoption of electric vehicles is expected to substantially raise electricity demand. This could require significant grid investment to maintain secure electricity supply, which has traditionally been provided through infrastructure upgrades. The potential of smart technologies like Vehicle-to-Grid (V2G) to contribute to security of supply has prompted the need to quantify their impact. We hypothesize that the F-Factor methodology can effectively quantify V2G's security of supply contribution. Applying F-Factor analysis to V2G through optimization modeling and sensitivity studies, we find that key parameters like V2G charger ratings, EV battery capacities, and load profile peakiness significantly influence the results. We conclude that the F-Factor provides a valuable tool for assessing V2G's potential to enhance security of supply, with implications for more efficient grid planning in the context of transport electrification.

Keywords Electric vehicles, F-Factor, Optimization, Security of supply, Vehicle-to-Grid

Introduction

Motivation

The ongoing electrification of the transport sector, through the increasing adoption of electric vehicles (EVs), marks a significant shift toward a more sustainable and environmentally friendly transportation. This transition is also driven by advances in battery technology, electricity demand management technologies, such as demand-side response, and EV charging technologies, such as smart charging, Vehicle-to-Building (V2B), and Vehicle-to-Grid (V2G) (Amann et al., 2022).

While the adoption of EVs offers substantial environmental benefits, such as reduced emissions and decreased reliance on fossil fuels, it also presents challenges, particularly in terms of electricity demand (Giannelos et al., 2023a). The widespread use of EVs can lead to a significant increase in peak electricity demand, as charging these vehicles adds a considerable amount of electricity load. Therefore, to maintain the same level of security of supply, substantial investments may be necessary to upgrade the grid infrastructure. These investments may not only be in traditional technologies but also in smart technologies. Specifically, the advent of new smart technologies and concepts, like demand response systems, smart charging, and V2G, have been shown to have the potential to enable more efficient management of the increased load and facilitate the seamless integration of EVs into the existing energy ecosystem (Borozan et al., 2022a).

The motivation for this research stems from the urgent need to address the challenges posed by the rapid adoption of EVs while maximizing their potential benefits to the grid. As countries worldwide set ambitious targets for EV adoption to meet climate goals, the pressure on electricity grids is mounting. Traditional

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grid reinforcement approaches are often costly and time-consuming, making it crucial to explore innovative solutions that can provide flexibility and enhance grid resilience.

V2G technology emerges as a promising solution in this context. By enabling bidirectional power flow between EVs and the grid, V2G has the potential to transform EVs from mere loads into valuable distributed energy resources. This capability could significantly alleviate peak demand pressures, improve grid stability, and potentially defer or reduce the need for costly grid upgrades. However, to fully leverage the benefits of V2G, it is essential to develop robust methodologies for quantifying its contribution to grid security and reliability.

In this context, V2G can be seen as an investment option that can reduce peak demand by enabling the bidirectional flow of electricity from the grid to EVs and vice versa (Most et al., 2020). This peak reduction has been shown to be equivalent to the provision of security of electricity supply to consumers since by alleviating peak loads, V2G helps in preventing overloading of the grid infrastructure, thereby ensuring a more stable and reliable electricity supply (Ilo et al., 2019). Since V2G technology can indeed contribute to the provision of a secure electricity supply, the focus is then on how this contribution can be quantified. In this regard, the current paper presents the F-Factor methodology, which allows the quantification of the contribution of V2G technology to the security of electricity supply. The current work is the first-ever application of this methodology to V2G.

Furthermore, the motivation for this research is driven by the need to bridge the gap between theoretical potential and practical implementation of V2G technology. While numerous studies have highlighted the technical feasibility of V2G, there remains a lack of standardized methods for assessing its value to the grid, particularly in terms of security of supply. This gap hinders the development of appropriate regulatory frameworks and market mechanisms that could incentivize V2G adoption and fairly compensate EV owners for the grid services they provide. Note that current regulatory frameworks do not prescribe any formal methodology for the quantification of the contribution to the security of supply from smart technologies. This is the case, for example, with Engineering Recommendation P2/6 (Electricity Networks Association, 2006), which is the distribution network planning standard followed by the Distribution Network Operators in Great Britain. A lack of consistent methodology may pose an obstacle to the realization of the electrification of the transport sector and of the transition to a smart grid in general (Beulertz et al., 2019; Charousset-Brignol et al., 2021; Giannelos et al., 2023b; Münster et al., 2020).

Hence, an update of the planning standards is necessary so that the security contribution of non-network solutions, such as V2G, can be taken into consideration. In this context, the current publication formalizes an approach, called F-Factors, for quantifying the security contribution of V2G; this approach is crystalized through a case study both qualitatively and quantitatively.

Literature review

Traditionally, the security of electricity supply has been provided through investment in conventional technologies (Greenwood et al., 2020), including power transformers and electricity transmission and distribution lines. However, in recent years, there has been an ongoing development of smart grid technologies, such as V2B, dynamic line rating (Giannelos et al., 2018a), demand-side response (Giannelos et al., 2017, 2018, 2018b), coordinated voltage control (Konstantelos et al., March 2017), energy storage (Giannelos et al., 2019), and soft open points (Giannelos et al., 2015, 2016). This technological progress as well as plans for the wide-scale deployment of such technologies (Giannelos et al., 2021) has led to a rethinking of the concept of security of supply, prompting calls for its update to include such non-network solutions (Giannelos et al., 2020).

Regarding energy storage, its ability to provide security of supply was first recognized in a study conducted by EPRI in 1976 (Public Service Electric & Gas Company, 1976) that underlined the fact that utilities can treat long-duration storage devices (such as pumped hydro storage) as sources of reliable capacity since they can discharge during periods of peak demand. Then research was focused on methodologies to calculate the energy storage contribution to security of supply, such as dynamic programming as in Sioshansi et al. (2014), taking into consideration the effect of power system outages on system operation. However, this method was focused on outages rather than on the reduction of peak demand. Authors in Konstantelos, (2018) used a probabilistic methodology based on chronological Monte Carlo simulations for computing the effective load-carrying capability of energy storage, which is a proxy of its security contribution, taking also into account its ability to charge during partial outage conditions such as when only some of the substation transformers are online. However, the complexity of this methodology involved significant large solution times, ranging even weeks, which was prohibitive for conducting large scale sensitivity studies. Moreover Abdullah et al., (2013) computes the security contribution of energy storage, when it is used for smoothing the output of a wind farm, again with a focus on outages. Authors in Leite da Silva et al. (2006) compute the energy storage security contribution by focusing on energy storage assets installed at islanded microgrids rather than on the main grid. The aforementioned approaches focused on energy storage, without considering the integration of electric vehicles (EVs).

Regarding the V2G technology, ongoing research is focusing on its impact on the distribution grid in terms of alleviating the need for conventional reinforcements. The authors in Mastoi et al. (2023) emphasize the importance of V2G technology particularly during outages, suggesting a role for V2G in enhancing grid resilience. A reference to the potential of V2G to contribute to the security of supply is made in Sultan et al., (2022), outlining also a list of other potential benefits. Authors in Owens et al. (2022) explain how V2G can operate as part of an aggregator business model, where the aggregator will optimize the charge and discharge of individual vehicles to function as a synergistic, bulk energy resource, and load. Moreover, Bayani et al., (2022) reviews the implications of transportation electrification, including how EVs can operate as loads or distributed power resources while taking into account the V2G technology. This suggests a role for V2G in balancing the grid and providing security of electricity supply to consumers. Furthermore, O'Neill et al., (2022) mentions that V2G can support the integration of variable distributed renewable generation, suggesting a positive impact on grid stability and sustainability. Authors in Tirunagari et al., (2022) address how EVs, through smart charging and V2G, can impact the electricity and energy sectors and contribute to the security of electricity supply.

Authors in Sachan and Adnan (2018) investigate the impact of various electric vehicle (EV) charging methods on distribution grids, focusing on reducing network peak load demand and improving voltage stability. The paper introduces a stochastic model that incorporates the variability of EV availability, such as arrival and departure times, and wind power generation to optimize charging costs and network constraints. The study also proposes modifications to grid infrastructure to enhance the integration of EVs without significant reinforcement, ultimately suggesting a coordinated charging scheme to optimize EV integration while minimizing costs and grid losses.

Moreover, Sachan and Kishor, (2016) proposes a strategy to determine the optimal number of electric vehicles (EVs) that can be safely integrated into a distribution network without violating its constraints. It assesses the impact of contingencies on EV charging by redistributing EV loads from affected feeders to nearby feeders using a performance index. The study also develops a communication network for smart charging to manage the EV load efficiently during contingencies, ensuring grid stability and minimizing operational costs.

Then Sachan et al., (2020) examines the impact of various charging infrastructures—distributed, fast charging, and battery swapping—on the power grid. It compares these infrastructures based on factors like availability, driving patterns, and charging costs, finding that distributed infrastructure is most cost-effective and provides better regulation power. In addition, the paper evaluates smart charging strategies, concluding that intelligent, coordinated charging (especially power factor control) mitigates peak load impacts and optimizes grid performance compared to uncoordinated charging.

Authors in Sachan et al., (2022) provide an extensive review of existing standards and practices for integrating electric vehicle (EV) charging stations with utility grids. The paper emphasizes the importance of standardization and best practices to ensure safe, dependable, and interoperable grid integration. The paper also discusses the role of distributed energy resources (DER) and V2G technology in power system operations, addressing technical challenges and offering recommendations for future implementation and research.

Authors in Sachan et al., (2021) present a novel approach for the optimal placement and operation of electric vehicle (EV) charging stations using a chicken swarm optimization (CSO) algorithm. The study integrates the planning and operational aspects into a multi-objective framework that considers cost, voltage stability, and grid reliability. Three charging strategies—uncoordinated charging, coordinated charging, and bidirectional V2G—are evaluated, with results indicating the advantages of coordinated charging and V2G over uncoordinated charging in terms of grid stability and efficiency.

However, none of the existing literature presents a methodology for the quantification of the contribution to electricity supply by V2G. Consequently, the current paper is the first one presented in the literature that offers a comprehensive framework for the quantification of the contribution to security of supply from V2G technology. Note that, in most of the literature, the capacity value of energy storage has been quantified based on the use of reliability parameters and technoeconomics as in Black and Strbac, (2007); Denholm and Sioshansi, (2009; Drury et al., (2011); Thatte, (2012). However, the F-Factor methodology does not take into consideration reliability parameters of grid assets such as mean time to repair or mean time before failure. Rather, F-Factors focus on the maximum peak reduction achieved.

Contributions

The contributions of the present publication are as follows:

- Presentation, for the first time in the literature, of the F-factor methodology for the quantification of the security contribution of the V2G technology.
- Demonstration of the mathematical optimization framework that models V2G operation for the minimization of peak demand.
- In-depth sensitivity analyses to observe the effect of system parameters on the security contribution of V2G.

Building upon these core contributions, this paper makes several additional significant advancements in the field of V2G integration and grid security assessment:

First, it introduces a novel, quantitative approach to evaluate the security contribution of V2G technology. The F-Factor methodology presented in this paper provides a standardized, reproducible metric that can be used by grid operators, policymakers, and researchers to assess the impact of V2G on grid security. This contribution is particularly valuable as it offers a concrete tool for comparing V2G with other grid reinforcement options, potentially influencing investment decisions and policy formulation in the energy sector.

Second, the paper bridges the gap between theoretical V2G potential and practical grid planning. By developing a mathematical optimization framework that models V2G operation for peak demand minimization, this research provides a practical tool for grid operators to integrate V2G considerations into their planning processes. This framework not only demonstrates how V2G can be optimally utilized but also lays the groundwork for more sophisticated models that could incorporate other grid services provided by V2G, such as frequency regulation or voltage support.

Third, the comprehensive sensitivity analyses presented in this paper offer invaluable insights into the factors that influence the security contribution of V2G. By examining how various system parameters affect the F-Factor, this research provides a nuanced understanding of the conditions under which V2G can be most effective. These insights are crucial for grid operators and policymakers in designing targeted strategies to maximize the benefits of V2G deployment.

Furthermore, this paper contributes to the broader discourse on the integration of distributed energy resources into the grid. By quantifying the security contribution of V2G, it provides a model that could potentially be adapted or extended to other forms of distributed storage or flexible loads. This has implications not only for EV integration but also for the overall transition toward a more decentralized, flexible, and resilient grid infrastructure.

Lastly, the research presented here lays the foundation for future work in areas such as dynamic pricing mechanisms for V2G services, regulatory frameworks to incentivize V2G adoption, and the development of more advanced grid management systems that can fully leverage the potential of V2G technology. By providing a quantitative basis for assessing V2G's contribution to grid security, this paper opens up new avenues for research and practical applications in the rapidly evolving field of smart grid technologies.

Organization of the paper

The paper is structured as follows. In Sect. "The methodology of F-Factors for V2G", the methodology of F-Factors is presented in detail, and the associated mathematical formulation is shown. Sect. "Case study: evaluation of the V2G security contribution via F-Factors" presents an in-depth sensitivity analysis that demonstrates the presents key parameters impacting on F-Factors. Sect. "Discussion" discusses the findings, while Sect. 6 presents future work pathways and concludes.

The methodology of F-Factors for V2G

In the previous section, it was mentioned that V2G technology can provide security of electricity supply, which can be evaluated using the F-Factor methodology.

Definition of the F-Factor metric

The charging and discharging operation of EVs through V2G chargers can be conducted in such a way that can lead to peak load reduction. Specifically, during periods of relatively low system demand, the EVs can be charged; this charge is subsequently released during periods of peak or near-peak demand, consequently leading to reduction. This can trigger deferral or displacement (i.e., prevention) of expensive conventional network reinforcement that would otherwise be required for the secure accommodation of power flows. It can also contribute to security of supply since, during periods of peak demand, a sudden loss of a critical network asset may lead to interruptions in the supply of electricity to consumers, which can be avoided if the peak demand is minimized via V2G.

The current paper presents the application, for the first time, of the F-Factor metric for the evaluation of the security contribution of the V2G technology. Specifically, the F-Factor metric is defined as the ratio of the optimal reduction in peak electricity demand, represented by P, over the power capability of the V2G technology, represented by C, as shown in Eq. (1) below. In this regard, since both the numerator and denominator are measured in the same units, this metric is dimensionless, and it is, therefore, often expressed in percentage terms.

$$F = \frac{P}{C} \quad (1)$$

The numerator is the optimal solution of the mathematical optimization model, which is presented in subSect. "The optimization model". This model is able to optimize the reduction of the peak demand using V2G. On the other hand, the denominator is an input parameter and is not the solution of an optimization study.

The F-Factor methodology framework

To facilitate a comprehensive understanding of the approach, we present a detailed methodology framework for quantifying the security contribution of V2G technology using the F-Factor metric. Figure 1 illustrates this framework, providing a visual representation of the key components and their interrelationships in our study.

The methodology framework consists of five main components, each representing a crucial step in our analysis:

1. Input data: This initial component encompasses the essential data required for the analysis. It includes load profiles, which represent the baseline electricity demand patterns; V2G charger ratings, which define the power capacity of the charging infrastructure; and EV battery capacities, which determine the energy storage potential of the electric vehicle fleet. These inputs form the foundation of our subsequent analyses and directly influence the potential security contribution of V2G technology.
2. Optimization model: At the core of the methodology lies the optimization model. The mathematical formulation aims to minimize peak electricity demand by optimally scheduling V2G operations. The model incorporates various constraints, including EV state of charge limitations and charger power limits, to ensure realistic and feasible solutions. By solving this optimization problem, we determine the maximum potential peak reduction achievable through V2G technology.
3. F-Factor calculation: Following the optimization, we calculate the F-Factor, which quantifies the security contribution of V2G. The F-Factor is defined as the ratio of the achieved peak demand reduction (determined by the optimization model) to the total V2G

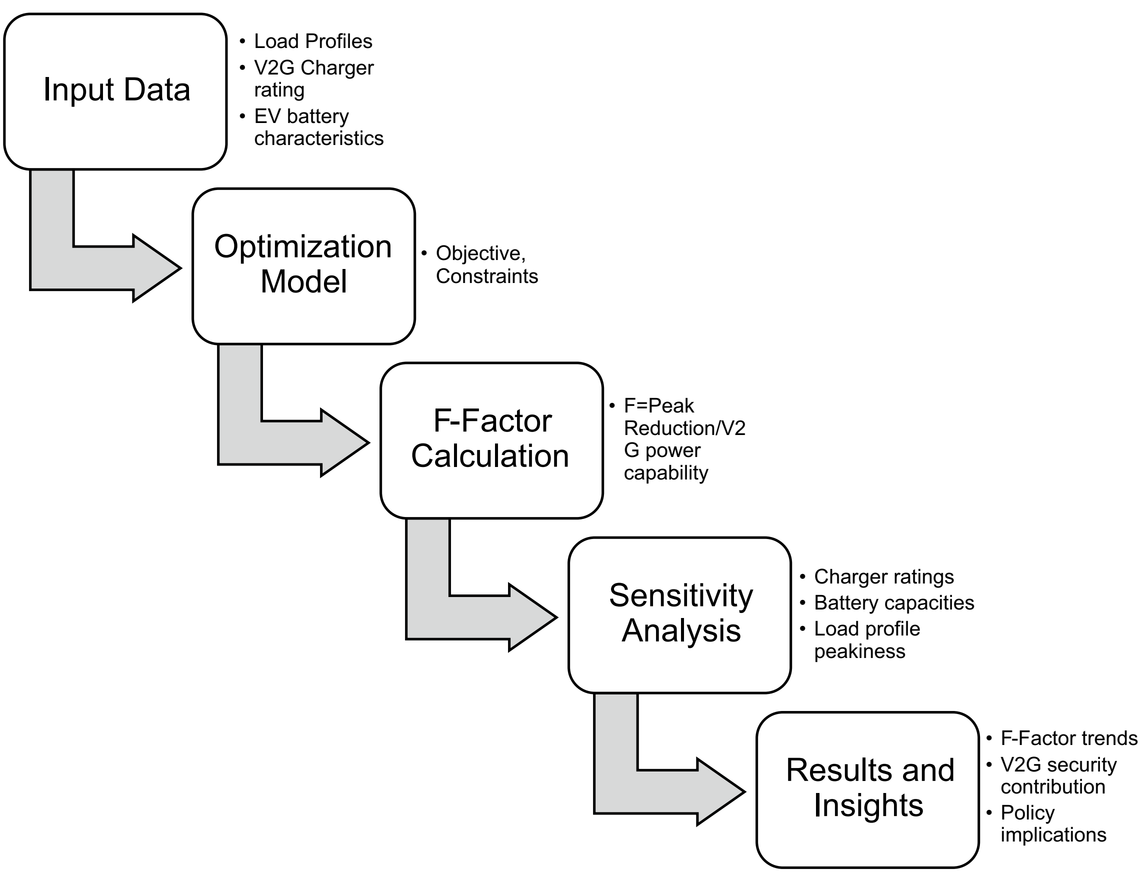

Fig. 1 V2G F-Factor methodology framework diagram

power capability. This metric provides a standardized measure of V2G's effectiveness in enhancing grid security.

4. Sensitivity analysis: To gain deeper insights into the factors influencing V2G's security contribution, we conduct comprehensive sensitivity analyses. These analyses explore how variations in key parameters—such as charger ratings, battery capacities, and load profile characteristics—impact the F-Factor. This step is crucial for understanding the robustness of V2G's contribution under different scenarios and system configurations.
5. Results and insights: The final component of our framework focuses on interpreting the outcomes of our analyses. Here, we examine F-Factor trends across various scenarios, assess the overall security contribution of V2G technology, and derive policy implications. This step translates our technical findings into actionable insights for grid operators, policymakers, and other stakeholders in the energy sector.

The arrows in the diagram illustrate the logical flow of the methodology, from input data through to final insights. This framework ensures a systematic and comprehensive approach for evaluating V2G's potential in enhancing grid security.

The optimization model

As mentioned, the numerator of Eq. (1) can be found by solving an optimization model. Particularly, (2)–(8) below describe the specified optimization model, which corresponds to a system that an EV fleet charges and discharges through V2G chargers.

The objective function is described in (2) where P_{max} is a decision variable representing the maximum (peak) electricity demand. The peak demand, as defined in (3), is greater than or equal to the summation of the baseload demand represented by input parameter D_t, with the power charged/discharged by the EV fleet. Specifically, the baseload demand D_t is the demand that does not correspond to the charging/discharging operation of EVs. In addition, P_t^{in} is a decision variable that represents the power charged into the battery of an electric vehicle, while P_t^{out} is a decision variable representing the power discharged from an electric vehicle into the grid. Also, input parameter N^{EV} is the total number of electric vehicles in the system. The parameter a_t is also known as "availability" and is a time series of values between 0 and 1, modeling the connection pattern of the EVs to the V2G chargers. In other words, the product $N^{EV} \cdot a_t$ yields the number of electric vehicles that are connected to a V2G charger at time *t*.

Constraint (4) models the state of charge of the EV fleet at time period *t*. Specifically, the state of charge (SOC) of a single electric vehicle is a decision variable represented by E_t (kWh), which is multiplied by $N^{EV} \bullet a_t$, which is the number of electric vehicles that are connected to V2G chargers at time period t. In essence, the left-hand side of (4) calculates the SOC of the EVs that are connected to V2G chargers at period *t*.

Regarding the right-hand side of (4), the first term is the state of charge of the EV fleet at time period *t*-1, whereE_{t-1}, is the SOC of an electric vehicle at time *t*-1, multiplied by the number of electric vehicles connected to V2G chargers at period *t*-1. Then the second term of the right-hand side refers to the charging and discharging operation of the connected EV fleet, while taking into account the efficiencies. Specifically, δ is the duration of a time period, which in this case study is equal to 1 h, and η^c, η^d are the efficiencies of charging and discharging. Then the third term of the right-hand side takes into account the energy stored in the EVs that connect to the V2G chargers at time period *t*. Specifically, input parameter r_t represents the percentage of the total number of electric vehicles that arrive at V2G chargers after a journey. Input parameter R is the power capability of the battery of an electric vehicle, while input parameter μ is the duration (hours) of the battery of an EV, which is the number of hours required for its full charge. Hence, the product $R \cdot \mu$ is equal to the energy capacity (kWh) of the battery of an EV. Then the input parameter π^{in} is the state of charge of an EV expressed as a percentage of its energy capacity. For instance, $\pi^{in} = 40\%$ means that the EV's state of charge is equal to 40% of its energy capacity at the time when it gets connected to a V2G charger as described in Borozan et al., (2022b). In a similar vein, the last term of the right-hand side refers to the time when the EVs disconnect from the V2G chargers. In this context, the input parameter q_t is the percentage of the total number of electric vehicles that get disconnected from the V2G chargers at time period t. The parameters a_t, r_t, and q_t are constructed as follows: $a_t = a_{t-1} + r_t - q_t$ meaning that the number of electric vehicles connected to V2G chargers at t is found by summing the number of EVs connected to chargers in the previous time period, plus the number of vehicle just connecting to the chargers at *t*, minus the number of EVs disconnecting at *t*. Also, π^{out} is the state of charge of an electric vehicle when it disconnects from the V2G charger, expressed as a percentage of its energy capacity.

Constraint (5) states the assumption that the SOC of an electric vehicle at the last period of the horizon, represented by E_T, is equal to the SOC in the beginning, represented by E_0. Also, constraint (6) specifies the bound for the SOC of the battery of an electric vehicle, symbolized by $\widetilde{E_{max}}$. This upper bound is the energy capacity of the battery of an EV. Finally, (7)–(8) set the upper bound to the amount of power charged into the battery of an EV and discharged from it, where $\widetilde{P}$ is the rating (kW) of the V2G charger, which is assumed to be equal to the power capability R (kW) of the battery of the EV. Note that $\widetilde{E_{max}} = \mu R$, i.e., the energy capacity of the battery of an EV is equal to the product of its duration with its power capability.

$$minimize\, P_{max} \tag{2}$$

$$P_{max} \geq D_t + \left(\left(P_t^{in} - P_t^{out} \right) \cdot N^{EV} \cdot a_t \right) \forall t \in T \tag{3}$$

$$\begin{aligned} E_t \cdot N^{EV} \cdot a_t = E_{t-1} \cdot N^{EV} \cdot a_{t-1} + N^{EV} \cdot a_t \cdot \left(\delta \cdot \eta^c \cdot P_t^{in} - \delta \cdot \frac{P_t^{out}}{\eta^d} \right) \qquad \forall\, t \in T \\ + N^{EV} \cdot r_t \cdot \left(R \cdot \mu \cdot \pi^{in} \right) - N^{EV} \cdot q_t \cdot \left(R \cdot \mu \cdot \pi^{out} \right) \end{aligned} \tag{4}$$

$$E_0 - E_T = 0 \tag{5}$$

$$E_t \leq \tilde{E}_{\max} \qquad \forall\, t \in T \tag{6}$$

$$P_t^{in} \leq \widetilde{P}\, \forall t \in T \tag{7}$$

$$P_t^{out} \leq \widetilde{P}\, \forall t \in T \tag{8}$$

The FICO Xpress Optimization process

In this paper, we utilize the aforementioned optimization model designed to minimize the peak electricity demand by optimally scheduling V2G operations. This optimization is essential for determining the numerator of the F-Factor, which quantifies the optimal reduction in peak demand. The optimization process can be outlined in the following steps.

1. Model setup: The optimization model is implemented using FICO Xpress Mosel, a modeling language for mathematical optimization. The model closely follows the mathematical formulation presented in Eqs. (2)–(8) of sub-Sect. "The optimization model".
2. Objective function: The primary objective, as stated in Eq. (2), is to minimize the peak electricity demand (P_{max}).
3. Constraints: The model includes several constraints to ensure realistic and feasible scheduling, as described in Eqs. (3)–(8).

a. Specifically, the peak demand constraint as in (3), ensures that the peak demand (z) is greater than or equal to the base demand plus the net V2G power flow. In FICO Xpress constraint (3) is written as follows: *forall(t in Periods) z > =PDemand(t)+(V2GPchar(t)—V2GPdisch(t)) * number_of_EV * avail(t).*

b. State of charge (SOC) balance as in (4): This constraint is implemented for each time period, balancing the SOC of the EV fleet based on the previous period's SOC, charging/discharging activities, and EV arrivals/departures. In FICO Xpress, constraint (4) is written as follows: forall(t in 2..NPer) do V2G_SOC(t) * number_of_EV * avail(t) = V2G_SOC(t-1) * number_of_EV * avail(t-1) + number_of_EV * avail(t) * duration * V2GPchar(t) * ev_eff_charge—number_of_EV * avail(t) * duration * V2GPdisch(t) / ev_eff_discharge + number_of_EV * arr(t) * energy_capacity_ev * ev_minStor—number_of_EV * dep(t) * energy_capacity_ev * ev_outStorend-do

c. Initial and final SOC equality, as in (5): This constraint ensures that the SOC at the beginning and end of the optimization horizon are equal. In FICO Xpress, this is written as follows: V2G_SOC(NPer) = V2G_SOC(0).

d. Charger and battery constraints as in (6)–(8)**:** These constraints limit the charging and discharging rates. Specifically, they limit the SOC of each EV to its maximum capacity, and limit the charging and discharging power to the charger rating.

4. Solving the model: The FICO Xpress solver is then called to minimize the objective function subject to these constraints. The optimization process is implemented using the FICO Xpress Optimization Suite, with the command *minimize(obj),* where *obj* is the objective function.
5. Solution extraction: Once the optimization model is solved, the solution is extracted using the FICO command *getsol*, which allows to capture the optimal solution from a decision variable after the model has been solved.

The optimization process described above systematically minimizes the peak electricity demand using V2G operations and effectively provides the numerator for the F-Factor.

The following section presents the case study.

Case study: evaluation of the V2G security contribution via F-Factors

Figure 2 shows two typical electricity load profiles (Energy Networks Association, 2018), where the horizontal axis shows the 168 h of the week, while the vertical axis has normalized values (i.e., between 0 and 1). The two profiles characterize the baseload electricity demand (i.e., without the consideration of the electric vehicle charging load). Both profiles contain the same energy (kWh), with the difference being that the distance between the maximum and minimum values for profile 1 is greater than that for profile 2, meaning that profile 1 is the 'peaky', while profile 2 is the 'flat' one.

The analysis that will follow will also show that whether a profile is peaky or not can have an impact on the F-Factor; the results of the analysis are independent of the selection of the profiles and apply for any selection of peaky and flat profiles.

Sensitivity analysis is performed by considering a series of studies, each of which involves solving the aforementioned optimization problem each time for a different combination of the following parameters: charging efficiency η^c, rating of the V2G charger $\widetilde{P}$, and storage durationμ. In addition, sensitivity analyses have been carried out to determine how the peakiness of a load profile can affect the F-Factors. Finally, sensitivity analysis has been conducted for different values for the duration of the peak demand for profile 1.

The results are shown in Tables 1, 2, 3 below. Table 1 includes the F-Factors when the peaky profile 1 is used to represent the baseload demand, while Table 2 includes the F-Factors when the flat profile 2 is used. Furthermore, Table 3 includes the F-Factors for profile 1 where the duration of the peak demand is equal to 6 h. Note that in both Tables 1, 2, the duration of the peak demand is 1 h, as shown in Fig. 2. That is, in Table 3, profile 1 is identical to that shown in Fig. 2 except that the peak demand, which occurs on day 4, lasts for 6 h instead of 1 h.

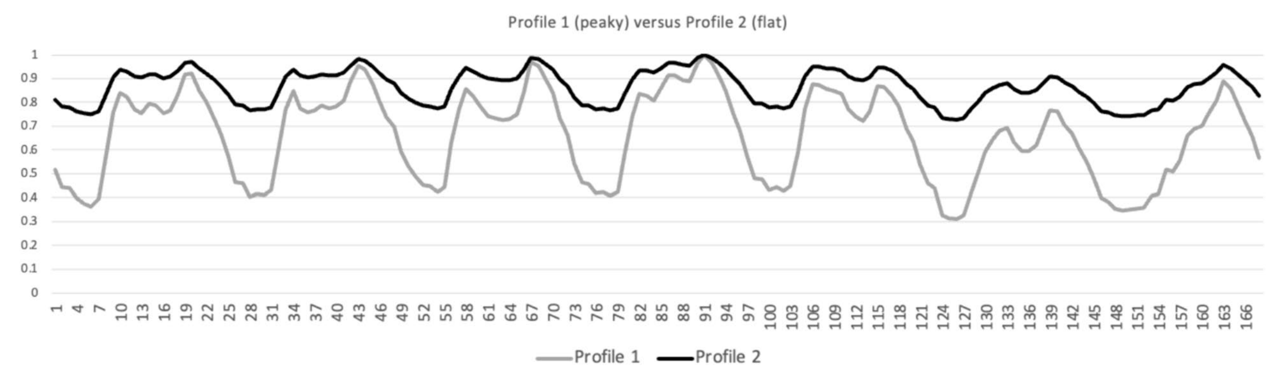

Fig. 2 Normalized time series for weekly electricity load profiles 1 and 2, with profile 1 having a peak demand of 7035 kW, while profile 2 having a peak of 5361 kW

Table 1 F-Factors for different values of the duration μ of the battery of an EV (between 1 and 6 h), rating $\widetilde{P}$ of a V2G charger, and the efficiency of charging the battery of an EV (80–100%), corresponding to profile 1, and for 1-h duration of its peak

μ	$\widetilde{P}$= 7.4 kW			$\widetilde{P}$= 15 kW			$\widetilde{P}$= 30 kW			$\widetilde{P}$= 43 kW			$\widetilde{P}$ = 70 kW		
	Efficiency			Efficiency			Efficiency			Efficiency			Efficiency		
	100%	90%	80%	100%	90%	80%	100%	90%	80%	100%	90%	80%	100%	90%	80%
1h	66.51	66.34	66.15	44.59	44.59	44.59	33.42	33.42	33.42	28.59	28.37	28.12	20.08	20.03	19.98
2h	83.53	83.53	83.53	66.85	66.85	66.85	44.80	44.63	44.45	35.00	34.97	34.94	26.06	26.02	25.99
3h	83.53	83.53	83.53	82.86	82.27	81.63	50.99	50.96	50.93	41.07	41.01	40.94	31.30	31.30	31.30
4h	83.53	83.53	83.53	83.53	83.53	83.53	57.18	57.18	57.06	46.32	46.31	46.30	35.40	35.38	35.35
5h	83.53	83.53	83.53	83.53	83.53	83.53	62.55	62.49	62.43	51.56	51.56	51.56	38.93	38.93	38.93
6h	83.53	83.53	83.53	83.53	83.53	83.53	67.79	67.79	67.79	55.82	55.76	55.69	42.46	42.01	40.08

Table 2 F-Factors for different values of the duration μ of the battery of an EV (between 1 and 6 h), rating $\widetilde{P}$ of a V2G charger, and the efficiency of charging the battery of an EV (80–100%), corresponding to profile 2, and for 1-h duration of its peak

μ	$\widetilde{P}$= 7.4 kW			$\widetilde{P}$= 15 kW			$\widetilde{P}$= 30 kW			$\widetilde{P}$= 43 kW			$\widetilde{P}$ = 70 kW		
	Efficiency			Efficiency			Efficiency			Efficiency			Efficiency		
	100%	90%	80%	100%	90%	80%	100%	90%	80%	100%	90%	80%	100%	90%	80%
1h	35.84	35.84	35.84	25.54	25.39	25.22	15.92	15.92	15.92	12.85	12.83	12.82	9.89	9.87	9.85
2h	51.59	51.27	50.93	31.83	31.83	31.83	21.39	21.39	21.39	17.45	17.44	17.43	12.98	12.44	11.85
3h	58.00	57.88	57.76	37.53	37.49	37.46	25.48	25.47	25.47	20.98	20.46	19.51	12.07	11.35	10.52
4h	64.19	64.19	64.18	42.77	42.77	42.77	29.02	29.02	28.23	20.53	19.63	18.65	10.46	9.59	8.57
5h	70.39	70.26	70.13	47.41	47.34	47.28	30.01	28.74	27.36	19.46	18.27	16.91	8.75	7.73	6.51
6h	75.54	75.64	75.49	50.98	50.95	50.93	29.22	27.92	26.36	17.87	16.56	14.99	7.03	5.85	4.42

Table 3 F-Factors for different values of the duration μ of the battery of an EV (between 1 and 6 h), rating $\widetilde{P}$ of a V2G charger, and the efficiency of charging the battery of an EV (80–100%), corresponding to profile 1, and for 6-h duration of its peak.

μ	$\widetilde{P}$= 7.4 kW			$\widetilde{P}$= 15 kW			$\widetilde{P}$= 30 kW			$\widetilde{P}$= 43 kW			$\widetilde{P}$ = 70 kW		
	Efficiency			Efficiency			Efficiency			Efficiency			Efficiency		
	100%	90%	80%	100%	90%	80%	100%	90%	80%	100%	90%	80%	100%	90%	80%
1h	13.49	13.49	13.49	13.49	13.49	13.49	12.44	12.37	12.29	11.70	11.69	11.69	11.03	11.03	11.03
2h	26.97	26.97	26.97	24.88	24.74	24.60	22.42	22.42	22.42	21.68	21.68	21.28	17.13	17.03	16.93
3h	39.91	39.47	39.03	34.86	34.86	34.86	32.25	31.74	31.17	26.71	26.50	26.28	21.77	21.71	21.64
4h	49.89	49.60	49.30	44.84	44.84	44.84	36.90	36.54	36.16	31.34	31.26	31.17	25.83	25.81	25.78
5h	59.87	59.73	59.58	54.82	54.82	54.82	41.52	41.34	41.15	35.93	35.83	35.72	29.89	29.89	29.83
6h	69.85	69.85	69.74	64.51	63.46	63.46	46.16	46.06	45.97	39.98	39.92	39.86	33.26	33.22	33.17

Each of these tables shows the F-Factors for six possible values for the duration μ of the EV battery (1 h until 6 h), for five possible values for the rating $\widetilde{P}$ of the V2G charger, and three possible values of the efficiency of charging η^c (80, 90, and 100%), which are typical efficiencies for EV batteries. That is, a total of 90 optimization models are run for each of the 3 tables.

Note that 7.4 kW chargers are typically used for residential charging in the U.K. and are acceptable options for EV owners who do not require fast charging. Regarding 15 kW and 30 kW chargers, they offer faster charging than the standard 7.4 kW home chargers and fall into the fast-charging category. The 43 kW chargers can be found in rapid AC charging stations, suitable for public locations where a quick charge is needed. Finally, 70 kW chargers also fall into the rapid charging category and provide a very high-power output, making them ideal for public charging stations where a fast turnaround is necessary. The distribution network is assumed to have a total of $N^{EV} = 50$ electric vehicles. The studies are conducted with the use of the FICO Xpress Optimization platform on a Xeon 3.46 GHz computer.

Discussion on the results follows in Sect. "Discussion" below.

Discussion

The results obtained in the previous section allow us to make key observations about the F-Factors for V2G technology.

The F-Factors as a function of the V2G charger rating

The results indicate that the F-Factors reduce or stay the same as the rating (kW) of the V2G charger increases; this rating is denoted by R in the aforementioned formulation. This can be witnessed by observing the values of the F-Factors from left to right across any row of the above tables.

This can be explained by the definition of the F-Factor metric as the ratio of the achieved peak demand reduction divided by the power capability as shown in Eq. (1) above. For example, in the first row of Table 1, the rating of the V2G charger is 7.4 kW, and the efficiency is equal to 100%. In this case, the optimal peak reduction is 246.1 kW; this is the numerator of the F-Factor ratio. Whereas the V2G power capability is found by multiplying the rating of the V2G charger, which is 7.4 kW, with the number of chargers in the system, which is 50, assuming they are equal to the number of vehicles. Hence, the corresponding F-Factor stands at 246.1 kW/370 kW = 66.51%. On the other hand, when the rating of the V2G charger increases from 7.4 kW to 15 kW, the peak reduction becomes 334.4 kW, i.e., exhibits an increase equal to (334.4—246.1)/246.1 = 35.88%. In this case, the V2G power capability becomes equal to the product of 50 * 15 kW = 750 kW, i.e., it exhibits an increase of (750–370)/370 = 102.8%. That is, the increase in the numerator and denominator are 35.88% and 102.8%, respectively. Since the denominator increases more than the numerator, the F-Factor reduces; in this case, it is equal to 334.4 kW/750 = 44.59%, as it can also be seen in Table 1 (the fourth white cell from the left).

In conclusion, as the rating of the V2G charger increases, the increase in the optimal peak reduction is less than the increase in the V2G power capability. Hence, when the rating of the V2G charger increases, the optimal peak reduction also increases. However, the F-Factor reduces since the V2G power capability increases.

The F-Factor of V2G as a function of the duration of the EV battery

A further observation that can be made is that the F-Factors increase or stay the same as the duration μ (hours) of the battery of an electric vehicle increases. This can be seen by observing any of the Tables 1, 2, 3 above where the values of the F-Factors along any column either increase or stay the same as the duration increases.

This happens because the increase in duration μ leads to an increase in the battery capacity of the EV, thereby increasing the potential of the EV fleet to reduce the peak demand. Since the rating of the V2G charger stays the same, the reduction in peak demand will cause the F-Factor to increase. The F-Factors are also possible to stop when the EV battery has sufficient capacity after which additional capacity does not reduce the peak demand. For example, see the first column in Table 1, where the increase in storage duration does not cause the F-Factor to increase beyond the value of 83.53%, because neither the peak demand reduction changes nor the V2G power capability.

The F-Factor of V2G as a function of the level of peakiness of the load profile

As mentioned, profile 1 is peaky, while profile 2 is flat. This essentially means that there are more pronounced peaks in Profile 1 than in Profile 2. By comparing the values in Table 1, which corresponds to the peaky profile 1, with those in Table 2, which corresponds to flat profile 2, it can be seen that the F-Factors of the former are higher than the ones of the latter. Figure 3 below illustrates these results.

This is caused by the shape of the load profiles and mainly the shape of the peaks. In a peaky profile, there are narrower peaks of higher magnitude, meaning that the peak can be reduced even with a small output from the EV battery units when discharging via V2G, thereby providing a significant security contribution. On the other hand, a flatter profile that is characterized by a long period of high values for load and a small peak requires EV batteries with a significant amount of energy capacity to make a significant security contribution. Such contribution largely depends on the

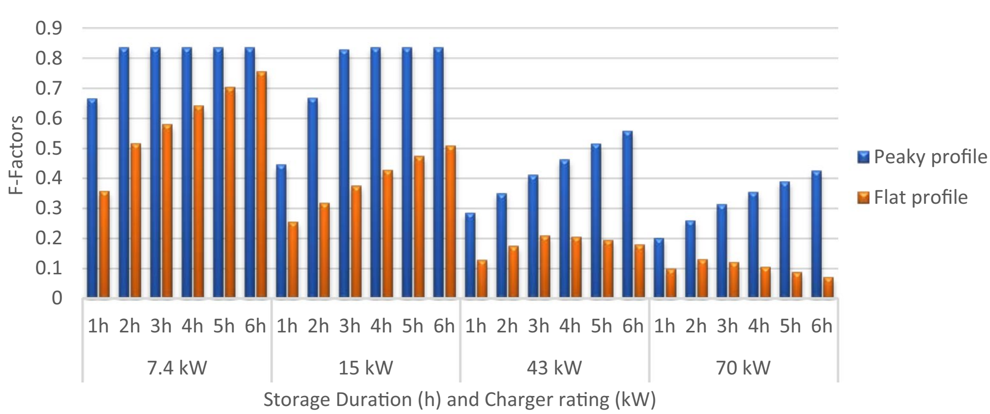

Fig. 3 The F-Factors (vertical axis) as a function of storage duration (1–6 h), charger rating (7.4, 15, 43, and 70 kW) and the peakiness of the load profile (peaky profile shown in blue)

difference in the height of the peak demand with the subsequent largest peaks; if a load profile has a peak that is much higher than the second-highest peak, then reducing the highest peak will provide considerable security contribution leading to a high value for the F-Factor.

The F-Factor of V2G as a function of the duration of the peak demand

The F-Factor values can change as a function of the duration of the peak. Specifically, both Tables 1, 3 correspond to profile 1, but in the case of Table 1, this profile has a peak demand of 1-h duration, while in the case of Table 3, the duration of profile 1 is 6 h; Fig. 4 below illustrates the load profile 1 for the two values of peak demand duration, where in blue color is this profile for 1-h peak duration.

The results indicate that the peak demand duration has an impact on the F-Factor values.

By observing Tables 1, 3, it can be seen that the F-Factor values for 1-h peak duration are higher than those for a 6-h peak duration. This can also be seen in Fig. 5 below.

This means that the security contribution drops as the duration of the peak demand increases, which is expected given that peaks that last longer are more challenging to reduce than shorter ones, with the same storage capacity.

Overview

Our analysis of the F-Factor methodology for quantifying the security contribution of V2G technology has revealed several key insights:

1. V2G charger rating: As the rating of V2G chargers increases, the F-Factor tends to decrease or remain constant. This is due to the F-Factor's definition as the ratio of peak demand reduction to V2G power capability. While higher-rated chargers can achieve greater peak reductions, the increase in power capability outpaces this reduction, leading to lower F-Factor values.

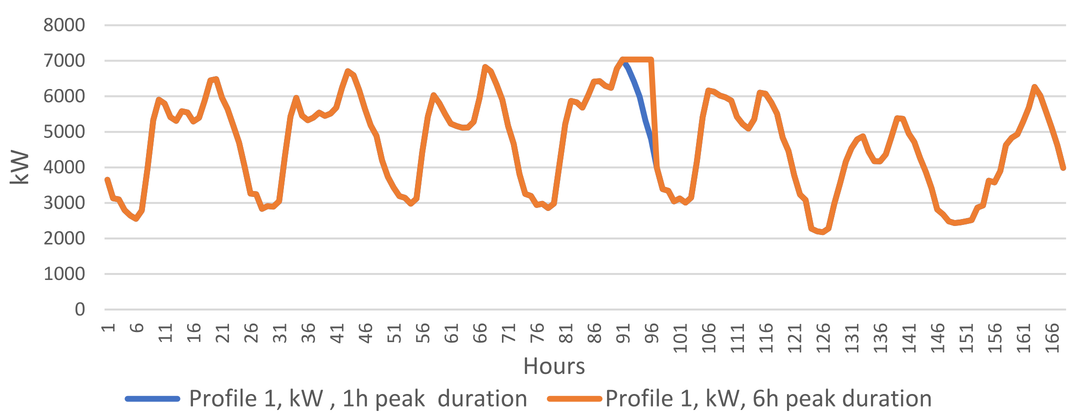

Fig. 4 Load profile 1, illustrated for 1-h and 6-h peak demand durations. The difference affects the fourth-day profile since this is where the peak is

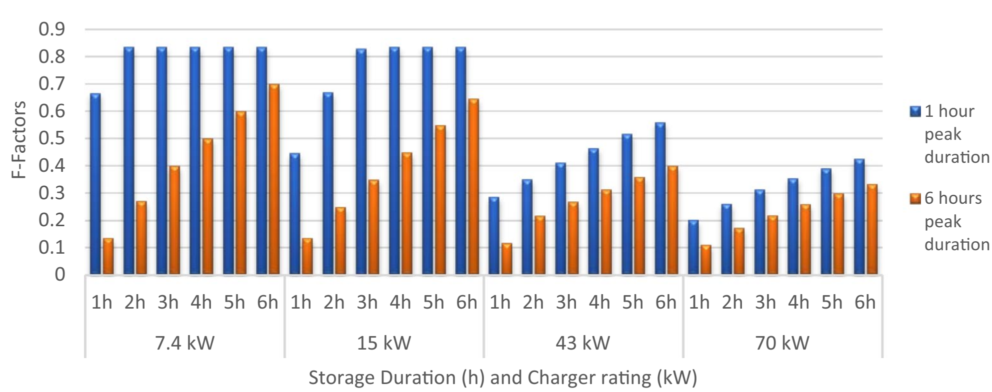

Fig. 5 F-Factors (vertical axis) as a function of storage duration (1–6 h), charger rating (7.4, 15, 43, and 70 kW) and different durations (1 h versus 6 h) for the peak of profile 1

2. EV battery duration: Longer battery durations generally result in higher F-Factor values. This is because increased battery capacity allows for greater potential in peak demand reduction without changing the V2G power capability. However, there is a saturation point beyond which additional capacity does not further reduce peak demand.
3. Load profile peakiness: Peakier load profiles tend to yield higher F-Factor values compared to flatter profiles. This is because V2G technology can more effectively reduce pronounced peaks, even with relatively small energy contributions from EV batteries.
4. Peak demand duration: Longer peak demand durations result in lower F-Factor values. This reflects the challenge of sustaining peak reduction over extended periods with limited storage capacity.

These findings collectively underscore the complex interplay between V2G system parameters and grid characteristics in determining the security contribution of V2G technology. The F-Factor methodology proves to be a valuable tool for quantifying this contribution, offering insights that can inform grid planning and V2G implementation strategies.

However, it is important to note some limitations of our study. We did not account for factors such as seasonal variations or unexpected demand spikes. Future research could explore these aspects to provide a more comprehensive understanding of V2G's security contribution under diverse real-world conditions.

Our results have significant implications for various stakeholders:

- For grid operators, they highlight the potential of V2G in enhancing grid security, particularly in areas with peaky demand profiles.
- For policymakers, they provide a quantitative basis for incorporating V2G into grid security standards and incentive structures.
- For V2G technology developers, they suggest focusing on optimizing battery capacity and charging rates to maximize security contribution.

Looking ahead, further research could explore the integration of V2G with other flexible technologies, such as stationary storage or demand response, to provide a more holistic view of smart grid security enhancement strategies. In addition, investigating the economic aspects of V2G deployment in relation to its security contribution could offer valuable insights for investment decisions.

In conclusion, the F-Factor methodology provides a robust framework for assessing V2G's contribution to grid security. By quantifying this contribution under various scenarios, we have demonstrated V2G's potential as a valuable tool in the transition toward more secure and flexible electricity grids.

Conclusion and future work

This paper presents the F-Factor methodology used for the evaluation of the security contribution of V2G technology. Specifically, the F-Factor metric is defined as the ratio of the maximum (optimal) reduction in peak demand divided by the capability of the V2G technology. A mathematical optimization model is presented for obtaining the maximum peak reduction, thereby allowing for the estimation of the numerator of the F-Factor. The value of the F-Factor is shown to be dependent on the power rating of the V2G chargers, the duration of the battery of the EV, the level of peakiness of the load profile (i.e., the difference between its maximum and minimum values), and the duration of the peak electricity demand.

The key findings include:

1. **V2G charger rating:** The F-Factor tends to decrease or remain constant as the rating of V2G chargers increases. This is due to the definition of the F-Factor as the ratio of peak demand reduction to V2G power capability. While higher-rated chargers can achieve greater peak reductions, the increase in power capability outpaces this reduction, leading to lower F-Factor values.
2. **EV battery duration:** Longer battery durations generally result in higher F-Factor values. This is because increased battery capacity allows for greater potential in peak demand reduction without changing the V2G power capability. However, there is a saturation point beyond which additional capacity does not further reduce peak demand.
3. **Load profile peakiness:** Peakier load profiles tend to yield higher F-Factor values compared to flatter profiles. V2G technology can more effectively reduce pronounced peaks even with relatively small energy contributions from EV batteries.
4. **Peak demand duration:** Longer peak demand durations result in lower F-Factor values. This reflects the challenge of sustaining peak reduction over extended periods with limited storage capacity.

The present paper can have implications for a range of stakeholders, as follows.

- **Grid operators:** The findings highlight the potential of V2G in enhancing grid security, particularly in areas with peaky demand profiles.

- **Policymakers:** The research provides a quantitative basis for incorporating V2G into grid security standards and incentive structures.
- **V2G technology developers:** The study suggests focusing on optimizing battery capacity and charging rates to maximize the security contribution.

Future work may include the application of Machine Learning concepts (Giannelos, 2024; Giannelos et al., 2023c), as well as robust optimization approaches in the study of F-Factors (Chen et al., 2014; Inuiguchi et al., 1999), (Giannelos et al., 2024b). In addition, the application of heuristic approaches, such as Backwards Induction (Giannelos et al., 2022) and incremental planning analysis (Giannelos et al., 2024a), is of interest to the authors to observe how a different methodology may affect the resulting F-Factors. The F-Factor can also be derived for V2B technology so that a comparison can be made with the F-Factors for V2G.

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S.G. wrote the main manuscript text and T.Z. prepared the figures and checked references. W.K. provided feedback and G.S. had the overview and provided feedback as well.

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Declarations

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Consent for publication
All authors consent for the publication of the manuscript.

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