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Impact of public and residential smart EV charging on distribution power grid equipped with storage

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ABSTRACT

The large-scale penetration of electric vehicles (EV) in road transport brings a challenging task to ensure the balance between supply and demand from urban districts. EVs, being shiftable loads can provide system flexibility. This work investigates the potential role of smart charging of EVs in mitigating the impact of the integration of a mix of residential and public EV charging infrastructure on power networks. Furthermore, the impact of integrating solar photo-voltaic (PV) and battery energy storage systems (BESS) has been explored where BESS improves PV self-consumption and helps in peak shaving during peak load hours. Annual losses, transformer congestion, and cost of electricity import assessment are detailed by considering the power network of Stockholm as a case study. Smart charging with loss-optimal and cost-optimal charging strategies are compared to uncoordinated charging. The cost-optimal charging strategy is more favorable as compared to the loss-optimal charging strategy as it provides more incentives to the DSOs. The loss-optimal charging strategy reduces 35.5 % of losses in the network can be reduced while the cost-optimal solution provides a 4.3 % reduction in the electricity cost. The combined implementation of smart charging, PV, and BESS considerably improves energy and economic performance and is more effective than EV smart charging alone.

1. Introduction

Cities are responsible for more than 70 % of the emissions and electrification of the transport fleet is one of the promising solutions to reduce them (Charly et al., 2023). It is expected that by 2026 electric vehicle (EV) sales will outnumber Internal Combustion Engine vehicles (ICEV) sales and EV sales will approach 90 % share by the end of the decade (Jan Hughes, 2022). This uptake of EVs in turn results in increasing electric loads impacting the grid stability due to an imbalance between supply and demand and requiring robust distribution equipment to support increased power flows (Jones et al., 2021). Early adopters mostly used home charging. However, as the uptake increases, there will be an increased demand for public chargers driven by those without access to off-road parking and those living in multi-welling apartments (Conzade et al., 2022). This paper, therefore, explores the impact of a mix of public and private chargers and how the use of local renewable generation using solar photovoltaics (PV) and battery energy storage systems (BESS) can mitigate some of the adverse impacts.

The operation of EV chargers has a significant impact on the quality of the power. (Deb et al., 2018) studied the impact of EV chargers on the IEEE-13 bus test system in terms of voltage stability, reliability, power losses, and economic losses. They found out that the placement of a new charging station caused severe degradation in the voltage stability, an increase in losses, and increase interruption in the grid. However, this study was only limited to the impact of placing fast charging stations in the network. (Kaya et al., 2020) provided with a framework for the placement of EV charging stations in the context of electric taxis. The study evaluates the number and optimal placement of charging stations in the city of Istanbul. However, the analysis lacks the consideration of EV ownership in commercial and residential sectors. (Dharmakeerthi et al., 2014) also studied the impact of EV charging stations with different load characteristics on voltage stability and found that EV chargers can significantly impact voltage stability. (Mets et al., 2012) concluded from a study that peak load increased by 1.5 times in a residential area with the introduction of new PHEVs with uncontrolled charging. This study was only limited to the impacts of chargers in residential setups. In another study carried out in the UK, the authors found that with a 20 % level of EV penetration in the transport network, peak load increases by 35.8 % in the case of uncontrolled charging (Qian et al., 2011). Several other works have studied the impact of EV chargers on the power grid and power quality (Mitra & Venayagamoorthy, 2010;

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Nomenclature

Symbol	Explanations
BESS	Battery Energy Storage System
EC	European Commission
EV	Electric Vehicle
GHG	Green House Gas
ICEV	Internal Combustion Engine Vehicle
MPP	Maximum Power Point
NEPP	North European Power Perspectives
PV	Photovoltaic
THE	Total Harmonics Distortion

Putrus et al., 2009).

The challenges posed by EV integration can be reduced through grid reinforcements and design upgrades. EV charging demand changes frequently throughout the day and the losses that appear with it can be shifted by shifting the loads through smart charging. In order to reduce the peak demand and level the loads, the alternate solution is to implement coordinated charging of EVs. Several works have investigated the impact of coordinated charging on power network in demand-side flexibility. (Crozier et al., 2020) proposed a coordinated charging strategy for EVs to reduce the losses in the distribution network. Monte Carlo simulations were used to obtain the loads in both controlled and uncontrolled charging scenarios. The study was carried out on IEEE European distribution network with data specific to the UK and only for residential setup. They found that 30–70 % of losses were reduced in the network without an increase in the peak demand by the implementation of the proposed charging scheme. (Karlsson, 2020) studied the impact of uncontrolled and smart charging of PEVs on the low voltage distribution network of a neighborhood of Stockholm. It was found that smart charging, adapting to the prices of the electricity led to a significant decrease in the peak demand during evening peak hours, and this led to a 15 % reduction in the charging cost while losses were reduced to 5 % in the simulated grid. This study was limited to the impact of only slow EV chargers rated at 3.496 kW while a majority of chargers being set up today in the commercial sector are fast chargers, to reduce the charging time. (Azizi et al., 2022b) studied the potential of energy flexibility from EVs and residential appliances using a price-based DR model. They concluded that by exploiting the potential of the flexibility of shiftable appliances, consumption can be flattened by up to 25 % at the aggregated residential level. (Sachan & Adnan, 2018) studied the impact of different EV charging methods on the distribution grid and proposed that EV smart charging provides the maximum economic benefit to the EV owners while dumb charging cannot be supported by the network with maximum loading conditions. (Zeng et al., 2017) studied the impact of EV integration on the reliability of the power system and concluded that a significant reduction in investment and operation costs is possible with smart charging. (Sachan et al., 2020) propose smart charging with distributed charging infrastructure in their study as it has more potential to provide flexibility services and generates lesser peak demand as compared to dumb charging. (David Steen, 2012) studied the different PEV charging strategies on the distribution network in the area of Gothenburg. The proposed cost-optimal charging strategy reduced costs but increased the load peaks while loss optimal did not peak increase peak demand. However, this study is limited to the installation of slow chargers rated at 3.68 kVA and does not consider fast chargers which are installed nowadays in commercial sectors. (Ali et al., 2020) investigated the usage of EVs as storage assets for microgrids that can be used to supply energy and observed that EVs can increase the resiliency of the grids without additional investment costs. (Gamil et al., 2022) studied the impact of integrating EVs with V2G and BESS in a microgrid. They found that EV integration increases the load in the system but with control techniques, the total system cost and CO_2 emissions can be reduced. Controlling BESS charging and discharging can further reduce the total system cost and carbon emissions. The increase in demand can be balanced by the increase in supply and distributed generation (DG) sources such as PV systems can be integrated with EV charging stations to increase the power supply independent of the grid.

Several works have studied the integration of PV as a potential mitigation option. (Galiveeti et al., 2018) studied the impact of PEV charging integrated with PV in terms of the reliability of distribution networks and found that system reliability increases with the integration of DG sources. It is important to note that PV as an independent DG also has an impact on the power grid. (Singh et al., 2019) studied the impact of PV on the IEEE 13 bus network and found that as the solar irradiance increased during the day, voltage fluctuations appeared on the busses and the impact of the variation was more on the busses far from the substation. On-load-tap-changer (OLTC) in transformers and smart inverters were suggested as the solution to voltage fluctuation. However, there is another way to store the excess power and use it for reducing the loads during peak times or as a backup power service. The research found that combining BESS and power curtailment led to the least losses in the network and was the most economical solution (Omran et al., 2011). (Eriksson, 2020) studied the potential of PV and BESS in the area of Stockholm considered for this study and concluded that adding BESS leads to peak shaving in the network. There is a great potential for PV in the locality during summer as during the day, solar PV generation can fulfill the demand. A dispatch strategy for BESS was developed for peak shaving during peak load hours. Self-consumption of PV is nearly 100 % during the morning hours, which reduces the morning peaks while evening peak reduction is possible with BESS integration. However, the authors do not consider the integration of EV charging with BESS in these studies, and is a gap in the literature studied.

This study, therefore, presents an integrated techno-economic impact for a distribution grid with increased residential and public EV charging facilities combined with PV and BESS. The novel contributions of this paper are stated below.

1. Impact of a mix of private residential and public fast chargers on a distribution network.
2. Smart charging with loss-optimal and cost-optimal charging strategies and their impact on the distribution network in terms of losses, transformer congestion and cost of power import from the grid.
3. Integration of PV and BESS with EV chargers to reduce dependence on the grid.
4. Real-life case study using real distribution network data.

The remainder of this paper is organized as follows – Section 2 discusses the case study, input data collection, and solar PV profile of the area. Section 3 discusses the methodology adopted for this work, the mathematical model for the smart charging solutions and solar PV with BESS, and test cases to evaluate the impact of smart charging. Section 4 explains the results for all the scenarios considered for this study and Section 5 concludes the findings of this paper.

2. Methodology

The methodology adopted is shown in Fig. 1 which includes the distribution network equipment data for modelling the network, distribution loads data, chargers, and solar PV data for optimizing the EV chargers operation with a certain objective. The time resolution for all datasets is one hour and simulations were run for one whole year. This research uses the measured distribution network loads data for a residential area in the neighbourhood of Stockholm to validate the results. The chosen methodology allows to validate the results on the actual power network. The previous works (Crozier et al., 2020; Singh et al., 2019) have considered the IEEE-13 bus network and IEEE test networks for validating the results. However, in this study, the IEEE network is

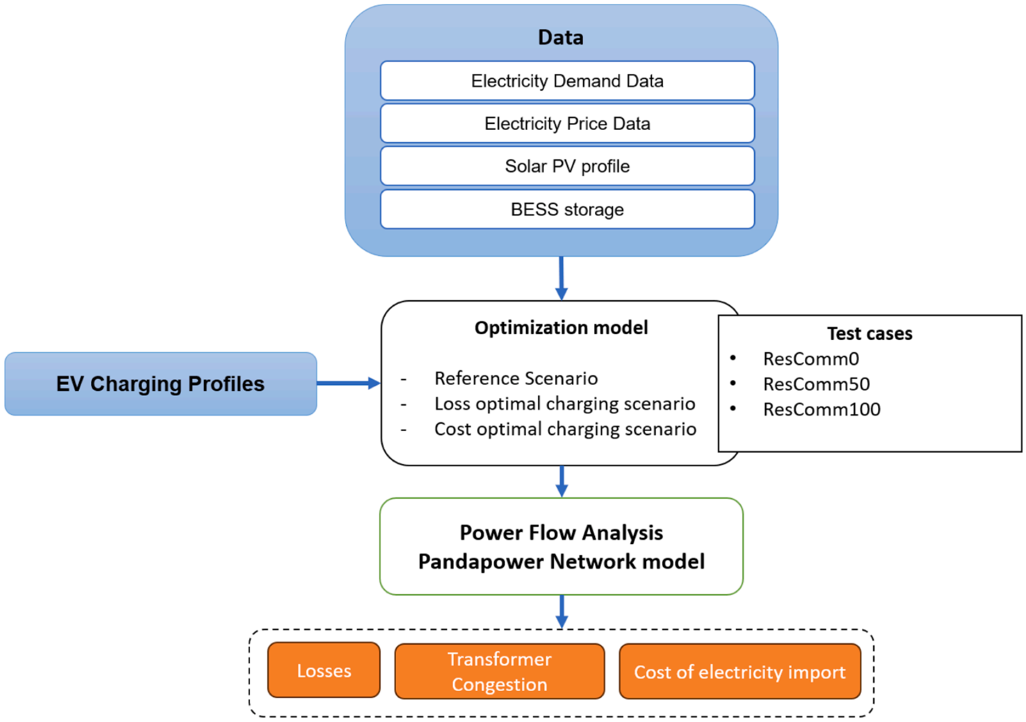

Fig. 1. Methodology overview.

replaced by the actual power network modelled in Pandapower. A similar approach has been taken by (Karlsson, 2020; Topel & Grundius, 2020) for the validation of the results as mentioned in Section 1 where different locations from the study were chosen to model the network and results validation.

Assumptions

Certain assumptions have been considered for the simplification of the model and problem formulation. The assumptions considered allow simplification in optimization problem formulation as has been done previously in different literature (Abdi et al., 2017; An et al., 2023; Kandpal et al., 2022).

1. All EVs follow a home-office-home driving pattern during work days. The charging pattern is considered the same throughout the week regardless of the day of the week. If there is no commercial activity, it is assumed that chargers will be occupied by customers during the evening (Lee et al., 2020).
2. EV battery is charged to a maximum of 80 % of SOC and can be discharged up to 20 % of SOC to ensure linear charging and discharging profiles according to findings from the literature review (Abdi et al., 2017).
3. All EV chargers both residential and public EV chargers are controllable throughout 24 h period.
4. EV chargers can operate on power less than their rated power. The losses due to operation at lower power are assumed to be zero.
5. Car ownership is assumed to be 210/1000 inhabitants (Karlsson, 2020). It is assumed that in future growth scenarios, car ownership will remain the same.
6. All commercial vehicles will be able to charge only on public chargers.
7. 100 % occupancy of the chargers is considered.
8. The electricity prices are the spot electricity prices collected from Nordpool. The prices do not include the grid fee.
9. For commercial chargers, peak demand charges are not considered. These charges are applied to ensure that industrial consumers keep their demands in check and spread energy usage over time.

2.1. Data collection

The demand data refers to the load profiles from the residential load demand. The load demand data provided corresponds to the year 2016 and with the projection of electricity loads to 2025, the demand exceeds the rated transformer power in 2025. Therefore, it becomes an interesting borderline case to study the impact of chargers in the year 2025. North European Power Perspectives (NEPP) projections were used as a reference for creating future scenario projections which suggest an average of 0.5 – 1 % increase in electricity demand during the year 2015–2030 (NEPP, 2016). This growth rate in electricity demand may deviate due to recent changes of events with increased heating demand being fulfilled by electricity. NEPP report suggests an increase in energy consumption, not power while the panda power loads are given in terms of power. However, according to Robert Karlsson (2020), there is a strong correlation between the peak power and the energy as they follow the same trend which makes it convenient to use the same growth rate for the power peaks as well. a. Electricity Prices

The electricity prices for the year 2019 were collected from Nord pool spot prices for region SE-3 which refers to Stockholm while for the year 2025, the electricity prices were projected through the procedure mentioned in (Baskar and Sridhar, 2020). The prices considered here are wholesale electricity prices and do not reflect the grid fees. The projections of electricity prices assumed that there will be a complete phase-out of nuclear power generation by 2040 (Sjögren et al., 2020), and Sweden's electricity production is based on 100 % renewable energy production. The electricity prices projected for 2025 do not account for the unpredictable change of events. With the new Swedish government's policies and recent change of events which impacted the energy prices throughout the EU significantly (applied after the work was completed), complete nuclear phase-out seems blurry but price signals for 2025 assume complete nuclear phase-out. The average price data for both years is shown in Fig. 2. b. Solar profile

The solar PV production data was collected from Renewable Ninja (2021) where geospatial data of the area under study was provided to generate annual PV generation profiles with hourly resolution. c. EV chargers

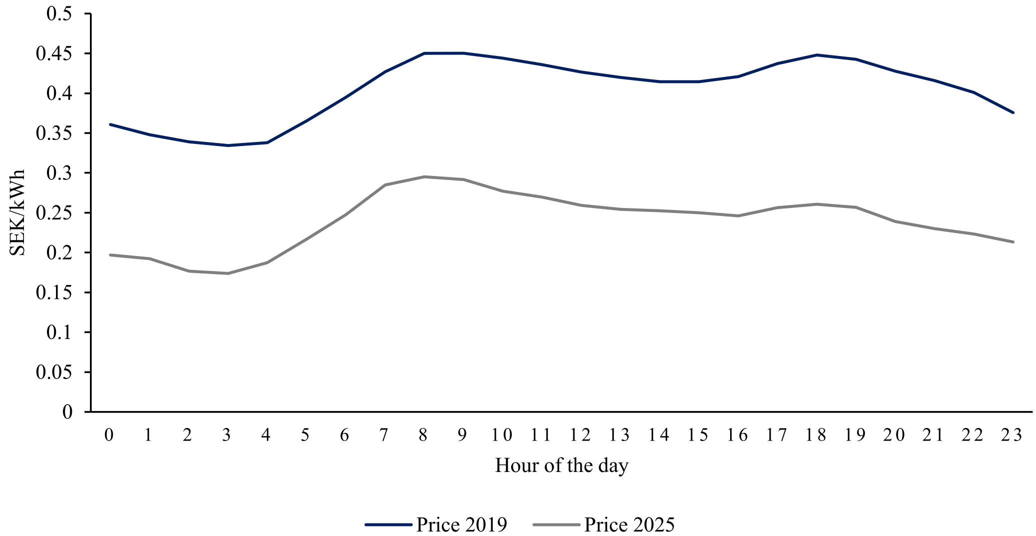

Fig. 2. Prices comparison 2019 vs 2025.

The EV chargers are categorized into two categories i.e., public and private residential EV chargers. Public chargers refer to the charging stations installed at public parking spaces where people leave their cars for a few hours to complete the intended activity. The time of commercial activities is identified from these activities which occur mostly during the day hours when people go for groceries, shop, or work during working hours. Since EVs are available for a short period, public chargers will be AC fast chargers with a rated power capacity of 22 kW. Residential chargers are those which are installed by EV owners in garages where they leave their cars for charging overnight. This general trend has been observed among EV owners because of the range anxiety issue. The residential chargers are slow chargers with a rated power capacity of 3.68 kW.

2.2. Optimization model

The controlled charging model assumes certain input values to determine the optimal charging strategy. Charging strategies with two different objectives were explored which are *cost-optimal* and *loss-optimal* strategies to compare the impact of both on the final results. *Loss-optimal* strategy tends to schedule the EV charging when there is less demand and EVs are available for charging. It does not respond to the price signals and the objective is to minimize the electricity imported from the grid. *Cost-optimal* strategy tends to minimize the cost of importing electricity from the grid. It optimizes considering the price signals and further two cases were explored for this strategy. One with the historic price data from Nordpool for region SE–3 for the year 2019 while the other case referred to using price data for the year 2025 using forecasting techniques explored in (Baskar and Sridhar, 2020). Table 1 below shows the scenarios considered for this study.

Where ResCommx represents the operation of all residential charging spots while 'x' represents the percentage of commercial charging spots. The cases have been explained in Table 2.

Table 1
Scenarios and cases.

Scenario No.	Name	Cases
1	Reference Scenario	*ResComm0* *ResComm50* *ResComm100*
2	Integration of PV and BESS	*ResComm0* *ResComm50* *ResComm100*

Table 2
Test cases explanation.

Cases	Explanation
ResComm0	All residential customers own an EV charger which is powered at 3.68 kW and commercial chargers are not available during the evening hours for charging EVs
ResComm50	All residential customers can use commercial chargers at half of the rated power i.e., 11 kW during the residential charging times
ResComm100	All residential customers can use the commercial charger at full power i.e., 22 kW during the residential charging times

2.3. Smart charging models

2.3.1. Reference scenario

The objective function for both of the scenarios is expressed in the equations [1,2]. Eq. (1) represents the objective function for the loss optimal solution while Eq. (2) represents the objective function for cost-optimal solution.

$$minimize \sum_{t=1}^{hours}\left(\sum_{i=0}^{i=FS} P_{i,t}^{EG}\right) \tag{1}$$

$$minimize \sum_{t=1}^{hours}\left(\sum_{i=0}^{i=FS} P_{i,t}^{EG} \ . \ price\right) \tag{2}$$

Where $P_{i,t}^{EG}$ is the power injected from the external grid in kW, 'FS' represents the primary substation, 'i' represents the number of FS, 't' represents the hours and *price* is the hourly electricity price in SEK/kWh. These representations will be followed in all subsequent equations.

The network constraint from the transformer rated power restricts the grid limit which is given by the following equation.

$$P_t^{load} + P_t^{EV} \leq P_t^{TRAFO} \tag{3}$$

Where P_t^{load} represents the demand from residential loads in kW, P_t^{EV} represents the demand from EV charging in kW, P_t^{TRAFO} represents the rated power in kW of the transformer in a particular substation and 't' represents each hour.

The energy balance of the system is represented by the equation [4].

$$P_t^{EG} = P_t^{load} + P_t^{EV}, \ \forall t \tag{4}$$

Where P_t^{EG} represents the energy in kW imported from the grid.

In order to calculate the battery energy level at each time step, it is assumed that the charging process will have some inefficiencies, therefore, to incorporate this factor, η^c is considered which represents the charging efficiency in the equation [5].

$$E_t^{EV} = \eta^c \ P_t^{EV} + SOC_{t-1}^{EV} \ B_{cap}^{EV} \tag{5}$$

Where B_{cap}^{EV} represents the battery capacity of an EV in kWh, SOC_t^{EV} represents the state of the charge of EV battery at time ‘t’, E_t^{EV} represents the energy level of the EV battery at each hour in kWh and η^c represents the charging efficiency.

A set of constraints were also imposed on the State-of-Charge (SOC) to enhance the battery life and extend battery health.

$$SOC_{min}^{EV} \leq SOC^{EV} \leq \ SOC_{max}^{EV} \tag{6}$$

$$SOC_{min}^{EV} = 0.2, \quad SOC_{max}^{EV} = 0.8 \tag{7}$$

Where SOC_{min}^{EV} represents the minimum state of the charge of the EV battery, SOC_{max}^{EV} represents the maximum state of the charge of the EV battery while B_{cap}^{EV} shows the battery capacity of an EV in kWh.

SOC of an EV is also associated with EV availability. All EVs that arrive for charging on the charging station will have 20 % of SOC and will have 80 % of SOC at the end of the charging session.

$$E_t^{EV} = SOC_{min}^{EV} \ . \ B_{cap}^{EV} \ \text{if} \ EV_t^{available} = 0 \tag{8}$$

$$E_t^{EV} = SOC_{max}^{EV} \ . \ B_{cap}^{EV} \ \text{if} \ EV_t^{available} \neq 0 \ \text{and} \ EV_{t-1}^{available} = 1 \tag{9}$$

Where $EV_t^{available}$ represents a binary variable EV availability which is 1 when EVs are available for charging and 0 when there is no availability.

2.3.2. Scheduling constraints

Eq. [10–11] represents the constraints to ensure that charging occurs only during the specific hours for each category of vehicles.

$$P_{comm,t,n}^{EV} \geq \ P_{comm,t,n}^{min} \ \in \left[\ h_{arrive}, \ h_{dept} \right]_{comm} \tag{10}$$

$$P_{res,t,n}^{EV} \geq \ P_{res,t,n}^{min} \ \in \left[\ h_{arrive}, \ h_{dept} \right]_{res} \tag{11}$$

Where $P_{comm,t,n}^{EV}$ represents the charging power in kW of each commercial charger during each hour while $P_{res,t,n}^{EV}$ represents the charging power in kW of each residential charger during each hour, h_{arrive} *and* h_{dep} represent the hour of arrival and departure respectively. Here ‘n’ represents the total number of chargers.

2.4. Integration of PV and BESS

The primary aim of solar PV is to reduce the dependence on the grid and lower the power imported from the grid. All the electricity generated by PV will be used for charging EVs and fulfilling the baseload demand. The loss optimal and cost-optimal objectives are similar to Scenario 1 given by Eqs. [1] and [2]. However, constraint equations will be different in this scenario.

The transformer power constraint equation involves the PV generation given by the equation [12].

$$P_t^{load} + \ P_t^{EV} - \ P_t^{PV} \leq \ P_t^{TRAFO} \tag{12}$$

Where P_t^{PV} represents the power generation from the PV sources in kW.

Grid balance equation is given by the equation [13].

$$P_t^{EG} \ + \ P_t^{PV} = \ P_t^{load} + \ P_t^{EV}, \ \forall t \tag{13}$$

With the addition of BESS, the grid balance equation involves charging and discharging power requirements of BESS.

$$P_t^{EG} \ + \ P_t^{PV} = \ P_t^{load} + \ P_t^{EV} + P_t^{BESS} - D_t^{BESS}, \ \forall t \tag{14}$$

Where P_t^{BESS} represents the charging power in kW and D_t^{BESS} represents the discharging power in kW.

With the addition of BESS, more power will be imported from the grid which will be reflected in the transformer rated power constraints.

$$P_t^{load} + \ P_t^{EV} + \ P_t^{BESS} \leq \ P_t^{TRAFO} \tag{15}$$

BESS charging and discharging balancing equations ensure that BESS charges only through the grid and PV while discharging power goes in fulfilling demand and EV charging is only given by the equations [18,19].

$$P_t^{BESS} = \ Pbess_t^{PV} + \ Pbess_t^{grid}, \ \forall t \tag{18}$$

$$D_t^{BESS} = Dbess_t^{load} + \ D_t^{EV}, \ \forall t \tag{19}$$

Where, $Pbess_t^{PV}$ is charging power for BESS from PV generation, $Pbess_t^{grid}$ is the charging power for BESS from energy imported from the grid. Similarly, $Dbess_t^{load}$ is the energy discharged from BESS to fulfil the load demand while D_t^{EV} is the energy discharged from BESS to fulfil EV charging demand.

The charging and discharging cycles are given by the equation [20].

$$B_t^{BESS} = \ SOC_{t-1}^{BESS} \ B_{cap}^{BESS} + \ \eta^c \ P_{t-1}^{BESS} - \ \frac{D_{t-1}^{BESS}}{\eta^d}, \ \forall \ t \tag{20}$$

Where B_t^{BESS} is energy stored in BESS in kWh at the time ‘t’, SOC_{t-1}^{BESS} is the energy level of the battery at time ‘t - 1′

To keep track of the charging and discharging of BESS, two binary dimensionless variables C_t^{state} and D_t^{state} are considered and they ensure that there is no simultaneous charging and discharging of the BESS battery.

$$C_t^{state} + D_t^{state} = 1, \ \forall \ t \tag{21}$$

The EV charging cycle is the same as discussed previously, given by the equation [5].

However, EV charging is now also supported by BESS which is represented by the equation [22].

$$P_t^{EV} = EV_t^{grid} + EV_t^{PV} + EV_t^{BESS}, \ \forall \ t \tag{22}$$

Where EV_t^{grid} represents the EV charging power imported from the grid in kW, EV_t^{PV} represents the EV charging power from PV in kW and EV_t^{BESS} represents the EV charging power from BESS in kW during each hour.

BESS size was calculated through the excess power available in the system. BESS was included to improve the self-sufficiency of the PV system which is calculated through the following equation

$$BESS \ size = P_{peak}^{PV} - P_t^{demand} - P_t^{EV} \tag{23}$$

Where P_{peak}^{PV} represents the peak PV power production in kW, P_t^{demand} represents the load demand in kW at the time ‘t’ which is the peak solar production hour and P_t^{EV} is the EV chargers demand in kW at the time ‘t’. Since it is hourly power, therefore BESS size is in kWh.

2.4.1. Techno-economic parameters calculations

The losses in the network for the whole year are calculated according to the following equation.

$$Total \ Losses = \sum_{t=0}^{8760} \left(P_{grid-import} - P_{loads} \right) \tag{24}$$

Where $P_{grid-import}$ is the total power imported from the grid in kW to meet the load demand while P_{loads} is the total power required by the loads in kW connected to the grid. Eq. [25] represents the mathematical formulation for the calculation of costs of electricity import from the grid.

$$Total\ Cost = \sum_{t=0}^{8760} (P_{grid-import} * price) \tag{25}$$

Where $P_{grid-import}$ is the total power imported from the grid in kW to meet the load demand and the price is the hourly electricity price in SEK/kWh.

2.5. Load flow analysis

Panda Power is used for carrying out power flow analysis of the simulated network. Panda Power is an open-source tool for power system modeling and analysis. It is built upon Pandas (data analysis library in Python) and power system modeling toolbox (PYPOWER) which makes the analysis and optimization of power networks easier (Pandapower, 2021). Panda Power uses the default Newton–Raphson method for solving the non-linear power flow equations. Newton-Raphson method is superior to other methods because of its quadratic convergence which makes it more efficient for large power systems. In a study carried out by the authors (Vijayvargia et al., 2016) with various power flow algorithms, the Gauss-Siedel method was found easy to execute but required more iterations as the number of busses increased, Newton Raphson was found accurate and provided better results in a lesser number of iterations, and Fast-Decoupled method is the fastest but less accurate. Hence Newton-Raphson method was chosen for this study (Figs. 3 and 4).

The blue dots in the figure represent the buses, green circles represent the transformers, red-filled boxes represent the closed line switches, red boxes (unfilled) represent the open switches, black arrows represent the loads and yellow boxes represent the feeder stations.

Only 4 substations out of 20 were considered for this study, the results obtained for these substations can be scaled to other substations and case studies. The choice of the substations was made based on the residential and commercial distributions of HS given in (Topel & Grundius, 2020). The areas with the most residential and commercial activity were chosen so that the results obtained from those can be scaled to the other areas.

3. Case study

Hammarby Sjöstad (HS) is located in the inner part of Stockholm City. It is considered one of the most successful urban renewal districts and is currently undergoing a major urban change (GroenBlauw). This area was formerly an industrial district and was planned to be rebuilt into an ecological city. The area of HS is built with the concept of social equity which means to make it inclusive for people belonging to all strata of life to ensure sustainability (Lindholm, 2019). Currently, 1/3 of the apartments in HS are rented by the municipality while 2/3 are rented by private rental companies. Upon the completion of HS by 2031, it is estimated that it will house a total of 31,000 residents who will live and work there (Stockholm Stad, 2021) while 11,500 residential units are estimated to be built there (Lindholm, 2019).

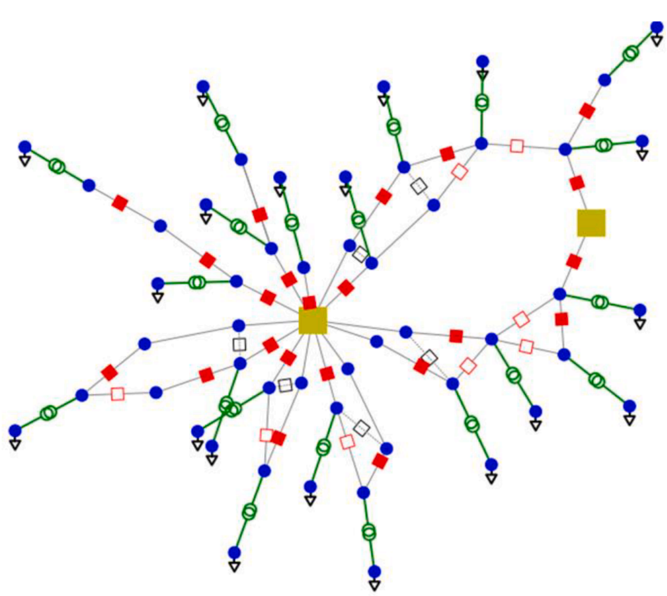

Fig. 3. Network diagram of the area.

HS is considered to be charging friendly space in Sweden. The "Charge at Home" project in HS aims at increasing the number of EVs in the locality and reducing carbon emissions. In this spirit, many housing associations have underground car parks where a charging facility is available. There are more than 400 charging points available in HS with 31 charging points in the outdoor charging facility (Hammarby Sjöstad, 2020). By the end of the year 2030, 80 % of the vehicles in HS will be climate neutral while at least 250 charging points will be installed (Electricity Innovation, 2020), which presents a strong test case for research on public charging.

3.1. Case study specific data collection

a. Demand Profiles

The load demand data for each substation in the area and the specifications of the distribution equipment which includes transformers, buses, and lines was provided by Ellevio AB, the DSO of the area. The peak load demand is 1528 kW while the average load demand from the area is 733 kW. Fig. 5 below shows the electricity consumption data for both summer and winter for the year 2025.

a. Solar PV data

Fig. 6 shows the PV generation profiles during different seasons of the year. Due to its geographical location, Sweden presents a sharp contrast in solar insolation during summer and winter which is evident in Fig. 6.

a. EV Chargers profile

i. Projections for commercial chargers

All the public parking spaces in the areas of HS are considered to have public charging points in the future. Therefore, it is assumed that if all the parking spaces are electrified, then 100 % commercial EV penetration in the transport network is realized. It is considered that all chargers will not be electrified immediately rather this is a perpetual process that will grow over time as the number of EVs increases in the future. The parking spaces are calculated from Parkopedia (*Parkopedia*, 2021) where the number of parking spaces has been specified. ii. Projections for residential chargers

The projections for the residential chargers are based on the population in the areas of HS under study and the number of BEVs based on the vehicle ownership ratio. To calculate the estimates for the number of future EV owners, the residential population distribution of the areas was calculated using the numbers from ratsit.se (*Ratsit*, 2019). All the loads were aggregated at the substation level and there was no disaggregation of the loads. The population register provided population numbers for 2019 while the demand loads were projected for 2025. Therefore, the population numbers were also projected for the year 2025 with a constant growth rate. As per the HS plan, by the year 2031, the population will reach its maximum of 31,000 (Topel & Grundius, 2020). The population numbers for 2015 and 2025 were known which gives an average growth rate of 3 %.

To calculate the number of chargers, it is assumed that 210/1000 people will own an EV according to the present vehicle ownership ratio of HS (Hammaby Sjöstad, 2015) and all of them will have their private

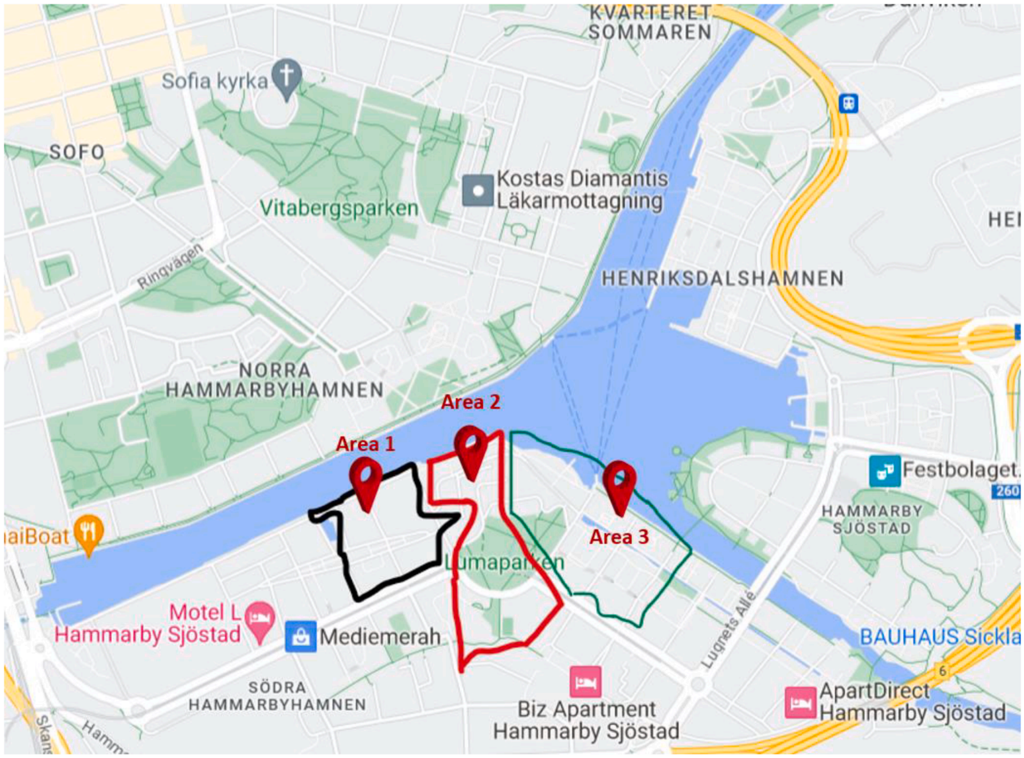

Fig. 4. Hammarby Sjostad Map with the areas considered for this study are mapped.

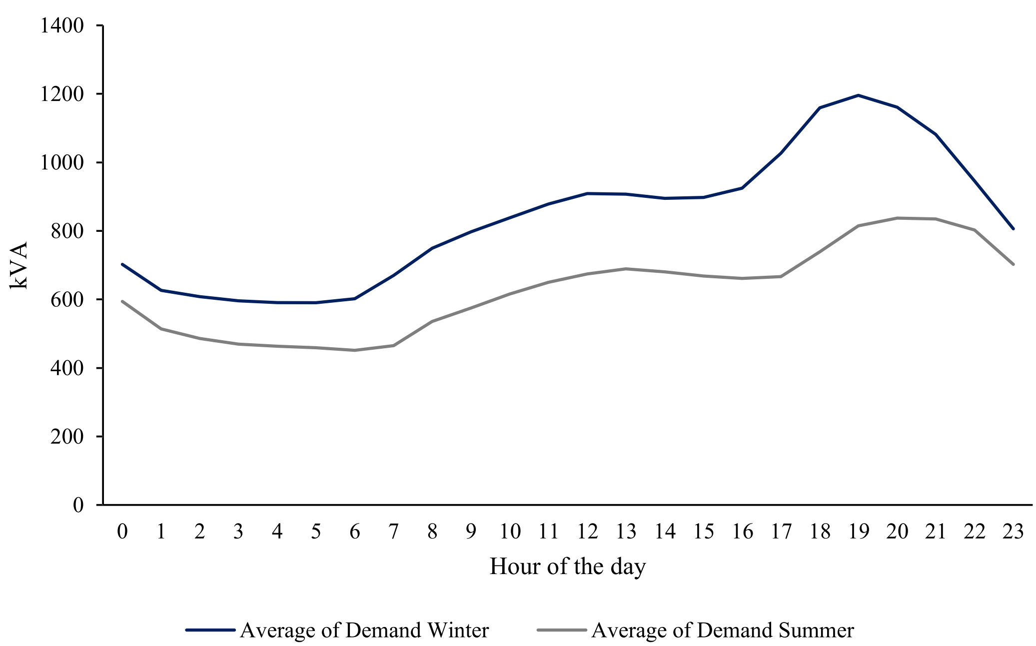

Fig. 5. Summer and winter monthly average daily load demand profile.

residential EV chargers. This provides us with the number of EVs and eventually their chargers which will appear as the demand load in addition to the residential load demand.

The loads added for the residential and commercial charging are different because of different EV chargers' power during different times. All of these requirements were reflected in load profiles with EV charging which was later added as a load in panda power loads.

4. Results

This section explains the impact of EV chargers combined with PV and BESS on grid losses and the economic calculations related to different scenarios. Three cases were developed to analyze the impact of EV chargers in different scenarios which have been explained in Table 2.

All of the cases were studied with different percentages of EV chargers calculated in each of the areas. These percentages varied from 10 % to 100 % with each step of 10. The bottleneck appeared in one of the 4

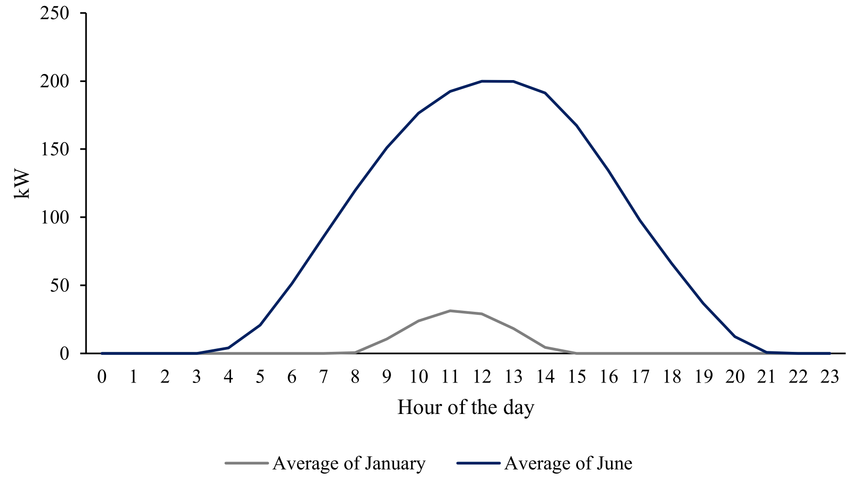

Fig. 6. Monthly hourly average solar PV profile.

substations considered for this study where it was found that a maximum of 40 % of the projected number of EVs can be integrated, therefore, all of the results presented here are for 40 % of the EVs in the areas. The transformers present the major bottleneck in the whole situation while distribution lines do not create congestion issues.

4.1. Reference scenario

The critical day of the year is presented as the absolute worst case for this study, and it can be seen in Fig. 7 where distribution loads after the addition of EV chargers to the base loads in both uncontrolled and controlled charging scenarios are shown. Both summer and winter days are presented here for comparison.

In the case of uncontrolled charging, two peaks are observed in the demand profile when EV chargers start operating and there is a peak-to-valley gap. In the *ResComm0* case, the first peak is due to high charging demand from commercial chargers at 0900 h which are rated at 22 kW each while the evening peak appears due to the residential EV charging at 1900 h. In the *ResComm50* case, the morning peak remains the same while the evening peak is increased due to the availability of commercial chargers for residential EV owners. In the *ResComm100* case, the morning peak remains the same while the evening peak is higher than the morning peak because commercial chargers operate at 100 % rated power. This is also reflected in the transformer loading in Figs. 9and 10 where it is seen that during evening hours, the loading of the transformer is more than morning peaks. Here, it is important to note that in normal circumstances evening peaks are considered a potential hazard for the network, while in this situation, transformer loading exceeds even during the day hours.

Fig. 8 shows that demand peaks are reduced with smart charging. The system load profile becomes much more leveled when smart charging is implemented. Both loss optimal and cost-optimal strategies reduce the peak by 54 % on average during a summer day while the reduction in peak during winter is 55 % on average. This peak reduction also reduces the stress on transformers as demand is not allowed to increase beyond the rated transformer power. The flexibility provided by EV allows the system to incorporate DG where power curtailment from PV can be reduced.

The overloading of the transformer in the uncontrolled charging case reflects the impact on the network. The transformer is overloaded up to 270 % during the hour when commercial chargers start their operation at 0900 h as shown in Fig. 10 which is a crucial situation and can lead to a blackout in the substation. However, with controlled charging in implemented, the transformers are within the safe operation limits and loading does not increase beyond 100 %.

Figs. 11and 12 show the heatmap for transformer congestion during

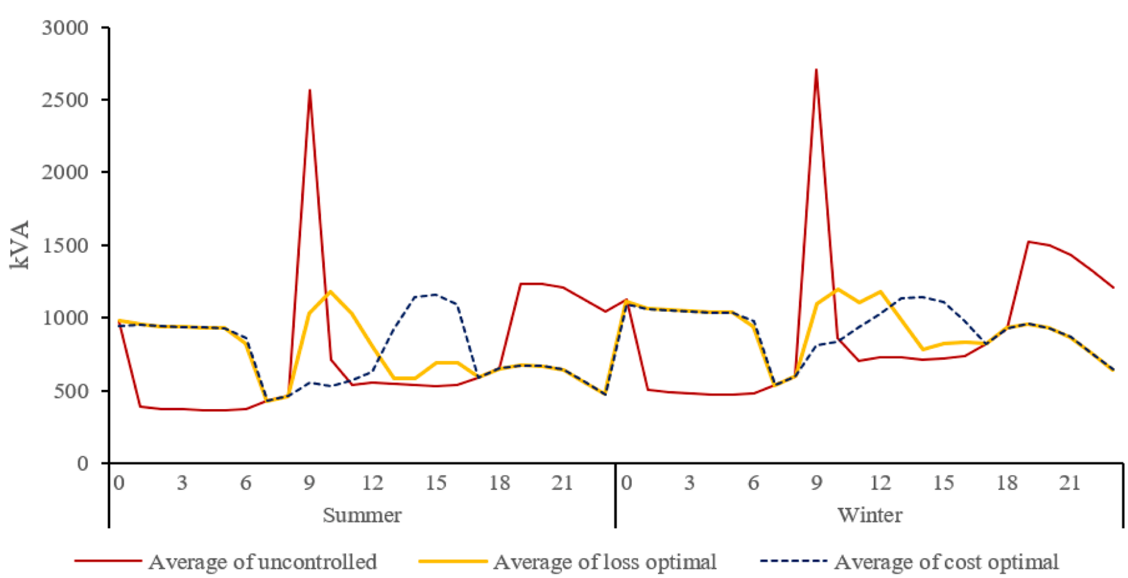

Fig. 7. Demand Profile - ResComm0.

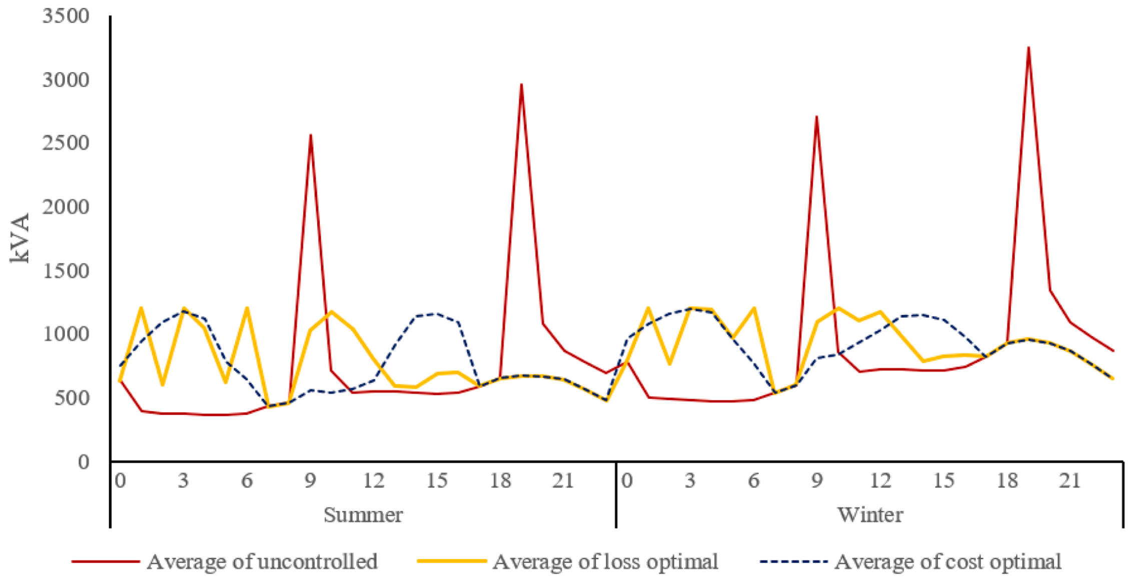

Fig. 8. Demand Profile- ResComm100.

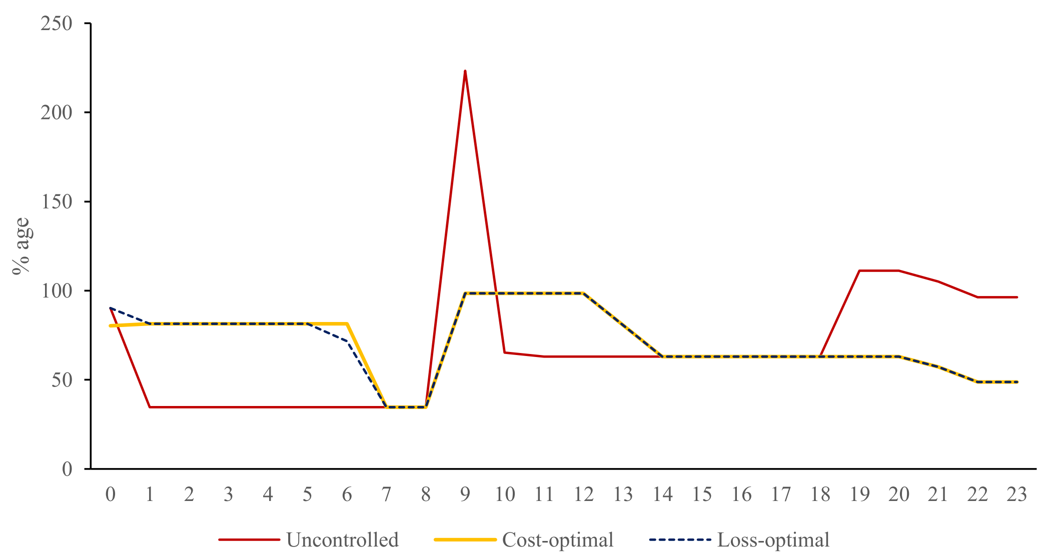

Fig. 9. Hourly transformer loading in the ResComm0 scenario.

the whole year for *ResComm0* and *ResComm100* cases. The heatmap shows that both smart charging strategies schedule charging late at night when both load and electricity prices are low. During the day hours, the loss optimal strategy ignores the price signals and tends to spread the charging over certain hours of the day. This is why some dark regions are observed in the loss-optimal solution in Fig. 12 while this is not the case in the cost-optimal solution. The cost-optimal strategy considers the price signals for optimizing the charging schedules and prices remained quite similar during 0900 h–1800 h when commercial charging was scheduled.

4.1.1. *Losses*

Table 3 shows the reduction in total annual losses from smart charging compared to uncontrolled charging for all the test cases. If we compare the loss and cost-optimal solutions, it seems that in some cases, there is not much appreciable difference in the losses due to the high demand from EV charging loads. Since we are importing maximum power from the grid considering the transformer constraints, the difference is quite less in both charging strategies. However, the difference is appreciable between uncontrolled and controlled charging scenarios where up to 35 % reduction in losses is achieved by smart charging.

4.1.2. *Cost of electricity import*

It was found that the losses in *ResComm50* and *ResComm100* are more than in the *ResComm0* case, however, the cost of electricity import is lesser in *ResComm50* and *ResComm100* scenarios. This is due to more power import during low price periods to fulfill the EV charging demand. In *ResComm50* and *ResComm100* scenarios, commercial chargers are also available which have more rated power and can fulfill the same charging demand in less time compared to residential chargers. However, it is important to note here that the difference is not substantial because of the transformer's rated power constraints but the cost savings from grid reinforcements are much more substantial which are not reflected in this case here.

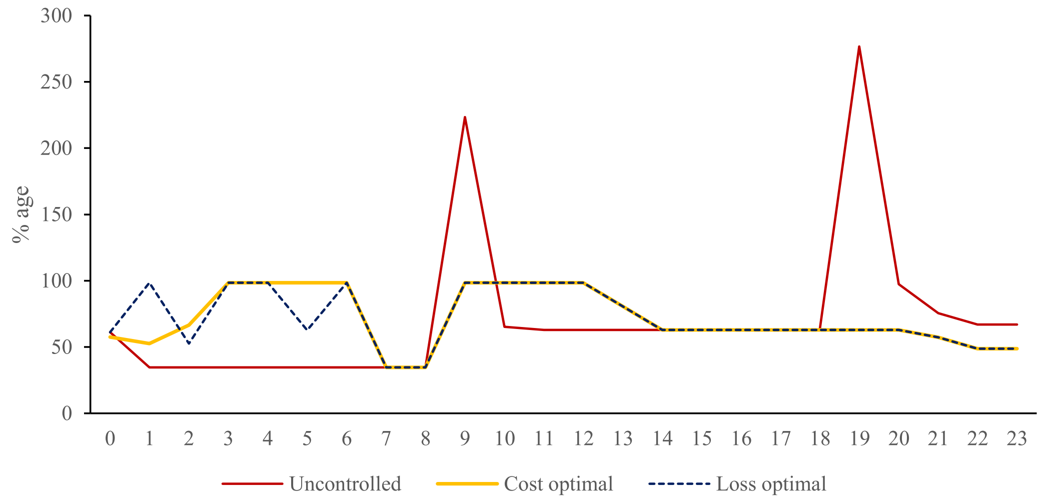

Fig. 10. Hourly transformer loading in the ResComm100 scenario.

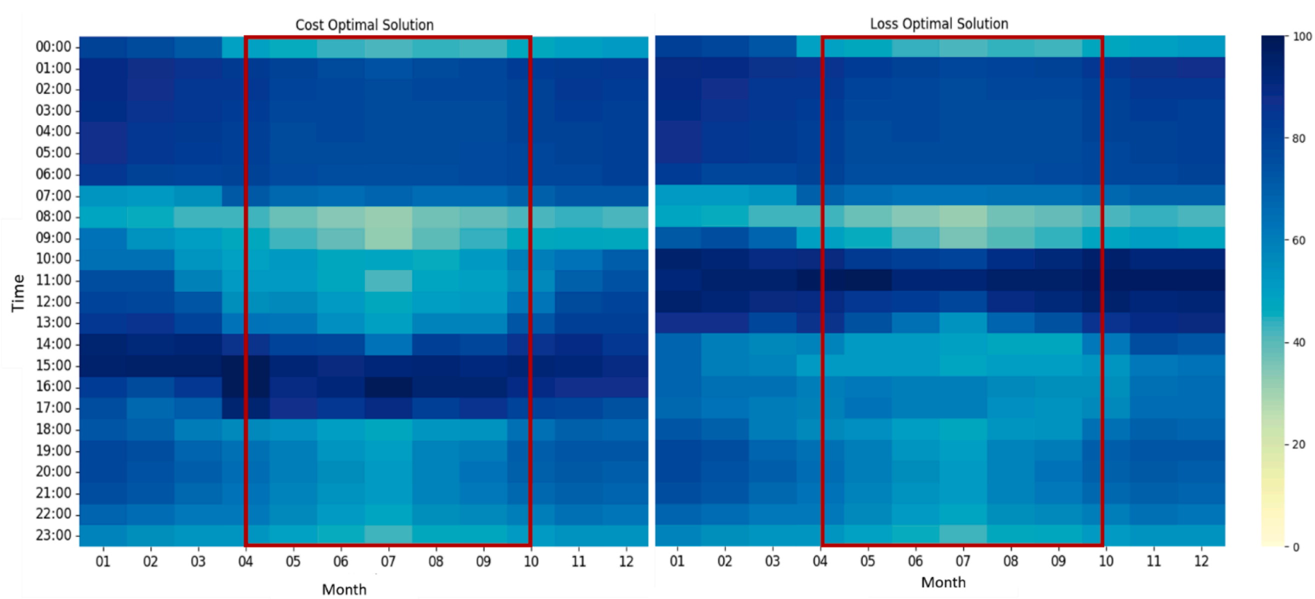

Fig. 11. Transformer loading - ResComm0: Transformer loading heatmap in cost-optimal strategy and loss optimal strategy.

4.2. Integration of PV and BESS

4.2.1. Integration of PV

As we have established in the previous scenario that EVs being flexible loads can follow DG output and help in reducing power import from the grid. The addition of PV results in less import of electricity from the grid which also affects the grid losses i.e., they are reduced by a significant amount. A larger amount of PV power can be utilized by EV loads during the day hours where commercial charging demand can be fulfilled fully or partially depending on the demand from other loads. The reduction in the losses with the addition of PV generation is shown in Table 4. The demand profile is the same as it was in the previous scenario.

The addition of PV to the same system leads to a maximum of 7.35 % reduction in total annual power losses. It is quite interesting to see here that there is not a big difference between uncontrolled and controlled charging scenarios because the same amount of power is consumed by the chargers during controlled charging. However, there is a significant decrease in the power losses which also affects the demand profile from the grid's perspective. DG integration will keep the system from approaching its operational limits which will lower the investment cost for grid reinforcement.

The cost of electricity import is also affected by the addition of PV which is shown in Table 5. The difference in the cost of electricity import is quite apparent because the cost-optimal strategy uses the price signals to schedule EV charging.

4.2.2. Impact of PV on transformer loading

The network was simulated for the whole year with all the distribution equipment in place. The impact on the transformers in the *Reference* scenario and upon the addition of PV was observed. Fig. 13 (Left) heatmap represents the *Reference* scenario where it is apparent that charging occurs during the early hours of commercial activity duration while for the residential it is during the later hours of the day. Fig. 13 (Right) shows the transformer loading with the addition of PV. The EV chargers' scheduling is quite similar in both cases, however, there is a stark difference in the transformer loading during the early morning hours i.e., 0700 h–0900 h.

The heatmap shows that during summers, when solar production is at its peak and there is higher solar insolation, the transformer loading

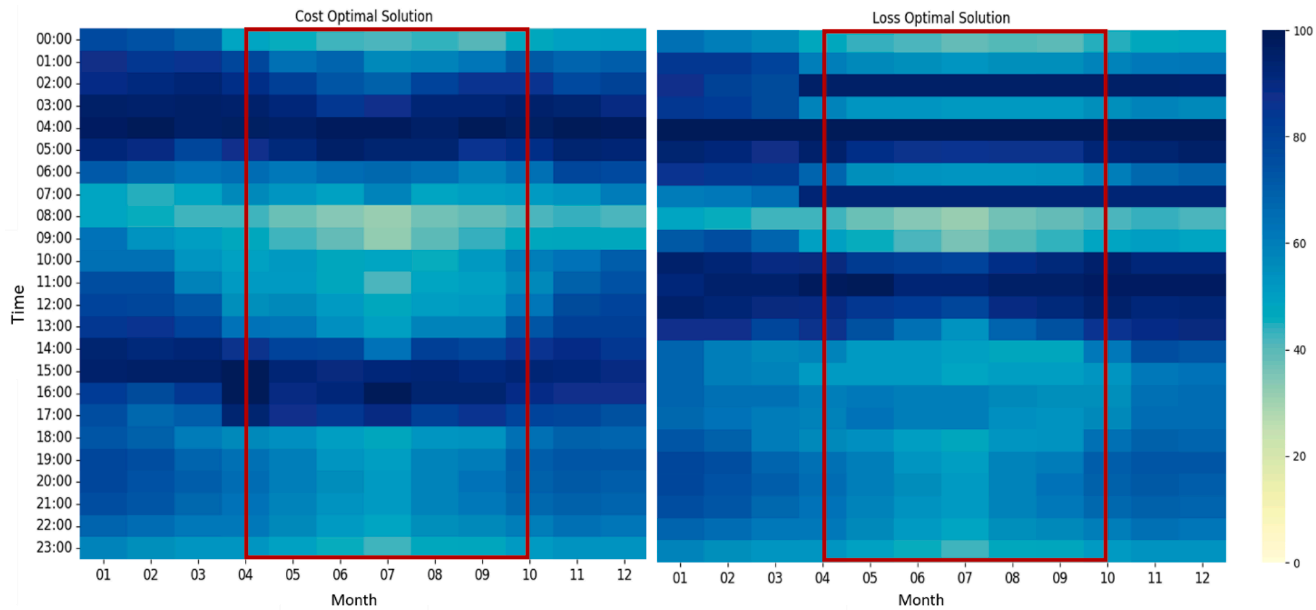

Fig. 12. Transformer loading - ResComm100, Transformer loading heatmap in cost-optimal strategy and loss optimal strategy.

Table 3
Reduction in total annual losses.

Reduction in total annual losses by smart charging strategies (%age)			
Test Case	Loss-optimal	Cost-optimal (Y2019 prices)	Cost-optimal (Y2025 prices)
ResComm0	23.3	22.9	23.1
ResComm50	27.7	27.4	27.6
ResComm100	35.5	35.2	35.3

Table 4
Reduction in annual losses with PV generation compared to the Reference Scenario.

Reduction in annual losses with PV generation compared to Reference scenario (%age)				
Test Case	Uncontrolled	Loss-optimal	Cost-optimal (Y2019 prices)	Cost-optimal (Y2025 prices)
ResComm0	7.35	7.30	7.07	6.75
ResComm50	6.7	7.07	6.74	6.38
ResComm100	6.03	7.07	6.72	6.34

Table 5
Total annual reduction in the cost of electricity imports from the grid.

Total annual reduction in the cost of electricity imports from the grid (%)				
Test Case	Loss-optimal (2019)	Loss-optimal (2025)	Cost-optimal (2019)	Cost-optimal (2025)
ResComm0	0.09	0.57	0.7	1.73
ResComm50	1.57	2.09	2.77	3.9
ResComm100	1.62	2.13	3.0	4.33

drops during the 0700 h–0900 h in the morning. This is because of less import from the grid and there are instances when PV generation alone can fulfill the demand. This phenomenon occurs during early hours as well i.e., 0700 h and 0800 h of the day when no EVs are available for charging.

4.3. Impact of adding BESS in the network

It is clear from the results above that adding PVs to the network leads to a substantial reduction in the losses and also during the day when the solar potential is at its peak, solar power production exceeds the demand from the residential loads. The size of the battery was chosen based on the maximum excess energy in the network which is equal to 145 kW. The battery size, therefore, is considered 150 kWh to store excess PV power. Fig. 14 shows the demand profiles along with the charging and discharging of BESS for the *ResComm100* case. *ResComm0* and *ResComm50* both have similar profiles. It can be seen that BESS charges when electricity prices are lowest and discharges when prices are higher, thereby providing flexibility services to the grid during peak hours. The BESS discharges at the time when prices are higher during morning hours between 0800 h and 1000 h while in the evening, it discharges during 1800 h–2000 h when prices are highest. During winters, the peaks due to charging and discharging from BESS are lower because of higher demand from base loads. It is to be noted that BESS size is quite small as compared to the peak load demand, if a larger battery pack is installed, peak shaving will become more evident.

Table 6 shows the reduction in the cost of electricity import from the grid with the installation of BESS to increase PV self-consumption and reduce peak loads. It can be seen that the addition of PV reduces the cost of electricity purchase from the grid on average by 6.23 % on an annual basis while the addition of BESS leads to a 6.43 % reduction on average. The sharp difference in the PV BESS scenario is due to more power requirements from EV chargers and BESS charging in *ResComm50* and *ResComm100* scenarios. In these scenarios, BESS power is not enough to provide peak-shaving or load-shifting services. BESS of larger size compared with the load demand can effectively provide flexibility services which have been excessively explored in previous research.

5. Discussion

The results are presented for the year 2025 when the grid operators will face challenges in keeping the demand and supply balance in the grid. The uncontrolled charging scenario in today's case may work because of quite fewer charging stations but, in the future, the transformers will not be able to cope with the loading situations that EV charging will bring. It was found from the PandaPower simulations that the cables are well-designed to support EV charging. It is demonstrated that by implementing controlled charging of EVs, the grid reinforcement costs be reduced with no transformer upgrades required and the losses can be reduced by up to 35.5 %. The cost of EV charging in controlled charging scenarios is also reduced by 61.22 % as compared to

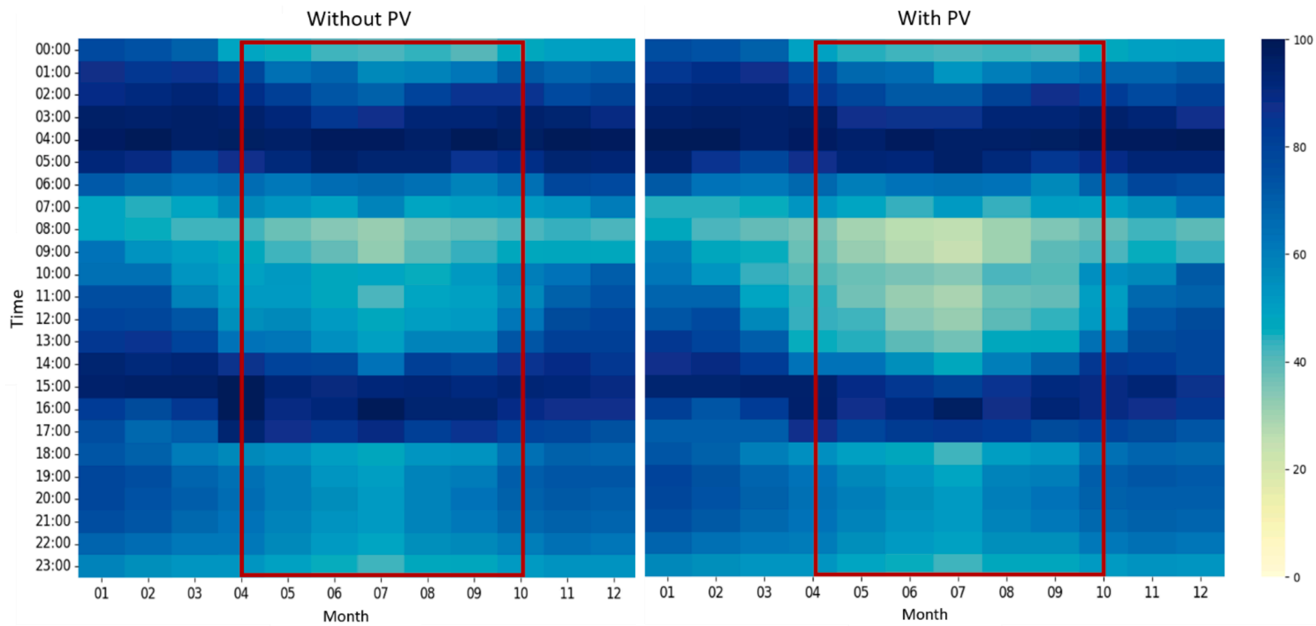

Fig. 13. . Yearly transformer loading (Left): Reference Scenario (Right): Integration of PV.

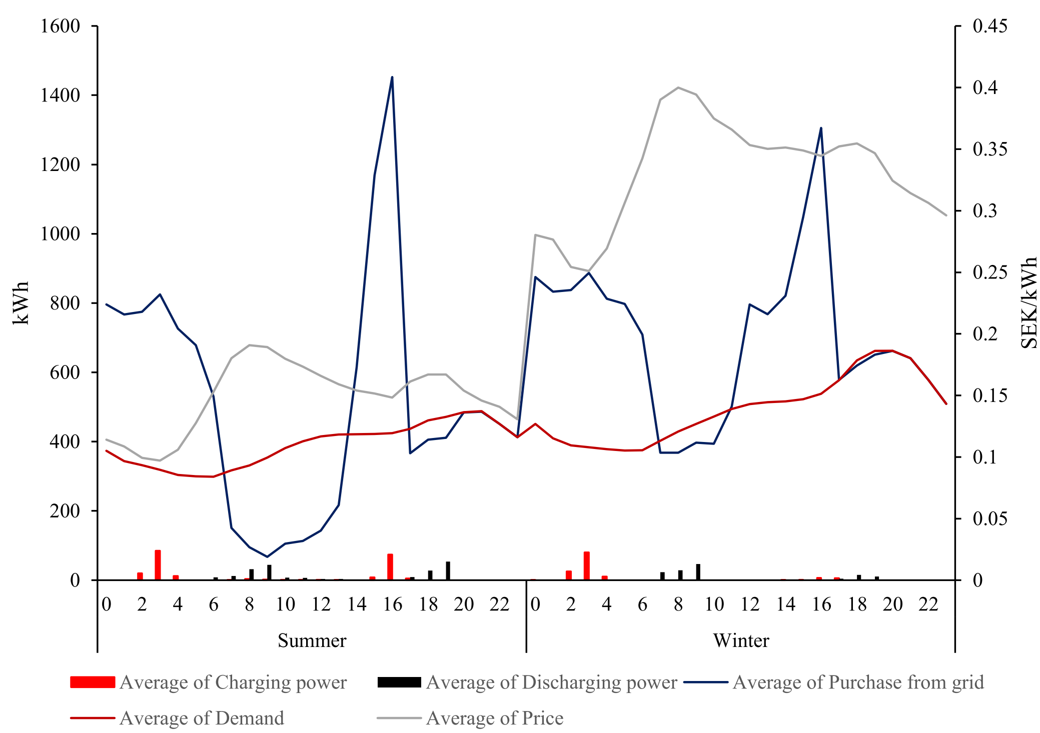

Fig. 14. BESS installation with PV.

Table 6
Annual reduction in electricity import cost compared to the Reference scenario.

Total Annual Reduction in electricity cost compared to *Reference* Scenario (%) with cost-optimal solution		
Test Case	With PV only	With PV & BESS
ResComm0	6.3	6.87
ResComm50	6.2	6.2
ResComm100	6.2	6.2

uncontrolled charging scenarios. Similarly, the peak demand due to EV charging in uncontrolled charging is also leveled out and peak-to-valley gaps are filled to ensure that the transformer power constraint is taken care of all the time. The results of *ResComm50* and *ResComm100* look quite similar because of the similar power levels scheduled by the optimizer to fulfill the demand from EV chargers before the charging window ends and also meet the transformer-rated power constraints at the same time. The addition of the grid fee (fixed subscription fee and variable distribution fee) will not have any impact on EV charging schedules. From a DSO perspective, the grid fee is reflected in the consumer bills. However, for the commercial chargers, the addition of peak demand charges in the electricity tariff will affect the optimization of the EV chargers scheduling because the algorithm will consider reducing the peak electricity import from the grid. The change in the electricity prices will lead to an impact on the cost of electricity imports and the EV charging schedules. If the electricity prices are lowered in the future due to increased RES integration, it will lead to a reduction in the cost of electricity import which is beneficial from DSO's perspective. The price schedules will also affect EV charger scheduling in a cost-optimal solution because the optimization process is sensitive to electricity prices. With the change in the EV charging schedules, the difference in the losses will not be as pronounced as it will be in the costs.

The addition of PV which is a zero-emission source of energy leads to quite less power import from the grid and fewer losses in the network. The lower the amount of power imported from the grid; the lesser will be the losses. The addition of PV presents a strong case for developing policies to foster the implementation of PVs on the rooftops and incentivize the prosumers accordingly. The addition of PV leads to an almost 6.03 % reduction in losses in uncontrolled scenarios while in controlled charging scenarios, loss optimal presents the major reduction with a 7 % reduction in losses while with cost optimal 6.34 % power losses are reduced. The use of PV-sourced energy also leads to less strain on transformers which will further reduce the cost of grid reinforcement if required in the future and will add to the gains of grid operators. However, it is highly ambitious to fulfill all the demand through PV. There is a maximum of one or two hours during the summers when residential demand can be entirely fulfilled by PV production. With additional EV demand, it will be challenging for HS to become self-sufficient and isolate itself from the national grid.

The addition of BESS in most of the applications is meant to reduce the peaks and ensure peak shaving during peak demand times. BESS is usually implemented with sizes comparable to demand loads in most cases while in this case, the capacity was constrained by the amount of excess power from PV. To increase the self-consumption of PV because of excess PV generation during an hour of the day, BESS stores the excess power, and it also increases the power import from the grid as well which increases the losses. The charging and discharging of BESS follow the price signals but due to quite less power capacity, it leads to almost negligible peak shaving in this study. The purpose of BESS is not to reduce power consumption but rather to reduce the peaks and shift the peaks to off-peak hours. The results show that choosing a battery with enough capacity and properties will lead to more power peak reduction and if BESS can be charged with other sources, it will also lead to better outcomes for peak power reduction and power reduction in general.

Another dimension can be the discharging of EV batteries to employ V2G in the system. This in itself is a challenging task since V2G leads to a reduction in the battery health of EVs due to large current and battery cycles. However, maximum peak shaving during the evening hours from residential loads can only be realized effectively in this way or by installing a large BESS to fulfill the load demand. Sweden is rich in renewable energy resources of which water and biomass are the largest. These RES have the highest share in the renewable energy for electricity production and heating respectively however, the major challenge for grid operators is hourly power production and to fulfill the power demand at all times of the day. Installing new microgrids will lead to less dependence on the national grid and enable the integration of growing DERs.

6. Conclusions

The paper evaluated the impact of a mix of residential and public EV charging facilities on the power grid. The stable and reliable grid operation is at stake with new load demand that appears from fast EV chargers installed at public charging points. This paper presents a methodology to control EV charging to reduce losses in the distribution power network and cost of electricity import i.e., loss-optimal and cost-optimal charging strategy. The study covers the impact of residential and public EV charging on the distribution power network and compares the scenarios for uncontrolled and smart charging of EVs. Solar PV and BESS systems were integrated with EV chargers to reduce the dependency on the grid and increase the self-sufficiency of solar PV. The EV loads with uncontrolled charging and with smart charging were added to the base demand loads in a distribution power network modelled in pandapower with real power network parameters. Simulations were run for one year on a power network modelled with parameters of a real power network of Stockholm's locality. It was found that if charging is left uncontrolled, the transformer rated power becomes a limitation due to increased load demand. However, up to 35 %, losses can be reduced with the controlled EV charging while the cost of EV charging can be reduced by 61 % compared to uncontrolled charging.

The significant improvement from the costs and losses perspective makes the cost-optimal solution more favourable. The integration of PV with chargers led to the reduction of a maximum of 7 % losses compared to *Reference scenario*. This might not be a substantial reduction in the losses but given the maximum potential of PVs in Sweden due to its geographical location, this reduction is promising. It was found that the installation of a well-sized BESS with a higher capacity comparable to peak demand will ensure peak reduction. Overall, controlled charging leads to promising results and ensures that grid capacity never becomes a constraint due to the influx of EV chargers. With proper incentive schemes and efficient coordination among the prosumers and grid operators, Sweden can continue on the path of transition to low-carbon technologies smoothly. The results of such frameworks will not only be limited to Sweden but to the whole EU which is on its way to bringing 30 million EVs onto EU roads by 2050.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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