An integrated techno-economic approach for design and energy management of heavy goods electric vehicle charging station with energy storage systems

Article

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An Integrated Techno-Economic Approach for Design and Energy Management of Heavy Goods Electric Vehicle Charging Station with Energy Storage Systems

O. Shariati, P.J. Coker, S.T. Smith, B. Potter, W. Holderbaum

School of Built Environment, University of Reading, UK

Highlights:

Assesses the benefit of co-locating ESS with HGEV charging applications.

Intelligent ESS solution addressing long-term sizing & short-term management.

Analyses on-route and depot charging cases with & without separate charge management.

Reflects impacts of recent trends in ESS cost decline & electricity price volatility.

Abstract:

The global rise of electrified transport is bringing significant attention to provision of charging infrastructure and subsequent increases in electricity demand. Whilst much research to date has concentrated on light vehicles these challenges are more extreme for Heavy Goods Electric Vehicles (HGEVs), with power demands exacerbated by larger batteries and the need for rapid turnaround when charging on-route. Colocation with Energy Storage Systems (ESS) could have potential to help, as could intelligent charge control. This paper presents a novel integrated elitist intelligent algorithm that can simultaneously optimise the multiple numerous technical and economic factors needed here, including long term, independent sizing of battery capacity and power-electronic rating, short term ESS management / charger dispatch, and consideration of dynamic electricity price variability. The work goes beyond previous studies by examining the particular challenges of heavy-duty vehicles, considering both charge management of individual vehicles and co-location of static battery storage, and also by contrasting plausible on route and depot-based charging cases. To support this, a method is developed to estimate patterns of HGV attendance at UK fuelling stations, applicable for other countries. Results highlight the economic challenge of on-route charging. Where fleet operation allows idle time at depots, smart control of vehicle charging can track the lowest price electricity time periods. Depot energy delivery cost was seen to reduce from 18.32 to 11.90 p/kWh comparing on-demand and managed charging (based on 2021, UK, half hourly wholesale electricity prices). On-route charging costs can be reduced by the co-location of static ESS but only to 15.74 p/kWh, without consideration of additional commercial costs. All day stations can deliver electricity at a lower average price than daytime only stations and can benefit from comparatively smaller ESS. Cost benefit analysis was applied for a range of assumptions, revealing insight into the non-linear relationship between battery capacity, charger rating, and subsequent energy delivery price.

Keywords: Heavy Goods Electric Vehicle, Charging Station, Energy Storage System, Demand-Side Management, Optimal Arrangement.

Nomenclature

Abbreviations

AC	Alternative Current
CCL	Climate Change Levy
CRM	Conditional Range Metric
DC	Direct Current
DF	Depot Factor
GA	Genetic Algorithm
EGA	Elitist Genetic Algorithm
ESS	Energy Storage System
EMS	Energy Management System
EV	Electric Vehicle
FOM	Fixed Operating and Maintenance cost
GB	Great Britain
HGEV	Heavy Good Electric Vehicle
MIT	Massachusetts Institute of Technology
PSO	Particle Swarm Optimisation
SoC	State of Charge
ToU	Time of Use

Variables

x_d	Daily travelled distance, km
E_{Sp}	Specific energy consumption, kWh/km
E_{Bat}	Battery capacity, kWh
P_T	Transformer flow, sequence of 48 charging power values
P_{T_i}	Transformer loading during half-hour *i* of the day, kW
P_B	Battery flow, sequence of 48 charging power values
P_{B_i}	Battery charging/discharging power during half-hour *i* of the day, kW
P_C	Charging flow, sequence of 48 charging power values
P_{C_i}	Vehicle's charging consumption during half-hour *i* of the day, kW
Δt	Timestep, hour
ΔE_i	Energy variation, kWh
P_i	Power flow of half-hour *i* of the day, kW
ΔE_B	Daily battery energy flow, sequence of 48 charging values
SoC_0	Initial state of charge, kWh
SoC_B	Battery SoC, sequence of 48 values, kWh
SoC_i	SoC at the beginning of half-hour *i* of the day, kWh
P_{Con}	Converter rating power, kW
C_{Bat}	Battery Capital Cost, £/kWh
C_{Con}	Converter Capital Cost, £/kW
CC	Total Capital Cost, £
OMC	Operating and Maintenance Cost, £
C_{Bat}^{FOM}	Energy-based Operating, and Maintenance Cost, £/kWh
C_{Con}^{FOM}	Power-based Operating and Maintenance Cost, £/kW
TC	Total Cost of the energy storage system, £
TEP	Total Energy Price, £
C_{E_t}	Energy price in time step *t*, £/kWh
T	Measurement Time Constant, hour
TCF	Total Cost Function
OF	Objective Function
P_{T_max}	Maximum permissible transformer loading, kW
$\Delta \mathrm{P}_T$	Step change of transformer loading
IRL_{Max}	Maximum Incremental Rate of Loading, kW
DRL_{Max}	Maximum Decremental Rate of Loading, kW
E_{In}^{Sys}	Input energy of the system, kWh
E_{Out}^{Sys}	Output energy of the system, kWh
E_{Sch}	Energy input scheduling, kWh

1. INTRODUCTION

Global plans for transport decarbonisation include a significant growth in electrification. Whilst uncertainty remains in the effectiveness of this option for heavy duty transport, manufacturers are developing numerous vehicles with battery electric solutions as either an optional or sole powertrain [1]. For the UK, change is now on the way as a set of emission standards have been introduced for Heavy Goods Vehicles (HGVs), buses and coaches. Due to the battery capacities and fast charging requirements, heavy-duty truck electrification will have profound impacts on the power grid, proportionately greater than light vehicle electrification. Consequently, the aggregated load profile of the system could see significant changes due to the integration of HGEV charging loads.

High power charging is needed for HGEV applications to be feasible. However this brings a threat for the security and stability of power systems, as well as a highly uncertain cost for vehicle operators, especially when the HGEV charging station maximum demand and the connected network peak are coincident [2, 3]. Looking only at light vehicles, it is stated in [4] that uncontrolled EV fast charging could result in up to five times the peak load in residential areas [5].

ESSs play a pivotal role in facilitating the global transition towards sustainable development objectives, both in the UK and worldwide. They serve as a crucial enabler for achieving affordable and clean energy goals by storing renewable energy generated during off-peak periods and releasing it during peak demand, thereby reducing reliance on fossil fuels and mitigating greenhouse gas emissions. Furthermore, ESSs contribute to the establishment of sustainable cities and communities by offering grid stabilisation capabilities in urban areas with high penetration of renewable energy sources. To reduce costs and improve network resilience, it has been proposed to couple stationary Energy Storage Systems (ESS) with fast charging stations[6, 7]. ESS can reduce the energy cost of charging vehicles by shifting energy purchases away from expensive peak load periods [8, 9], and also save connection upgrade cost by reducing, or eliminating, any increase in peak demand [10, 11].

Among various ESS technologies such as Flywheel Energy Storage, Redox Flow Batteries, Sodium-ion Batteries, and Pumped Hydroelectric Storage, Lithium-ion (Li-ion) batteries currently stand out as the dominant choice. This dominance can be attributed to their advantages, including high energy density, efficiency, scalability, and maturity of technology [12]. Several studies have been conducted to analyse the benefits of coupling stationary ESS with fast charging stations [13, 14]. Their findings emphasised that to achieve the maximum benefits of utilising the ESSs, the storage system optimal design and the consumption management for the station should be addressed simultaneously, considering the local load profiles and the dynamic tariff. However, no work in the literature has focused on HGEV charging load profiles or dynamic HGEV charge scheduling schemes.

A variety of approaches and definitions can be seen regarding ESS. Several studies either focus solely on energy capacity (kWh) [15, 16] or address energy consumption management for existing storage systems [17, 18], overlooking the distinct load dynamics of HGEV charging stations. Some now ascribe both energy and power (kW) capacities as essential properties of storage systems; meanwhile, it can be preferable to see the power capacity of power-electronic ancillaries distinguished from the energy capacity of the core storage unit. Studies which adopt a network perspective, typically seek ESS sizing [19, 20] and setting [21, 22] that can improve the effective operation of smart distribution systems [23, 24] or solve renewable generation [25, 26] and load profile diversities [27, 28].

When considering design variables, there has been a tendence for studies to either adopt fixed converter ratings (pre-determined values) [29, 30] or to optimise the size of the battery while assuming an identically rated converter [31, 32]. The authors in [12] noted that sequential sizing of battery and converter or fixed-size converters are considered in most of the available studies. However, this policy can result in under or oversizing of ESS, especially for fast charging stations, where batteries are usually charged and discharged daily (charging during off-peak price intervals and discharging during peak price intervals). The aforementioned study [12] employs a stochastic model with the objective of minimizing the annual cost of the ESS, taking into account the equipment's lifetime and a consistent interest rate.

A new model is proposed in [33] to combine the planning models of renewable energy systems, ESSs, thyristor-controlled series compensators, and transmission lines into a combined EV-based planning problem. Their first objective aimed to maximise EV penetration, the second sought to lower carbon dioxide emissions, and the third sought to minimise both initial investment and operating costs. This study represents appreciable progress in integrating multiple aspects of the problem; however, their main objective is limited to maximising EV charging penetration and not the design of the best-fuelling system.

Further system modelling approaches adopt a range of perspectives in combining ESS, EV charging and renewable resources. The authors in [17] developed an efficient unit commitment strategy to optimise battery cycling of both the EV batteries and local storage system for a workplace charging case. In turn, [34] presents a new Energy Management System (EMS) for the optimised operation of a hybrid, grid-connected charging station for EVs and fuel cell vehicles. The proposed EMS is designed to reduce the utilisation costs of the ESS and manage charging to optimise efficiency across all system components. Meanwhile [15] used an equivalent circuit battery model to size and allocate the lithium-ion ESS for a system combining a high penetration of renewable generation with electric ferry charging stations.

A range of numerical approaches have been applied to solve the multi-objective constrained optimisation problems presented by ESS applications. [35] and [36] evaluate the parallel application of ESS and renewable resources, in both stand-alone and grid-connected arrangements. The authors in [35] employed an exhaustive search for this task, while in [36], the ESS capacities are determined using the Conditional Range Metric (CRM) and desired power profiles from forecasts. A fuzzy logic system is designed in [37, 38] to improve efficiency of the system operation while a Particle Swarm Optimisation (PSO) algorithm is used to solve the optimisation function.

Heuristic and metaheuristic methods are used in [16] and [37, 39] addressing optimal hybrid ESS systems, which include battery sizing for grid operation and smart buildings respectively. Techno-economic aspects are considered including battery lifetime and daily electricity cost. In a detailed techno-economic analysis presented in reference [40], a comprehensive evaluation of different metaheuristic techniques is conducted to address similar optimisation problems with constraints. The analysis demonstrates the significant capabilities of these methods. However, it is important to note that achieving slightly superior results may require careful selection of the most suitable technique and fine-tuning of the control parameters.

The review of the literature shows that little attention has yet been given to charging heavy duty vehicles including HGEVs and the associated challenges that emerge. Table 1 maps the contributions from relevant studies that relate to aspects of this problem. There is a need for an integrated method that can simultaneously optimise both long-term ESS design and short-term scheduling, while effectively managing constraints such as connection limits. The proposed approach must consider battery energy capacity and power-electronic rating as two independent design variables not only due to the significance for the technically efficient performance of the system and total (capital, operating and maintenance) costs but also because this issue is more severe given the power consumption range and fast change rates required for HGEV charging stations. Metaheuristic approaches with an updated design and adjusted control parameter values can be well suited to perform this task.

The work described below assesses the challenge of charging HGEV fleets, examining options to take best advantage of a dynamic, time varying electricity price. This goes beyond previous studies by including charge management of individual vehicles and co-location of static battery storage, as well as considering plausible on route and depot-based charging cases. A novel integrated, elitist, intelligent algorithm approach is developed that combines long-term storage sizing with short-term storage management to minimise the electricity purchase price. Whilst the analysis uses data for half hourly, wholesale UK electricity prices, the method could be readily applied to any market with a time varying price signal. A method is also developed to estimate patterns of HGV attendance at UK fuelling stations that could similarly be applied across other geographies. The analysis reflects significant, recent trends in storage price reduction and electricity cost escalation and volatility. Finally, a long-term cost-benefit analysis is conducted to evaluate the effectiveness of the proposed approach in dealing with the rapidly changing tariff dynamics observed in recent years.

TABLE 1. REVIEW SUMMARY: COMPARISON OF ADDRESSED GAPS IN RECENT KEY WORKS RELEVANT TO THIS RESEARCH

Reference No.	HGEV Charging		Optimal ESS Design		Demand-side Management	Cost-Benefits Analysis
	Depots	On-route	Battery	Converter		
[6]		*	*		*	
[7]		*	*		*	
[9]			*	*	*	
[12]			*	*	*	
[14]			*	*		*
[19]			*	*	*	
[23]			*		*	*
[24]			*	*		*
[30]			*		*	
[37]			*		*	
Current Work	*	*	*	*	*	*

2. METHODOLOGY

The distinction identified above between depot and on-route charging has a number of practical implications and leads to a requirement for different methodological approaches. Depot based operation presents an opportunity for delayed charging or charge management between vehicles to take advantage of the inherent storage within the vehicles' own batteries. By contrast it is assumed here that on route stations will seek to charge every vehicle as quickly as possible providing little or no opportunity to balance charging load between vehicles. This section describes the approach developed to address aspects of each case, before describing a model to simulate and then optimise a separate static battery which could, in principle at least, be added to either case. We then describe our approach to assessing the long-term cost effectiveness of the model outputs.

A. Cases Considered and Data

1) Vehicle and charger capacities

Whilst much early EV development has concentrated on passenger cars and light duty vehicles, a growing number of manufacturers are now developing or have released fully electric HGVs. Table 2 presents the essential characteristics for a snapshot of vehicles currently advertised by four well known manufacturers. From this, we take a typical HGEV to have a battery capacity of 400 kWh and a specific consumption of 1.8 kWh/mile, which reflects the higher, though not extreme, range of the possible energy and therefore charging capability requirement. A 2016 study found that in the previous year some 71% of UK HGVs were part of fleets of 50 or fewer vehicles [41]. A few fleets extended to 3000 vehicles or more, but these were distributed across multiple depots and no further breakdown was available. In our analysis we concentrate on fleets of 25 to 100 vehicles operating at individual depots, to represent the dominant UK situation.

TABLE 2. ELECTRIC TRUCK SPECIFICATIONS [42-46]

Company	Vehicle name	Range (km)	Battery Capacity (kWh)	Consumption (kWh/km)
Daimler Trucks	Mercedes Benz eActros	200	240	1.2
Volvo Trucks	Volvo FH	Up to 300	180-540	0.6 – 1.8
	Volvo FM	Up to 300	180-540	0.6 – 1.8
	Volvo FMX	Up to 300	180-540	0.6 – 1.8
	Volvo FL	Up to 300	-	-
	Volvo FE	Up to 200	Up to 211	1.05
	Volvo VNR	Up to 240	264	1.10
Tesla	-	480 or 800	600 - 1000	1.24
Nikola Motors	Nikola Tre	Up to 560	750	1.34

TABLE 3 CHARGING POWER RATING AND GRID CONNECTIONS [47-50]

EVSE	Charging Type	Power Level	Grid Connection
Mode 1 (AC)	AC charging	Up to 3kW	Single phase/ 230 V
Mode 2 (AC)	AC charging	Up to 7.4kW	Single phase/ 230 V
Mode 3 (AC)	AC charging	Up to 22kW (Fast)	Three phase/ 400 V
		up to 43kW (Rapid AC)	Three phase/ 400 V
Mode 4 (DC)	DC charging	50 kW- 350 kW (Rapid DC: 100>P>50 kW) (Ultra-Rapid DC: P>100 kW)	(400 V, 11 kV, 33 kV)

In parallel with the development of batteries and vehicles, charger technology is also seeing a rapid transformation with an accompanying evolution of standards and terminology. Table 3 presents an overview of current charger classifications, drawn from [48, 49, 51-68]. By considering that vehicles with battery capacities of 500 kWh or higher may want to fully recharge during one overnight period at most, it is clear that, as a minimum, Rapid AC chargers will be needed for depot charging. In what follows we adopt a standard 50 kW charger unless otherwise specified. Depending on the fleet size and the availability of parallel charging points, the depot can take advantage of either an 11kV or 33kV grid connection.

For HGVs 'refuelling' on route, there is commercial pressure to minimise downtime, ideally delivering fuel in the short periods of a few minutes traditionally delivered by liquid fuels or during a driver rest break. According to regulations set by both the UK and the EU, it is mandatory for HGV drivers to pause their driving duties after a continuous 4.5-hour driving session, and they are prohibited from exceeding 9 hours of driving within a single day. When a driver has been behind the wheel for 4.5 hours, they must allocate at least 45 minutes for a break, which can be either a single uninterrupted break or a combination of shorter breaks throughout their driving period [69-71]. To enable HGEVs to recharge during brief stops along their routes, they will require extremely high-power capacities, potentially reaching up to 350kW. Such capabilities are typically available only through ultra-rapid DC chargers, typically necessitating a 33kV connection. However, in the UK, if the distance to the substation is short and the total consumption remains below 10MW, an 11kV connection could also be a viable option [72, 73].

2) Energy Price

To reflect the half hourly GB wholesale electricity price, we use data from Elexon, the operator of the balancing and settlement code for the GB electricity market. Elexon's Market Index Price database [74] provides a publicly accessible record of the wholesale cost of electricity in the GB short term market, as defined at [75]. The variations in the average MIP across weekdays and seasons for 2021 are illustrated in Figures 1 and 2.

To represent the perspective of an EV charge provider with access to a dynamic electricity price we use MIP as a starting to point to reflect the half hourly variability. This is then inflated to represent a commercial rate for an appropriate size of electricity customer, to develop an annual time series with an average price equivalent to that provided in [76], as shown in Table 4. The non-domestic customer's average network charge is determined by dividing the commercial rate for the customer size by the yearly average MIP price for the same period.

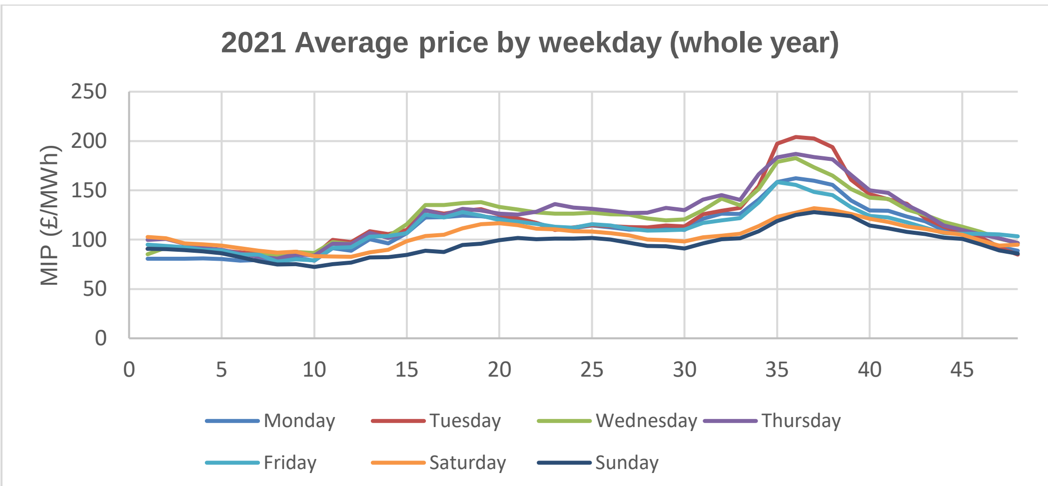

Figure 1. Typical weekdays Market Index Price (MIP) for the UK

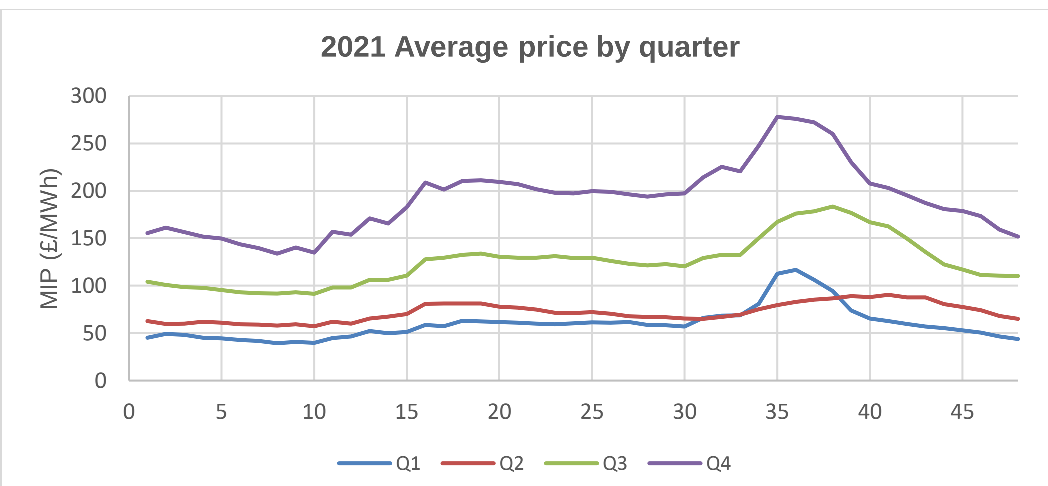

Figure 2. Sample of the seasonal Market Index Price (MIP) dynamics for the UK

The consumption bounds associated with the prices in [76], are shown in Table 5, while the yearly consumption for the case studies (on-route stations and depots) are summarised in Table 6. All cases can be seen as 'Medium' sized customers, so an average electricity price of 14.30 p/kWh is used for 2021.

TABLE 4. PRICES OF ELECTRICITY PURCHASED BY NON-DOMESTIC CONSUMERS IN THE UNITED KINGDOM (INCLUDING THE CLIMATE CHANGE LEVY) (ANNUAL) [76]

Year	Electricity: Very Small (Pence per kWh)	Electricity: Small (Pence per kWh)	Electricity: Small/Medium (Pence per kWh)	Electricity: Medium (Pence per kWh)	Electricity: Large (Pence per kWh)	Electricity: Very Large (Pence per kWh)	Electricity: Extra Large (Pence per kWh)	Electricity: Average (Pence per kWh)
2021	17.99	16.25	15.75	14.30	14.08	13.84	14.18	15.08

TABLE 5. ANNUAL CONSUMPTION BANDS FOR ELECTRICITY [76]

Electricity: Bands Name	Electricity: Annual consumption MWh
Very Small	0 - 20
Small	20 - 499
Small/Medium	500 - 1,999
Medium	2,000 - 19,999
Large	20,000 - 69,999
Very Large	70,000 - 150,000
Extra Large	>150,000

TABLE 6. YEARLY CONSUMPTION OF VARIOUS HGEV CHARGING STYLES

Station Time	Annual Consumption [MWh]
Daytime On-route	2690
24-Hours On-route	3086
Depot-Min fleet (50)	2772
Depot-Max fleet (100)	6352

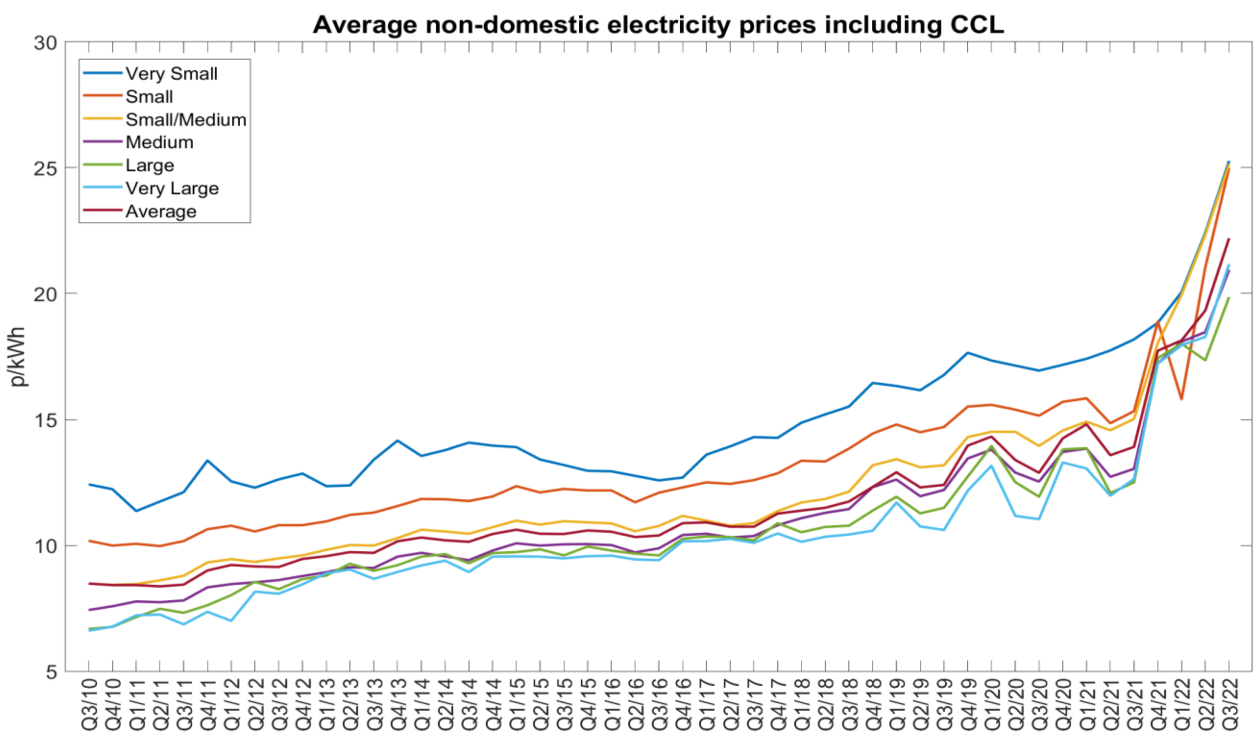

Figure 3. Average Non-Domestic Electricity Prices Based on Department for Energy Security & Net Zero Database, UK [76]

To avoid the distorting variations that have recently been experienced in the world energy price, and consequently in the UK, due to the pandemic and the Ukraine war, 2021 is selected as a base year. The prices of electricity purchased by non-domestic consumers in the UK, as published by the Department for Energy Security & Net Zero [76] and plotted in Figure 3, confirm rising energy prices, reflecting post-pandemic economic recovery. However, this inflation is not as extreme as the effects of the Ukraine war across 2022, which are likely to be temporary.

3) Storage Parameters

In a recent study, MIT researchers estimated the cost elements for Li-ion batteries over a time duration between 2020 and 2050 [77]. This reference used the lower-bound, median, and higher-bound projections from a broad literature review to present low-, mid-, and high- assumptions for the cost elements of various ESS types, as given in Table 7. In what follows we adopt the mid values unless stated otherwise. Section 3.B.2 explores the implications of the full cost range from the MIT study.

TABLE 7. THE LI-ION ESS ESTIMATED AND PROJECTED COSTS AND EFFICIENCY ELEMENTS [77]

Year	**Charging Capital Costs (£/kW)**	**Storage Capital Costs (£/kWh)**	**FOM (£/kW-Year)**	**FOM (£/kWh-Year)**	**Efficiency-Charge (%)**	**Efficiency-Discharge (%)**
2020	205.6	221.6	1.1	5.4	92%	92%
2050 Low	25.6	56.7	0.2	1.1	92%	92%
2050 Mid	88.0	100.6	0.6	1.8	92%	92%
2050 High	123.2	141.6	1.1	2.6	92%	92%

B. Model Development

1) On-Route Charging Demand Profile

The proposed modelling system calculates the real-time consumption of the selected on-route station, achieving a second-scale resolution. For on-route charging we assume that vehicles charge immediately on connection. Therefore, the charge delivery requirement is primarily set by the arrival pattern of vehicles. With an absence of publicly available time series data for vehicle refuelling, a method was developed to estimate charging demand based on location attendance data accessed from Google Maps [78]. Charging profiles were developed by combining this attendance data with a stochastically sampled estimate of vehicle charge requirement.

The 'HGEV travelled distance' function produces a population of distances travelled based on the total number of vehicles attending the station during a typical day. A typical probability distribution for the distance distribution is shown in Figure 4.

In the next step, the 'State of Charge (SoC)' function determines the SoC vector using the daily distance travelled (x_d) and the specific energy consumption (E_{Sp}) of typical HGEVs, as outlined in [9]. This formulation has been tailored to suit the specific requirements of this research, as described in equation (1).

$$SoC = f(x_d) = E_B - (x_d \cdot E_{SP}) \tag{1}$$

where battery capacity (E_B) and specific energy consumption (E_{SP}) are constant for a heavy vehicle, while the daily distance travelled (x_d) has a stochastic nature, with probability distribution shown in Figure 4.

A crucial initial step in charging station modelling is to sample the charging profile for an individual vehicle, determined by the proposed model and depicted in Figure 5, showcasing the power demand profile and SoC variation. The methodology entails deriving the power demand profile based on the vehicle's arrival SoC, the charging time (which can be either equal to the arrival time for on-route scenarios or controlled by the fleet operator in depots), and the vehicle's specifications. Within this modelling framework, the battery's charge acceptance is modelled as a linear function, and the charging points are assumed to operate at a constant power level. This primary graph adheres to standard practices, as supported by references [80, 81], while being adjusted for the HGEV battery size and relevant fast charging systems. Depending on the operational style of the charging station (depot or on-route), the subsequent step in demand modelling involves aggregating individual charging profiles to determine the station's overall demand profile.

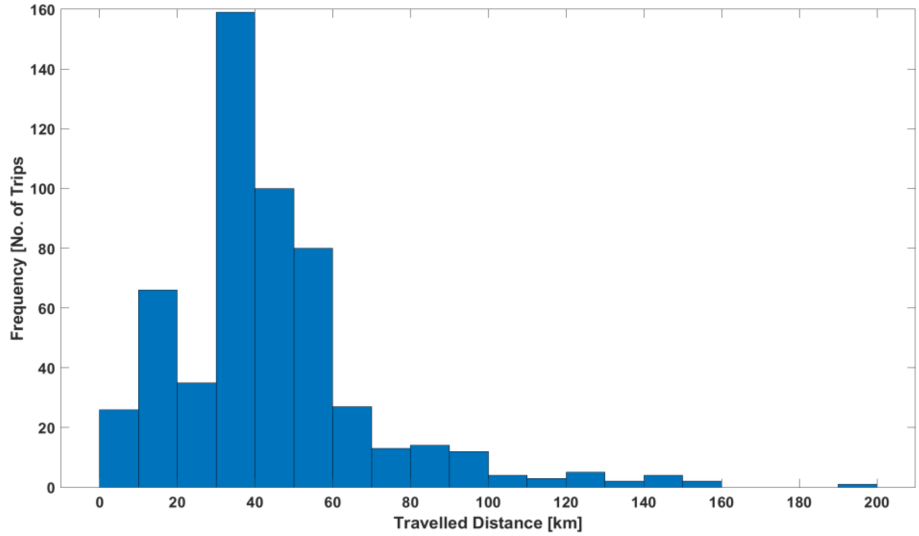

Figure 4. Daily travelled distance [79]

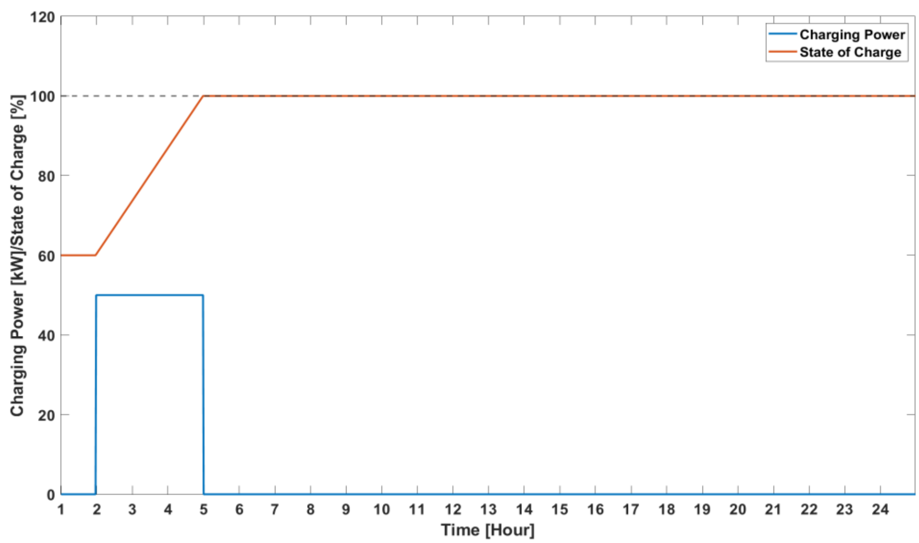

Figure 5. Charging load profile of an individual vehicle.

The ‘vehicle attendance’ function is employed to generate the vehicle-time distribution based on the popular time curve for the station and the number of vehicles being serviced per typical weekday. These popular time curves are a feature of Google Maps showing how busy a location is during different times of the weekdays and presented in the form of graphs [78]. The statistics indicating popular times are derived from the annual average of historical data specific to the selected property or location. As an illustration, Figure 6 displays the attendance rate over weekdays at an on-route service station, namely Oban in Scotland, with the working time interval from 6:00 a.m. to 9:00 p.m., with Thursday delineated by dashed lines. The proposed stochastic model uses the ‘vehicle charging’ function to model the load profile of the vehicles, based on their SoCs, and the rating power of the chargers available in the station.

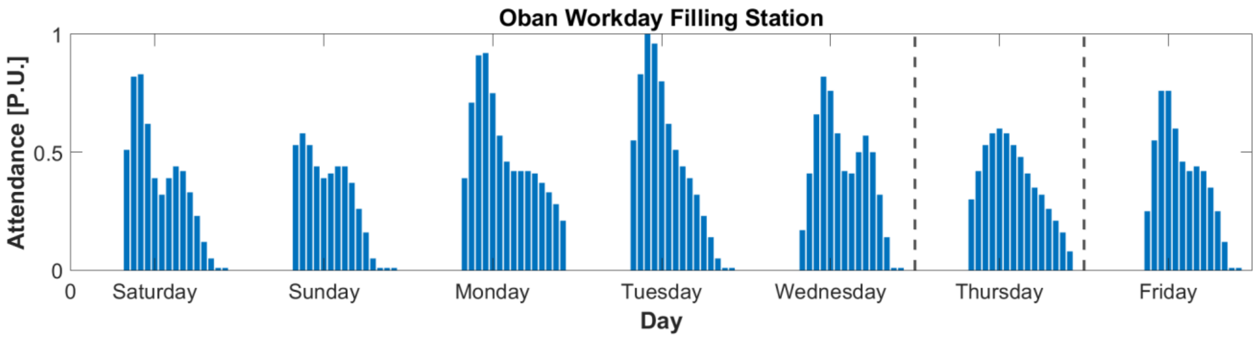

Figure 6. Google map popular time distribution for Oban, Scotland

Depending on the scenario, the model's output resolution can be customised by employing an averaging method over a specified time window, in this case half-hourly intervals. Finally, the 'load profile plotting' function provides visual representations of both instantaneous and half-hourly load profiles for the case study. The workflow of this innovative function-based charging station modelling system is depicted in Figure 7.

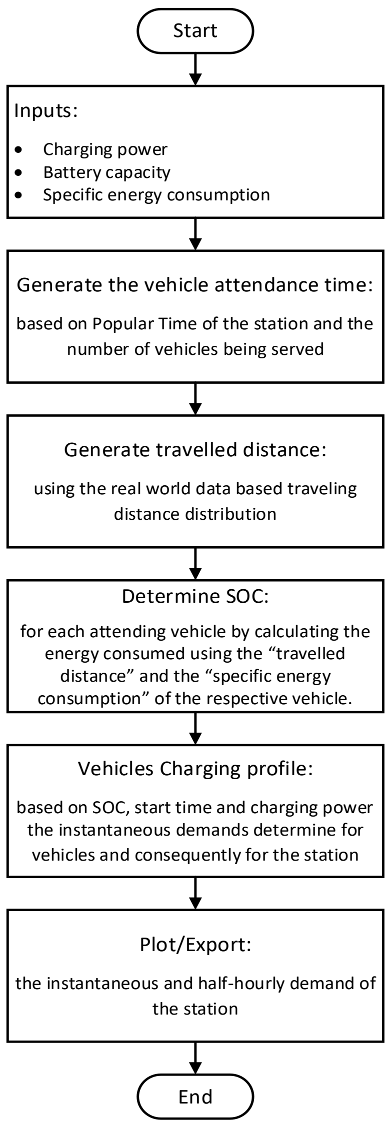

Figure 7. Flowchart of on-route charging station model

The charging station load model, developed above, is used to determine the demand profile of the daytime on-route charging station, Oban Filling station, Oban, UK, and for the 24-hour on-route charging station, Roadking (Hollies) truckstop public station, Cannock, UK. The model's input data is derived from the UK's typical probability distribution of distance travelled (Figure 4) and the HGVs' attending time distribution, which aligns with the average yearly attendance for the day at the target station (Figure 6). Daily consumption profiles for both daytime and 24-hour on-route charging stations were generated using the specified parameters. The model outputs are illustrated in Figure 8 and Figure 9. Despite the alignment of the determined station demand profiles (Figure 8 and 9) with the study's assumptions for the UK, the shape analysis of the profiles, based on the limited available references [7, 82], shows consistency with the earlier demand profiles. In all cases, the load profiles primarily consist of power step signals, with the rise times and charging durations dependent on arrival time, initial State of Charge (SoC), and charger power rating. The aggregation process in all studies is influenced by the arrival time distribution, resulting in a staircase signal. Various assumptions were made in the research regarding charger power ratings and the number of available parallel chargers, leading to variable step heights. Despite different assumptions for arrival time distribution, charger power ratings, and the number of available plug-ins in the current UK case studies, the fundamental framework and output profiles remain consistent with the referenced studies.

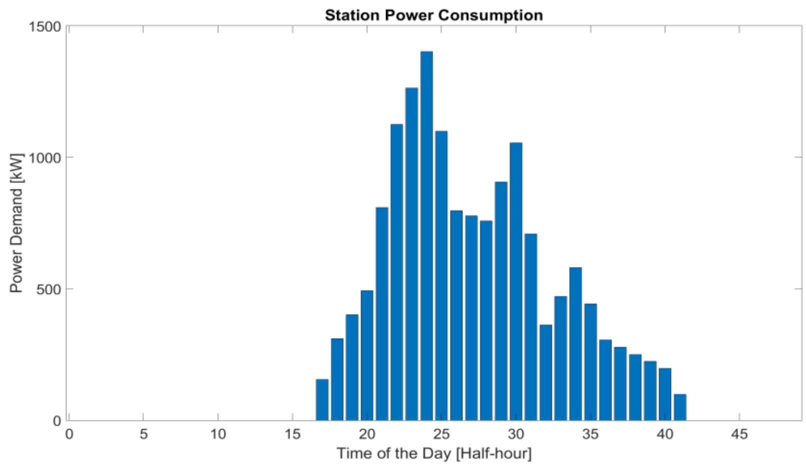

Figure 8. The station load profile for the daytime only on-road charging station

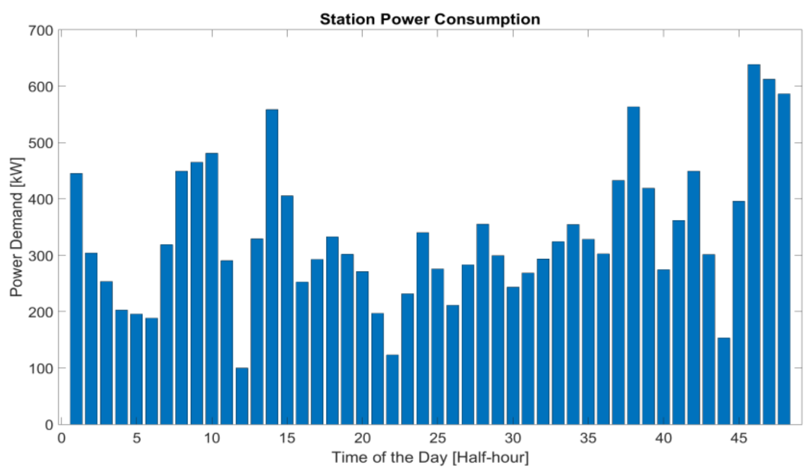

Figure 9. The station load profile for the 24-hours on-road charging station

2) Depot Charging Station Modelling

Depot charging profiles were developed for two scenarios: an uncontrolled, on-demand case and a scenario in which depot-wide price management is applied. In cases where vehicles spend significant idle time at a depot, there is potential for cross-depot charge management to control the charging time and rate of individual vehicles. This becomes crucial in situations where the number of chargers is less than the number of vehicles or when grid connection capacity is limited. The importance of the ratio between available charging infrastructure and fleet size is well-established in the literature [83] while emphasising the need for optimisation. Building on this, "Depot Factor" (DF) is defined in the current work as the ratio of available charging plugs at the depot to the fleet size. Alternatively, as assumed here, charge control could be implemented in order to benefit from price managed charging.

As with public charging stations, HGEV fleet charging is influenced by key stochastic variables such as daily distance travelled. However, the management rules of HGEV depots change the nature of some parameters deemed stochastic in the description of on-route modelling above to parameters that are effectively deterministic, e.g. the SoC and starting time of charging or time of arrival. It is assumed that all vehicles return to the depot at the end of the working day, and the vehicle batteries are fully recharged during the night to be ready for the next daily operation.

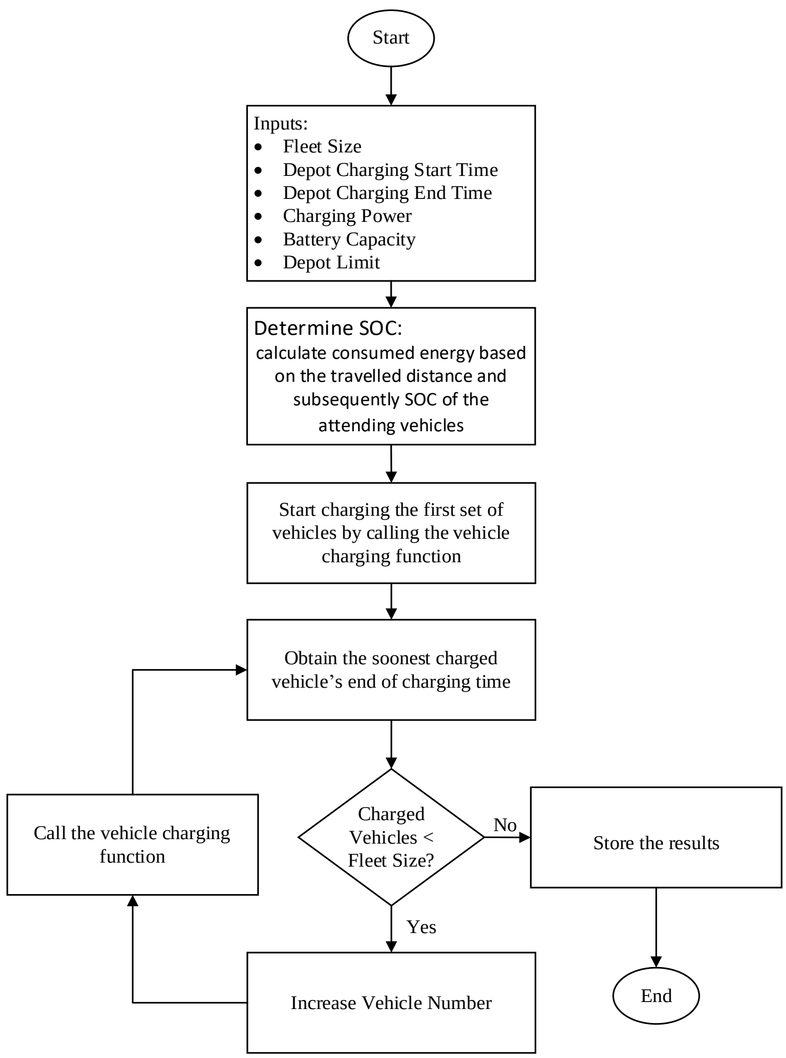

Figure 10. Depot fleet charging flow chart.

In the unmanaged strategy, the model considers the main parameters of the fleet and the depot, along with the start and end times for the charging events. The available time slots are allocated considering the SoC of the vehicles and the available charging power at the depot. In the managed strategy, the half-hourly electricity market price index has been used as a control signal to coordinate the recharge of the fleet to minimise electricity cost, assuming access to dynamic Time of Use (ToU) pricing. As outlined in references [5, 6], linear optimisation methods suffice for cost reduction in conventional depot fleet charging, and Figure 10 offers an overview of the suggested linear optimisation procedure.

3) Techno-Economic Model of the ESS-HGEV Charging Station

In designing energy management and storage systems, there is a critical trade-off between the capital and operating costs of energy storage and the resulting benefits. This trade-off is not fixed and is heavily influenced by factors such as storage costs, changes in electricity tariffs, and variations in demand profiles. Given the significant increase in energy tariffs in recent times, it is essential to analyse how fluctuations in energy prices might impact the overall approach.

To develop a techno-economic model for an HGEV charging station with an ESS, first, it is required to have an overview of the whole system and distinguish between controllable and uncontrollable variables while assessing the key influencing factors. Figure 11 provides an overview of the charging station, taking into account the potential power flow directions.

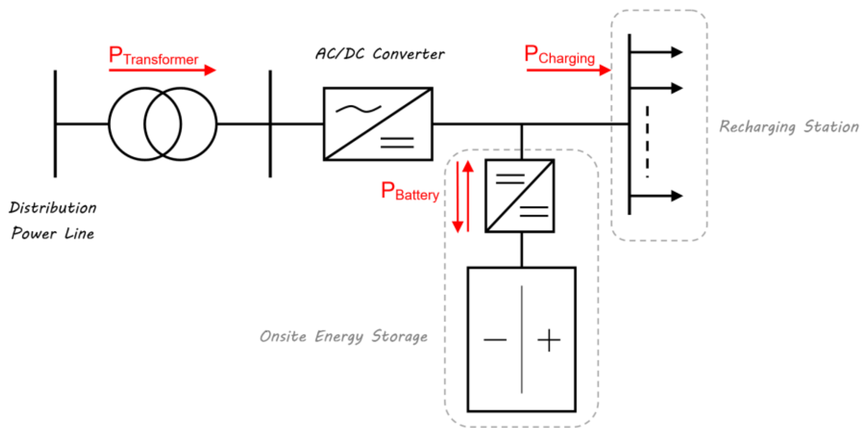

Figure 11. The arrangement and typical power flow for the HGEV charging station.

Based Kirchhoff's Current Law (KCL) [84], there is a momentary equilibrium in the related node between the three power flow elements shown, transformer flow (P_T), battery flow (P_B) and charging flow (P_C) [85]. This equilibrium is described as follows:

$$P_T = P_B + P_C \tag{2}$$

of these three elements, only the battery exhibits bidirectional flow. Acknowledging the fundamental relationship between power and energy [9, 84], an analogous balance exists between energy flow elements over a specific time interval (Δt). This can be expressed as follows:

$$\Delta E_T = \Delta E_B + \Delta E_C \tag{3}$$

where, $\Delta E_i = P_i . \Delta t$ is the energy variation over a timestep while P_i is the power flow during this time.

The effective control variable available in a charging station is the battery flow. As is common practice in smart distribution systems, a day ahead consumption estimation is used for day ahead battery charging-discharging scheduling to minimise the total energy cost through optimal demand side management.

Optimal energy scheduling over a day or longer period is also affected by battery capacity and converter rating power, treated here as design parameters.

TABLE 8. OPERATIONAL PARAMETERS AND VARIABLES OF BATTERY ENERGY STORAGE SYSTEM

Type			Units
Operational Parameters	P^{min}	Minimum charging/discharging power	MW
	P^{max}	Maximum charging/discharging power	MW
	η	Charging/Discharging efficiency	%
	E_{max}	Maximum energy capacity	MWh
	E_{min}	Minimum residue energy capacity	MWh
Variable	P_t	Charging/Discharging Power	MW
	u_t	Binary variable of charging state	/
	SoC_t	Stored energy E_t or State of Charge	MWh

Table 8 lists the parameters and variables that can be directly used in the mathematical formulations for optimal power system planning and dispatch, subject to the capacity limits of the battery and converter. For example, the stored energy of ESS must be balanced and managed to stay within its permissible minimum and maximum energy levels at all time intervals.

Of all operational variables at HGEV charging stations, battery scheduling provides the greatest control for station owners to enact effective demand-side management. Consequently, this research concentrates on optimising the scheduling of ESS power segments within a day-ahead framework, synchronising with the half-hourly resolution of market price signals. Mathematically, the battery scheduling over a 24-hour time window can be described as follows:

$$P_B = [P_{B_1} \quad \cdots \quad P_{B_{48}}] \tag{4}$$

where $P_{B_i}$is the battery charging/discharging power, depending on the sign, during half-hour *i* of the day. Considering a half-hourly time window, the power flow described in equation (4) and the fundamental relationship between power and energy ($\Delta E_i = P_i \cdot \Delta t$) yield a sequence of 48 values, denoted as ΔE_B, representing the daily battery energy flow. Each element in ΔE_B, representing the battery energy variation over timestep *i*, reflects the charging or discharging power scheduled for that timestep.

By having the initial SoC available at the start of the day, or extending the scheduling horizon as suggested in [86], we can determine the variations in SoC as follows:

$$SoC_i = SoC_{i-1} + \Delta E_i \tag{5}$$

where SoC_i is average SoC during timestep *i* while ΔE_i is the battery energy flow at the same time and $SoC_{i-1}$is the SoC by the end of the earlier timestep. The SoC variation determined using equation (5), assuming an initial state of charge ($\mathrm{SoC_0}$) is available, can be represented by a sequence of SoC values (SoC_B) associated with the 48 half-hourly time steps across a day.

Similarly, the consumption profile for the same period can be determined using the stochastic model outlined in sections B.1 and B.2. The resulting output is a sequence (P_C) of 48 charging power values representing the daily consumption profile, where P_{C_i} denotes the vehicle's charging consumption during half-hour *i* of the day.

Given equation (2) and the descriptions provided for P_B and P_C, the transformer/connection power (P_T) loading during the same period can be represented by a similar sequence of 48 daily power values, where P_{T_i} denotes the transformer loading during half-hour *i* of the day. It is crucial to note that the power flow of a transformer is constrained by factors beyond its rated power and permissible overloading. The current capacity and thermal limitations of the connection cables can also impose limitations.

Capital cost components are summarised in two factors: battery capital cost (£/kWh) and converter/power electronic capital cost (£/kW) [77]. Similarly, all operating and maintenance (O&M) costs have constant rate (FOM) for routine component servicing and replacement due to wear and tear [77]. The operational costs are also determined by defining the battery FOM (£/kWh-year) and power electronic FOM (£/kW-year). Adding the charge and discharge efficiencies (in %) to the above factors allows us to develop a comprehensive ESS system model for lithium-ion (Li-ion) batteries.

These economic factors are combined with the technical descriptions from the previous sections to develop an efficient model of the entire system. The converter rating power (P_{Con}) for the proposed station arrangement is equal to the maximum absolute battery charging/discharging power over the design time window, as shown below:

$$P_{Con} = max(|P_B|) = max|[P_{B_1} \quad \cdots \quad P_{B_{48}}]| \tag{6}$$

Similarly, the maximum SoC, determined based on the proposed power scheduling over the design time window, determines the storage capacity (E_{Bat}) required for the proposed station arrangement, as:

$$E_{Bat} = \max(SoC) = max[SoC_1 \quad \cdots \quad SoC_{48}] \tag{7}$$

Considering the battery sizing and converter rating power determined in (6) and (7), and the storage (C_{Bat}) and converter capital costs (C_{Con}) defined earlier, now the total capital cost (CC) can be defined as follows:

$$CC = (E_{Bat} \cdot C_{Bat}) + (P_{Con} \cdot C_{Con}) \tag{8}$$

Given the fixed operating and maintenance cost factors, and assuming that the battery sizing and converter rating power are determined using equations (6) and 7), the total operating and maintenance cost (OMC) is as follows:

$$OMC = (E_{Bat} C_{Bat}^{FOM}) + (P_{Con} C_{Con}^{FOM}) \tag{9}$$

where C_{Bat}^{FOM} is the energy-based operating, and maintenance cost in [£/kWh-year] and C_{Con}^{FOM} is the power-based operating and maintenance cost [£/kW-year]. The base values for the recent coefficients are planned on a yearly basis [77], but should be adjusted depending on the case and the time window initiated for energy management.

The Total Cost (TC) of the ESS is the sum of the capital costs and the operating and maintenance costs. Considering equations (8) and (9), the total cost is as follows:

$$TC = CC + OMC \tag{10}$$

Moreover, assuming that the dynamic tariff is accessible for the decision-making time frame and aligning with previous references [86], the Total (daily) Energy Price (TEP) can be calculated as follows, utilising the transformer power described earlier (P_T):

$$TEP = \sum_{t=1}^{48} (P_{T_t} \cdot C_{E_t} \cdot T) \tag{11}$$

where P_{T_t} is the transformer power in time step t, C_{E_t} is energy price in time step *t*, and T is the measurement time constant which is 0.5 [hour] for the case.

Given the above, the total cost function (TCF) can be described as follows:

$$TCF = TC + TEP \tag{12}$$

where the primary aim of the optimisation process is to minimise the total cost by managing the trade-offs between ESS capital and operating costs, and energy purchase cost.

The lengths of the sequences described above, and consequently the upper limit for the summation (11), are determined by the daily time window with a half-hourly measurement resolution, resulting in a length of 48. When employing a weekly time window, the lengths of the sequences and the upper limit should be adjusted to 336, which corresponds to the number of measurements in a week using the same measurement time intervals.

C. *Multi-Objective Optimisation Framework*

This work proposes an integrated intelligent techno-economic approach to address this multilateral problem. The parameters of the simultaneous ESS design and energy management for on-route and depot charging stations are not independent variables, and there are nonlinear relationships and interactions between them. This method determines the optimal battery capacity (E_{Bat}), power electronic rating (P_{Con}), and battery scheduling of the HGEV charging station (P_C), which is a series of demand values in a half-hourly resolution for the time window. It considers tariff dynamics, constrains the resulting load profile within the available connection capacity and converter loading capacity, and maintains the system energy balance. The multilateral problem can be formulated into a single objective function with multiple constraints.

GA is a meta-heuristic algorithm that reflects the process of natural selection where the individuals with the best fitness are selected for reproduction to produce offspring of the next generation. In previous studies GA have been shown to be powerful optimisation tools for solving nonlinear, complex problems [40, 87-90]. The problem to be solved is to transform inputs into solutions through a process modelled on genetic evolution. An expert-recommended initial population is assigned to the desired design variables, and the objective function is evaluated for each candidate solution. Then a set of operators (including reproduction, crossover, and mutation) are adjusted for the current application, with due attention to the available experiments [91-93] to process the population and generate successive populations by which the global optimum of functions is obtained effectively.

In some cases, a GA with remarkable mutation rates and population-elitist selection can outperform the traditional GA [91, 94]. This method is based on the conservation of the most appropriate corresponding gene of the previous generation, associated with the random selection of the corresponding pair. Accordingly, the elitist algorithm is used here to solve the hybrid problem of ESS design and energy management. The flowchart in Figure 12 illustrates the procedure of the genetic algorithm optimisation, which was implemented in MATLAB (R2023a).

1) *Objective Function*

In these circumstances, the optimisation objective is to minimise the total cost. Drawing from existing experiences in similar applications [9, 86], the objective function (OF) can be formulated as follows:

$$min\ OF = \min\{TCF(P_{Con}, E_{Bat}, P_C)\} \tag{13}$$

where P_{Con} and E_{Bat} are the storage system design variables of function TCF, and P_C introduces 48 energy management variables (8) on a daily scale. The 50-dimension space of the possible solutions was searched to minimise the objective function. However, solving the problem for a longer period of time increases the number of energy management variables as the half-hour resolution is considered a base. For instance, a 338-dimensional space would need to be searched for a weekly optimisation solution.

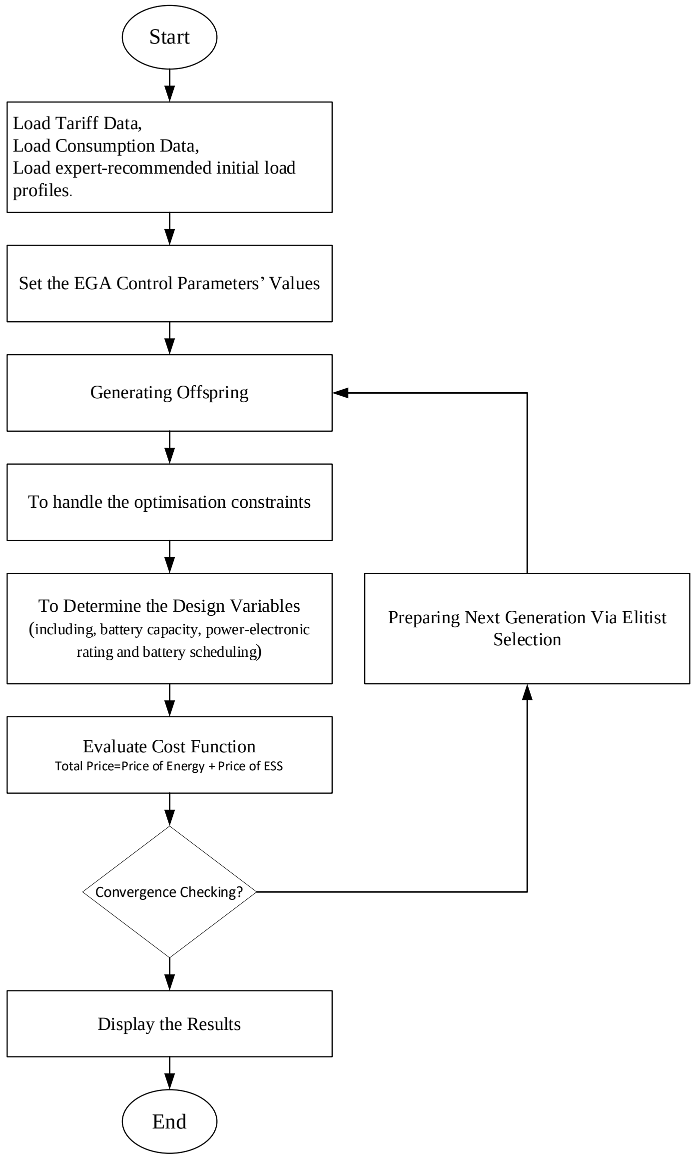

Figure 12. Flowchart of the proposed approach

2) Constraints handling

The proposed approach begins by formulating transformer loading scenarios as potential solutions for the problem, subject to constraints related to rated power and permissible overloading of the network connections (considering transformer and cable limits). It is important to note that the cable's maximum permissible current should align with the transformer's power rating to effectively cover the peak charging demand in a direct charging system (i.e., a charging station without battery storage). The transformer's power rating can be specified according to the country's (UK in this case) standard transformer ratings to meet the charging station's peak load. This is achieved by identifying feasible solutions using the capacity of the defined bounds, as described below:

$$0 \leq P_T \leq P_{T\_max} \tag{14}$$

where P_{T_max} is the maximum permissible transformer loading.

The approach is able to constrain the maximum rate of charger loading. To achieve this the feasibility of solutions are preserved by checking the step change of loading variation and replacing any out-of-step values with the associated boundary values given as follows:

$$-DRL_{max} \leq \Delta P_T \leq IRL_{max} \tag{15}$$

where $\Delta \mathrm{P}_T$ is the step change of loading, IRL_{Max} is the maximum incremental rate of loading and DRL_{Max} is the maximum decremental rate of loading. Considering that the power electronic converters' loading time is 5-times smaller (i.e., 6-minutes) than the half-hourly time-step of the demand scheduling resolution, the maximum rate of charger loading across a half-hourly time-step is not restricted by the converter loading time. It is just limited by the maximum power rating of the electronic converter. This limit can be determined by dividing twice the power electronic board rating (i.e., amplitude of minimum to maximum charging rate - positive for reaching the maximum charging rate and negative for reaching the maximum discharging rate) by the time-step of the demand duration. Defining this constraint opens the possibility of updating this package for P2X system design by acknowledging that the loading rate of electrolysers and synthesisers is significantly lower compared to fully electric systems.

Another constraint is required to maintain system energy balance, taking into account the system's efficiency. This is addressed by implementing a repairing infeasible individual method. When an imbalance exists between the system's energy input and output, considering its efficiency, a revising coefficient is employed to restore the energy balance of the proposed solution. This is formulated as follows, where the required energy input is denoted by:

$$E_{In}^{Sys} = \left(\frac{1}{\eta}\right) \cdot E_{Out}^{Sys} \tag{16}$$

E_{In}^{Sys} and E_{Out}^{Sys} represent the system energy input and the system energy output, respectively. The system energy input, referred to here as the scheduling energy input, can be determined as follows:

$$E_{Sch} = P_T \cdot T \tag{17}$$

Then, the revising coefficient and process can be described as:

$$K_{Scale} = \begin{cases} 1, & if\ E_{Sch} = E_{In}^{Sys} \\ K_{Scale} = \frac{E_{Inp}^{Sys}}{E_{Sch}}, & if\ E_{Sch} \neq E_{In}^{Sys} \end{cases} \tag{18}$$

$$P_{New}^{Sch} = K_{Scal} \cdot P_{Old}^{Sch} \tag{19}$$

The last constraint arises from battery SoC variations, where the battery capacity acts as the upper bound. The minimum feasible SoC is zero. This constraint is addressed through two methods. The first is to add a conditional death penalty to the objective function. The second method exploits the fact that the minimum battery level is inherently zero. This is done by repairing invalid solutions in the population. Both methods have been demonstrated to effectively enforce this constraint.

3) Elitist optimiser control parameters adjustment

Certain GA control parameters can have a strong influence on the performance of the GA, with those deemed crucial including the population size, crossover rate, mutation rate and number of iterations [80]. To identify the optimal values for the control parameters in the current application, this study conducted an exhaustive search of the experienced range for these parameters. This range, extracted as the "Common-Range" in Table 9, was determined based on available experiences regarding the application of GA for similar optimizations [81, 82]; Subsequently, the maximum feasible variations of these parameters were further explored to identify the optimal setting for the current case. The research findings reveal that the time window used for optimisation affects the optimal values for these control parameters. The optimal settings for various EGA-based optimisation and scheduling algorithms applied to daily and weekly time windows are presented in Table 9. To demonstrate the reliability of the metaheuristic method, the optimization convergence rates for both ESS design and demand-side management at the daytime-only charging station, considering daily and weekly time-windows, are presented in the Appendix, Figure A.1-A.4. These results confirm that the process reached stable conditions in all cases.

TABLE 9. THE COMMON GA CONTROL PARAMETER RANGES AND OPTIMISED SETTINGS FOR THE CURRENT APPLICATION

		Gens	Population	Crossover Rate	Mutation Rate
Common Range		3-26	10-160	0.25-1.0	0.00-1.00
Optimal Setting	Daily Optimisation	50	202	0.5	0.25
	Weekly Optimisation	338	502	0.5	0.25
	Daily Scheduling	48	202	0.5	0.75
	Weekly Scheduling	336	502	0.5	0.60

3. SIMULATION STUDIES AND DISCUSSION

The new approach's robustness is evaluated by applying it to depot charging scenarios with varying fleet sizes, depot factors, and operation styles. It is further applied to two on-route cases, based on representative data for daytime and 24-hour service stations in the UK. Next, the impacts of the optimisation time window on the process, results, and consequently, the unit fuel price are investigated. Finally, the process's validity is established through comparative cost-benefit analyses for the charging stations subject to various operational terms and tariff dynamics. The detailed flow diagram for the integration of the charging demand profile models and simultaneous optimization approach for the ESS-equipped charging station design and demand-side management through battery charging/discharging scheduling is illustrated in Figure 13.

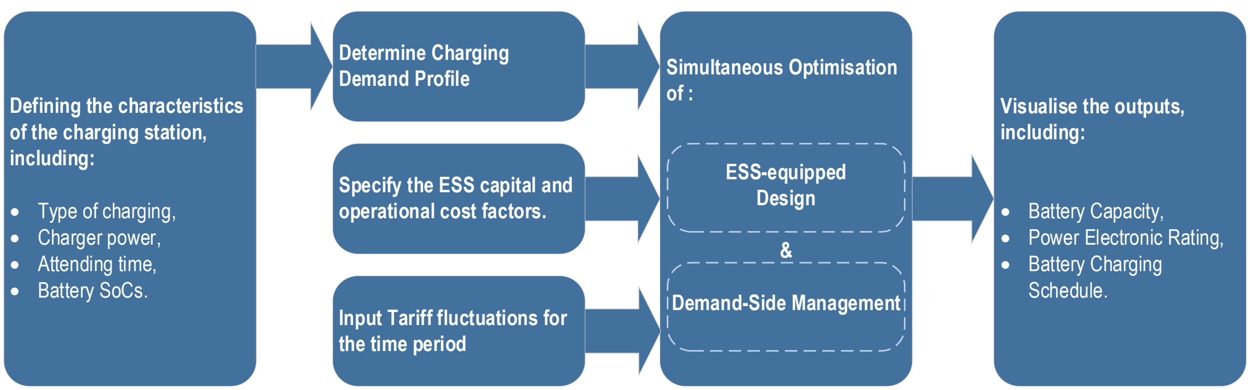

Figure 13. Flow Diagram illustrating the Integration of Charging Demand Modelling and Optimization Process

A. HGEV depot charging station load profiles

Section 2.B.2 presents the depot charging model, which is used to determine the demand profiles for depots with fleet sizes of 50, 75, and 100 vehicles, under depot factors of 0.7 and 1.0, and with unmanaged and price-based management styles (see Figures 14 and 15). In this stage, consistent vehicle assumptions have been maintained, with battery capacities of 400 kWh, specific consumption of 1.8 kWh/mile, and charger ratings of 50 kW.

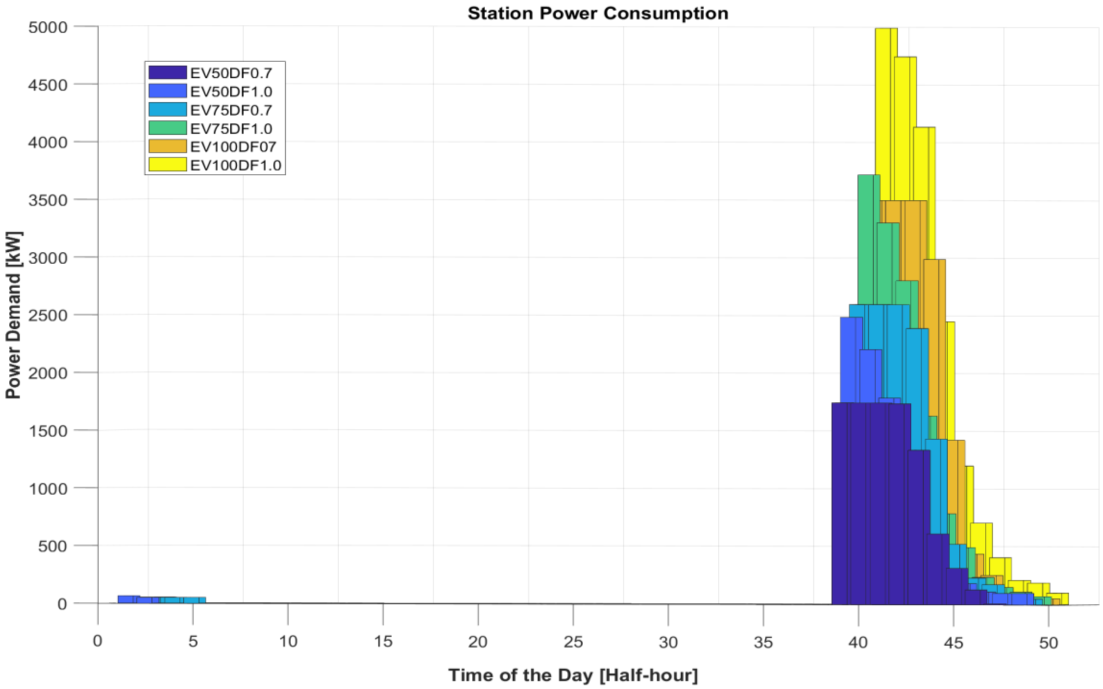

Figure 14. Unmanaged depot charging, fleet size=50, 75 & 100, depot factor=0.7 & 1.0

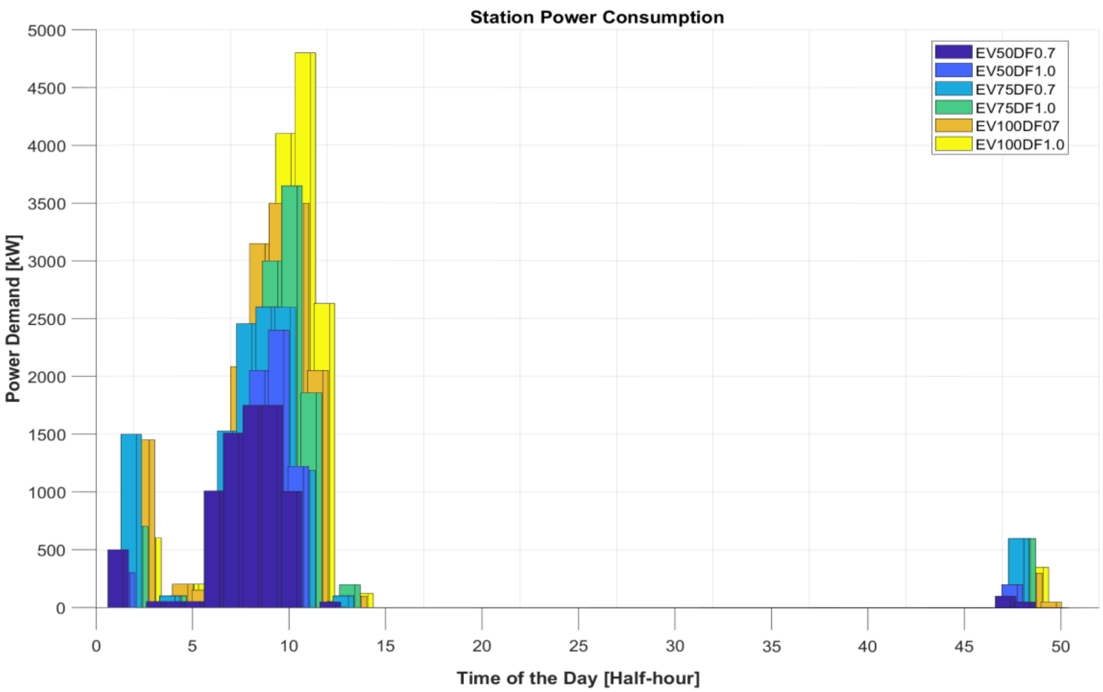

Figure 15. Managed depot charging, fleet size=50, 75 & 100, depot factor=0.7 & 1.0

The station demand profiles determined in the research align with the assumptions made about depot sizes and operational styles. Shape analysis of these profiles, supported by limited references [7, 95], indicates a satisfactory level of reliability. In all studies, the base charging power forms a step signal aggregated in accordance with the fleet manager's daily scheduling, resulting in stairstep signals representing daily demand profiles. The peak value and timing of these signals are influenced by the charging management policy and the number of chargers available at the depot.

B. Simultaneous Optimised Battery Sizing and Scheduling for Expanding Time Horizons

The performance of the proposed model has been evaluated hierarchically, beginning with the application of predetermined load profiles representing depot charging, daytime-only on-route and 24-hour on-route cases. Subsequently, a comprehensive range of cost-benefit analyses was conducted to further assess the effectiveness of the proposed approach. In all cases, the determined results are compared with those of the direct charging station (without an available ESS), not only to verify the reliability of the results but also to assess the robustness of the proposed approach.

1) Analysis across 24-hour windows

To speed up computations, the model was initially run on a 24-hour daily time window. It was able to select any power electronic rating and storage capacity within the connection limit. It sought to minimise the overall cost of energy delivered to vehicles, considering ESS capital and operating costs, as well as electricity purchase costs. The results are presented for the daytime and 24-hour on-route stations, along with various sizes of unmanaged and price-managed depots, as shown in Figure 16-(b) through 16-(e). The summary metrics are compared in Tables 10 and 11.

The model was run for each of the charging load profiles described above. Friday attendance with a medium variation between weekdays is selected as a base input for on-route stations, along with various depot sizes, as shown in Figures 8-9 and Figures 14-15. The main economic inputs of the model are the ESS capital and operating cost consistent with the medium price estimated by MIT, as described in Table 7, and the Market Index-based average daily tariff as determined for 2021 and presented in Figure 16-(a).

Table 10. Energy Storage System Optimal Design for the various charging style via a daily time-window

	Unit	**Daytime station**	**24-hour station**	**Unmanaged depot**	**Price managed depot**
Power Elec. Rating	[kWh]	1661	746	4134	184
Storage Capacity	[kWh]	6004	3358	7180	97
Energy cost (with battery available)	[p/kWh]	12.80	13.08	11.60	11.77
Energy delivery price (Bill + Capital & Operating Costs)	[p/kWh]	15.48	14.39	15.81	11.81
Direct charging cost (without battery)	[p/kWh]	17.13	15.71	18.37	12.07
Daily benefits	[£/Day]	126	106	190	17

Table 11. Comparative Analysis of the ESS Optimal Design and Operational Variables for the Depot Cases

Charging Policy	**Depot Factor**	**Fleet Size**	**Power Elec. Rating [kW]**	**Battery Size [kWh]**	**Energy Cost [p/kWh]**	**Energy Delivery Price [p/kWh]**	**Direct Fuelling [p/kWh]**
Unmanaged	0.7	50	1944	4954	11.80	15.50	17.84
		75	2887	6811	11.71	15.50	18.00
		100	3888	8556	11.65	15.61	18.22
	1.0	50	2765	4543	11.61	15.83	18.46
		75	4134	7180	11.60	15.81	18.37
		100	5541	10249	11.62	15.74	18.32
Price-based Managed	0.7	50	27	15	11.75	11.78	12.16
		75	92	46	11.88	11.93	12.61
		100	85	42	11.80	11.83	12.35
	1.0	50	34	21	11.68	11.71	11.88
		75	184	97	11.77	11.81	12.07
		100	133	69	11.70	11.75	11.90

Comparing the results of the on-route charging arrangements reveals a nonlinear relationship between the size of the ESS, the capacity for demand-side management, and consequent economic benefits, which is strongly affected by the consumption profile. For instance, in the case of the 24-hour on-route station, a lower storage system capacity can effectively cover higher energy consumption, resulting in a daily profit close to that of a higher storage system capacity for the daytime station.

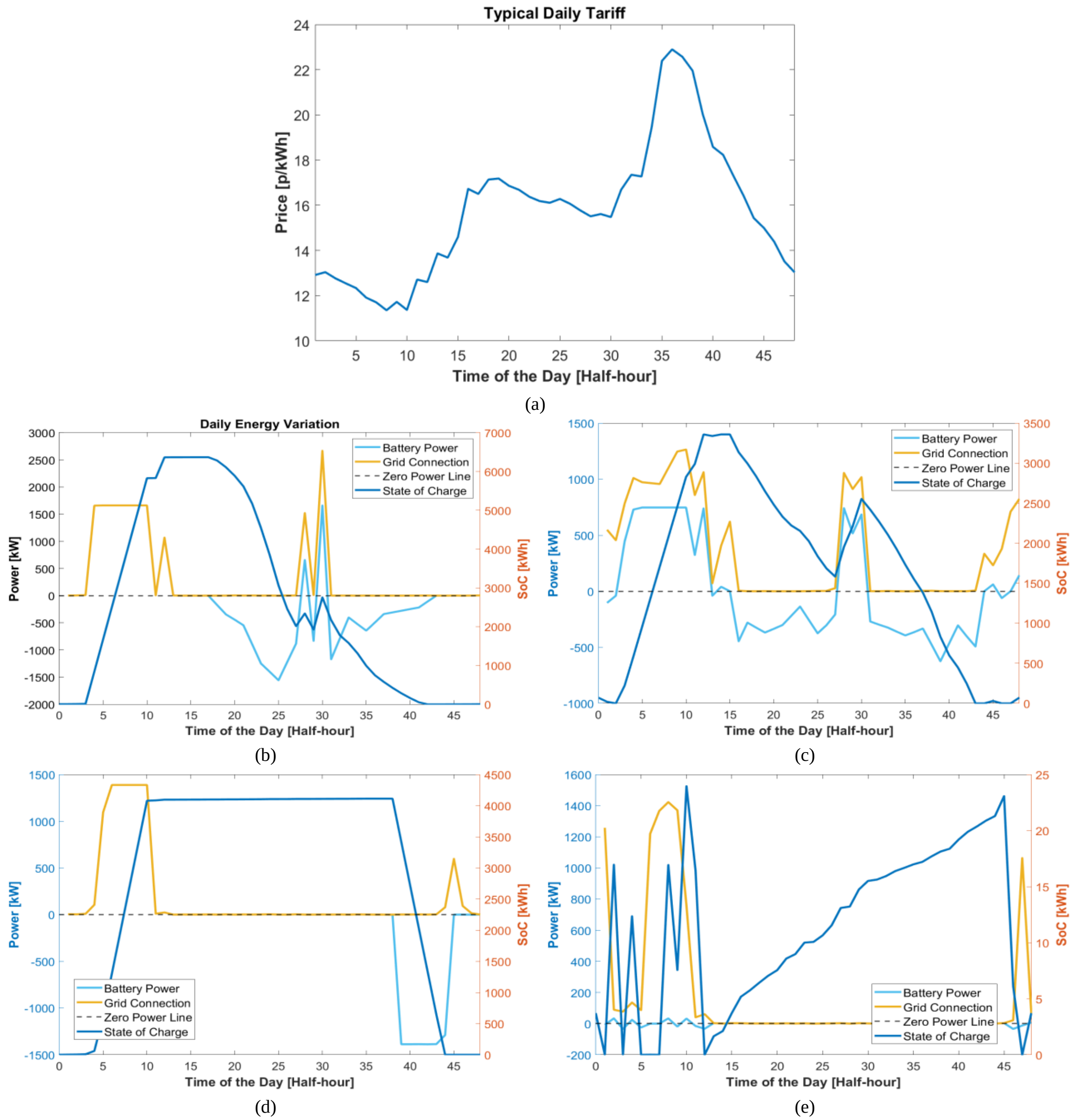

Figure 16. (a) Market Index based Average Daily Tariff Variation for the UK, (b) The results for the integrated method application for daytime charging station, (c) The results for the integrated method application for 24-hour charging station, (d) The results for the integrated method application for unmanaged depot charging, (e) The integrated method application for managed depot charging

To investigate further, the proposed approach was applied to a wider range of depot assumptions, including various management policies, depot factors, and fleet sizes. The results are summarised in Table 11, which details the optimal battery capacity and power electronic rating, in addition to the unit energy cost and total energy delivery price (including the ESS capital and operating costs).

The results show that the contribution of the ESS and subsequent demand-side management is highly dependent on the case and its inherent capacity for consumption management. For depot charging, a price-based management approach can eliminate the need for additional battery installation and subsequent extra management. However, the fleet size and the depot factor have a considerable influence, as seen with the cases that feature a lower depot factor or more restricted charging time revealing reduced benefits from price-based charge management.

2) Examining input parameters

Future battery costs are a significant cause of uncertainty with implications for the results presented above. Figure 17 takes the example of the daytime on-route charging station (Oban) to show how the build-up of battery cost components compares with the reduction in unit electricity purchase price as battery size increases. Analysing the uncertainty of input parameters by examining variations in capital and operating costs adds value not only in validating the optimisation process but also in ensuring the reliability of the results. The outputs not only align with the fundamental equations' structure but are also reinforced by the references that address similar concerns [96, 97]. The ratio between battery capacity and converter rating power is kept equal to the optimal ratio determined in section 3-B-1 over the incremental steps. In turn, Figure 18 combines the battery and electricity costs to establish a total cost of fuel delivered. This is presented for the three storage cost assumptions determined by MIT (refer to Table 6). It demonstrates how the optimal battery size increases as the costs decrease.

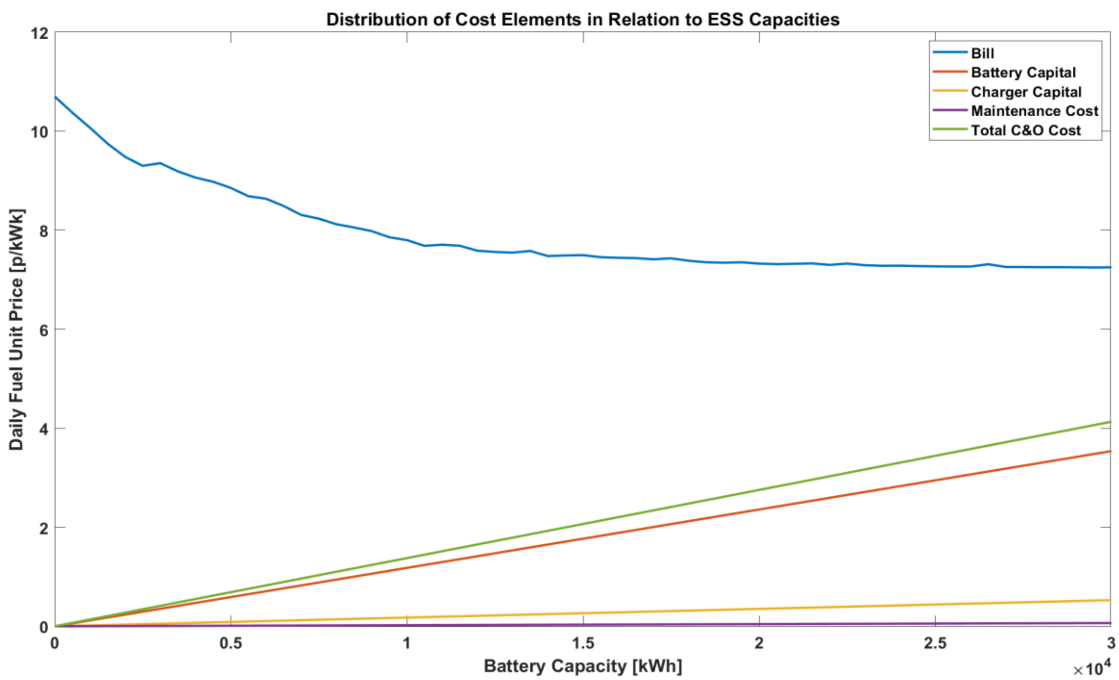

Figure 17. Impacts of battery capacity on the elements of energy price

An optimistic estimation of the ESS price, or minimum estimated price, leads to a 41.17% higher capacity. Conversely, a pessimistic prediction, represented by the maximum estimated price, results in a 64.70% lower size compared to the medium-value base price (see Table 6). These findings provide a clear understanding of the influence of battery cost factors for station owners’ decision making.

3) Impacts of inflation

Electricity prices present a similar, or arguably greater uncertainty. The UK Quarterly Energy Prices [98] indicate a consistent upward trend in average non-domestic electricity prices, including the Climate Change Levy (CCL), since the second quarter of 2011. However, a notable surge in average electricity prices occurred in the third quarter of 2021, continuing into the third quarter of 2022, as depicted earlier in Figure 3. As identified above (Table 4 and Table 5), HGEV charging stations can typically be expected to be categorised as Medium band consumption customers [76]. To assess the impact of recent inflation on the optimal design of ESS and subsequently on energy delivery prices, the effects of inflation over the first three quarters of 2022 are compared to the average price across 2021. The results, in Figure 19, show how the storage size that achieves minimum cost varies as electricity price assumptions are altered.

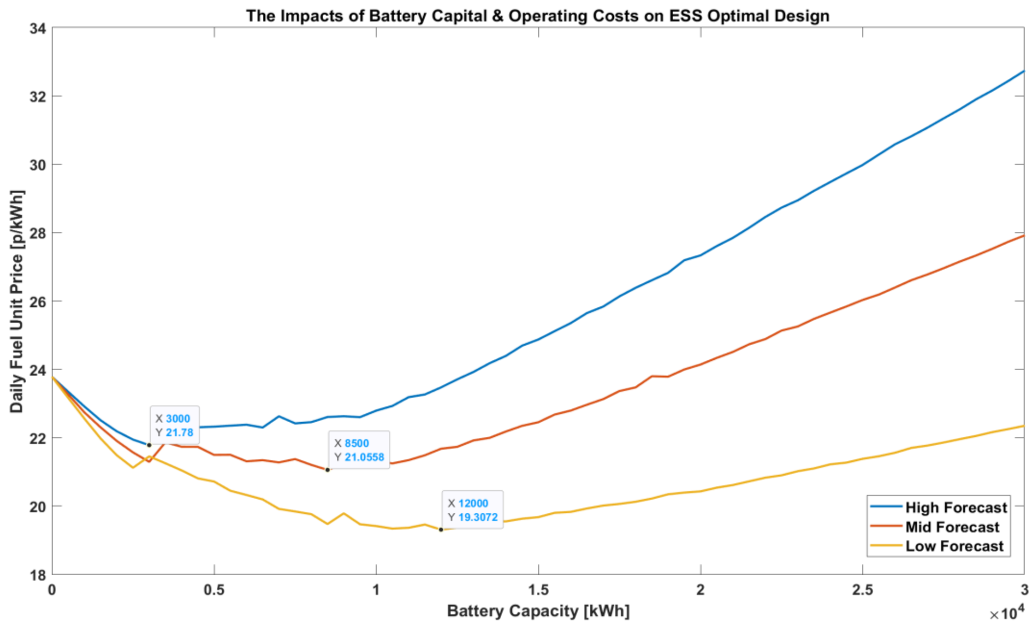

Figure 18. Total impacts of the storage and power-electronic capital costs on the station energy price

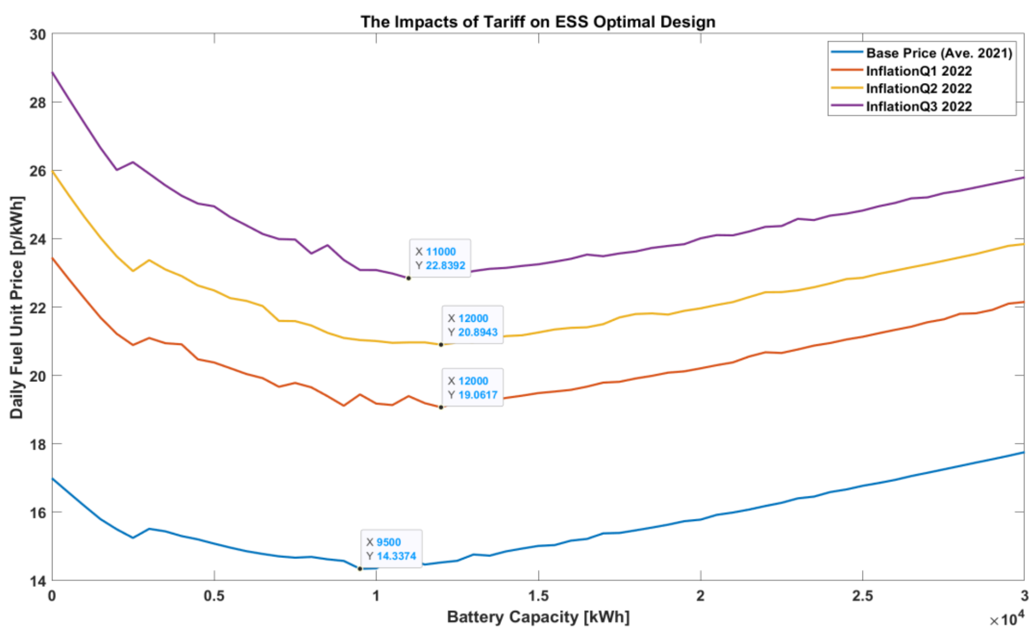

Figure 19. The impacts of tariff variations on the charging station optimal arrangement

Analysing outputs across a range of input assumptions for key input parameters, such as MIP dynamics and the capital and operating cost factors variations (as depicted in Figures 18 and 19), not only supports the validity of the optimisation process but also evaluates the reliability of the results amidst uncertainties. The sizing results of the ESS in terms of shape and ratios align with the conclusions of other research studies [97], including an available industrial case study [96]. The consistency of the new approach's outputs has been tested, confirming that the method is robust and not highly sensitive to factors such as inflation. This is particularly evident when reliable assumptions are made regarding key factors like capital and operational costs [77].

4) Impacts of Optimisation Time-Windows on the ESS Design

There is a risk that an inappropriate optimisation time window could adversely affect ESS design, associated consumption management, and subsequent energy delivery price. Using a longer optimisation window has potential to increase cost benefit by taking advantage of differences in tariff between days. To address this, a full year of MIP-based data was processed to determine a typical weekly tariff variation, defined to span from Saturday to Friday, as illustrated in Figure 20-(a). The proposed integrated method was also adjusted to determine a continuous optimisation for this case. The model was then run to take account of the weekly tariff and the typical weekly consumption determined earlier.

The updated approach was used to determine ESS requirements and associated consumption management on a weekly scale for all the base cases, including the daytime-only and 24-hour on-route stations, as well as the unmanaged and price-based managed depots. Samples of the results, each including battery power scheduling, grid connection load profile, and SoC variations during the time, are shown in Figure 20-(b) to (e) and summarised numerically in Table 12.

Table 12. Energy Storage System Optimal Design for the various charging style via a Weekly time-window

	Unit	**Daytime station**	**24-hour station**	**Unmanaged depot**	**Price managed depot**
Power Elec. Rating	[kWh]	1218	658	4115	969
Storage Capacity	[kWh]	4235	1545	6744	1216
Energy bill (with battery available)	[p/kWh]	14.59	14.41	13.38	12.25
Energy delivery price (Bill + Capital & Operating Costs)	[p/kWh]	17.33	15.36	19.19	13.38
Direct charging bill (without battery)	[p/kWh]	34.05	30.74	36.57	23.52
Weekly benefits	[£/Day]	1232	1304	1166	695

The weekly results for cost and benefit indices are compared with the earlier daily scheduling in Table 13. ESS capital and operating costs dominate the energy bill reduction on a weekly scale. As this limits the optimal ESS size it is not economic to charge the battery during lower weekend tariff periods to cover energy consumption during weekday peak times.

TABLE 13. ENERGY STORAGE SYSTEM OPTIMAL DESIGN FOR THE 24-HOURS CHARGING STATION AND CONSEQUENT DAILY BENEFITS

	Unit	**Weekly Scheduling**	**Daily Scheduling**
Power Elec. Rating	[kWh]	658	746
Storage Capacity	[kWh]	1545	3358
Energy bill (with battery available)	[p/kWh]	14.41	13.08
Energy delivery price (Bill + Capital & Operating Costs)	[p/kWh]	15.36	14.39
Direct charging bill (without battery)	[p/kWh]	30.74	15.71
Daily benefits	[£/Day]	1304	106

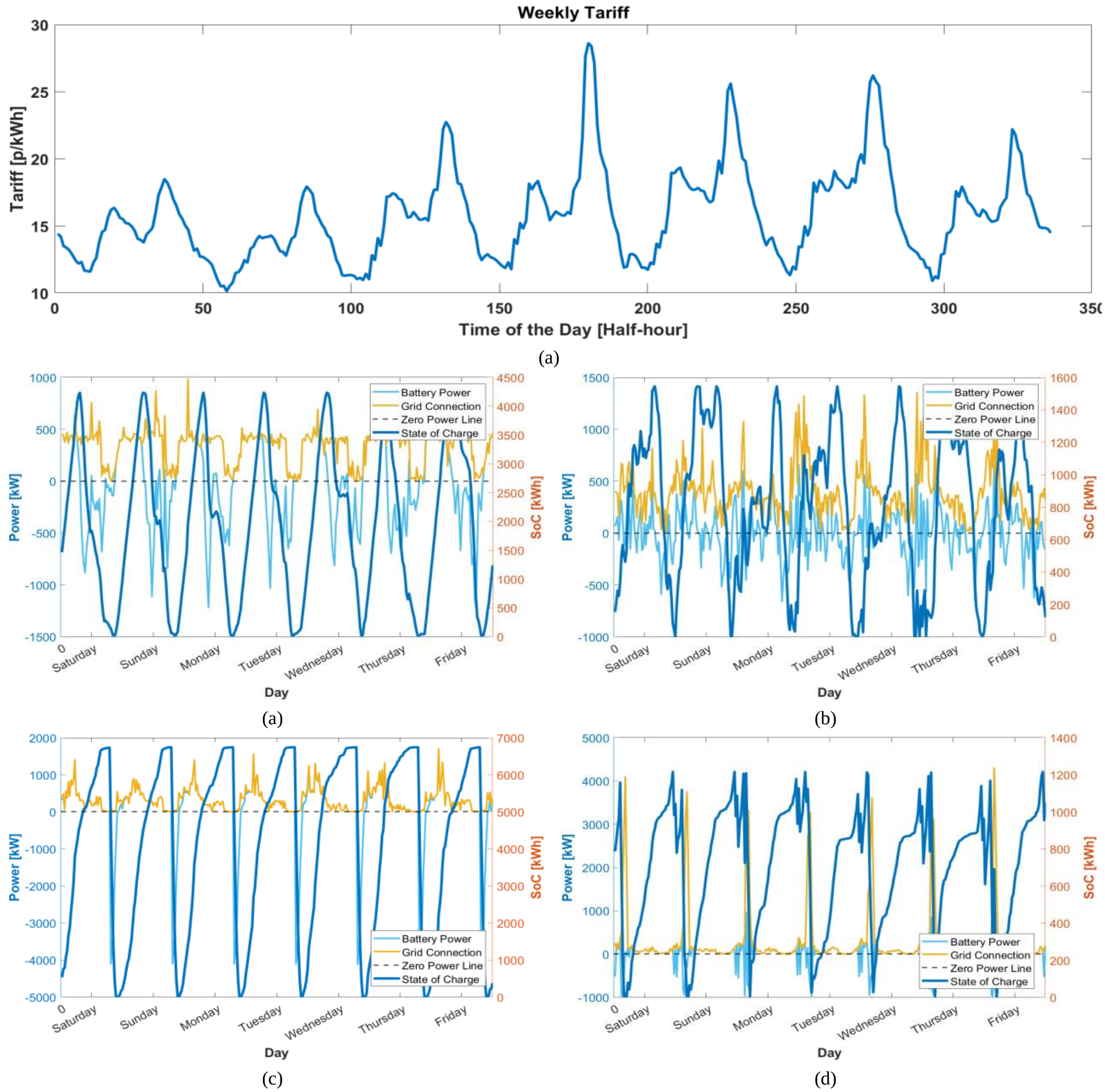

Figure 20. (a) A typical weekly tariff deviation for the UK, (b) The results for the adjusted integrated method application for daytime charging station weekly optimisation, (c) The results for the adjusted integrated method application for 24-hour charging station weekly optimisation, (d) The results for the adjusted integrated method application for unmanaged depot charging weekly optimisation, (e) The Adjusted integrated method application for managed depot charging weekly optimisation.

5) Cost-benefits analysis of the Proposed Approach

Further long-term analysis was conducted, using both daily and weekly time windows to optimise ESS management. The method was applied to the daytime on-route station, together with full year MIP based electricity prices for 2021, including the network charge for the relevant consumption bound of non-domestic customers (as shown in Figure 21). The current long-term cost-benefit analysis, while visualising the variations in the optimised energy delivery price compared to the station's direct charging (without an available ESS and associated potential for demand-side management) price, along with the analysis of profit variations, show optimised energy price to be consistently preferential in profit regardless of MIP variation and the HGEV charging profile fluctuations, which demonstrates robustness of the method. Alternatively, implementing a daily and weekly demand-side management package throughout a year (specifically in 2021 for this case study) to create a targeted cost-benefit analysis is akin to evaluating the developed consumption management using 365 varied input MIP dynamics and station demand profiles for daily scheduling, along with 52 tests for weekly scheduling. The approach consistently produced outputs across numerous test scenarios, indicating stable modelling performance. This not only helps evaluate the robustness of the proposed demand-side management but also ensures the reliability of the results.

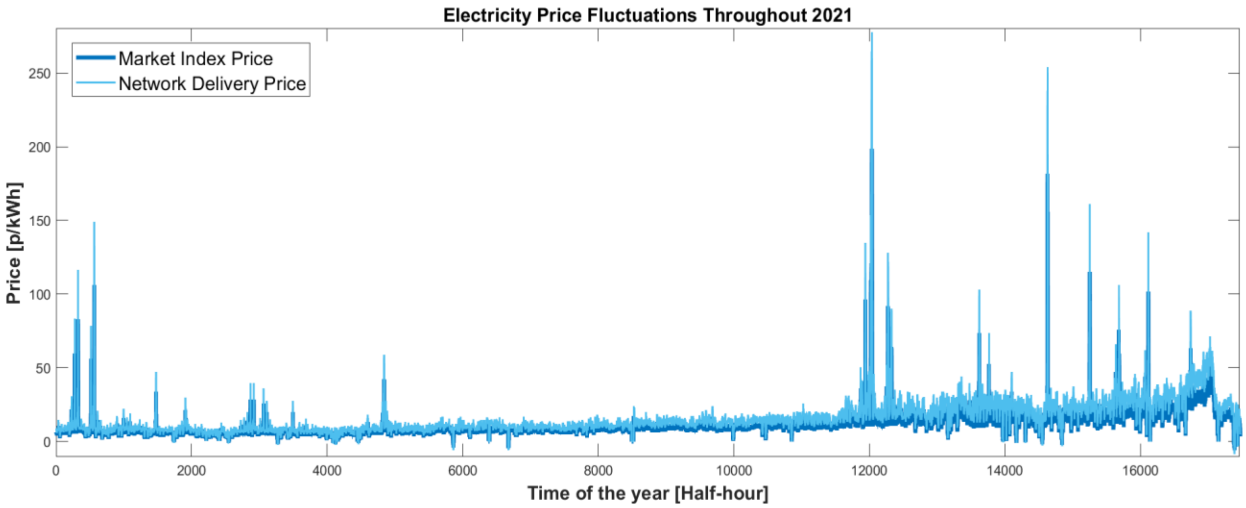

Figure 21. Yearly UK Market Index Price (MIP) and Tariff Dynamics Across 2021

The conventional approach adopted in 3.B.1 and 3.B.4 used daily and weekly average tariffs as inputs for daily and weekly time-window ESS design. Given the significant impact of tariff dynamics on ESS sizing, the days and weeks of the year with maximum and minimum tariff deviations, can be incorporated as boundaries into the design method. Consequently, battery storage capacity and charger power ratings can be planned for these scenarios. Additional scenarios have been incorporated into the analysis to gain a broader understanding of the energy delivery prices and associated benefits trend, along with ESS size variations to incremental and decremental values with a step change of 25%, similarly incorporated for battery capacity and power electronic rating relative to adjacent boundary values. All ESS configurations have been evaluated using both daily and weekly scheduling strategies to provide a comprehensive insight into not only the impact of ESS sizing but also the role of scheduling time-window in load management and resulting advantages. The identification of extreme days and weeks across 2021 is depicted in Figures 22 and 23, while the ESS design outcomes for the scenarios are summarised in Table 14.

TABLE 14. HGEV CHARGING STATION ESS OPTIMAL DESIGN CONSIDERING 2021 MIP BASED PRICE DATA

Time-Window	Tariff Dynamics	Power Elec. Rating [kW]	Battery Capacity [kWh]	Energy Delivery Price [p/kWh]
Daily Optimisation	Max. Range	2115	8481	18.87
	Average	1661	6004	15.48
	Min. Range	407	371	09.58
Weekly Optimisation	Max. Range	1397	8098	20.84
	Average	1218	4235	17.33
	Min. Range	966	3354	11.69

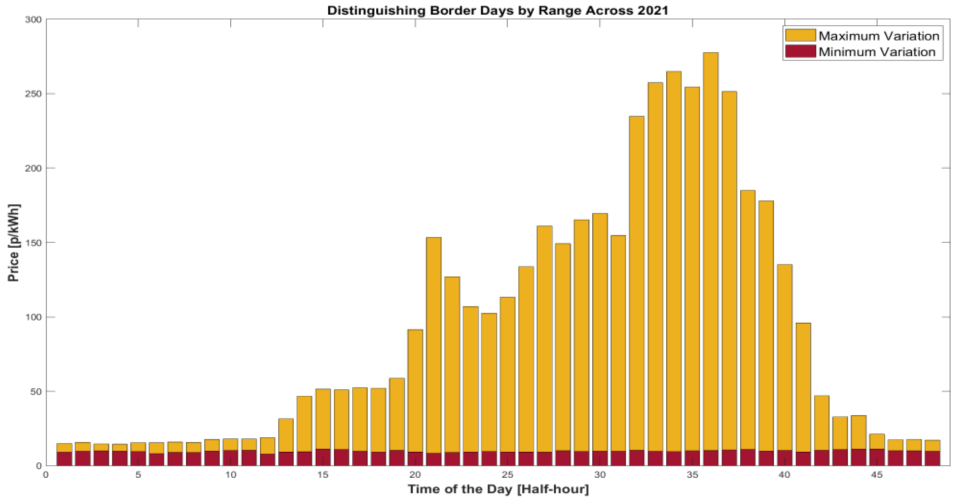

Figure 22. Distinguishing Border Days by Range Across 2021

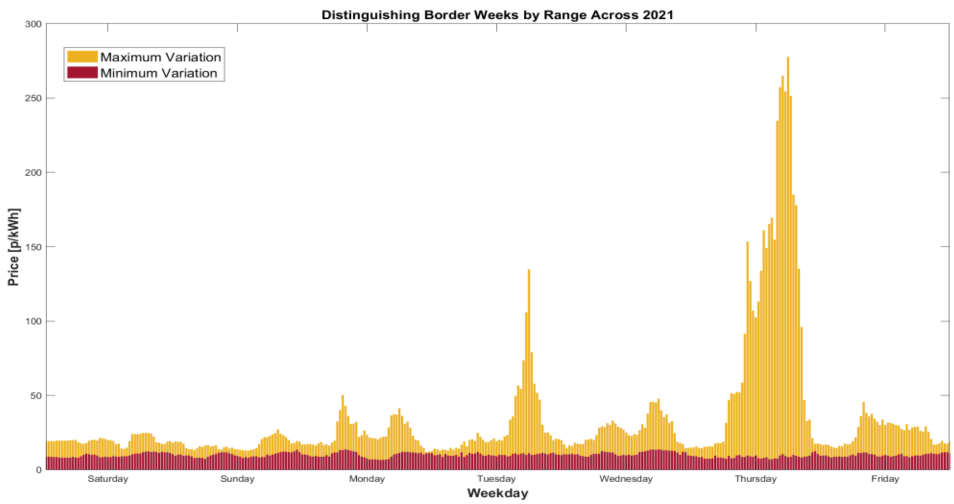

Figure 23. Distinguishing Border Weeks by Range Across 2021

To gain a deeper understanding of trends, the analysis included two additional scenarios where the ESS capacities and power electronic ratings were incrementally and detrimentally adjusted by 25% and 50% for extreme days and weeks. This led to a total of 10 scenarios being considered. Cost-benefit analysis adopting the daily scheduling strategy is presented first. Figure 24 shows the resulting energy delivery prices, across 2021, for the maximum, average, and minimum ESS capacities, compared to the direct fuelling scenario. In turn, Figure 25 shows the daily net profits for each scenario. Finally, summary data for the year is presented in Table 15.

The energy delivery prices in Figure 24 show notable benefits from ESS-based demand-side management during autumn and winter days, when electricity market prices are higher. By contrast, benefits are lower in spring, and summer and some days are seen where ESS benefits are not sufficient to offset the associated capital and operating expenses. A similar picture is seen with the net profit variations in Figure 25. ESS installation offers significant advantages during autumn and winter, while it may be a less cost-effective approach in spring and summer.

All cases presented in Table 15 show a profit from the addition of ESS-based demand-side management. This benefit reduces for larger ESS assumptions where the energy bill is still seen to decrease but additional ESS costs begin to outweigh this saving. From the cases presented here, the ESS sized for the average day leads to the lowest energy delivery price and highest profit. During analysis, minor numerical discrepancies were seen to arise due to the optimisation algorithm's low rate of convergence or reaching the maximum iteration limit, both of which can halt the optimisation process.

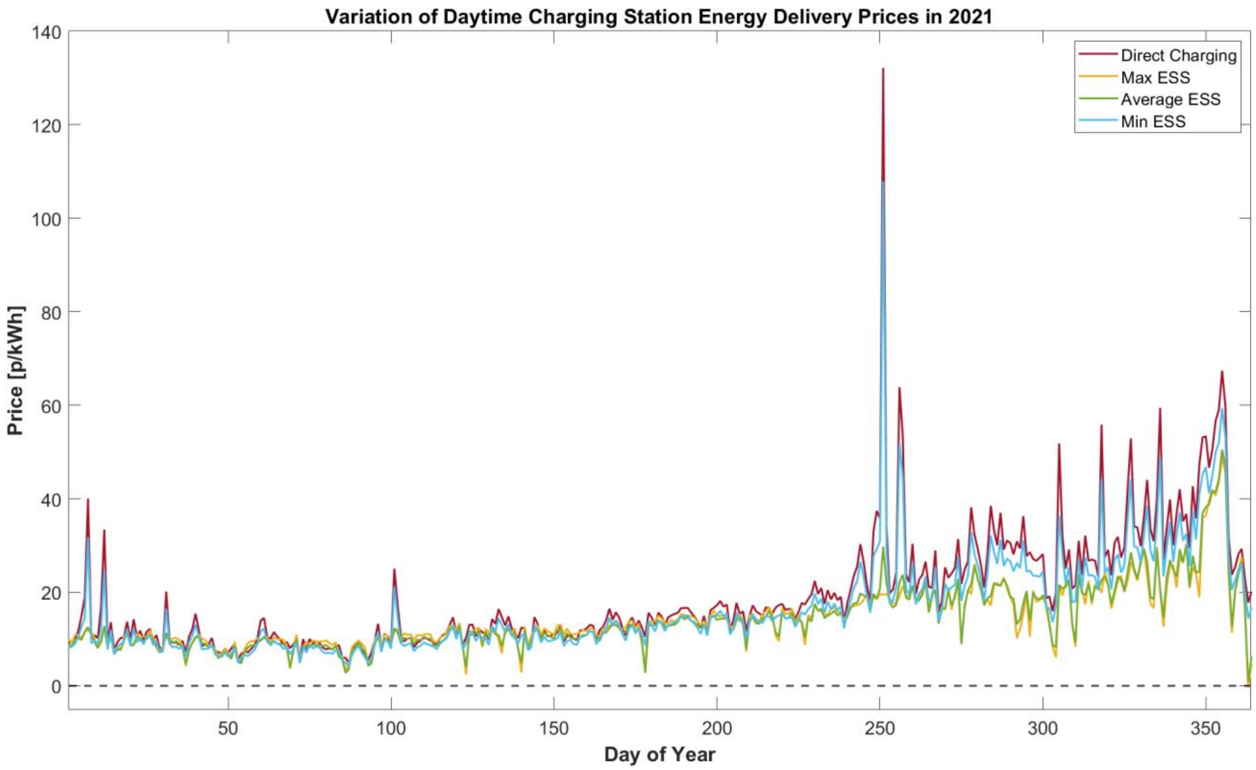

Figure 24. The daytime on-route charging station comparative energy delivery price analysis

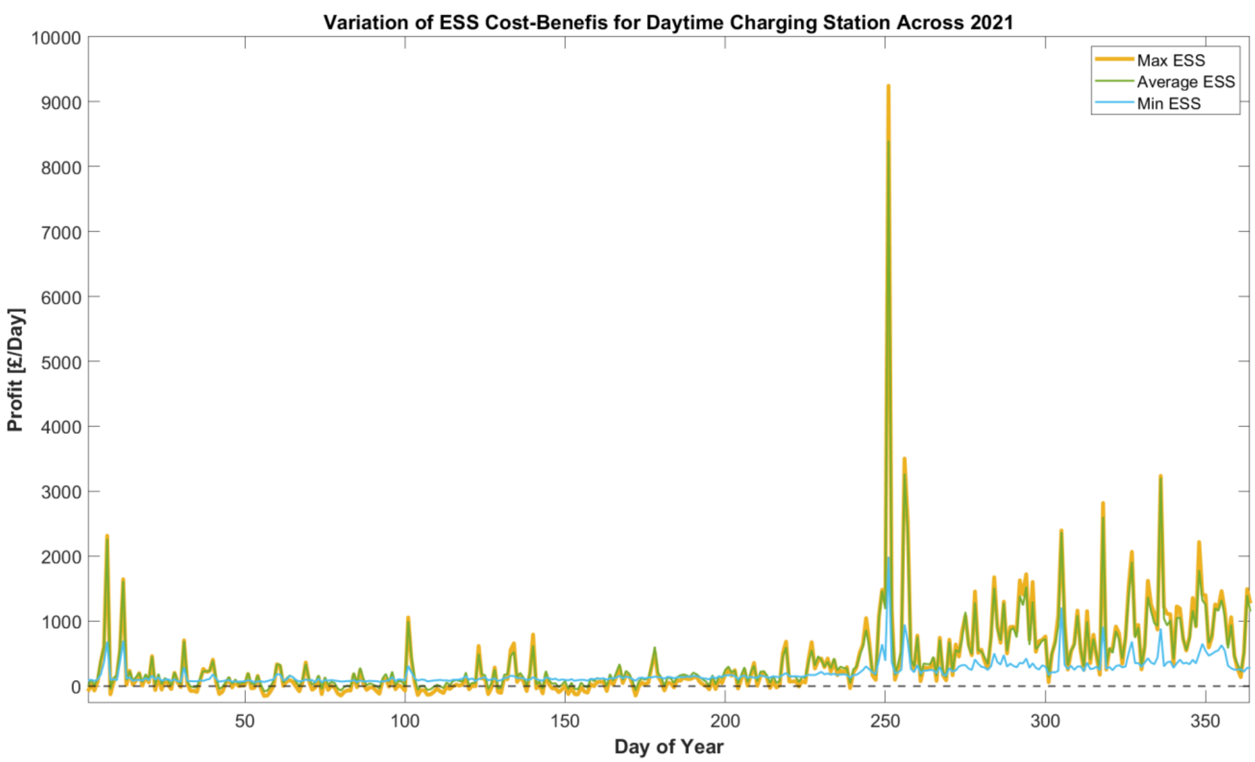

Figure 25. The daytime on-route charging station comparative daily profit analysis

TABLE 15. SUMMARY OF 2021 ESS-BASED DAILY DEMAND-SIDE MANAGEMENT COST-BENEFIT ANALYSIS

Scenario No.	**ESS Size**	**Daily Scheduling Based**		
		Energy Bill [p/kWh]	Energy Delivery Price [p/kWh]	Profit [£/Day]
1	**Max. Daily Design +50%** (12721 [kWh], 3172 [kW])	10.09	15.60	287.4
2	**Max. Daily Design +25%** (10601 [kWh], 2643 [kW])	10.35	14.94	341.4
3	**Max. Daily Design** (8481 [kWh], 2115 [kW])	10.73	14.40	385.7
4	**Max. Weekly Design** (8098 [kWh], 1397 [kW])	11.25	14.57	371.9
5	**Ave. Daily Design** (6004 [kWh], 1661 [kW])	11.56	14.21	401.3
5	**Ave. Weekly Design** (4235 [kWh], 1218 [kW])	12.56	14.45	382.2
6	**Min. Weekly Design** (3354 [kWh], 966 [kW])	13.11	14.60	370.0
7	**Min. Daily Design** (371 [kWh], 407 [kW])	16.41	16.67	202.2
8	**Min. Daily Design -25%** (281 [kWh], 308 [kW])	16.63	16.82	190.0
9	**Min. Daily Design -50%** (185 [kWh], 203 [kW])	16.82	16.95	180.0

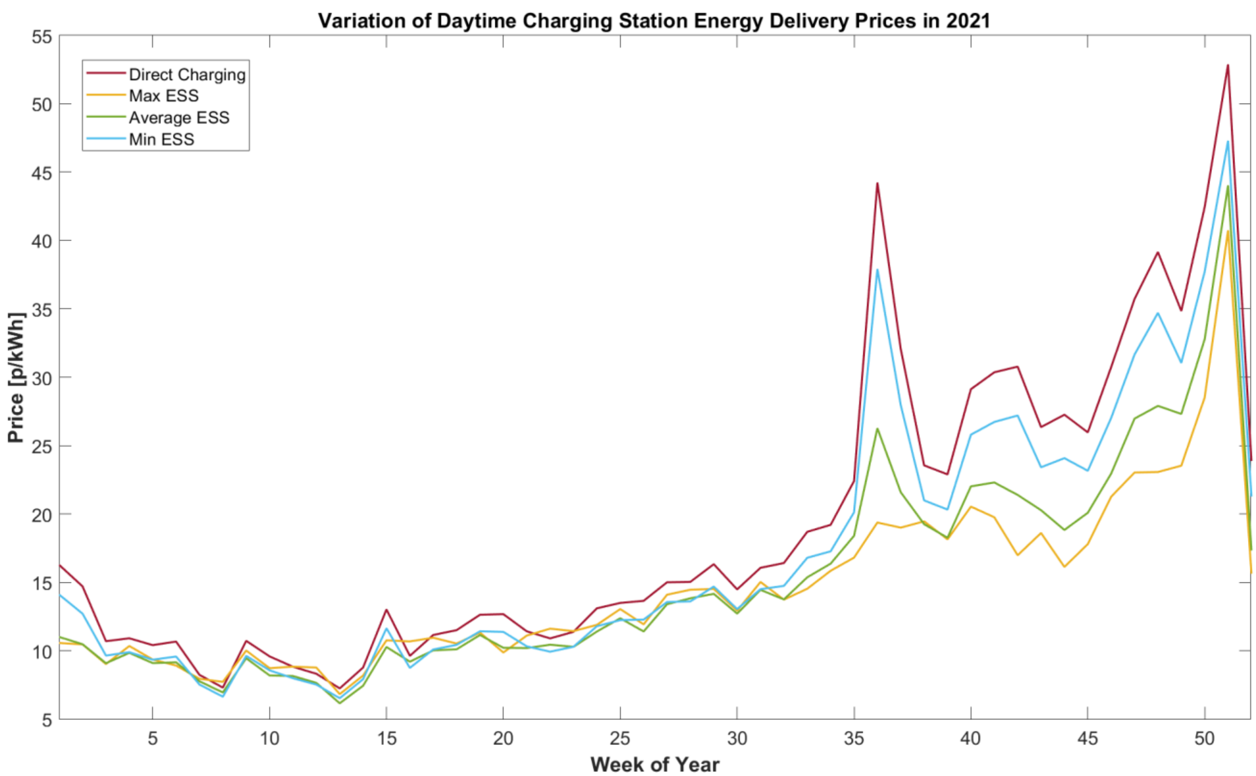

Figure 26. The daytime on-route charging station comparative energy delivery price analysis

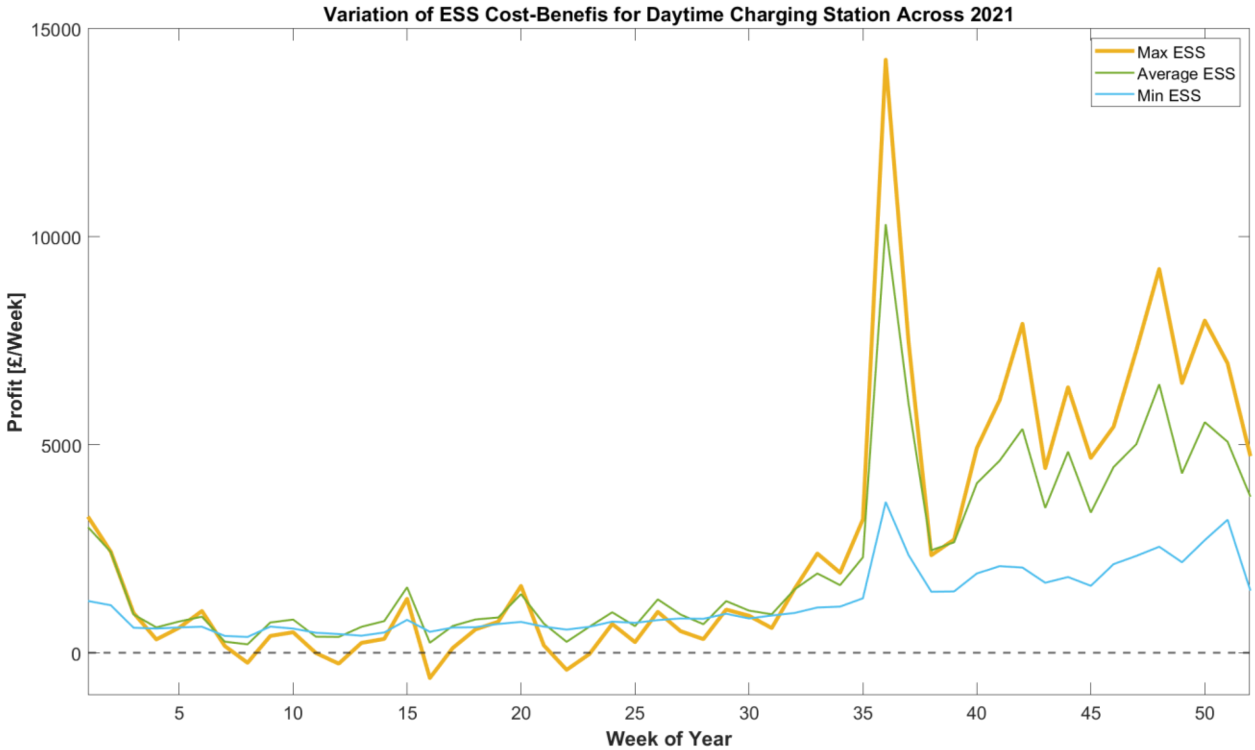

Figure 27. The daytime on-route charging station comparative daily profit analysis

The cost-benefit analysis was next carried out using a weekly scheduling time window. The outputs are shown in Figures 26 and 27 and summarised numerically in Table 16. As with the daily scheduling results, all scenarios show a positive profit; however the energy delivery prices are consistently higher, and the profit values lower than those obtained in the earlier daily scheduling results. Furthermore, upon considering the scenarios that yield the highest benefits, namely scenario 5 for daily scheduling and scenario 4 for weekly scheduling, it becomes evident that weekly scheduling approaches tend to offer greater capacity compared to their daily counterparts. Similarly to the daily results, the preferred scenario now becomes the case where the battery is sized based on an average weekly electricity price. However, the differences between scenarios 3 and 4 are also very small, and this may simply be a reflection of the numerical solution convergence issue.

To explore these results further, the values from Tables 15 and 16 are plotted in Figure 28. Here, trend curves have been added using non-linear regression curve fitting. The comparative evaluation of the time window's impact on demand-side management and process outputs, as demonstrated both numerically and visually in the current section, represents the final phase of testing the capacity and resilience of the proposed approach. Throughout this analysis, the demand-side management outputs exhibited consistency and stability, even as adjustments were made to the time window, transitioning from daily to weekly scheduling. This shift affected various aspects, including the size of input variables like MIP dynamics, the decision dimensions such as the number charging power terms of the battery, as well as the optimal values of control parameters like mutation rate in EGA and optimization constraints like energy input-output balance. These findings not only showcase the efficacy of the proposed method in consumption management but also underscore the reliability of the results. The daily and weekly curves show similar trends albeit with modest vertical and horizontal offsets. These curves emphasise the lower energy delivery price suggested by daily optimisation as well as the preference of the daily analyses for a somewhat smaller ESS capacity. Examination of weekly results (see Figure 20-(b) to (c)) suggests that minimal benefit is achieved from energy exchange between days as the increased ESS size required, and therefore increased cost, offsets any purchase price reduction.

TABLE 16. SUMMARY OF 2021 ESS-BASED WEEKLY DEMAND-SIDE MANAGEMENT COST-BENEFIT ANALYSIS

Scenario No.	ESS Size	Weekly Scheduling Based		
		Energy Bill [p/kWh]	Energy Delivery Price [p/kWh]	Profit [£/Day]
1	**Max. Daily Design +50%** (12721 [kWh], 3172 [kW])	9.75	15.25	314.6
2	**Max. Daily Design +25%** (10601 [kWh], 2643 [kW])	10.24	14.82	349.6
3	**Max. Daily Design** (8481 [kWh], 2115 [kW])	10.83	14.50	376.1
4	**Max. Weekly Design** (8098 [kWh], 1397 [kW])	11.16	14.47	378.3
5	**Ave. Daily Design** (6004 [kWh], 1661 [kW])	12.16	14.80	350.1
5	**Ave. Weekly Design** (4235 [kWh], 1218 [kW])	13.29	15.17	320.7
6	**Min. Weekly Design** (3354 [kWh], 966 [kW])	13.95	15.44	298.9
7	**Min. Daily Design** (371 [kWh], 407 [kW])	16.75	17.00	170.6
8	**Min. Daily Design -25%** (281 [kWh], 308 [kW])	16.86	17.05	166.7
9	**Min. Daily Design -50%** (185 [kWh], 203 [kW])	16.96	17.09	163.9

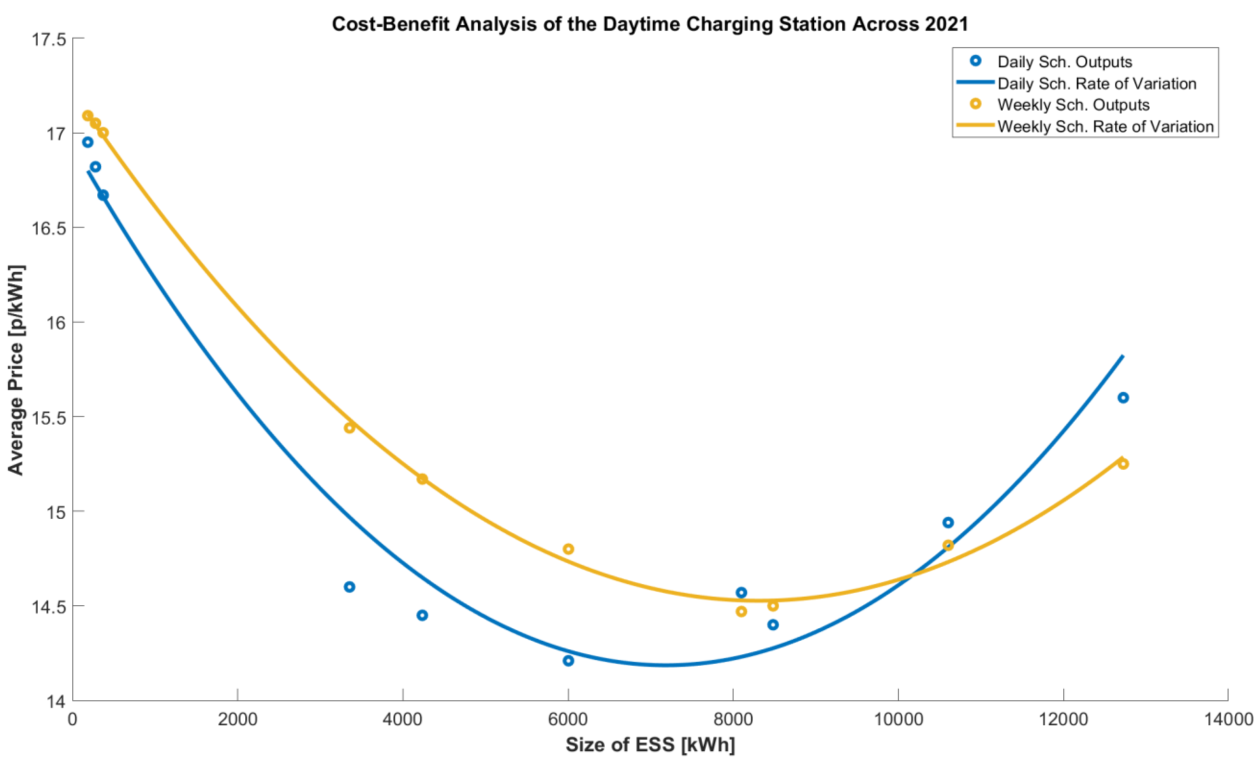

Figure 28. Comparative analysis of the daytime on-route charging across daily and weekly scheduling

In essence, while daily scheduling aims to optimize the balance between system energy inputs and outputs more efficiently, weekly scheduling extends this constraint to a weekly scale. This extension permits potential energy exchange between weekdays, consequently leading to a tendency towards higher ESS capacity in the weekly approach. This is evidenced by scenario 4 exhibiting the highest benefit compared to scenario 5 in the daily scheduling approach. It is important to note that this trend is primarily observed in on-route stations with stochastic weekday load profiles. Depot charging, with its typically periodic charging pattern over weeks, exhibits similar performance under daily scheduling as under weekly scheduling, as illustrated by the SoC variation in Figure 20-(d) to (e).

The lower profits seen from weekly optimisation are initially surprising. It might be expected that this longer window would achieve at least some advantage from storing energy between days. Further analysis of the process identified a higher turnover in weekly scheduling compared to daily scheduling making the optimisation less sensitive to similar deviations due to their smaller proportion of the total cost. For instance, comparing the optimal solutions in Tables 15 and 16, a difference of 23 £/day (161 £/week) in profits, across the first week of 2021, reveals that this portion is equal to 0.038% of the energy bill and 0.02% of the total cost, while for the weekly approach, it is only 0.019% of the energy bill and 0.015% of the total cost. If similar convergence conditions have been defined as $\epsilon = 0.0002$ for both approaches, this deviation (23 £/day) would be detectable in daily scheduling but would be negligible on a weekly scale. This is an example of the 'masking effect' in numerical optimisation techniques.

Furthermore, extending the scheduling time window from daily to weekly basis while preserving half-hourly measurement resolution increases the number of decision variables sevenfold. This leads to a substantial increase in processing time and a reduction in the accuracy of the optimisation methods. Here, computational constraints restrict the potential to increase the population size and maximum generation limit. When utilizing a Dell Inspiron 16 with an AMD Ryzen 7 processor, determining ESS design and consumption scheduling for a daily time-window typically takes less than 10 minutes, whereas it extends to 31 minutes for a weekly time window. Conducting a yearly cost-benefit analysis using the same system, the daily scheduling package necessitates approximately 8 hours, while the weekly scheduling package demands approximately 16 hours. This increase in calculation time occurs while the control parameter rates offer a higher level of reliability in daily scheduling (see Table 9).

In summary, considering the current ESS capital and operating cost assumptions, extending the ESS scheduling time window may result in very limited scheduled energy exchange between weekdays in on-route cases, but it can significantly increase processing time, reduce optimisation accuracy, and increase the risk of the 'masking effect'. Assuming different capital and operating cost assumptions and tariff rates become available in the future, the optimal solution may need to be reevaluated.

4. CONCLUSION

This paper proposes an integrated techno-economic framework that addresses the interconnected issues of HGEV charge management and station ESS design. Whereas previous EV research has mostly concentrated on light vehicles, this examination of multiple HGEV scenarios brings new challenges. This reflects larger batteries, higher power charging and the new temporal patterns that come from fleet operating regimes. Novel stochastic and semi-stochastic models were successfully developed to determine resultant consumption patterns. An intelligent elitist approach was then developed to optimise ESS battery and converter size while simultaneously solving optimal battery scheduling to meet these charge requirements. Multiple constraints are effectively handled using a combination of an adaptive penalty function and repair of infeasible solutions. This was applied to identify the minimum energy delivery price, reflecting the costs of ESS installation and dynamic energy purchase in line with the half-hourly UK wholesale electricity price.

HGEVs needing to charge on route were seen to face a cost penalty, although adding static ESS can bring a modest benefit. Fleet operation that allows overnight depot charging shows lower costs, with dynamic charge management enabling access to lower electricity prices. On route charging costs as high as 15.48 p/kWh contrast with 11.81 p/kWh for the managed depot case, considering ESS installation and electricity purchase costs. Commercial costs of operating on route stations could be expected to further increase this price gap. In the depot case, charge management of individual vehicles delivers a higher cost saving (in one configuration, reducing energy delivery cost from 18.32 to 11.90 p/kWh) than installing a static ESS (15.74 p/kWh).

The relationship between battery capacity, charger rating, and subsequent energy delivery price was seen to be nonlinear and sometimes inverse, depending on the load profile dynamics. For example, for the 24-hour, on route station examined, optimal battery capacity was determined to be 55.9% of the size for the daytime station, while maintaining a 7% reduction in comparative energy delivery price. This was also associated with a decrease in charger rating power to 44.9% of that needed for the daytime station. Results were unsurprisingly sensitive to cost assumptions with lower ESS costs allowing for a fourfold increase in the optimal battery size identified.

An adapted EGA-based package was developed to implement ESS and charge management across a full year, considering daily and weekly optimisation windows. Whilst the latter window enables inter-day energy shifting, very little benefit was seen from this, reflecting the influence of ESS cost. Moreover, the disadvantages of dealing with a significantly larger number of decision-making components and the risk of masking outweigh any potential advantages. Although the differences were small, the shorter daily optimisation window was seen to identify solutions with slightly greater cost savings.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Omid Shariati: Investigation, Modelling, Visualisation, Writing - original draft. **Phil Coker**: Conceptualisation, Writing - review & editing. **Stefán Thor Smith**: Project administration, Conceptualisation, Writing - review & editing. **Ben Potter**: Conceptualisation. **William Holderbaum**: Writing - review & editing.

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APPENDIX.

See Figures A.1, A.2, A.3, A.4

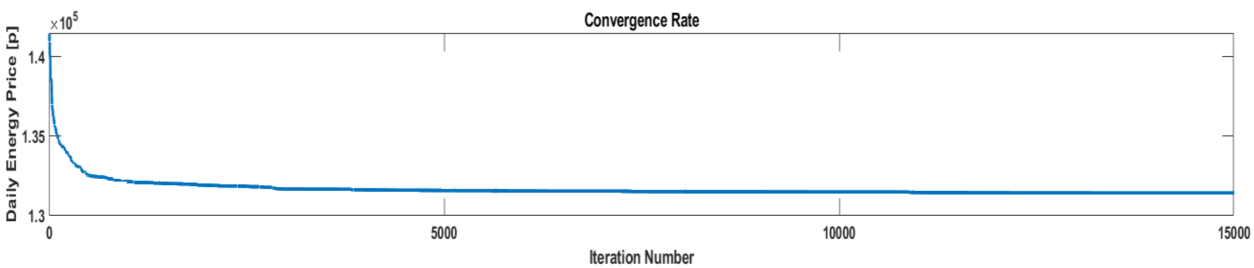

Figure A.1. Performance of the proposed optimisation method in ESS design with a daily time window

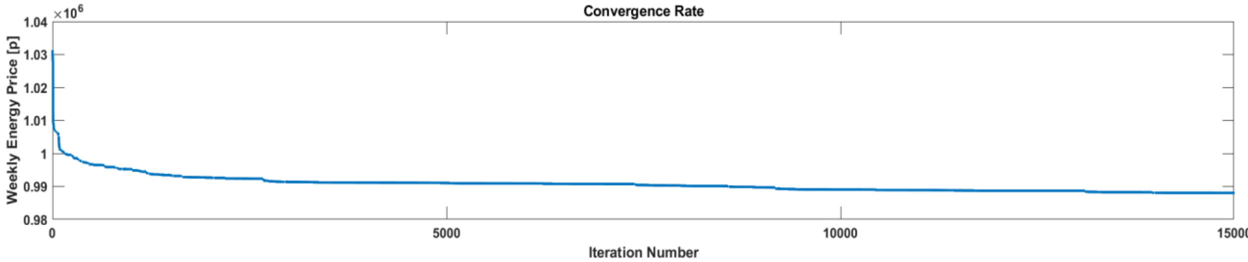

Figure A.2. Performance of the proposed optimisation method in ESS design with a weekly time window

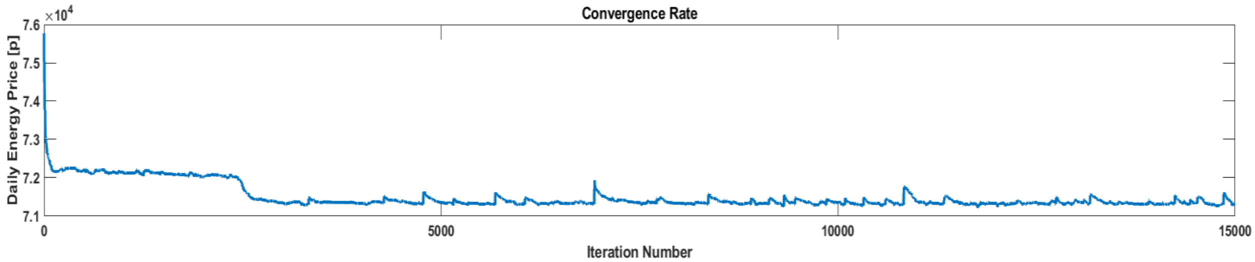

Figure A.3. Performance of the proposed optimisation method in demand-side management with a daily time window

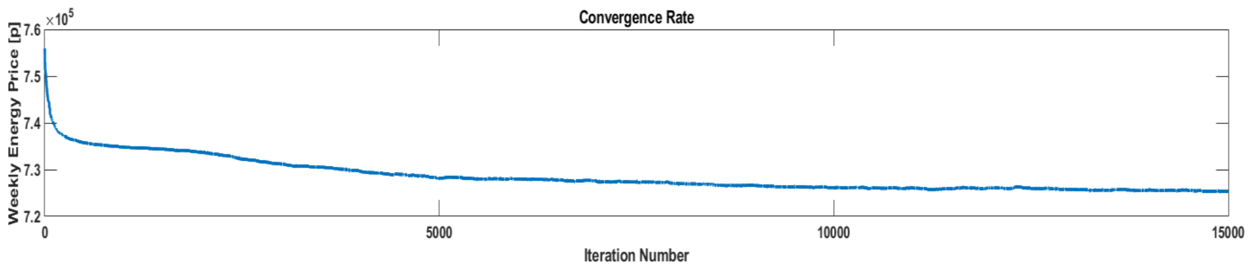

Figure A.4. Performance of the proposed optimisation method in demand-side management with a weekly time window

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