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Techno-economic optimization and assessment of solar-battery charging station under grid constraints with varying levels of fleet EV penetration

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ABSTRACT

The integration of electric vehicles (EVs) into power systems worldwide will be challenged in many locations by grid constraints, such as load shedding in developing countries or active network management in developed countries. Nevertheless, an opportunity exists for EV fleets to alleviate financial and operational repercussions of these constraints while reducing carbon emissions through integrated photovoltaic-energy storage-charging station (PV-ES-CS) systems. However, the effectiveness of PV-ES-CS systems depends on the load they serve, and many commercial fleets may only partially electrify their vehicle stock, thus limiting their energy demand. Consequently, there is a need for methodologies that incorporate grid constraints into the design and techno-economic assessments of PV-ES-CS systems, alongside an understanding of the impact of varying levels of fleet EV penetration on system performance.

We develop a novel methodology that incorporates grid constraints into a PV-ES capacity optimization model, and investigate the impacts of optimistic and conservative grid constraint scenarios and different degrees of fleet EV penetration on PV-ES-CS system performance through a case study of a paratransit fleet in Dobsonville, South Africa. To determine the most cost-effective design of the systems, the PV and ES components are optimized to maximize net present value (NPV).

Three generalized insights emerge from the analysis: The first relates to the importance of timing PV-ES investments based on the planned fleet electrification strategy. The second sheds light on the sensitivity of PV-ES system performance to grid constraint frequency and forecasting, emphasizing the need for nuanced understanding and adaptive strategies in regions with pervasive grid constraints. The third explores the influence of trickle charging on system feasibility and economic performance, particularly at lower levels of EV penetration. Enhanced utilization of trickle charging emerges as a promising avenue to improve the economic viability of PV-ES systems, especially for fleets with morning and evening peak loads.

Collectively, these insights contribute to advancing the understanding of renewable energy integration in commercial fleet operations in grid and capital-constrained environments. Moreover, the methodology provides a robust framework for fleet owners in these environments to optimally plan PV-ES investments, fostering informed decision-making and propelling the transition towards sustainable and economically efficient transportation.

1. Introduction

Due to their energy efficiency and pollution benefits, electric vehicles (EVs) are likely to lead future automotive markets [1]. In the contemporary landscape of sustainable energy systems guided by the United Nations Sustainable Development Goals (SDG), the intersection of renewable energy and EV technology stands as a pivotal frontier in the pursuit of economic and low carbon mobility [2]. The confluence of these two domains has given rise to the concept of solar-storage integration at EV charging stations, presenting an innovative solution to the challenges of grid reliability, energy efficiency, and carbon emissions reduction. As the global transition towards renewable energy intensifies, the deployment of photovoltaic (PV) arrays coupled with energy storage systems at EV charging stations not only promises to augment the resilience of the power grid but also provides a tangible pathway to the realization of sustainable and decentralized transportation networks.

Against this backdrop, this paper aims to address the questions of how grid constraints (such as load shedding or active network

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Nomenclature

AP	Annual capital payments
CS	Charging station
$CF_{\mathrm{PV}}(h)$	Capacity factor of solar PV in hour h
COE	Cost of electricity
CRF	Capital Recovery Factor
$D_{\mathrm{ES}}(h)$	Load served by ES in hour h
$D_{\mathrm{grid}}(h)$	Load imported from grid in hour h
$D_{\mathrm{load}}(h)$	Total load at charging station in hour h
$D_{\mathrm{PV}}(h)$	EV load served by PV in hour h
$D_{\mathrm{sys}}(h)$	Load served by PV-ES-CS in hour h
$D_{\mathrm{veh}}(i,h)$	Load from vehicle i in hour h at CS
$\eta_{\mathrm{ES}}^{\mathrm{DC}}$	Discharge efficiency of ES
$E_{\mathrm{ES}}(h)$	Energy available in ES in hour h
$EC_{\mathrm{base}}^{\mathrm{t}}$	Energy cost without system
$EC_{\mathrm{sys}}^{\mathrm{t}}$	Energy cost with system
ES	Energy storage
ES^{t}	Energy cost savings in period t
$E_{\mathrm{PV}}(h)$	Energy output of solar PV in hour h
EV	Electric vehicle
H	Number of hours per period
NPV	Net present value
ICE	Internal combustion engine
IC_{ES}	Investment cost of ES
IC_{sys}	Investment cost of PV-ES-CS
IC_{PV}	Investment cost of PV
$\mathrm{kWh}_{\mathrm{LS}}^{\mathrm{t}}$	kWh lost to load shedding in period t
$LCOE$	Levelized cost of electricity
LS	Load shedding
$MC_{\mathrm{ES}}^{\mathrm{t}}$	Maintenance cost of ES in period t
$MC_{\mathrm{PV}}^{\mathrm{t}}$	Maintenance cost of PV in period t
$MC_{\mathrm{sys}}^{\mathrm{t}}$	Maintenance cost of PV-ES-CS in period t
OS^{t}	Operational savings in time t
π	Inflation rate
$P_{\mathrm{grid}}(h)$	Grid electricity price in hour h
$P_{\mathrm{PV\text{-}rated}}$	Installed PV capacity in kW
PV	Photovoltaic
ρ	Interest rate
ST2	Stage 2 load shedding
ST4	Stage 4 load shedding
T	Number of periods in project lifespan
TC	Trickle charging
VoR	Value of resiliency

management) and varying levels of fleet EV penetration affect the techno-economic performance of PV-ES-CS systems. To address these questions, we develop a novel methodology which integrates grid constraints into a PV-ES capacity optimization model that maximizes the net present value (NPV) of the investment. Then, through a case study on a paratransit fleet in Dobsonville, South Africa, we examine the effects of optimistic and conservative grid constraint scenarios, as well as varying degrees of fleet EV penetration, on the system's techno-economic performance.

The insights gleaned from our analysis and methodology developed herein are of significant value to automotive stakeholders such as fleet owners, infrastructure developers, or policymakers in regions with grid or capital-constraints. Furthermore, while achieving the stated objectives of answering the above research questions, this paper also establishes benchmark of the feasibility and performance of these systems for sub-Saharan African (SSA) paratransit. Given that paratransit is SSA's dominant road transport modality and is in urgent need of decarbonization solutions and attention from investors [3–5], the findings presented here hold considerable relevance and potential impact.

2. Background and literature review

In this section we review the literature and provide background on the electrification of paratransit, modeling grid constraints in PV-ES-CS systems, analyzing PV-ES-CS systems for mixed fleets, and the mathematical modeling of PV-ES-CS systems. We identify three primary research gaps and list this study's main contributions to the literature.

2.1. Electrification of paratransit

The informal, privately operated, public transportation system known as paratransit plays a crucial role in meeting the commuting needs of a substantial percentage of the population in sub-Saharan Africa, accounting for 50%–98% of daily commutes in most major cities of the region [6]. The backbone of the paratransit industry is the minibus taxi, which completes approximately 83% of the sector's trips [7–10]. Given the high operating expense and environmental impact of these vehicles, along with a global shift to EVs, cities in sub-Saharan Africa must in a practical sense be well-prepared for the imminent electrification of this sector [3,11,12].

In recognition of the imminent electrification of transport in the Global South, the volume of research on paratransit electrification has sharply risen in recent years. Abraham et al. [11], Booysen et al. [4], Hull et al. [13], Giliomee et al. [14], Hull et al. [15], Abraham et al. [16] and Ndibatya and Booysen [17] study the energy requirements and mobility patterns of paratransit vehicles under varying conditions. Giliomee and Booysen [18] analyze the possibility of decarbonizing long-distance paratransit trips with battery swapping. Hull et al. [19] conduct a survey analysis of paratransit owners and drivers, identifying cost as one of the main deterrents of EV adoption intention. Giliomee and Booysen [20] analyze the ability of solar and storage to offset the grid impact of an electric paratransit fleet. Giliomee and Booysen [18] and Narasipuram and Mopidevi [21] show that installing renewables and energy storage at paratransit charging stations can reduce grid impact and benefit grid operators.

However, despite the drivers for paratransit electrification, the significant upfront investment costs of transitioning fleets coupled with challenges related to electricity supply pose formidable barriers to widespread EV adoption in sub-Saharan Africa [19]. In service of United Nations SDG 7 [22], Collett and Hirmer [3] recommend a strategy to mitigate such challenges by coordinating investment in PV panels at charging stations (CS) with the adoption of EVs. Energy storage (ES) alongside the PV has been proposed in this context as well to alleviate grid strain [20]. In addition to mitigating grid impact, these integrated approaches serve a dual purpose: reducing charging expenses, thereby facilitating the cost recovery of charging infrastructure, and enhancing energy resilience during power outages, which occur frequently in the region.

While there are a few papers that allude to the application of solar and storage technologies for electric minibus taxis [4,11,20], there is a gap in the literature at the nexus of evaluating techno-economic feasibility and benefits of PV-ES-CS systems for paratransit or the notorious minibus taxi. The aforementioned surge in research on paratransit electrification primarily focuses on energy consumption and mobility patterns. These factors are crucial inputs into the assessment of PV-ES-CS systems. Consequently, the advancements in the field unlock a newfound opportunity to undertake comprehensive technical and economic evaluation of PV-ES-CS systems for electric paratransit (*research gap 1*).

2.2. Grid constraints

When considering the performance of PV-ES-CS system for a minibus taxi fleet in South Africa, the question arises, how do we account for grid constraints due to load shedding? Load shedding refers to the ongoing rolling blackouts resulting from inadequate generation capacity, during which an EV would be unable to charge. It is a serious problem in South Africa, where load shedding occurred from Sep 6, 2022 to Sep 6, 2023, South Africa experienced load shedding in 360 out of 365 days [23]. It also occurs regularly in other countries around sub-Saharan Africa, as well as countries such as India, Pakistan, Lebanon, and Sri Lanka [24].

Furthermore, it is not just vehicle fleets in South Africa or other developing countries with load shedding that will be impacted by grid constraints. The methodology in this study is relevant to developed contexts where Active Network Management (ANM) schemes may be expanding, such as the UK Grid [25]. Under ANM schemes, energy supply units can be instructed, manually or via automated controls, to limit their power output thus avoiding energy supply and demand imbalances that could cause system faults. Functionally, ANM could have similar effects on EV fleets as load shedding, in that vehicles would be unable to charge during planned or unplanned outage events.

A number of studies have focused on the grid implications of a PV-ES-CS system, or designed systems to work in various grid mode scenarios. For instance, Singh et al. [26] look at the feasibility of a PV-wind turbine hybrid system to power a shopping mall with an EV charging station incorporated to reduce small communities' reliance on the grid. Singh et al. [27] design a grid-tied PV-ES-diesel generator-CS system for successful technical operation in islanded (constrained) and grid-connected mode to verify that the station can provide constant charging to EVs, but do not optimize system size. Hassoune et al. [28] present power management strategies for grid-tied PV-ES-CS systems to minimize stress on the grid during peak hours. Amrollahi and Bathaee [29] analyze how demand response affects the benefits and performance of an optimized hybrid renewable system. Amry et al. [30] examine the engineering efficiency of a grid-tied PV-flywheel system for a workplace EV charging station. Bakht et al. [31] model a PV-ES-diesel generator system to mitigate load shedding for a grid in Pakistan, but do not model the system for an EV CS and do not incorporate resiliency provided by the system directly in the optimization. Zieba Falama et al. [32] design a PV-ES system to reduce load shedding at households in Cameroon, but again not for an EV charging station.

However, none of these studies have provided an approach to incorporate grid constraints into the system capacity optimization with the goal of maximizing system economic performance (*research gap 2*).

2.3. Mixed fleets

In addition to modeling grid constraints, it is important to consider how the level of fleet EV penetration affects system performance. For various reasons including capital and manufacturing constraints, many fleets are likely to electrify only partially, or in stages over time, rather than all at once.

Several studies have considered different fleet mixes in the optimization of hybrid renewable energy systems for charging stations: [33] investigate the grid and cost impact of a PV-based highway charging station for a mix of large and small EVs. Ampah et al. [34] do a performance assessment for PV-wind-biomass system to charge fleets of 30 and 70 fuel cell electric vehicles in Ghana, however they consider the same system for both fleets. Analysis of how differently sized fleets affect the optimal solar-battery system remains missing. This leads to the third research gap, which is the lack of studies to analyze the effects of different degrees of fleet EV penetration on PV-ES-CS system feasibility and techno-economic performance (*research gap 3*).

2.4. Mathematical modeling

There are two main research methods used to study the integration of renewable energy into energy systems: mathematical modeling and integrated computer-based optimization software [21]. Mathematical modeling is a process of representing a real-world system in mathematical terms. This can be used to simulate the behavior of the system and to optimize its performance. Integrated computer-based optimization software is a type of software that combines mathematical modeling with optimization algorithms. This allows researchers to solve complex optimization problems that would be difficult or impossible to solve manually.

The most common tool that is used in the literature for these optimization problems is the computer software tool called Hybrid Optimization of Multiple Energy Resources (HOMER) [35], developed by the U.S. National Renewable Energy Laboratory. HOMER is often used out of convenience for modeling hybrid renewable energy systems, so that custom tools do not have to be developed for analysis. [36] provide a comprehensive summary of studies that apply HOMER to optimize hybrid renewable systems. It is easy to use, however, some limitations of HOMER are its financial cost and closed source, limiting users abilities to adapt the software with features such as variable load shedding. HYBRID2, HYBRIDS, TRYNSY, GAMS, and RETSCREEN are also traditionally used for system optimization design [35], however, in addition to financial cost barriers a review on recent sizing methods for hybrid renewable systems found that these traditional methods tend to be unsuitable for solving complex novel problems [35]. Thus we develop our own open source model, which can be customized for specific use cases and freely improved upon (link forthcoming).

2.5. Contributions

In light of the above literature review, this study addresses three key gaps in the research landscape concerning renewable energy-powered charging station system design and techno-economic feasibility assessments. The identified gaps and the novel contributions of this study are outlined as follows:

1. **Design and assessment of PV-ES-CS performance for an electric paratransit fleet in sub-Saharan Africa:** We conduct a comprehensive analysis of 36 scenarios under three different regimes (base case, significantly unplanned grid constraints, and feed-in-tariff). By addressing *research gap 1*, we provide a contextualized platform for further studies and practical applications for SSA's largest road transport sector.
2. **Development of a methodology to incorporate grid constraints into PV-ES capacity optimization:** A novel methodology is proposed to integrate grid constraints into the PV-ES capacity optimization model, aiming to maximize economic performance while ensuring system reliability. Through rigorous analysis, we elucidate the impact of grid constraints on system performance, addressing a crucial gap in existing literature (*addressing research gap 2*).
3. **Analysis of the effects of fleet EV penetration levels and incremental electrification:** This study investigates the techno-economic performance of PV-ES-CS systems under varying levels of fleet EV penetration and incremental electrification strategies. By examining the implications of these factors alongside conditions of grid-constraints, we contribute three valuable insights into optimizing PV-ES investments for commercial fleets, addressing *research gap 3*.

Additionally, this paper presents an open-source model for optimizing PV-ES-CS investments, providing a practical tool for researchers and practitioners in the field. The repository containing the model is available at (GitHub link forthcoming).

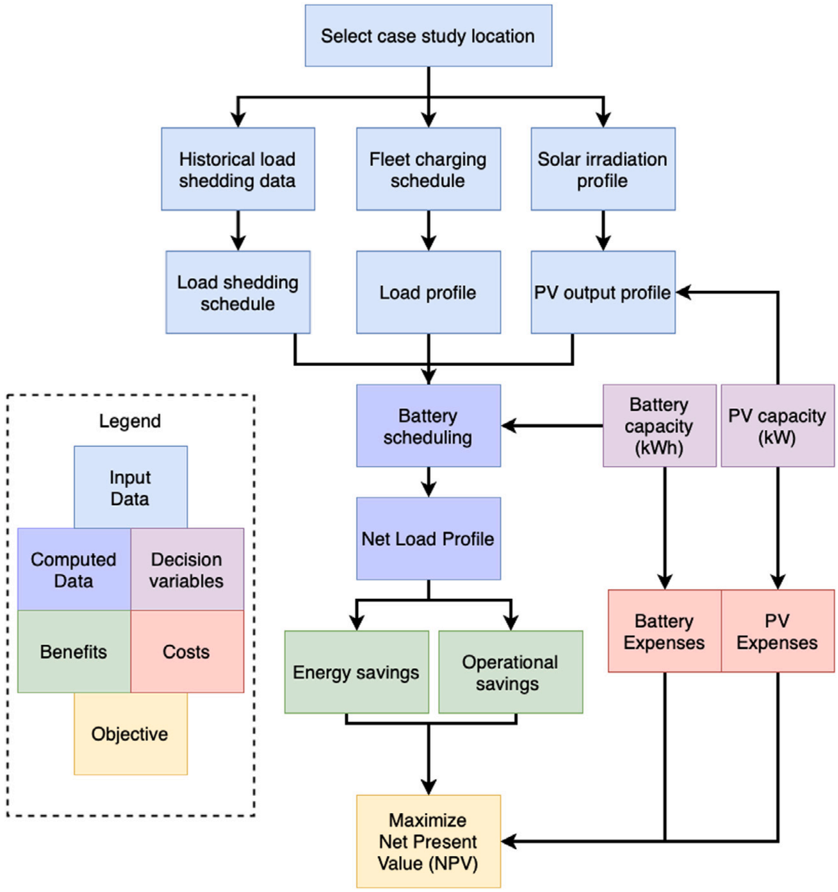


Fig. 1. Flow chart of optimization model to determine the PV and battery sizes that maximize net present value.

The rest of this paper is structured as follows: Section 3 describes the methodology for constructing the optimization model and evaluating the results. Section 4 provides details of the case study and the various grid constraint and fleet EV penetration scenarios that are considered. Section 5 reveals the findings of the model through the case study, draws three key insights from the analysis, and highlights the study's limitations. Section 6 draws the paper to a close by presenting conclusions and imparting recommendations for prospective research endeavors.

3. Methodology

In this section we present a techno-economic model to determine the size of the PV and ES components that will maximize the net present value (NPV) of the PV-ES-CS system. A visual summary of the capacity optimization process is depicted in Fig. 1.

At a high level, the optimization balances the cost-savings offered by the PV and ES with the associated capital and operational costs. More precisely, solar PV is employed to offset EV charging loads at zero marginal cost whenever solar resources are accessible, with surplus solar energy channeled to charging an external stationary battery storage system, provided there is available capacity within the battery. The battery is discharged to meet EV charging loads during periods when solar resources fall short. These energy saving benefits are weighed against the comprehensive total cost of ownership associated with the PV and battery storage.

3.1. System setup

A schematic of the PV-ES-CS system is shown in Fig. 2. The EVs charge directly from the solar power when available and directly from

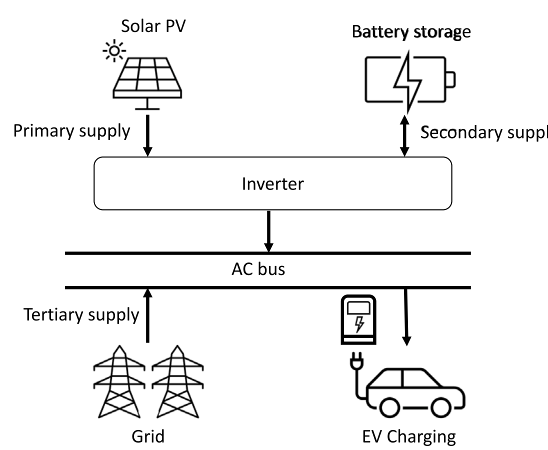


Fig. 2. Schematic of the grid-tied solar PV and energy storage-powered EV charging station.

the grid when solar or battery energy is unable to meet load demand. Excess electricity generated by the solar is either charged into the battery subject to its capacity constraints or curtailed. Positive net load can be served by the battery subject to its physical discharge constraints.

3.1.1. Solar PV

Solar capacity factor is the ratio of actual energy output to the rated energy output of the PV panel. A solar capacity factor profile is calculated using Pfenninger and Staffell's Renewables.ninja service [37].

This service takes weather data from global reanalysis models and satellite observations [38–40]. It then converts solar irradiance data into power output using the Global Solar Energy Estimator [41].

Within renewables.ninja, the hourly capacity factors are computed as a five-year average from 2015 to 2019 to mitigate the effect of outliers. Using the capacity factor profile, the solar PV output for hour h $E_{PV}(h)$ is calculated via Eq. (1):

$$E_{\mathrm{PV}}(h) = CF_{\mathrm{PV}}(h) \times P_{\mathrm{PV\text{-}rated}} \tag{1}$$

where $CF_{\mathrm{PV}}(h)$ is the capacity factor in hour h, and $P_{\mathrm{PV\text{-}rated}}$ is the installed PV capacity in $\mathrm{kW_{pk}}$.

3.1.2. Grid constraints

In this study, we model the effects of both planned and unplanned grid constraints on the value of the PV-ES-CS systems. Grid constraints are events such as load shedding or power outages that prevent electric vehicles (EVs) from drawing power from the grid, impacting their charging schedules and operational profile.

We assess how grid constraints affect EV charging and the economic performance of the PV-ES-CS system by considering different scenarios: no grid constraints, planned grid constraints, and unplanned grid constraints.

- **No Grid Constraints**: In scenarios with no grid constraints, EVs are able to charge exactly as they are scheduled.
- **Planned Grid Constraints**: Events with at least 24 h of forewarning, allowing fleet operators to adjust charging schedules.
- **Unplanned Grid Constraints**: Sudden events without prior notice, causing immediate operational impacts.

Planned grid constraints. Planned grid constraints occur due to foreseen issues such as scheduled maintenance, environmental factors, or network capacity limits. When a planned constraint is anticipated:

- **Notification**: Fleet operators receive at least 24 hours' notice.
- **Schedule adjustment**: EV charging schedules are modified to avoid constrained hours while maintaining a zero lateness condition to meet passenger demand.
- **Economic impact**: The only change is the timing of EV charging, potentially affecting electricity prices or solar resource availability.

For example, if a maintenance event is scheduled from 2PM to 4PM, EVs will be rescheduled to charge before or after this period, ensuring all trips are made on time. When we generate these new operational schedules, we enforce a zero lateness condition to ensure passenger demand can still be met satisfactorily despite the shifted schedule. Therefore, the only difference between scenarios with planned grid constraints and no grid constraints is exactly *when* the EV charging occurs. This may be significant, if charging is pushed into hours with differing electricity prices or solar resource availability.

Unplanned grid constraints. Unplanned grid constraints arise suddenly from issues like unscheduled maintenance, natural disasters, or accidents. In these cases:

- **Notification**: There is no forewarning and fleet operators are unable to reschedule EV charging schedules in advance.
- **Schedule adjustment**: EV charging schedules are not modified.
- **Economic impact:** Costs are incurred due to missed trips, calculated based on the mileage and kWh that could have been charged during the outage. However, the PV-ES-CS system can mitigate these costs by providing backup power during outages.

For example, the fleet had planned to draw 20 kWh of electricity from the grid from 2 PM to 4 PM. A sudden power outage means that they are unable to do so. The operational cost due to missed trips is calculated based on the mileage the EVs would have traveled using the kWh that would have been charged during the constrained hours. However, if the PV-ES-CS system can supply energy to cover or partially cover the outage, this operational cost is reduced based on the proportion of the energy shortage the PV-ES-CS system was able to cover. The detailed calculation method is provided in Section 3.5. Importantly, this is an economic benefit for the PV-ES-CS system, as the system can reduce the operational cost by providing resiliency during these hours.

The differences between the scenarios are summarized in Table 1.

Table 1
How grid constraints (GC) affect the EV charging schedules and economics of PV-ES-CS optimization.

GC schedule type	New EV charging schedule required?	Operational cost from missing charging opportunity?	Opportunity for PV-ES-CS system to provide resiliency?
No GC	✗	✗	✗
Planned GC	✓	✗	✗
Unplanned GC	✗	✓	✓

3.1.3. EV charging load

The EV charging load profiles are derived using the tool developed by Wust et al. [42], which inputs the operational schedule of a fleet of internal combustion engine (ICE) minibus taxis and proposes a feasible operational schedule for an equivalent fleet of EVs, including individual vehicle charging schedules. Given the complete lack of electric minibus taxis in sub-Saharan Africa, this step is essential for generating a realistic charging profile for such a fleet.

The tool bases passenger demand on measured (tracking) and validated (rank-observed) data. The vehicle schedules and charging demand profiles are based on an algorithm that works to match passenger demand to reduced vehicle supply and charging schedules through a optimizing heuristic. The scheduling tool ensures all passenger demand is met with zero lateness and that the usage of the EVs complies with the energy capacity of the battery as well as vehicle energy consumption rate (kWh/km), thus confirming the operational feasibility of the fleet.

As discussed in Section 3.1.2, the charging schedules shift with different load shedding scenarios. They also shift based on the number of vehicles in the fleet which are stipulated to be electric. For this study, we model low (25%), medium (50%), high (75%), and full (100%) fleet EV penetration, each of which possesses its own charging schedule.

From a simulated schedule, the total EV load in hour h, $D_{load}(h)$, is given by Eq. (2), which says that total EV load in any given hour at the charging station is equal to the sum of all loads from individual vehicles.

$$D_{\mathrm{load}}(h) = \sum_{\mathrm{i=1}}^{\mathrm{N}} D_{\mathrm{veh}}(i,h)\ \forall i \in [1,N] \tag{2}$$

where N is the number of vehicles charging.

3.2. Energy dispatch strategy

In this study, the conventional rule/logic-based strategy for ES charge/discharge is followed. The conventional rule/logic-based strategy is a typical strategy chosen for techno-economic assessments of hybrid solar and storage systems [30,43–45]. It must be noted that several energy dispatch/control strategies have been proposed in the literature for similar capacity sizing problems (e.g. [46–49]). The conventional rule/logic-based strategy is chosen for the benefits it brings in terms of low computational requirements and insensitivity to hyperparameter initialization. Furthermore, since this approach to ES management is not governed by an optimization function, the results of the ES size for the overall optimization will be conservative relative

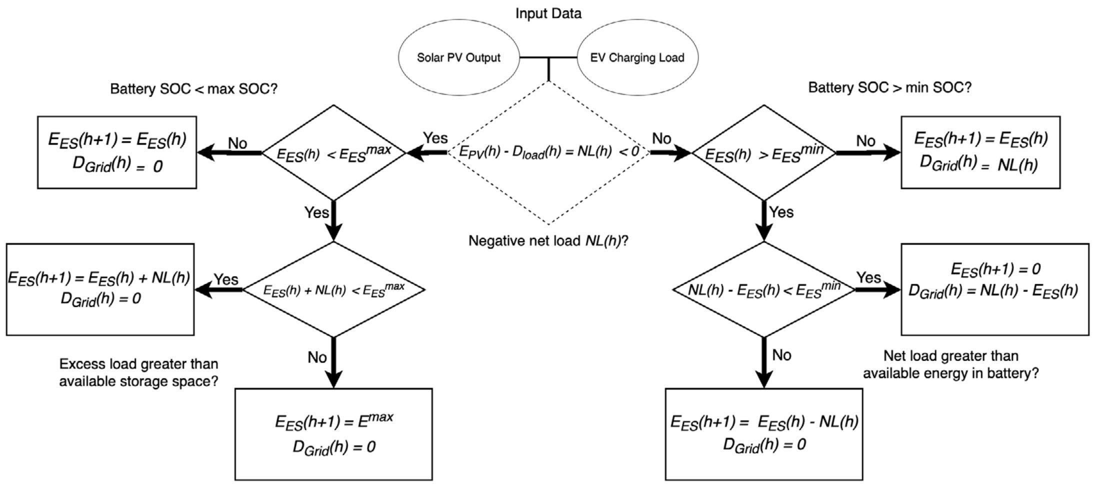


Fig. 3. Conventional rule/logic-based strategy for managing the ES system. We refer the reader to the nomenclature table for complete index of variable meanings.

to more sophisticated usage. In other words, if the system attains feasibility with the conventional rule/logic-based strategy, then it will do so with any further optimized usage of the ES.

The conventional rule/logic-based energy storage and dispatch algorithm obeys the following rules. First, load is served by the PV system. If there is excess PV left over, then it is charged to the battery as much as possible, governed by the ES charging limits. If there is remaining load, then the ES discharges energy to meet the load as much as it can, without exceeding its maximum depth of discharge. If there is remaining load after the ES discharge, it is imported from the grid. This process is outlined in Fig. 3.

Following Figs. 2 and 3, we can derive load served by PV production $D_{PV}(h)$ with Eq. (3), and load served by the ES $D_{ES}(h)$ with Eq. (4).

$$D_{\mathrm{PV}}(h) = \min(E_{\mathrm{PV}}(h), D_{\mathrm{load}}(h)) \tag{3}$$

$$D_{\mathrm{ES}}(h) = \min(D_{\mathrm{load}}(h) - D_{\mathrm{PV}}(h), E_{\mathrm{ES}}(h) \times \eta_{\mathrm{ES}}^{\mathrm{DC}}) \tag{4}$$

where $E_{\mathrm{ES}}(h)$ is the energy available in the ES in hour h and $\eta_{\mathrm{ES}}^{\mathrm{DC}}$ is its discharging efficiency.

Given the above, Eq. (5) models the demand met by the PV-ES-CS $D_{\mathrm{sys}}(h)$, and Eq. (6) finds the resulting energy imported from the grid $D_{\mathrm{grid}}(h)$.

$$D_{\mathrm{sys}}(h) = D_{\mathrm{PV}}(h) + D_{\mathrm{ES}}(h) \tag{5}$$

$$D_{\mathrm{grid}}(h) = D_{\mathrm{load}}(h) - D_{\mathrm{sys}}(h) \tag{6}$$

To briefly zoom out and provide context for the benefits of the PV-ES-CS, the EV load demand met by the system $D_{\mathrm{sys}}(h)$ will have a marginal cost of zero, while the marginal cost of $D_{\mathrm{grid}}(h)$ will be the electricity price in hour P_{grid}. This is the bridge between the technical and economic models, and the purpose of all of the equations thus far has been to facilitate solutions for $D_{\mathrm{sys}}(h)$ and $D_{\mathrm{grid}}(h)$. The following section delves into the economic side of the system modeling.

3.3. System economic model

The economic model of the proposed system consists of the investment and maintenance costs of the components, component degradation, and residual and replacement value.

3.3.1. Component costs

Investment cost for the solar PV (IC_{PV}) consists of cost of the PV and inverter modules, installation and commissioning cost, peripherals, and vendor markup, whereas the ES is just the battery. The PV and ES components have separate investment costs, IC_{PV} for the PV module and IC_{ES} for the battery. Total system investment cost is therefore expressed by Eq. (7).

$$IC_{\mathrm{sys}} = IC_{\mathrm{PV}} + IC_{\mathrm{ES}} \tag{7}$$

The investment cost is repaid in annual payments (AP), which are calculated by multiplying the initial investment by the Capital Recovery Factor (CRF). The CRF is a financial formula used to calculate the AP required to recover the initial capital investment over a specified period, typically with interest. The formula for calculating the CRF and AP are in Eqs. (8) and (9).

$$CRF = \frac{\rho(1+\rho)^{\mathrm{T}}}{(1+\rho)^{\mathrm{T}} - 1} \tag{8}$$

where ρ = interest rate per period and T = number of periods over which the capital investment is to be recovered. T is dictated by the lifetime of the PV module. For the battery, which may come to the end of its life before T periods, subsequent repurchases are amortized over the remaining lifetime of the overall project.

$$AP = CRF \times IC_{\mathrm{sys}} \tag{9}$$

Each component bears a maintenance cost in each time period t, (MC_{t}). The cost is constant each year but scales with inflation. The total maintenance cost of the system $MC_{\mathrm{sys}}(h)$ is expressed in Eq. (10).

$$MC_{\mathrm{sys}}^{\mathrm{t}} = (MC_{\mathrm{PV}}^{\mathrm{t}} + MC_{\mathrm{ES}}^{\mathrm{t}}) \times (1+\pi)^{\mathrm{t}} \tag{10}$$

where π is the inflation rate in time t.

3.3.2. Component degradation

PV system performance will decrease over time due to oxidation, temperature, thermal stresses, weather influences, interconnection degradation, and mechanical factors. [50] conducted a statistical analysis of over 11,000 solar systems in 40 countries, and found solar systems degrade at a median rate of $\delta = 0.5 - 0.6\%$ per year. We adopt a degradation rate of $\delta^{PV} = 0.6\%$, meaning that PV output drops by 0.6% each year.

The battery is considered to be at end of life when it reaches 80% of its rated capacity. For a calendar lifetime of 20 years for the lithium-ion battery [51], the battery loses 1% of its usable capacity per year until the battery reaches end of life, at which point the battery system must be repurchased. In this investigation, calendar life is used instead of energy throughput to model degradation since the vehicles have predictable load profiles. While energy throughput can be a valuable supplemental metric to assess how efficiently the battery is being used on a day-to-day basis, calendar life provides a more practical measure for evaluating the performance and economic viability of a battery system in the context of an EV charging station. It ensures that the station remains reliable and cost-effective throughout its expected lifespan.

3.3.3. Residual and replacement value

Residual value RV is the estimated value of an asset at the end of its useful life. Here, it is expressed as a percentage of the initial investment cost [29,30]. Residual value is recuperated during the final year of the system's lifetime, and is therefore added to the last cash flow and subject to the relevant discount rate.

Replacement value RC^t is the estimated value of replacing an asset in time period t. RC for a given component is assumed to be equal to its initial investment cost plus the inflation that has occurred up to time t.

3.4. Net present value

The objective of the optimization is to maximize the net present value (NPV) of all cash flows related to the system over the system's lifetime. NPV is a financial metric used to determine the value of an investment or project by comparing the present value of its expected cash inflows with the present value of its cash outflows. It uses discount rate Γ to take into account the time value of money, which means that a dollar received in the future is worth less than a dollar received today. A positive NPV indicates that the project is expected to generate more value than the initial investment, making it potentially desirable, while a negative NPV suggests that the investment may not be economically viable.

NPV ($) is calculated following Eq. (11), where T is the number of periods in the lifespan of the project and RV is the residual value during the final year of the system's life, which is added to the cash flow in the final period.

$$NPV = \sum_{t=1}^{T-1} \frac{NCF^t}{(1+\Gamma)^t} + \frac{NCF^T + RV}{(1+\Gamma)^T} \tag{11}$$

To calculate Net Cash Flow in a time period(NCF^t), we subtract annual capital payments AP^t_{sys}, maintenance cost MC^t_{sys}, and replacement cost RC^t_{sys} from savings in marginal energy costs due to the PV-ES-CS system ES^t (Eq. (12)).

$$NCF^t = ES^t - MC^t_{sys} - RC^t_{sys} - AP^t_{sys} \tag{12}$$

Energy savings ($) are defined as the difference between the energy cost at the charging station in the base case *without* the system in place EC^t, and the energy cost at the charging station in the base case *with* the system in place EC^t_{sys} (Eq. (13)).

$$ES^t = EC^t - EC^t_{sys} \tag{13}$$

EC^t_{base} is the total cost of electricity from the grid in time period t. As expressed in Eq. (14), it is the sum of all energy drawn from the grid in the time period D^{grid}_h multiplied by the energy tariffs charged for that hour P^{grid}_h. EC^{base}_t represents the energy cost with no solar resource available, and EC^{sys}_t represents the energy cost with the PV-ES-CS in place.

$$EC^t = \sum_{h=1}^{H} D_{grid}(h) \times P_{grid}(h) \times (1+\pi)^t \tag{14}$$

where H is the number of hours in time period t.

3.5. Value of resiliency

The value of resiliency (VoR) represents the operational savings that the PV-ES-CS system provides during unplanned grid constraint events. This value is derived by quantifying the operational savings associated with avoiding the kWh loss due to load shedding (kWh_{LS}), which the PV-ES system helps mitigate.

Under the assumption that fleet operators will deploy ICE vehicles to cover trips that cannot be fulfilled by EVs, the value of kWh_{LS} is calculated as the difference between the operational costs of an EV and an equivalent ICE vehicle. The operational cost of an EV for a trip is the price the electricity it uses to cover the trip's distance, while the operational cost of an ICE vehicle is determined by the fuel cost required to travel the same distance that kWh_{LS} would have enabled for the EV. This cost can be expressed as the product of the fuel consumption rate ($\frac{L}{km}$) and the fuel price ($\frac{\$}{L}$) for the distance that could have been covered by the EV ($kWh_{LS} \times \frac{km}{kWh}$).

Therefore, the value of resiliency is the additional cost incurred by serving the operational demand with an ICE vehicle as opposed to an EV. This can be mathematically represented by Eq. (15):

$$VoR^t = kWh^t_{LS} \times \left(\frac{km}{kWh} \times \frac{L}{km} \times \frac{\$}{L} - EC^t\right) \tag{15}$$

In the optimization problem, the VoR is added to the NPV of the system whenever the system provides electricity to vehicles during an unplanned load shedding event.

The assumption that ICE vehicles will cover the operational responsibilities missed by EVs during load shedding is justified by several considerations. Firstly, the transition from ICE to EV fleets is gradual, meaning many fleets will continue to operate ICE vehicles for some time. Secondly, even after replacing ICE vehicles with EVs, fleets will retain some ICE vehicles for operational flexibility. Thirdly, load shedding is a well-known challenge, prompting fleet owners to anticipate such events and develop contingency plans to maintain uninterrupted operations. These considerations collectively imply that fleet owners are cognizant of the potential for load shedding and will take proactive measures to ensure operational continuity during such interruptions.

3.6. Economic evaluation

The levelized cost of electricity (LCOE) is a classical metric used to understand how expensive the electricity from a given generation asset is over its lifetime. It expresses the total cost of an electricity supply asset per unit of electricity it provides over its lifespan. To estimate LCOE, net present cost of the investment is divided by the quantity of electricity it serves:

$$LCOE = \frac{\sum_{t=1}^{T} \frac{AP^t_{sys} + MC^t_{sys} + RC^t_{sys} - RV^t_{sys}}{(1+\Gamma)^t}}{\sum_{t=1}^{T} \frac{D^t_{sys}}{(1+\Gamma)^t}} \tag{16}$$

LCOE is most useful when comparing two investments, to determine which one will provide cheaper energy over its lifespan, while taking into account capital costs. In this investigation, the PV-ES-CS is being assessed against a charging station with no PV-ES-CS, rather than another investment. Thus, the comparison of LCOE versus the average cost of energy without the system is not an apples-to-apples comparison. The former accounts for the full lifecycle costs including maintenance and investment, while the latter reflects the marginal cost of producing electricity at that moment. In reality, during times when the PV-ES-CS does not cover all of EV load, the grid supplies the net load at the going tariff, which would affect the overall cost of electricity of the PV-ES-CS. Consequently we employ a normalized cost of electricity (COE) as a fairer indicator of economic performance:

$$COE = \frac{LCOE \times \sum_{t=1}^{T} \frac{D^t_{sys}}{(1+\Gamma)^t} + \sum_{t=1}^{T} \sum_{h=1}^{H} \frac{(P_{grid}(h) \times D^t_{grid}(h))}{(1+\Gamma)^t}}{\sum_{t=1}^{T} \frac{D^t_{load}}{(1+\Gamma)^t}} \tag{17}$$

which simplifies to

$$COE = \frac{\sum_{t=1}^{T} \frac{AP^t_{sys} + MC^t_{sys} + RC^t_{sys} - RV^t_{sys} + C^t_{grid}}{(1+\Gamma)^t}}{\sum_{t=1}^{T} \frac{D^t_{load}}{(1+\Gamma)^t}}, \tag{18}$$

where $C^t_{grid} = \sum_{h=1}^{H} (P_{grid}(h) \times D^t_{grid}(h))$.

(a) Location of case study within Johannesburg [52].

(b) Satellite image of Dobsonville Mall taxi rank (terminus) [53].

Fig. 4. Case study location [52,53].

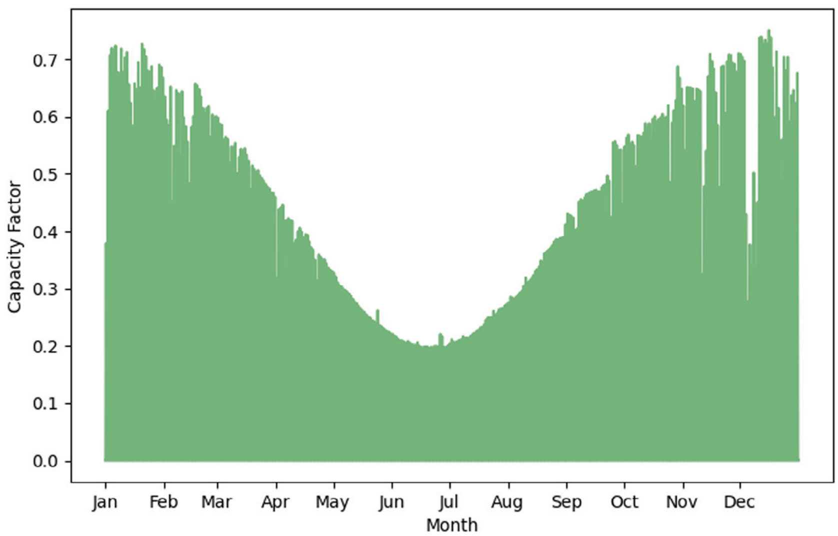


Fig. 5. Annual solar profile at the selected case study location, the Dobsonville Mall Taxi Rank in Dobsonville, Greater Soweto, Johannesburg.

Table 2
Geographical coordinates and elevation of selected case study location.

Province	City	Latitude (°N)	Longitude (°E)	Elevation (m)
Gauteng	Dobsonville	−26.21	27.87	1650 m

4. Case study

In this section, the technical specifications of the system components and relevant economic indicators are presented in the context of a case study. The estimated project lifetime T is 25 years. We adopt a time period t of one year, so $H = 8760$.

4.1. Study area

A minibus taxi fleet operating out of the Dobsonville Mall taxi rank (terminus) is selected as a research object. Dobsonville is a township in greater Soweto, Johannesburg, South Africa. The location is presented in Table 2 and Fig. 4.

4.2. Solar PV output profile

The simulation in renewables.ninja is set at Dobsonville Mall taxi rank at −26.2139°N, 27.8705E°, with system efficiency loss set at 10%. The panel tilt is set at 30 degrees facing North, which is suitable for South Africa [54]. Fig. 5 shows the capacity factor profile.

As expected, the capacity is highest in the summer months (Nov–Feb) aside from a slight dip from Dec. 5–Dec. 9, and lowest in the winter months (Jun–Aug).

4.3. Electricity pricing

The electricity price schedule for the first year of the optimization simulation is given in Table 3. These prices are based on the City of Johannesburg three-part time-of-use tariff rates for medium voltage users [55], and serve as a proxy for electricity prices for businesses in South Africa (prices in other large cities such as Cape Town are similar [56]). Prices in subsequent years are subject to inflation.

On weekdays, the hours for off-peak energy tariff are 22:00–05:00. The hours for standard energy tariff are 6:00, 10:00–17:00, and 20:00–21:00. The hours for peak energy tariff are 07:00–09:00 and 18:00–19:00. All hours on weekends are charged the off-peak tariff [56].

4.4. Load shedding schedule

To account for the grid constraints due to load shedding, we simulate load shedding schedules from historical load shedding data from Eskom [57], who control a monopoly on electricity supply in South Africa.

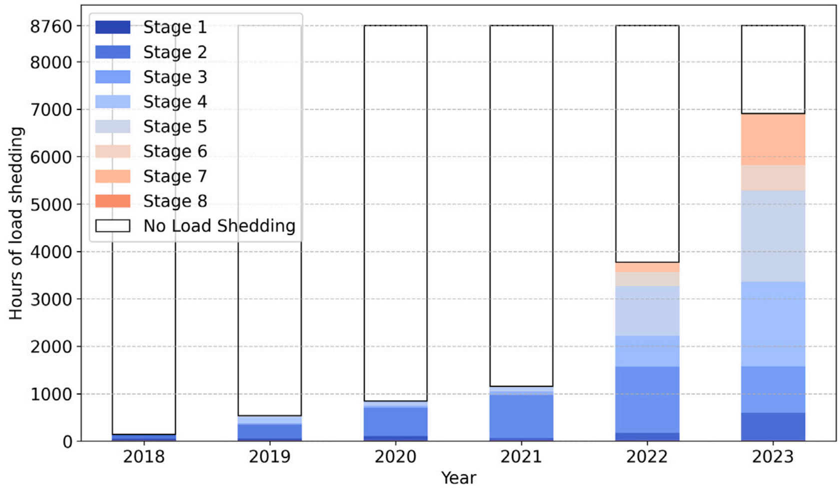


Fig. 6. Trend of hours spent in each load shedding stage over the past several years [57].

Table 3
Eskom seasonal time of use electricity tariffs for large users medium voltage [55][a].

Month	High/Low	Off-peak ($/kWh)	Standard ($/kWh)	High ($/kWh)
Jan	L	0.08	0.11	0.15
Feb	L	0.08	0.11	0.15
Mar	L	0.08	0.11	0.15
Apr	L	0.08	0.11	0.15
May	L	0.08	0.11	0.15
Jun	H	0.09	0.13	0.34
Jul	H	0.09	0.13	0.34
Aug	H	0.09	0.13	0.34
Sep	L	0.08	0.11	0.15
Oct	L	0.08	0.11	0.15
Nov	L	0.08	0.11	0.15
Dec	L	0.08	0.11	0.15

[a] Converted from South African Rand to US Dollar using a conversion rate of R0.054 to 1 USD, the average conversion rate in 2023 as of August, 2023.

Table 4
Sample Stage 2 and Stage 4 load shedding day schedules, with the starting and ending hour of each event. Vehicles cannot charge while load shedding is active.

Daily schedule ID		First event		Second event		Third event	
		Start	End	Start	End	Start	End
Stage 4	ST4-D0	0:00	2:00	8:00	10:00	16:00	18:00
	ST4-D1	2:00	4:00	10:00	12:00	18:00	20:00
	ST4-D2	4:00	6:00	12:00	14:00	20:00	22:00
	ST4-D3	6:00	8:00	14:00	16:00	22:00	0:00
Stage 2	ST2-D0	0:00	2:00	–	–	–	–
	ST2-D1	0:00	2:00	8:00	10:00	–	–
	ST2-D2	8:00	10:00	16:00	18:00	–	–
	ST2-D3	16:00	18:00	–	–	–	–
	ST2-D4	22:00	24:00	–	–	–	–
	ST2-D5	6:00	8:00	–	–	–	–
	ST2-D6	6:00	8:00	14:00	16:00	–	–

In South Africa, Eskom implements load shedding in stages from Stage 1 to Stage 8, with higher stages implying increased severity of shedding. For example, in Stage 1, Eskom will implement either three two-hour power outages over four days or three four-hour power outages over eight days. Stage 8 consists of power cuts up to six times a day, with the power off for up to 12 h daily. The definitions of all eight load shedding stages are available in Table A.1 in Appendix.

An analysis of Eskom's historical data indicate that, on a national level, there has been a trend of increasing load shedding for several years [57]. Fig. 6 shows the trends in number of load shedding hours in each month of the year over the past several years (values available in Appendix in Tables A.2 and A.3 for stages and months respectively). From 2018 to 2023, the total number of hours of load shedding in the year has increased from 141 to 6908, and the median hour moved from not being in load shedding, to being in Stage 3.

There are mixed reports on how the load shedding situation in South Africa will evolve in the coming years, with some reports portending a bleak outlook and increased energy supply shortfalls for the foreseeable future [58,59], while other reports optimistically predict an explosion in private sector power generation over the next several years [60,61]. Given the root causes of the load shedding crisis – a combination of Eskom's management and leadership issues, ageing energy infrastructure, and a complex regulatory landscape – and the requisite solutions – which include upgraded or new infrastructure, distributed renewables, energy efficiency improvements, and market-related energy pricing [62] – it is highly unlikely that load shedding will resolve soon.

The manner in which load shedding unfolds will depend on numerous external factors. In light of the reality of the situation, it is reasonable for fleet owners to expect to be subject to a fair degree of load shedding for some time even if one expects the situation to improve in the future. For the case study, we simulate both a conservative and an optimistic scenario. Based on historical trends, we simulate a conservative scenario that is characterized by an average of Stage 4 load shedding for the lifespan of the PV-ES-CS project — slightly worse than the current state of affairs as of 2023. For the optimistic scenario, we simulate an average of Stage 2 load shedding for the lifespan of the project. The conservative and optimistic scenarios are referred to as ST4 and ST2 respectively in the results section. To simulate Stage 4 and Stage 2 load shedding, we follow the definitions provided by Eskom in Appendix in Table A.1.

Simulating a week of load shedding requires two steps. The first step is to generate a set of daily load shedding schedules that, when stitched together in certain patterns, fulfill the definition of the given stage of load shedding. These daily schedules are presented in Table 4. The second step is to actually stitch these daily schedules together in a weekly pattern that meets the definition of the desired stage of load shedding.

The daily schedules are then stitched together in a specific order to create a weekly load shedding schedule (starting from Monday):

Weekly load shedding schedules (using daily schedule IDs from Table 4)

- **Stage 4:** ST4-D0, ST4-D1, ST4-D2, ST4-D3, ST4-D0, ST4-D1, ST4-D2
- **Stage 2:** ST2-D0, ST2-D1, ST2-D2, ST2-D3, ST2-D4, ST2-D5, ST2-D6

Table 5
Input parameters for scheduling EV fleet.

Parameter	Value	Source
Vehicle battery capacity	70 kWh	[16]
Energy consumption	0.55 kWh/km	[16]
Charger rating	22 kW	
Charging outlets	1 per vehicle	

This schedule indicates that the Stage 4 load shedding schedule starts with daily schedule 0 (ST4-D0) on Monday, which according to Table 4 has load shedding events from 00:00–02:00, 08:00–10:00, and 16:00–18:00. On Tuesday, S4T-D2 happens, meaning load shedding events occur from 02:00–04:00, 10:00–12:00, and 18:00–20:00. And so on for the rest of the week. Similarly, the Stage2 schedule, starts with ST-D0 on Monday, and so on.

As explained in Section 3.1.2, load shedding is sometimes planned and sometimes unplanned. These two circumstances have differing modeling requirements: as fleet owners can schedule their EVs to charge around load shedding hours when the load shedding is planned, but not when it is unplanned, therefore losing the ability to recharge their vehicles and serve operational demand. Based on Eskom's Weekly Unplanned Outages data portal [63] versus their total historical load shedding profile [57], we assume that 2/3 of outages are planned, and 1/3 outages ore unplanned.

4.5. EV charging load profiles

EV charging load profiles are simulated using real-world origin–destination data from a fleet of minibus taxis at the Dobsonville Mall taxi rank. With electric paratransit currently unavailable in the region, this paper employs state-of-the-art tools to generate operational schedules for such vehicles from the selected taxi rank. As real electric paratransit services become accessible, the model and insights can be refined through empirical data feedback loops.

To create these profiles, we input operational data from traditional ICE vehicles into an electric paratransit operations planning tool developed by [42]. This tool leverages ICE vehicle schedules to devise feasible schedules adaptable to electric vehicles (EVs) with specific characteristics. One notable advantage is the tool's ability to enforce zero lateness, ensuring punctuality for all passengers. The vehicle parameters used for generating the schedule are listed in Table 5.

To model the PV-ES-CS at varying levels of fleet EV penetration, we simulate load profiles for varying levels of EV penetration into the fleet: specifically, 25%, 50%, 75%, and 100% EV penetration. These are referred to as "low", "medium", "high", and "full" penetration respectively. In all scenarios, zero lateness for passengers is enforced to ensure that the resulting operational schedule is feasible. To facilitate this, we assume there is 1 charger per vehicle, so that a charger will always be available for the vehicle at the station when needed.

The weekly load profiles for each level of EV penetration within each load shedding schedule scenario are visualized in Fig. 7. The three scenarios are:

1. No load shedding (No LS): Base case (this scenario serves as a reference point).
2. Stage 2 load shedding (ST2): Optimistic scenario.
3. Stage 4 load shedding (ST4): Conservative scenario.

In the visualization, the gray bars represent times when load shedding restricts vehicle charging activities. A collective observation from these energy demand profiles reveals that the EV fleet tends to require more energy on the weekends than the weekdays, with daily peak load occurring mainly in the evenings, and weekly peak load occurring on Saturday. These trends hold true for most urban minibus taxi fleets in the Global South [11], supporting the external validity of the results.

Table 6 provides summary statistics regarding the different fleets featured in Fig. 7. The "per vehicle load" column indicates per vehicle load peaks somewhere between 50% and 75% EV penetration, and then declines from 75% to 100% EV penetration. This statistic is a manifestation of vehicle utilization rates, and shows that past a certain point of EV saturation in the fleet, each individual EV will be used less often.

It is clear from Fig. 7 that although peak load is high, there is room to spread the charging overnight, given the lack of charging that occurs in the early morning hours between midnight and 5:00am. This also means there is room to reduce the number of chargers, thus reducing charge point investment costs, which is not included in this paper. Future research can look into the peak shaving potential of feasible electric minibus taxi operational schedules that minimize the number of charge points or maximize solar utilization.

Lastly, the cost of electricity (COE) varies across the load shedding scenarios. This variation can be attributed to the adjustment of EV charging profiles induced by the load shedding schedules, which consequently impacts the time of use tariffs they incur.

4.5.1. Incremental fleet electrification scenarios

In addition to examining the low (25%), medium (50%), high (75%), and full (100%) fleet electrification scenarios as previously described in this section, we examine the viability and performance of the PV-ES-CS system under conditions of incremental fleet electrification. Incremental fleet electrification scenarios are defined by levels of fleet EV penetration increasing during the lifespan of the PV-ES-CS project.

We model two incremental fleet electrification scenarios: one fast (INC-F) and one slow (INC-S). The scenarios are outlined in Table 7. In the fast scenario, the fleet starts at 25% electrification, achieves 50% electrification in five years, takes another five years to reach 75%, and another five years to reach 100%, for a total of 15 years to full electrification. In the slow scenario, the fleet starts at 25% electrification, achieves 50% electrification in ten years, another eight years to 75%, and another four years to 100%, for a total of 22 years to full electrification.

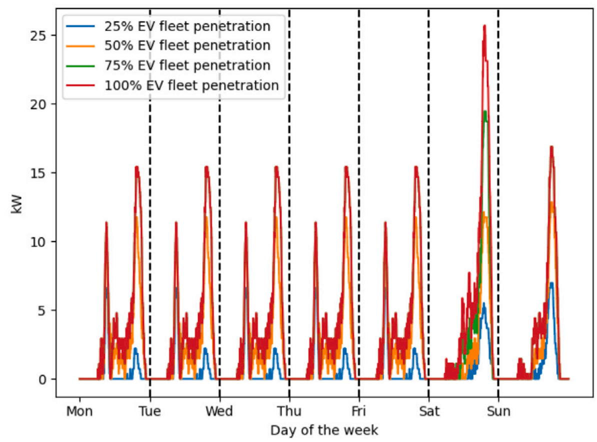
4.6. Trickle charging

By implementing the naive conventional rule/logic-based energy dispatch strategy this paper is assessing the system under a "worst case" usage scenario for the ES. We add a scenario featuring a basic trickle charging (TC) heuristic to showcase the advantage of marginally more optimal ES utilization. This underscores the potential for future research to explore how further optimization of the energy dispatch strategy can yield improved economic or technical outcomes.

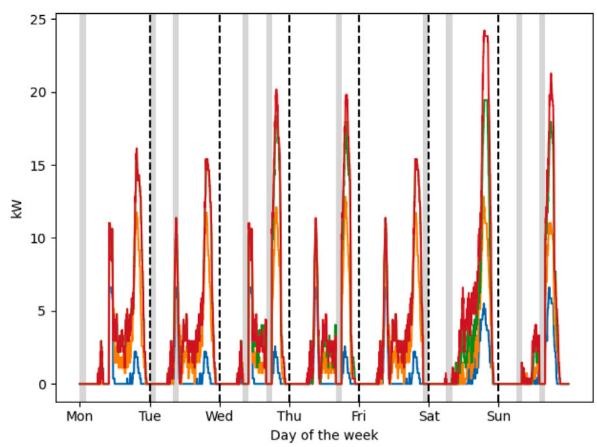
In the TC scenario, we allow the ES to charge at 2.2 kW from the grid during the night. Charging overnight ensures that there is positive economic outcome for the trickle charging, as it draws from the grid when electricity prices are cheapest and serves load during the morning hours when it is more expensive (refer to Section 4.3 for hourly pricing details).

4.7. System specifications

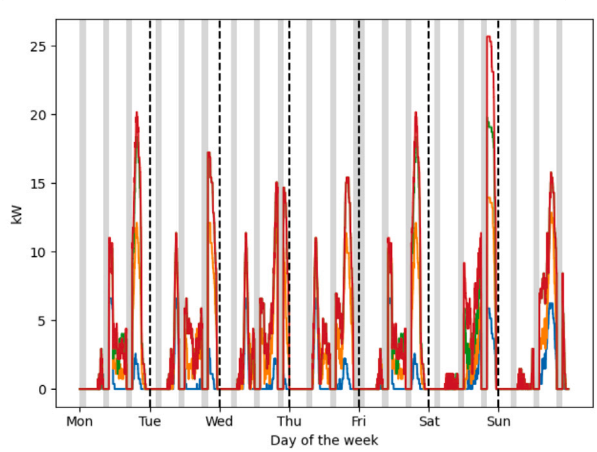
A summary of the technical specifications, relevant economic indicators, and energy market parameters that go into the techno-economic optimization model are given in Table 8.



(a) Weekly EV fleet load profile – No load shedding (No LS).



(b) Weekly EV fleet load profile – Stage 2 load shedding (ST2).



(c) Weekly EV fleet load profile – Stage 4 load shedding (ST4).

Fig. 7. Weekly charging load profiles at the Dobsonville taxi rank for varying levels of EV penetration and load shedding schedules (either no load shedding or stage 4). The gray shaded areas on the ST4 graph indicate times when load shedding is active and the EVs cannot charge. The dashed black lines demarcate midnight between each day.

5. Simulation, results and discussion

In this section, the optimal results for PV-ES-CS system sizing are the following scenarios: no load shedding (No LS), Stage 4 load shedding (LS-ST4), Stage 2 load shedding (LS-ST2), and all of these scenarios with trickle charging included (No LS + TC, LS-ST4 + TC, and LS-ST2 + TC).

Each of these scenarios is evaluated at the four considered levels of fleet EV penetration: low (25%), medium (50%), high (75%), and full (100%), as well as in the two incremental electrification cases INC-F(ast) and INC-S(low). The analysis is first conducted exactly as described for the case study in Section 4, and then repeated with slight augmentations in Sections 5.2.1 and 5.2.2: In Section 5.2.1, the ratio of planned:unplanned grid constraint events is shifted from 1:2 to 2:1 to investigate varying mixes of planned and unplanned load shedding

Table 6
Summary of fleet mobility, power, and economic characteristics under the different levels of EV penetration load shedding schedule scenarios. The load values are calculated on a weekly basis.

	EV. Pen	# EVs	Total (Per vehicle) load (kWh)	Peak load (kW)	Peak hourly average kW	Cost of electricity ($/kWh)
No LS	25%	19	6522 (343)	420	7.0	0.119
	50%	38	22,756 (599)	768	12.8	0.118
	75%	57	33,745 (592)	1164	19.4	0.115
	100%	76	35,637 (469)	1542	25.7	0.113
ST2	25%	19	6271 (330)	396	6.6	0.115
	50%	38	21,233 (559)	768	12.8	0.118
	75%	57	32,346 (567)	1164	19.4	0.115
	100%	76	35,583 (468)	1452	24.2	0.112
ST4	25%	19	6465 (340)	396	6.6	0.113
	50%	38	21,871 (576)	834	13.9	0.112
	75%	57	32,724 (574)	1188	19.8	0.110
	100%	76	35,128 (462)	1542	25.7	0.110

Table 7
The year in which each level of EV fleet penetration is reached during each of the two incremental fleet electrification scenarios (INC-F(ast) and INC-S(low)).

Scenario	Level of EV fleet penetration			
	25%	50%	75%	100%
INC-F (year)	0	3	7	10
INC-S (year)	0	10	18	22

Table 8
Summary of the PV-ES-CS capacity optimization model input parameters.

Specification	Value	Source
PV module		
Panel cost	$500/kW	[64]
O&M cost	$25/kW/year	[65]
Inverter cost	$140/kW	[66]
Lifetime	25 years	[64]
System efficiency	90%	[67]
Degradation rate	0.6%/year	[50]
Energy storage		
Pack cost	$300/kWh	[66,68]
O&M cost	10/kWh-year	[68]
Roundtrip efficiency	95%	[51]
Depth of discharge	90%	[51]
Lifetime	20 years	[51]
Degradation rate	1%/year	[51]
C-rating	0.5 C	
Economic indicators		
Inflation rate	7.04%/year	[69]
Discount rate	5%/year	[43]
Interest rate	13.75%/year	[70,71]
Residual value	10% investment cost	[29]
Vehicle parameters		
Energy consumption	0.55 kWh/km	[16]
Fuel consumption	13.8 L/100 km	[72]
Diesel fuel cost	$1.05/L	[73]

Table 9
Cost of electricity (COE) adjusted for inflation without the PV-ES system and with the PV-ES system over the lifetime of the project, and the percentage change in COE from the former to the latter.

Scenario	EV Pen	COE without [with] system ($/kWh)	Change (%)
No LS	25%	0.1191 [–]	–
	50%	0.1181 [0.1166]	−1.27
	75%	0.1152 [0.1124]	−2.43
	100%	0.1132 [0.1105]	−2.39
	INC-S	0.1148 [0.1146]	−0.17
	INC-F	0.1140 [0.1137]	−0.26
No LS + TC	25%	0.1191 [0.1175]	−1.33
	50%	0.1181 [0.1165]	−1.35
	75%	0.1152 [0.1122]	−2.60
	100%	0.1132 [0.1103]	−2.57
	INC-S	0.1148 [0.1144]	−0.35
	INC-F	0.1140 [0.1134]	−0.53
ST4	25%	0.1132 [–]	–
	50%	0.1115 [0.1103]	−1.05
	75%	0.1102 [0.1078]	−2.17
	100%	0.1090 [0.1065]	−2.25
	INC-S	0.1108 [0.1100]	−0.68
	INC-F	0.1104 [0.1083]	−1.56
ST4 + TC	25%	0.1132 [0.1120]	−1.05
	50%	0.1115 [0.1100]	−1.34
	75%	0.1102 [0.1076]	−2.34
	100%	0.1090 [0.1064]	−2.40
	INC-S	0.1108 [0.1096]	−1.11
	INC-F	0.1104 [0.1079]	−1.90
ST2	25%	0.1184 [–]	–
	50%	0.1171 [0.1156]	−1.27
	75%	0.1145 [0.1118]	−2.38
	100%	0.1132 [0.1105]	−2.39
	INC-S	0.1144 [0.1143]	−0.07
	INC-F	0.1137 [0.1134]	−0.30
ST2 + TC	25%	0.1184 [0.1168]	−1.33
	50%	0.1171 [0.1155]	−1.34
	75%	0.1145 [0.1116]	−2.54
	100%	0.1132 [0.1103]	−2.56
	INC-S	0.1144 [0.1140]	−0.33
	INC-F	0.1137 [0.1131]	−0.50

events. In Section 5.2.2, a feed-in-tariff is introduced to investigate the effects of a financial incentive for solar PV panels. The key insights which emerge from the results are discussed in detail in Section 5.3.

5.1. Main results

The primary techno-economic characteristics for each scenario are presented side-by-side in Fig. 8, and the cost of electricity (COE) for each scenario with and without the system is presented in Table 9.

Summary: System feasibility

Overall, Fig. 8 show that the PV-ES-CS system is economically feasible (i.e. positive NPV) in all scenarios with at least 50% EV penetration, with NPVs ranging from $2427 in LS-ST4/Inc-S to $52,832 in No LS + TC/100%. The system is still feasible but smaller and less economically beneficial in the scenarios with incremental fleet electrification, because the majority of the savings accrue in the future, when savings are discounted.

A striking feature of the figure is how small the increase in system size and NPV between 75% and 100% is compared to the increases between 25%, 50%, and 75%. This indicates there are diminishing returns for system performance with increasing EV fleet saturation. This is likely due to the decrease in per-vehicle load that occurs at some point when the fleet becomes saturated with EVs. To test this hypothesis, fleets at 58% and 66 (the tertile values between 50% and 75%) were added to the simulation. The results with the 58% and 65% cases included are visualized in Fig. 9. Summary characteristics of the

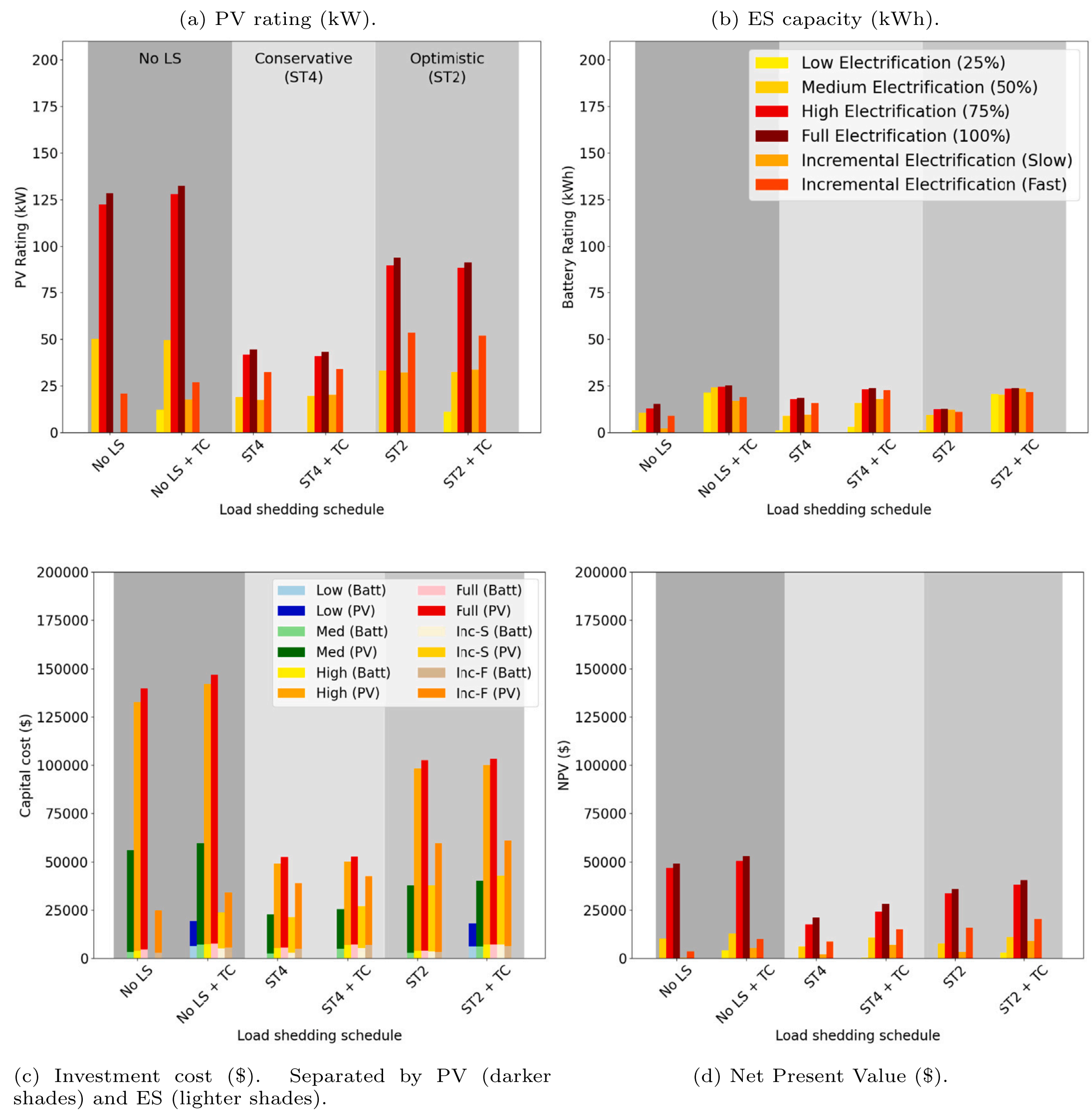


Fig. 8. Techno-economic characteristics of the optimally configured PV-ES-CS in each scenario. For each scenario, low (25%), medium (50%), high (75%), and full (100%) fleet EV penetration are assessed. Scenarios are color grouped by the no load shedding, optimistic load shedding outlook, and conservative load shedding outlooks.

58% and 65% vehicle fleets are added in Table 10 to highlight the per-vehicle load trends.

As hypothesized, the system size and performance increase sharply with per-vehicle load (a proxy for vehicle utilization). The No LS and ST2 scenarios see similarly large increases in per-vehicle load up to 66% penetration, after which they level off. However, ST4 is slightly different in that the system size does not experience the same sharp increase from 50% to 58% EV fleet penetration. This is likely due to the smaller increase in per-vehicle load (576 to 583, or 1.1%) between 50% and 58% EV fleet penetration as compared to what is seen in No LS and ST2 (7.3% and 4.1% respectively). The effects of this slightly different trend are borne out in Fig. 9, which shows a less steep gradient between system sizing results for each case in the ST4 and ST4 + TC scenarios.

5.2. Sensitivity of results to real-world uncertainty

5.2.1. Greater proportion of unplanned load shedding events

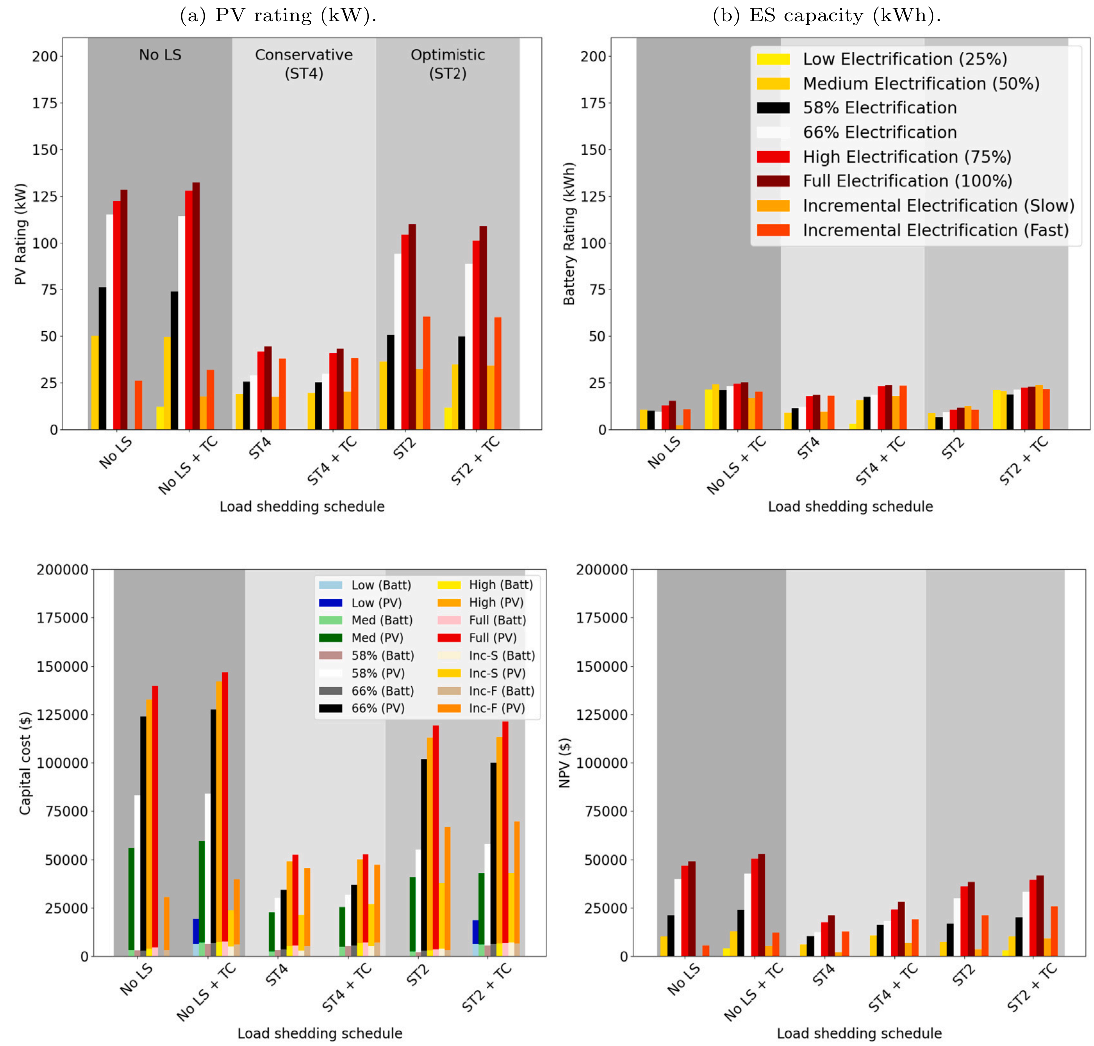
The main results are gathered with ratio of planned to unplanned load shedding events of 2:1. This is based on Eskom historical data (see Section 4.4). However, it is possible that this may change or be different in other areas, and the value of resiliency that the system can provide may mean that the results are sensitive to this ratio. Accordingly, we run the results with a ratio of planned to unplanned load shedding events of 1:2.

The results are available in Fig. 10. There is only a slight increase in system techno-economic performance, with the overall system sizes and NPVs increasing slightly, by about 5%. These increases is a direct result of the value of resiliency provided by the system during unplanned outage events.

5.2.2. Feed-in tariff

The environmental and cost-saving benefits of solar PV and energy storage technologies combined with their high capital cost make them a ripe target for government subsidies and incentives. One common example of a financial incentive for solar PV panels, available in many countries around the world, is a feed-in-tariff. Feed-in-tariffs allow PV owners to sell excess electricity back to the grid.

Fig. 11 shows the results of the techno-economic process when the scenarios are run with a feed-in-tariff of $0.05/kWh that activates ten years after the implementation of the project. The selection of a ten-year time frame for this case study is based on South Africa's political



(c) Investment cost ($). Separated by PV (darker shades) and ES (lighter shades).

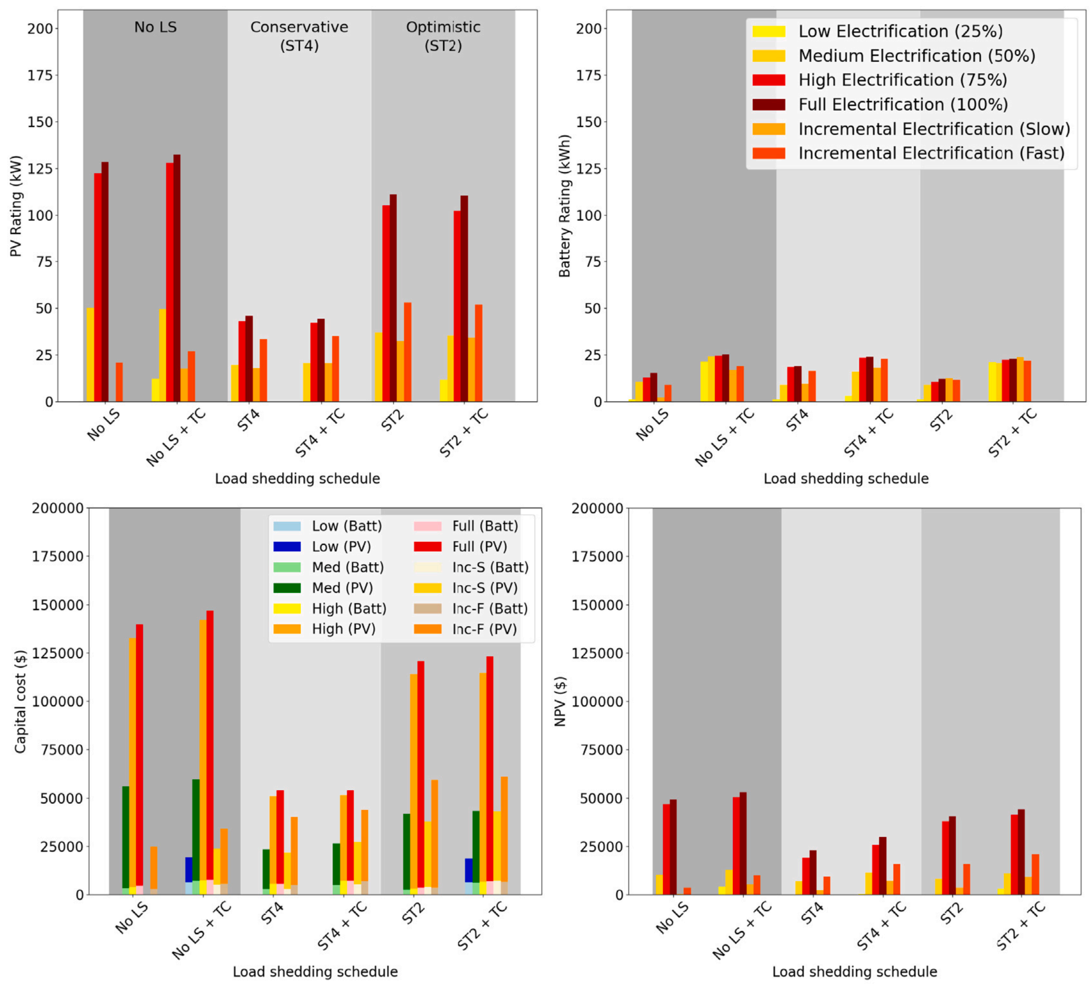
(d) Net Present Value ($).

Fig. 9. Techno-economic characteristics of the optimally configured PV-ES-CS in each scenario. Same as Fig. 8, but now including 58% and 66% EV fleet penetration scenarios (black and white respectively).

Table 10
Summary of fleet mobility, power, and economic characteristics under the different levels of EV penetration load shedding schedule scenarios. Same as Table 6 with 58% and 65% scenarios now included in red to highlight the effects of per vehicle load.

	EV. Pen	# EVs	Total (Per vehicle) load (kWh)	Peak load (kW)	Peak hourly average kW	Cost of electricity ($/kWh)
No LS	25%	19	6522 (343)	420	7.0	0.119
	50%	38	22,756 (599)	768	12.8	0.118
	58%	44	28,273 (643)	900	15.0	0.116
	66%	50	32,932 (658)	1014	16.9	0.115
	75%	57	33,745 (592)	1164	19.4	0.115
	100%	76	35,637 (469)	1542	25.7	0.113
ST2	25%	19	6271 (330)	396	6.6	0.115
	50%	38	21,233 (559)	768	12.8	0.118
	58%	44	25,623 (582)	900	15.0	0.116
	66%	50	30,022 (600)	990	16.5	0.116
	75%	57	32,346 (567)	1164	19.4	0.115
	100%	76	35,583 (468)	1452	24.2	0.112
ST4	25%	19	6465 (340)	396	6.6	0.113
	50%	38	21,871 (576)	834	13.9	0.112
	58%	44	25,643 (583)	966	16.1	0.111
	66%	50	29,732 (594)	1014	16.9	0.111
	75%	57	32,724 (574)	1188	19.8	0.110
	100%	76	35,128 (462)	1542	25.7	0.110

(a) PV rating (kW). (b) ES capacity (kWh).



(c) Investment cost ($). Separated by PV (darker shades) and ES (lighter shades). (d) Net Present Value ($).

Fig. 10. Same as Fig. 8 but with the ratio of planned to unplanned load shedding events adjusted from 2:1 to 1:2.

cycles, which operate on a five-year basis. It is presumed that this change will require at least two political cycles to take effect.

With the feed-in-tariff, system techno-economic performance increases but retains the same overall trends as the previous set of results. The PV and ES system sizes are an average of 57% and 10% greater across all scenarios, and the investment cost and NPV are an average of 50% and 78% greater.

5.3. Key insights

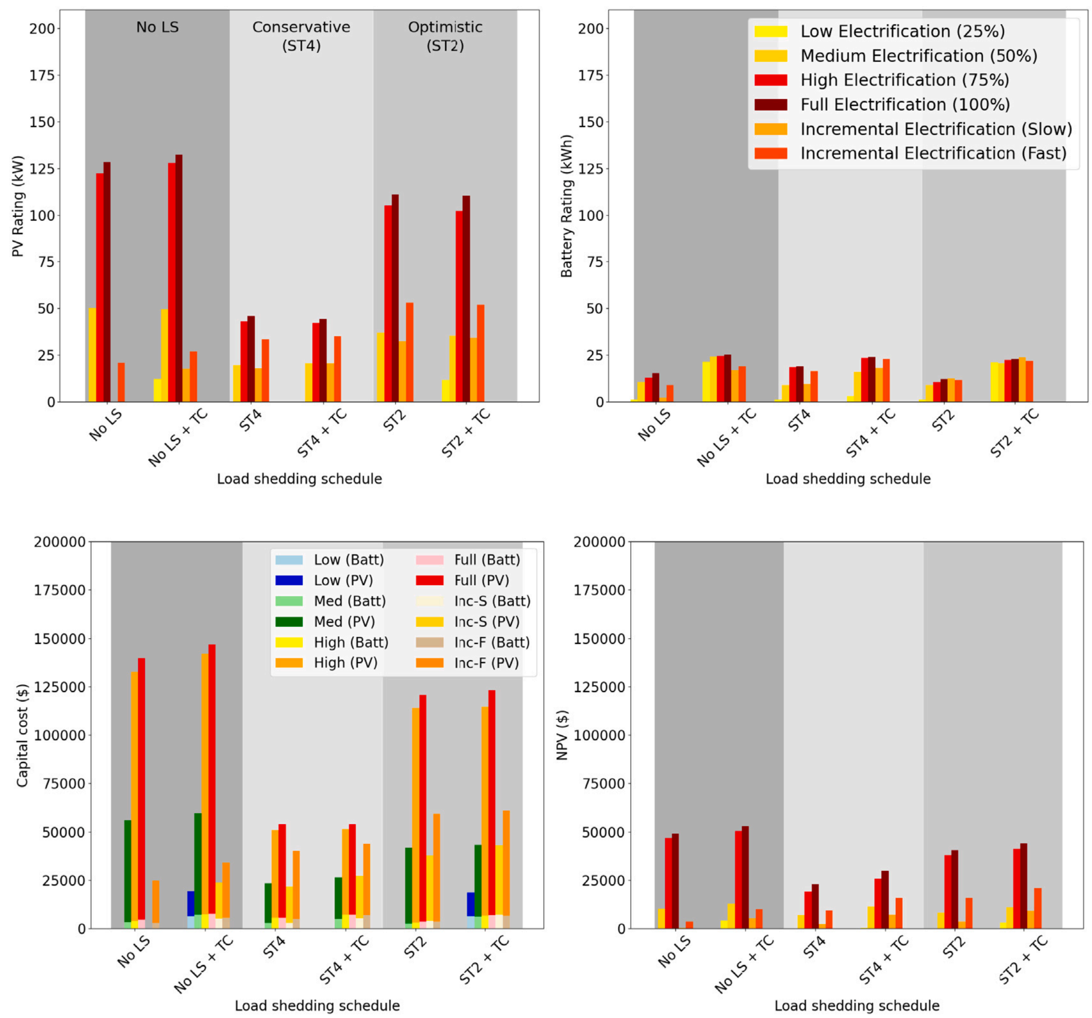
Key insight 1: Diminishing marginal returns

The first key insight from the results lies in the highly non-linear increase in PV system size and NPV as EV fleet penetration increases. In all scenarios, there is a large increase in system size and NPV from low to medium EV penetration and from medium to high EV penetration (dark yellow to light red bars), and a smaller jump from high to full (light red to dark red bars). On average across all scenarios, the increase in PV capacity, ES capacity, investment cost, and NPV between the 50% and 75% EV penetration scenarios are 145%, 37%, 133%, and 258% respectively. In contrast, the average increases in these characteristics are 4%, 5%, 5%, and 10% between 75% and 100%.

These diminishing returns are due to the drop-off in per-vehicle usage as the EVs saturate the fleet. Table 10 shows how per-vehicle load increases up to 66% EV fleet penetration before dropping. There are only two does where 50 EVs cannot cover all of the trips (Sat and Sun), and only one day (Saturday) where 57 EVs cannot cover all of the trips. Consequently, the disparity in energy demand in the 66%, 75% and 100% scenarios is mediated by only one or two days of the week, resulting in minimal differences in overall system utilization.

This trend has broader implications for other public transport fleets, particularly those with peak load demand occurring on weekends. Understanding the dynamics of EV fleet saturation and its impact on per-vehicle usage can inform strategic planning and resource allocation for these systems. By recognizing how the distribution of trips across different days influences overall energy demand, transportation authorities can optimize fleet management strategies to efficiently meet peak demands while maximizing the performance of PV-ES investments and minimizing vehicle costs.

Although system NPV does continue to increase slightly past the point of saturation since total load is still increasing, the benefits are negated if ICE vehicles are needed to cover operations during unplanned grid constraint scenarios. Simulations were run including an extra hiring cost of \$0.015/km for ICE vehicles in the 100% EV



(a) PV rating (kW).

(b) ES capacity (kWh).

(c) Investment cost ($). Broken down by PV (darker shades) and ES (lighter shades).

(d) Net Present Value ($).

Fig. 11. Same as Fig. 8 but with a feed-in-tariff implemented in year 10 onwards.

penetration scenarios, and it was found that this hiring cost entirely negated the benefits of the PV-ES-CS system in every scenario.

Key insight 1b: Sensitivity to incremental fleet electrification

Alongside the previous insight, it is evident that the returns to incremental fleet electrification are clearly inferior to when a certain level of fleet electrification is already established. This is true even if the incremental strategy ends up at a higher level of fleet EV penetration by the end of the PV-ES investment lifetime. Both the rapid and slow incremental fleet electrification scenarios under-perform when compared to the 50% fleet electrification scenario. The discrepancy arises due to the time value of money — savings realized earlier in the lifetime of the PV-ES system hold significantly greater worth. Therefore, the potential value of a PV-ES system installment is substantially higher when fleet electrification has already taken place. The insight for fleet owners is that premature investment in PV-ES systems is financially dangerous, and it may be sensible to delay investment as long as possible.

In summary, the diminishing marginal returns on system performance and the sensitivity to fleet size imply that, under grid and capital-constraints, fleet owners are likely achieve optimal financial outcomes with partial fleet electrification rather than full. Moreover, delaying investment in the PV-ES system until a substantial portion of their fleet is electrified proves advantageous.

Key insight 2: Sensitivity to load shedding frequency and forecasting

The second key insight lies in the sensitivity of system economic performance to grid constraints. Load shedding affects PV-ES system in two ways: (1) by necessitating charging schedule adjustments during planned events and (2) by offering resiliency during unplanned outages. Analysis shows that system NPV is greater in scenarios with less load shedding, implying that the negative effects of (1) (on PV-ES-CS system performance) outweigh the positive effects of (2).

The negative effect of (1) is visible in Table 9 – the COE without the PV-ES system is cheaper in ST4 than in No LS or ST2, belying how the shift in charging schedule around the planned load shedding events pushed charging into cheaper hours. Since the COE starts from a lower place, the economic potential of the PV-ES system (which provides energy at 0 marginal cost) is diminished. The sensitivity of results to the positive effect of (2) is explored in Section 5.2.1, where the proportion of planned to unplanned load shedding events was adjusted from 2:1

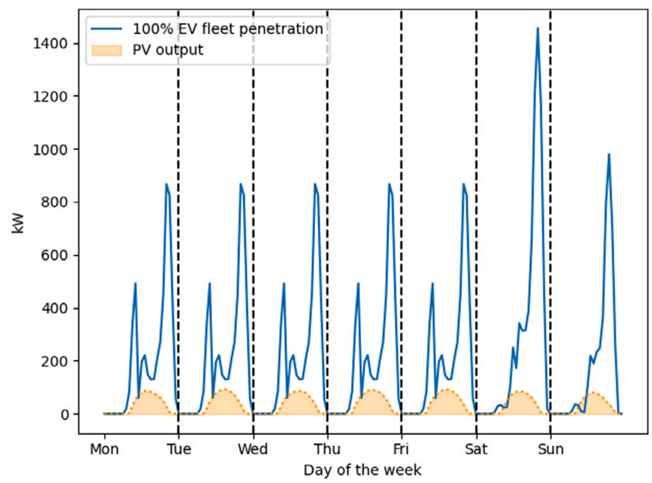


Fig. 12. Weekly charging load profile for the 100% EV fleet (No LS) with example week of solar output overlaid to exemplify when solar resource is available compared to when energy is demanded.

to 1:2. Results were found to change minimally, with system size and NPV in the load shedding scenarios increasing on the order of 5%.[1]

In regions experiencing frequent grid constraint events, fleet owners stand to benefit significantly from the methodologies proposed herein for assessing and planning PV-ES investments. This underscores the practical relevance of the findings in guiding decision-making processes towards more resilient and economically viable renewable energy solutions for fleet operations.

Key insight 3: Effects of intelligent energy storage management

The third key insight pertains to the impact of trickle charging (TC) on the feasibility and performance of the system. TC demonstrates its most significant impact at low levels of EV penetration, where its integration facilitates the feasibility of the PV-ES system. Beyond 25% penetration, the incremental benefits of TC on system size and economic performance become marginal.

The stability in the effect of TC across cases can be attributed to the existence of both a morning and an evening peak load at all levels of EV penetration (see Fig. 7). Since there is a dearth of solar resource during the evening peak load (depicted in Fig. 12), the battery will always enter the night time depleted. The battery will then fill up overnight at the cheap nightly trickle charging rate and then serve to partially offset the morning peak.

This benefit is enough to knock the 25% electrified fleet into feasibility in No LS and ST2, but not enough to more than marginally increase system size and economic performance at higher levels of EV fleet penetration. For example, the change in COE induced by the system in ST4, 50% is −1.05, while it is −1.34 in the ST4 + TC, 50%. Fig. 13 visualizes the impact of TC on COE in each EV fleet penetration scenario. Since the contribution from TC is relatively constant across levels of EV penetration as described above, the impact of TC is diminished in higher EV penetration cases because of the greater overall advantages of the system.

The insight is relevant to fleets which expect morning and evening peak, which is a commonality among commercial fleets. For such fleets, the results indicate that the improved usage of the ES component will be most impactful at lower levels of EV fleet penetration. Augmentations such as trickle charging may be able to render the overall PV-ES-CS system feasible when it otherwise would not be. Future research may explore whether a profit maximizing battery dispatch strategy or daytime trickle charging could lead to better economic outcomes for the same system size at higher levels of EV penetration.

Limitations and generalizability

The geographic specificity of this case study means that the system sizing results, investment costs, and economic returns detailed in Section 5 are specific to the paratransit fleet operating out of the Dobsonville taxi rank in Johannesburg, South Africa. While paratransit fleets of similar sizes and operational characteristics within South Africa may expect comparable return profiles, these specific results do not generalize beyond this context.

However, the three key insights derived from this study possess broader applicability due to their underlying drivers, making them relevant to electric fleets in other settings, particularly commercial and public transport fleets. Key insights 1 and 1b, namely *diminishing marginal returns* and *sensitivity to incremental fleet electrification*, are driven by the dynamics of electric vehicle (EV) fleet saturation and its impact on per-vehicle usage. Key insight 2, *sensitivity to load shedding frequency and forecasting*, is influenced by the economic value of resilience provided by the PV-ES system during power outages. Finally, key insight 3, *effects of intelligent energy storage management*, stems from the presence of morning and peak evening load patterns, which are commonly observed in commercial fleets.

6. Conclusion

This research paper presents a methodology for techno-economic optimization and assessment of co-located photovoltaic-energy storage-charging station (PV-ES-CS) systems under a range of grid constraint scenarios with varying degrees of fleet EV penetration. Through comprehensive analysis and simulation, we have uncovered three key insights that contribute to the understanding of PV-ES system dynamics and their implications for fleet owners and policymakers:

Our first key insight emphasizes the diminishing marginal returns of system performance and the sensitivity to fleet size. We have demonstrated that under grid and capital constraints, fleet owners are likely to achieve optimal financial outcomes by partially electrifying their fleets and delaying PV-ES system investments until a significant portion of the fleet is electrified. This finding underscores the importance of strategic planning and resource allocation in maximizing the economic benefits of PV-ES systems.

Building upon this, our second insight highlights the significant impact of load shedding scenarios on PV-ES system value. We have shown that the economic feasibility and performance of PV-ES systems are highly sensitive to the frequency of grid constraint events. Fleet owners operating in regions with pervasive grid constraint events stand to benefit significantly from our methodology for assessing and planning PV-ES investments, guiding them towards more resilient and economically viable renewable energy solutions.

Lastly, our third key insight delves into the influence of trickle charging (TC) on system feasibility and performance. We have demonstrated that while TC integration facilitates the feasibility of PV-ES systems, its impact diminishes at higher levels of EV penetration. This finding holds relevance for fleets experiencing morning and evening peak loads, suggesting that optimizing the energy storage component, such as through trickle charging, is most impactful at lower EV penetration levels.

Collectively, these insights contribute to the emerging body of knowledge on the integration of renewable energy solutions in commercial fleet operations. The methodology and insights presented in this paper hold relevance for fleet operators navigating the transition to electrified transportation and seeking optimal strategies for

[1] In addition to the analysis in Section 5.2.1, to confirm that (2) yields positive economic effects, simulations were run with entirely unplanned load shedding schedules (unrealistic), and system sizes and economic performance were greater than in the No LS scenario, confirming that the value of resiliency offered by the exceeds the operational cost of running an EV.

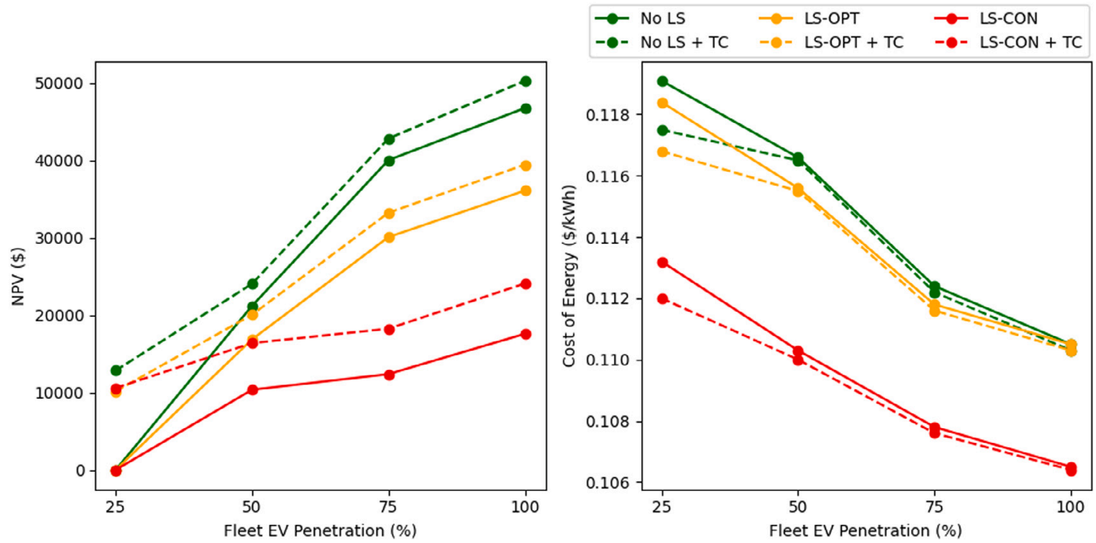


Fig. 13. Impact of trickle charging on NPV and COE in the 25%, 50%, 75%, and 100% cases for the No LS, ST4, and ST2 scenarios.

Table A.1
Definition of Eskom load shedding stages [74].

Stage	Energy shed (MW)	Definition
1	1000	Up to 3 times over a four-day period for two hours at a time, or 3 times over an eight-day period for four hours at a time.
2	2000	Up to 6 times over a four-day period for two hours at a time, or 6 times over an eight-day period for four hours at a time.
3	3000	Up to 9 times over a four-day period for two hours at a time, or 9 times over an eight-day period for four hours at a time.
4	4000	Up to 12 times over a four-day period for two hours at a time, or 12 times over an eight-day period for four hours at a time.
5	5000	Up to 12 times over a four-day period: 9 times for 2 h plus 3 times for 4 h.
6	6000	Up to 12 times over a four-day period: 6 times for 2 h plus 6 times for 4 h.
7	7000	Up to 12 times over a four-day period: 3 times for 2 h plus 9 times for 4 h.
8	8000	Up to 12 times over a four-day period for four hours at a time.

PV-ES investments. Furthermore, the study provides a foundation for future research, encouraging exploration into advanced battery dispatch strategies and further optimizations that could enhance economic outcomes in scenarios with higher levels of EV penetration.

CRediT authorship contribution statement

Christopher Hull: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Jacques Wust:** Writing – review & editing, Software, Methodology, Formal analysis. **M.J. Booysen:** Writing – review & editing, Supervision, Resources, Data curation. **M.D. McCulloch:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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.

Appendix

See Tables A.1–A.3.

Table A.2
Number of hours in each load shedding stage over the past several years [57].

Stage	Number of load shedding hours					
	2018	2019	2020	2021	2022	2023
1	62	67	119	72	190	611
2	79	290	597	915	1393	975
3	0	32	46	70	645	1786
4	0	141	83	96	1051	1926
5	0	0	0	0	298	536
6	0	0	0	0	199	1074
7	0	0	0	0	0	0
8	0	0	0	0	0	0
Total	141	534	845	1153	3776	6908

Table A.3
Trends in load shedding over the past several years [57].

Month	Number of load shedding hours					
	2018	2019	2020	2021	2022	2023
Jan	0	0	104	121	0	744
Feb	0	66	342	66	114	661
Mar	0	210	127	207	147	667
Apr	0	0	0	8	197	690
May	0	0	0	54	215	737
Jun	14	0	0	185	185	377
Jul	0	0	89	5	5	606
Aug	0	0	60	0	0	690
Sep	0	0	92	0	0	583
Oct	0	56	0	262	521	263
Nov	29	7	0	220	642	630
Dec	97	195	31	24	698	260
Total	141	534	844	1153	3776	6908

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