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Research Article

Sizing requirements of the photovoltaic charging station for small electrical vehicles

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Abstract.: Electric vehicles (EVs) are being introduced in Rwanda and becoming attractive for different reasons. For instance, these types of vehicles can help decrease air pollution and noise emissions. In addition, it presents an alternative to combustion engines, given the increased price of fuel resources in Rwanda and around the world. This paper presents a tool tailored to optimize the design of an electrical charging station serving small-sized electric vehicles, utilizing the algorithm to assist in sizing stand-alone mopped charging stations. The developed tool is based on the toolbox EventSim from MathWorks, which permits the combination of the simulation of discrete events (such as the arrival of customers at the station) with continuous states (such as the simulation of the charging process). The required PV power was estimated by utilizing solar resources, for the location, from renewables. Ninja. The number of customers arriving at the existing oil station is normalized to estimate the energy requirements of the mopped fleet. A Poisson distribution was proposed to model the battery discharge upon arrival, and different related parameters were evaluated through a sensitivity analysis to identify their effects on the performance of photovoltaic charging station. For the testing values, the station parameters were changed by ±25% to determine the impact of key design parameters on station performance, as well as other satisfaction measures such as average waiting time and average queue length. With a 25% increase in photovoltaic panels, the blackout period decreases by 2.12%, while a 25% decrease in photovoltaic panels causes an increase of 2.18% in the blackout period. Utilizing the energy management system (EMS), the waiting time was reduced by 8%.

Keywords: Electric vehicles, EventSim, blackout, sensitivity analysis, energy waste.

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1. Introduction

The development on power electronic systems and microgrids has permitted solutions to energize areas in developing countries. Productive use of energy has fostered the energization of remote areas in developing countries with difficult access to the main power electricity system. For example, the project modularity grid developed a microgrid in Rwanda to help local communities access electricity. Among the different project targets, the productive use of energy is among the priority lists. In this context, local communities are upgrading their mobility systems (mostly based on fuel engines) towards more sustainable vehicles, namely, electric vehicles (EV)s (Gabbar *et al.*, 2021)(Cabrera-Tobar *et al.*, 2022). However the increase in demand of recharging the EVs leads to the congestion of few available charging stations (Li *et al.*, 2020), The sizing of the infrastructure for charging EVs is an important aspect for the development of such areas to enhance the impact of EVs on public transport (Raf, 2021). The electric power charging stations in Rwanda are mostly dominated by grid power yet the region has enough solar energy that can be alternative and help to reduce gas emission that contribute to global warming; In addition, most of these charging stations are using the swapping methods. Other benefits of electricity generation from renewables include greater grid flexibility, reduced grid congestion, and reduced input electricity price (Huang *et al.*, 2021) (Ciceu & Serban, 2022). Photovoltaic charging stations combine photovoltaic (PV), battery energy storage system (BESS), and charging stations; therefore, there is a need to analyze charging stations that use solar energy to introduce EVs green energy charging stations. Nevertheless, the sizing of the stations must be done to provide good service to customers such that EVs gain momentum in the communities, while their cost must be optimized to guarantee an affordable facility. For electric cars (EVs) to be successfully used in Rwanda, solar charging station installation was determined to be a prerequisite, and the government has implemented a number of incentives to encourage EV usage (Rwanda EV Charger Market 2022-2030 | September 2023 Updated, n.d.). Motorcycle riders in rwanda, especially in Kigali, go around in the city in their daily work; thus, the enhancement of public charging stations is needed for those who use electrical motor

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cycles. The availability of electric charging stations affects EVs users differently in terms of access charging cost, traveling cost, waiting time, and charging time (Ahmad *et al*., 2022). The increasing number of industries that use vehicles that depend on fossil fuels has caused serious environmental deterioration(Su *et al*., 2018)(Yang *et al*., 2021). The increasing use of technology has increased the need to depend more on energy. However, the shortage of fossil fuels has become a constraint, and fossil fuel use leads to greenhouse gas (GHG) emissions that contribute to acid rain, global warming, and other long-term environmental problems (Shafiq *et al*., 2022).This global climate disorder causes a decrease in natural resources such as solar, wind, and biomass, and is becoming rare on some parts of the earth. Scientists are encouraging human beings to utilize renewable energy sources for survival (Nishanthy *et al*., 2022). Solar energy has garnered significant interest from researchers worldwide owing to its clean, abundant, and free nature. It is a renewable energy source with a vast potential and a wide range of applications (Xu *et al*., 2017)(Ram *et al*., 2018). This article focuses first on the development of a design tool for charging stations serving small EVs, to optimize the energy. Second, the developed model was used to simulate the demand for solar fast-charging stations and analyze the effect of variations in the main parameters on the performance of the solar charging station. Solar resources have been modelled using renewable. To fit the Poisson distribution to model the customers' arrival, a popular time pattern of fuel station was used. The normalized arrival per hour has been used as the expected mean arrival per hour. The customers 'arrival model and battery discharge level model were used into a developed Simulink model to analyze the sizing requirement of the charging station utilizing a discrete event systems simulation engine, available in MATLAB (SimEvents - MATLAB, n.d.) . Development of an energy Management System (EMS) to optimize the performance of the PV charging stations by ensuring that the small EVs are charged efficiently.

In (Wu *et al*., 2023)(Hussain *et al*., 2020), a Monte Carlo simulation tool was used to predict the charging demand, stationary energy storage system sizing, and vehicles arrival at a fast charging station, the simulation results indicated that the presented methodology can approximate real-world extreme fast charging demand. However, it was recommended to extend the methodology by considering the transportation dynamics because the EVs' charging load depends on drivers' behaviors. An agent-based simulation program was created to examine the daily charging demand patterns of electric vehicles at charging stations, using empirical mobility data. The waiting period was examined over the course of a week, and the simulation findings showed that, for the majority of those weeks, there was very little waiting. It was decided to add more charging stations because Friday afternoon's extreme (up to an hour) wait time was most likely caused by long-distance commutes, holidays, and leisure travel (Jochem *et al*., 2016). Under the suggested demand-side management of the EVs approach, EVs were able to charge at low tariff rates (Selim *et al*., 2021). Self-consumption-sufficiency balance (SCSB) was used to simulate a number of scenarios regarding the number of EV charging ports to balance self-consumption (SC) and self-sufficiency (SS). The results demonstrated that SCSB performance tended to be greater with a larger combined photovoltaic–electric car size (Fachrizal *et al*., 2022). Jayasankar Nishanthy et al. have used sensitivity analysis to design charging station for different region here the parameters such as solar global horizontal irradiation, temperature, and wind velocity were the parameters to be variated. It was found that these variables are proportional to the high cost of the nominal rate of interest for one of the three chosen regions to be analyzed, and it was shown that modifications are needed in the combination of solar photovoltaic and wind turbine ratings(Nishanthy *et al*., 2022). The modulated Poisson process was used to determine when each vehicle will arrive at a charging station, and it was found that the combination of renewable energy and storage systems provides a good cost efficiency solution (Domínguez-Navarro *et al*., 2019). Energy management system have been developed by means of python for electrical vehicle PV charging station , the results showed that the management can successfully reduce the energy taken from grid and maximize the use of local produced solar energy sources (Ciceu & Serban, 2022). Intermittent energy sources, such as wind and sun, require precise forecasting, and the developed quadratic price function has shown that an EV can enjoy a higher charging rate only by paying more, whereas others charge slowly at lower prices to avoid congestion (Kabir *et al*., 2020). The most recent studies considered the estimated average driving distance to model the charging demand, for this work the number of customers who have visited the charging station for service were considered, using the transportation dynamic of cell battery. Utilizing the SimEvent toolbox in Matlab to develop a hybrid discrete-event model to emulate the discrete arrival of customers and the continuous dynamics of electric charging. As a result, this work presents the design of simulation platform that can be customized to assess the needs and performance of a small-vehicle charging platform.

2. Modelling the demand and resource

This section presents the approach used to model the arrival of customers at the charging station and the solar resource of the chosen location to emulate a photovoltaic (PV) plant. The irradiance data for a specific location were obtained from (*Renewables.Ninja*, n.d.).

The city of Kigali (Rwanda) was chosen for this study. The webpage provides irradiance data on an hourly basis, and these data can be adjusted for different tilt and azimuth angles of the panels. The irradiance panels are considered to lie at an approximately tilted angle of 170(Wenham *et al.,2007,p.22)* (*Solar Panel Angle: How to Calculate Solar Panel Tilt Angle?*, n.d.) (Ajao et *al*., 2013). The average daily irradiances for Kigali are provided in Figure 1 for the year 2020. Based on this data, the days with the highest and lowest irradiance can be obtained, which correspond to days 8 and 246, respectively (see Fig 2).

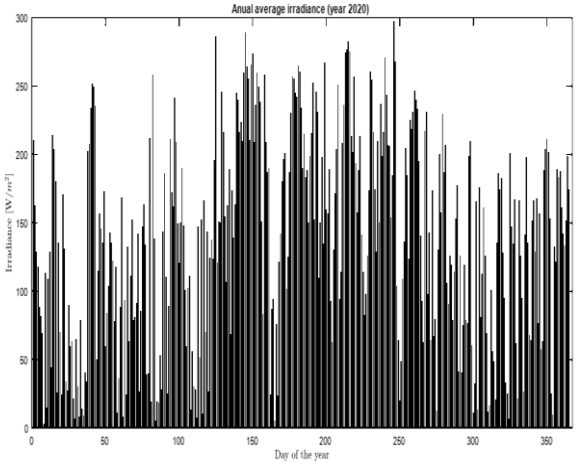

Fig.1 Average irradiance at Kigali per day

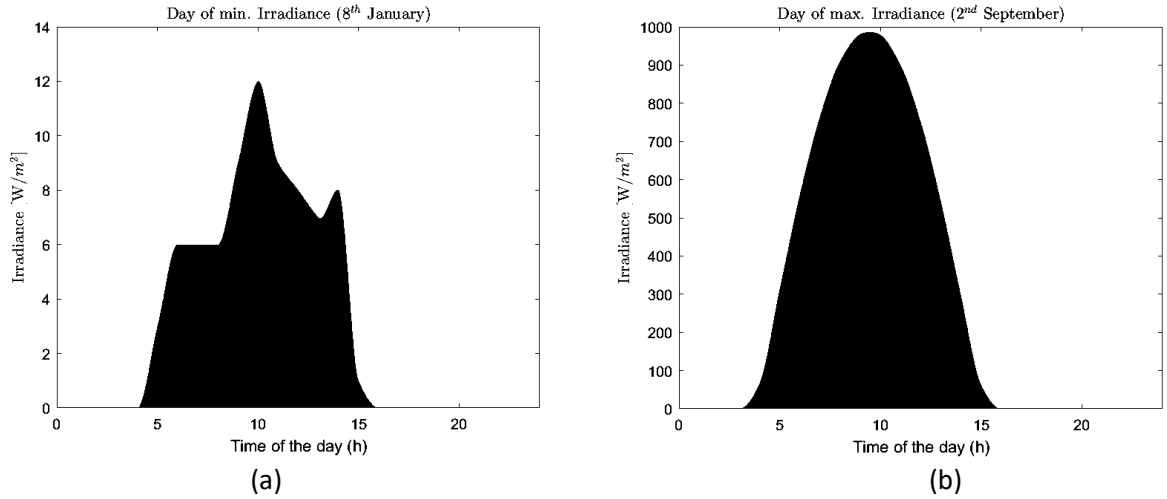

Fig. 2. (a) Minimum and (b) maximum irradiance days over the year.

2.1 Modelling the charging demand

This section describes the modelling of the charging demand and shows the development of a charging design tool that focuses on a simulation model capable of emulating the behavior of the charging station. It is assumed that the arrival of customers to charge the batteries at the station follows a certain pattern, although their arrival times must be randomized. Therefore, a probability model that counts random events in a given time interval was considered. For this purpose, the Poisson distribution, which is often used in the modelling of customers' arrival, was used (Parkin and Marlin, 2011). The Poisson probability density function is defined as in (1):

$$\boldsymbol{f(x)} = \frac{\boldsymbol{\lambda^x}}{\boldsymbol{x!}}\boldsymbol{e^{-\lambda}} \quad (1)$$

where $\boldsymbol{x}$ is the expected number of random events and λ is the expected mean (μ) of the density function (in this study, lambda represents the average discharge of the battery). Similarly, the standard deviation (σ) is $\sqrt{\boldsymbol{\lambda}}$.

2.2 Modelling the average arrival of customers

To fit the Poisson distribution to generate a randomized arrival of customers at the charging station, a popular time pattern of a fuel station in Kigali was considered for a simulation of 24 hours, the arrival of customers over a day at the station. The number of customers who visited the station is shown on an hourly basis. The number of customers was normalized to define the percentage of customers arriving each hour. Here, the peak demand considered was six customers. The expected average charges per hour can be defined and the average arrival of customers per hour is rounded to the nearest integer. The found data were used to fit density distribution in (1), to generate a randomized pattern of customer arrival at the charging station. The level of usage was determined based on the site data. The normalized arrival per hour was used as the expected mean arrival per hour (λ), and a randomized distribution pattern was generated for each time of day. Figure 3 shows the distribution pattern for one day; here, the Poisson inverse cumulative distribution function was used with a percentile of 0.8(Poisson Inverse Cumulative Distribution Function - MATLAB Poissinv, n.d.), and the data shown in figure3, have been used to model the emulation of customer arrival at the charging station over the desired period of time. The average arrival of customers was then multiplied by the average energy required by each customer. The average energy is calculated based on the estimated battery operating voltage (which is considered constant) and the average depth of discharge of the vehicle at the arrival time.

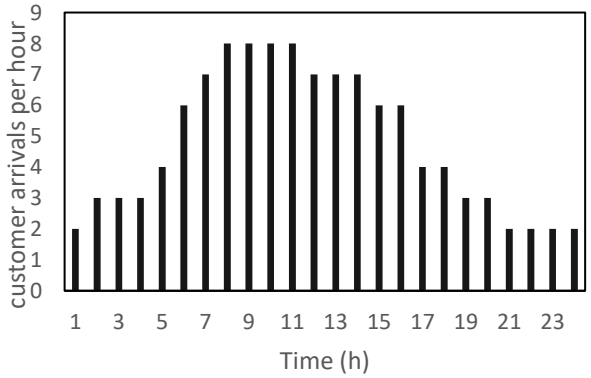

Fig. 3 Illustration of the 24-hours pattern of customer arrivals based on Poisson distribution.

3. Modelling the level of battery discharge at arrival

Besides the number of customers arriving at each time of the day, it is important to model the level of discharge of the battery at the arrival time, which is normally between 0 and 1 (Antarasee *et al.*, 2023)(Ikram *et al.*, n.d.). A normal probability function can be used to define the distribution of the amount of energy remaining in the battery. Based on the estimation of the charging requirements listed in Table 1, The Total Energy for the full battery is 2.88 kWh. The average discharge (λ) of the batteries on arrival was taken as 36%, which is equal to 1.0368 kWh, and the standard deviation (σ) considered is 1.0182 kWh.

Nevertheless, the normal distribution needs to be truncated based on the physical operating limits of the battery, the following assumption is made: The EV arrives with the following range of discharge: the minimum discharge of the battery is 30%=0.864 kWh, the maximum discharge of the battery before returning to the charging station is 80 %=2.304kWh. Then, the probability density and cumulative density functions of the charging state distribution upon arrival

Table 1
Estimation of charging requirements.

Parameters	Value
Average charging cycles per day	70
Estimated battery capacity	40 Ah
Estimated battery voltage	72V
Av. discharge of batteries on arrival	36%

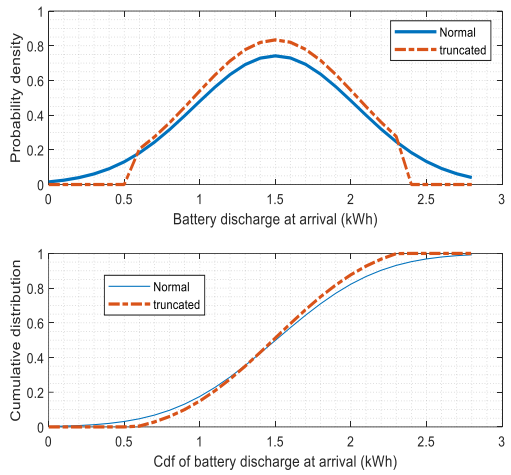

Fig. 4 Cdf of battery discharge at arrival.

are shown in Figure 4, where the red dotted line shows the truncated data used for the analysis.

The modelling of the customer arrival rate presented in section 2.2 and the modelling of the battery discharge discussed in Section 3 are combined to generate the data to be fed into the simulation model, and these data will be used to simulate the sizing requirements of the charging station.

4. Preliminary data estimation of energy requirements

The sizing of the PV plant is based on the solar irradiance data and the modules of choice, as well as the energy requirements for the charging station. Thus, the preliminary sizing of the system is based on certain assumptions regarding the charging demand. The preliminary data considered for estimating PV plant requirements are summarized in Table 1. The peak power of the PV generator (Ppv) (Omar & Mahmoud, 2019)(Ibrik, 2020) is obtained as in (2):

$$\text{Ppv} = \frac{E_d}{\eta_s \times PSH} \quad (2)$$

Where: $\boldsymbol{E_d}$ is daily energy consumed of the charging station (kWh/day), η_s the efficiency of the system components, PSH the peak sun hours

Considering the outlined parameter values, the obtained Watt peak (W_p) is 164, Refer to the calculated peak power of needed panel and Based data-sheet information in(Energy & Europe, n.d.), PV generator with a peak power of 235Wp is selected to secure continuous power availability. The following data are the other main information required for the sizing and modelling of the PV plant based on the data sheet:

- PV panel max. power: 235 W.
- PV panel useful area: 1.64 m^2.
- Module efficiency:14.9 %.

Based on the rated power of the chosen PV panels and the energy used by the charging station during the day, the number of required PV panels was calculated using MATLAB (https://www.leonics.com). The found number of PV panels(n) required to power the charging station is 166 from this number sensitivity analysis was performed to examine its effect on the performance of electrical vehicle charging station. The PV plant is modelled in the simulation platform based on the sizing requirements specified above. The battery storage system (BSS) should be large enough to store sufficient energy to operate the PV station at night and the cloud days. The required storage was sized by using equation (3) (Omar & Mahmoud, 2019); Where 0.85 is battery loss and 0.7 is depth of discharge, the considered days the system to operate where there is no power produced by PV panels are 2 days, the calculated value is 43kWh.

$$BSS = \frac{\text{Total watt-hours per day} * \text{Day of autonomy}}{0.85 * 0.5 * 12} \quad (3)$$

5. Waiting time and waiting queue Generation

This section clearly explains how the emulation of the customer arrival waiting time and queuing time was generated, to overcome the uncertainty issues of traffic conditions and dynamically arriving charging requests(Lee et *al.*, 2020).The emulation of customer arrivals at the charging station was based on the probability distribution presented in Section 2.2. The data generated regarding the usage of the fuel station and customer arrivals were randomized on a second-by-second basis to generate the customer arrival pattern (see Figure 5). These data are fed to the entity generator, which creates discrete events each time a new customer is generated by the arrival pattern. To feed the entity generator block, the customer pattern must be converted into intervals of successive events. A flowchart for waiting time and queue generation is shown in Figure 5, and the procedures are as follows:

- Step 1. Vehicle arrives: An electric vehicle arrives at a station seeking charging. A popular time pattern of the fuel station was used, and by utilizing the Poisson distribution, a random arrival of customers was generated, which was then randomized on a second-by-second basis to generate the customer arrival pattern (discrete event creations).
- Step 2. EV battery discharge generation: The entity generation block generates and associates a randomized deep discharge of the EV battery for each customer. (Randomized EV battery Discharge generation)
- Step 3. Waiting queue generation: This block manages the queue of customers and permits the visualization of metrics, such as the average waiting time or queue.
- Step 4. Availability check charger:
- Charger available: If a charger is available, proceed to the next step. No charger available**:** The vehicle enters the waiting queue.
- Step 5. Charger selection (Charging profile selection): Permits to remove one of the entities associated to a customer, which then permits to enter one of the customers of the waiting queue to the EV charging setup
- Step 6. Charge initiation: The charging process begins

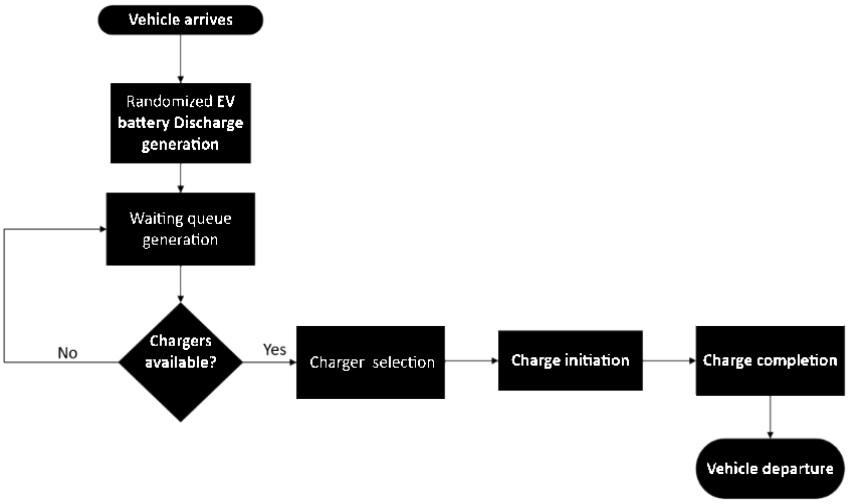

Fig.5 Flowchart for the waiting time and queue generation process at an EV

based on the selected profile and the vehicle specifications.

- Step 7. Charge completion (entities released): The charging process is completed when the battery reaches a desired level. The entities are released from the selected chargers, which are customers leaving the charging station after refilling their EV.
- Step 8. Vehicle departure: The vehicle departs from the station, freeing the charger for the next vehicle.

6. Charging Station

The charging station stage emulates the management of the docking ports and injection of current into the EVs. The converter-charging data block is a logic element that assigns a customer that has just arrived at a free dock. Likewise, prior to the arrival of a customer, this block frees a docking station when a flag signal is generated open at the completion of charging an EV. Each customer arriving at the plant is then associated with the battery discharge level, which determines the initial SOC of the battery.

The converter charging data system generates auxiliary variables that are assigned 1 for docking stations that are charging and 0 for those that are free. These variables are then multiplied by the charging rate of each of the docking stations. Note that during the CC stage, the charging rate is one, although this rate is curtailed when the charging process enters the CV stage (see Figure 6). Finally, the flowchart in Figure 6 corresponds to a logic element to prevent the charging process from entering a limit cycle, and it should be noted that the charging process is deactivated when the energy available from the PV panels and the ESS is lower than the demand at the station.

7. Description of the EMS algorithm

As a developing country, Rwanda is committed to promoting sustainable transportation. Reducing greenhouse gas emissions and the country's dependence on imported fossil fuels, which accounts for the majority of the country's foreign exchange

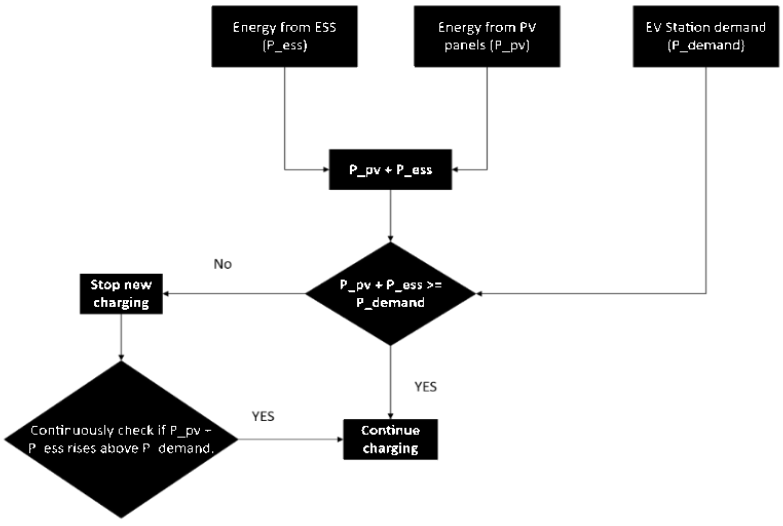

Fig.6 Flowchart to Avoid Limit Cycle in EV Charging with Lowered PV/ESS Energy

spending, are key elements of the plan. The government introduced several incentives to promote EVs. Electric vehicles, spare parts, batteries, and charging station equipment are exempt from import tax, special consumption tax, and VAT(Rwanda EV Charger Market 2022-2030 | September 2023 Updated, n.d.). There is greater emphasis on ensuring that the electricity used to charge electric vehicles, such as e-bikes, electric automobiles, and electric buses, is also sustainable(Ram et al., 2018). Thus, the design of the battery management system plays a significant role in battery life preservation and performance development of EVs because it is crucial to ensure that the battery being used is as reliable as fossil fuel(Ikram et al., n.d.). This section describes the Energy Management System (EMS) algorithm, which is used to optimize the performance of the charging station given a set of system parameters (e.g., number of PV panels, size of the ESS) to reduce the waiting time of customers to improve satisfaction metrics.

The EMS algorithm is based on the hourly energy balance. Based on the information on the PV resource, the estimation of the demand (based on the expected number of customers in the following hour), and the information available regarding the energy available in the ESS, the EMS decides how to curtail the charging process of the docking station. The curtailment is based on the charging process of the lithium cells, because during the CC stage, the cells refill quickly, but the charging speed is reduced during the CV stage. The SOC value at which the charging speed decreases is estimated to be 95 % (Volume II Equivalent-Circuit Methods, 2020). Then, the EMS evaluates the energy balance (4) and determines whether the charging process should be cut-off before the SOC reaches 100%.

$$Energy\ balance = E_{PV_{Predicted}} + E_{ESS_{Avaialable}} - E_{Demand_{Predicted}} \quad (4)$$

If the energy balance is positive, the energy demand for the following hour is expected to be lower than the energy generated from the PV panels and the energy available in the ESS. Under this scenario, SOC charging is maintained at 100 %, and the plant operates normally. However, if the energy balance is negative (e.g., the expected demand is larger than the energy from the PV and ESS), the charging process is curtailed. To do so, the charging process is stopped at 95% of SOC.

8. Results and discussion

This section presents how the model can be used to assess the sizing requirements of the charging stations. The simulated PV charging station model was used to analyze the behavior of the system under different operating conditions and design parameters. The impact of the system performance under different design parameters was studied by performing a sensitivity analysis**.** The results obtained can be used to reduce the construction cost of the plant and identify techniques for optimizing the operation of the system. Initially, the calculated number of PV panels was considered in the analysis, and the simulation was evaluated for the same usage (and the same solar resource) but considering variations of ± 25% in the calculated number of PV panels. Figure 7a illustrates the time that the system experiences a blackout against the total time that the charging is operating. Here, the term blackout refers to the period when the station does not have sufficient energy to supply charging demand. The total energy of the charging station is a combination of the energy generated by the PV panels and energy stored in the ESS. The information presented in Figure 7a shows that the time in (%) the system is not able to recharge EVs while there are customers waiting to do so, and it

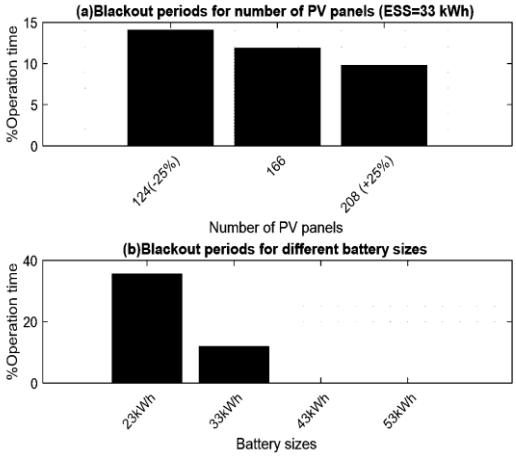

Fig.7 System blackouts for different numbers of PV panels and ESS size.

is clear that the number of PV panels affects the performance of the charging system. The impact of increasing or reducing the number of PV panels relative to the initial design choice (166 panels) is discussed here. Increasing the number of panels to 208 slightly affected the operation time, but this change increased the cost of the charging station. However, a reduction in the number of PV panels to 124 increases the blackouts period.

The effect of battery size was analyzed with respect to the system blackout (Figure7b), and it can be observed that the reduction in the ESS size impacts the operating times that the station can meet the demand, as the storage capacity sharply reduces the blackout. In Figure 7b, 43 kWh storage capacity is the size value; a value below the size value will increase the blackout period, utilizing the storage capacity of 53 kWh, as well other values above this value will cause excess unused energy and will require a higher initial cost.

The other design parameter chosen to evaluate its impact on system performance is the number of docking stations. The increment in docking stations implies an increase in the cost of the charging station, as shown in Figure 8a, which does not permit a reduction in the average waiting time. Figure 8a shows the average queue over the period of analysis (3months) for the base case (5docking stations) and variations of 25 % (i.e., 4 and 6 docking stations). The results show that while the number of docking ports increases from five to six, the queue size increases. For both cases in Figure 8a and b, it is clear that the

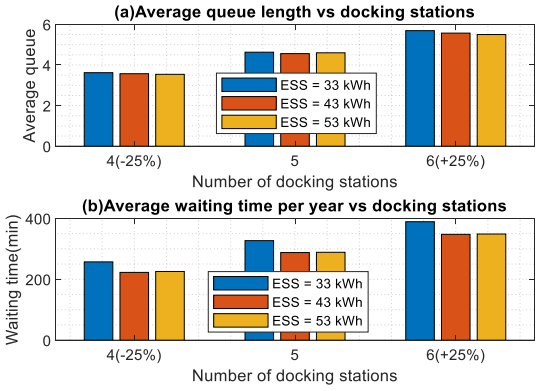

Fig.8 Waiting time and queue vs. number of docking stations.

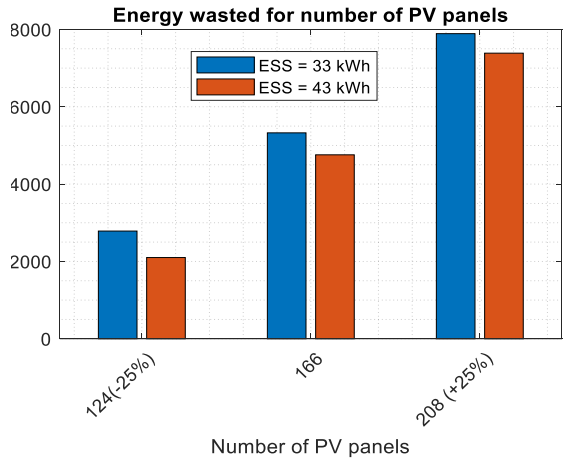

Fig.9 Energy waste with different numbers of PV panels.

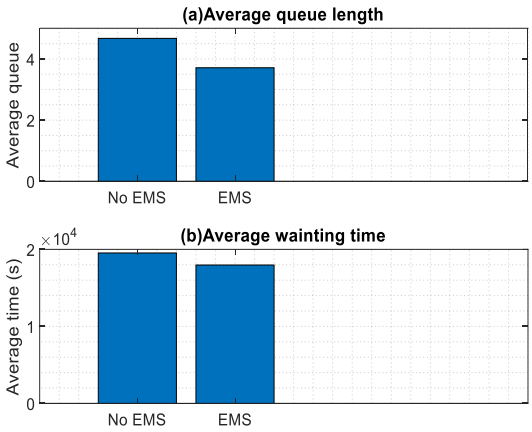

Fig 11. EMS for average waiting time and queue.

waiting time and waiting queues for the different scenarios are reduced by increasing the size of the ESS. However, a reduction in the number of docking stations would permit a decrease in the cost of the entire facility but would impact the customer satisfaction indices.

Another metric of interest for evaluating the effect of the number of PV panels is the energy wasted, to determine how this parameter impacts energy waste per year. The simulation results for different numbers of PV panels for the two different battery sizes are presented in Figure 9. In this case, the lower the number of PV panels, the lower the energy waste.

Finally, the performance of the EMS was evaluated using dynamic simulations with the same parameters described in the previous sections. The simulation was run twice with the same distribution of customer arrival and solar resources. In the first simulation, the EVs were charged until the completion of the charging process.

The second simulation was run by introducing the EMS algorithm, which modifies the completion of the charging process when the SOC of the vehicles reaches 95 %. Note that this modification is only active for a few periods of time when it is foreseen that the demand will be larger than the energy available over the next hour. First, Figure 10 shows the frequency of having outages due to running off of energy by comparing two scenarios with and without EMS. With the configuration of 166 PV panels and 33 kWh, 11.4 % of the operating time of the station would not be able to meet the demand. Nevertheless, the EMS algorithm achieves a reduction of nearly 3.23% by adjusting the final SOC of the vehicles during the periods of the blackout forecast.

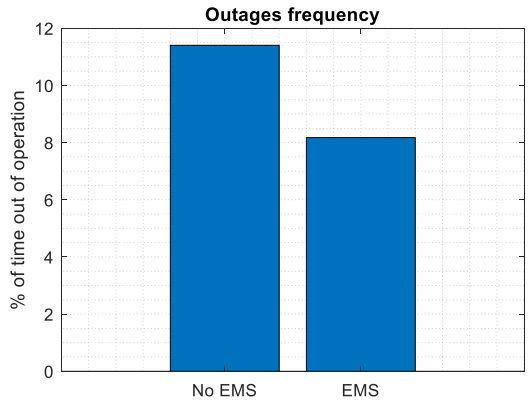

Fig 10. Comparison of outages frequency with and without EMS

The contribution of the EMS algorithm is also analyzed in terms of the average waiting time and queue. These internal metrics can be associated with customer satisfaction, and in both cases, EMS activation reduces the values obtained without it. First, figure 11a illustrates that the average queue without EMS is above 4.7 customers on average, while the addition of the EMS reduces the average queue by approximately 21 %. Similarly, Figure11b shows the average waiting time and how the time is reduced to approximately 1565.2 seconds, which is approximately 8% when the EMS is used.

9. Critical appraisal

For a given charging station capacity estimation; The estimation approach used in this paper for the charging requirements shown in Table 1 was also used in (Dai et *al.*, 2019) to meet the power demand of electric vehicles. To calculate the number of customers arriving each time, the normal probability function was used to define the distribution of the amount of energy left in the battery, which was also used in (Ding et *al.*, 2021) to obtain the optimal sizes of an energy buffer. The 25 per cent of the number of PV panels was varied from the calculated value to check its effect on the performance of the charging station. In figure8, the photovoltaic panel increment of 25%, the 2.12% of blackout period decreases while the decrement of 25% of the photovoltaic panels, causes the increase of 2.18% blackout period. It is clear that the change in the number of PV panels do not improve this metric significantly. In addition, the increment of Pv panels increases the cost of system; so, this information supports the initial design choice and demonstrates that a reduction of the number of Photovoltaic panels would have a negative impact on the performance of the PV station while the increment will cause the rise of the station cost. The considered points also, is the energy wasted, the simulation results for the different number of PV panels are also presented for two different battery sizes in Figure 9. For instance, the results shows that the number of panels selected (166) the energy wasted decreases slightly to 10.66% when the storage size changed from 33kWh to 43kWh. Nevertheless, the difference is most noticeable when the number of PV panels is changed, here for the ESS of 33kWh; when the number of Pv panels changes from 124 to 166 the energy waste increase to 47.69 %, for 43kWh ESS by changing the same number of Pv panels the waste energy increases to 55.84% from the previous one. Thus,

the lower the number of PV panels the lower the energy waste for larger ESS for a chosen storage capacity , this is supported by the research of Vinay Chamola and Biplab Sikdar, who used multistate Markov model to estimate the optimal cost of the Pv system; it was found that as the number of solar panels increases the number of batteries should be reduced (Chamola & Sikdar, 2015). For the different charging sizes of the storage, the energy waste reduces once the storage capacity increases. It was found that the storage capacity variation positively reduces the charging station's blackout period; this is proven by the works done by Vinay Chamola and Biplab Sikdar who proposed an analytic model to evaluate the power blackout probability of a solar powered base station, it was found that as the number of batteries increases the power outage reduces(Chamola & Sikdar, 2016). The number of dockings has not an effect on the waiting time at the EVs charging station, what mater is the storage capacity as the storage capacity increases the waiting time reduces.

10. Conclusion

This paper presented the potential of the tool developed for assessing the impact of the different design parameters of the PV charging station. As an initial case, the design parameters of the number of PV panels and size of the ESS. Simulations with the same operating values were performed by adjusting the design elements described. By running a sensitivity analysis on these parameters, the impact on the system performance can be observed. These results can be used to judge whether it is worth increasing capital cost in the sizing of the station or, on the contrary, their impact on the system is minimal and a larger expenditure is not justified. It has been shown that decreasing the number of PV is not recommendable because it increases the outage times significantly, although this would permit better use of solar resources. Similarly, it was shown that a reduction in the ESS below the initial case (43 kWh) is not recommended because it significantly increases the outage times to large values. An increase in the size of the ESS has been shown to reduce the outage times, as well as the energy waste, waiting queue, and time. This is a possible parameter that should be considered when comparing the implications of facility costs. It has also been shown that increasing the number of charging points is not recommended because it significantly increases the waiting times and queues, which proves that the main parameters to consider are the number of PV panels and energy storage systems. Finally, an energy management system was implemented, and it was found that by using EMS, the waiting time was reduced by 8% and the outage time was reduced by 3.23%.

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