Feasibility of EMS and Hybrid Energy Storage in Regenerative Railway Systems

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***Abstract*—This paper investigates the design and feasibility of an energy management system (EMS) for railway applications that integrates regenerative braking energy (RBE), photovoltaic (PV) generation, and hybrid energy storage systems (HESS) comprising a battery and a supercapacitor (SC). The objective is to test the performance of the HESS along with RBE and analyze its feasibility for implementation, as the combination of these technologies are assured to reduce grid dependency and operating cost as a result. Using a modified AC microgrid model that emulates a DC microgrid, simulations were conducted to evaluate four scenarios: a base case, PV-only, PV with battery storage, and a combination of PV, battery, and SC. Key performance indicators (KPIs) such as energy consumption, daily operational cost, and CO_2 emissions were assessed for both clear and cloudy days. Results demonstrate that incorporating PV and hybrid ESS significantly reduces grid dependency, operational costs, and CO2 emissions. The full integration of PV, battery, and SC achieved the highest energy savings and environmental benefits. The combination of PV and battery achieved a 93% reduction in grid energy consumption on clear days, while adding an SC further reduced consumption by up to 98%. CO_2 emissions dropped proportionally, with the full integration scenario emitting only 0.735 tons per day on clear days compared to 33.45 tons in the base case. This study demonstrates the potential of hybrid renewable energy systems to enhance energy efficiency and sustainability in railway operations, while identifying cost barriers that future technological advancements and subsidies could address.**

***Index Terms*—Energy Management Strategies, Hybrid Energy Storage System, Photovoltaic, Regenerative Braking Energy, Supercapacitor**

I. Introduction

As humanity heads towards technological advancement, an unaddressed problem raises questions about meeting the increasing demand of public transport electrification, the waste of Regenerative Braking Energy (RBE) and the challenge posed by energy storage solutions. Although some of these are large problems to be solved at society level, they can start to be approached by creating solutions where multiple types of energy recovery methods, along with Energy Storage Systems (ESS), and Energy Management Strategies (EMS) are applied in reversible substations where rail stations are found. For decades, humanity has been using rail transport systems with the knowledge that the energy lost in the braking process can be recovered at high efficiency and, as time passes, photovoltaics (PV) have become cheaper and easier to obtain, if rail stations don't already have them installed. What is now being researched involves how we use an ESS in combination with different energy generation technologies in rail stations and how to implement optimal charge and discharge algorithms such that the storage of generated power is optimized throughout the day. Given this, many studies have been done in which different technologies are evaluated in their daily energy savings capabilities for single- or multiple-line rail systems. Such technologies include the use of an ESS, PV generation, RBE recovery. and optimal EMS.

In this paper, a microgrid model found in the Mathworks Community file exchange [11] will be adjusted to approximate the operation of a DC Microgrid similar to the one used in the Netherlands to power trains. Furthermore, the model will be adapted to include PV generation, RBE, and a hybrid ESS composed of a battery and a Supercapacitor (SC). The HESS solution is predicted to perform better than simple ESS solutions as the addition of the SC will be able to reduce the impact of grid consumption by recycling the power of RBE back into traction. The outcome of the paper shall be to research the feasibility of the aforementioned technology combination, and speak on its efficiency and capability to reduce costs for train companies.

II. Literature Review

The study performed in [1] concludes that the best way to save energy in train stations is by incorporating an ESS like a battery as a way-side storage that is used to store energy coming from RBE and PV. The results of this study show cost savings of up to 35% when all above technologies are used compared to a base case where no PV, ESS or RBE is used. Furthermore, this study builds 90 scenarios where PV variability, state of energy (SoE) of the ESS and pricing schemes are considered to yield the savings. The study in [1] also concludes that only the ESS with PV incorporated can save up to 19% compared to the base case and only the ESS with RBE incorporated can save costs to 16% daily.

The study in [2] proposes that up to 99.8% of the energy lost in braking can be recovered. This can be linked to the claim of Alstom's HESOP recovery system, which rates a 99% of recovered energy according to their website [9]. The study in [2] however, considers that their system for efficient RBE should incorporate a Supercapacitor (SC) storage system to drive high energy over short time periods. The addition of the SC outperforms the use of a battery ESS, since the SC can handle the high power fluctuations over short periods of time like that coming from RBE, whereas a battery ESS alone can't. This is shown with the common power densities for both technologies, where SC range higher than 10 kW/kg and batteries range between 100 to 300 W / kg, which are significantly less in the case of a battery. This affects the response time to absorb power, where in the case of RBE the power spikes are high peaks with short durations, correlating to the behavior of the SC, and with the lower rated power of batteries, the pulses could be missed if a battery is used. The SC takes care of many key roles in the model of the study done in [2], like balancing the currents coming from the batteries in the train and the DC power supply as well as regulating the DC source voltage as well. The main operation is to store the recovered energy while braking to prevent it from being dissipated as heat in a braking resistor, which is later used to accelerate the train and improve energy efficiency this way. Finally, this allows for a dynamic state of charge control of the SC, where it can be charged or discharged according to the speed of the incoming train and to fulfill the high energy requirements of acceleration. SCs capture up to 95-99% of braking energy, compared to 70-85% for batteries, which is mainly due to the faster charge rates mentioned before. Study [2] also models a fuel cell that charges the train's batteries, however this technology shall be exchanged by a grid source, as most trains in the Netherlands are capable of running 100% electric [10].

Having a device that can handle high amounts of energy in short periods of time seems to be a common solution among some studies. Study [3] also uses a similar technology, but in the mechanical domain in the form of a flywheel. The flywheel modeled in this study is used in a very similar way than the aforementioned SC, to meet with energy charge and discharge characteristics of RBE. The flywheel in this study is integrated as part of a DC microgrid within the station, where the supply is provided using a battery in the station microgrid, and the AC grid as a means of supply for the battery in case there is not sufficient energy from RBE and PV in the case of the research planned. Simulations in this study effectively concluded that the use of the flywheel was necessary to obtain 0 RBE dissipation. Meaning that the system is highly effective at recovering breaking energy. Furthermore, the study also concludes that thanks to the flywheel, the station's overall energy demand from the external AC grid was reduced up to 93%. This links directly to the objective in the research to be done.

The study in [4] dates back from 2011, and the main focus of the study is centered around RBE. It provides a window into the past looking into how long ago scientists have been working on the same technology that will be further used for the upcoming research. The model done for this study considers RBE for generation, an ESS, and finally it incorporates EV charging stations, which is a nice addition, but is outside of the scope for the thesis. The authors of the paper reported back then that the efficiency of RBE ranges between 77% to 95% depending on the train frequency and system conditions. This would make sense given that in other recent studies the efficiency of RBE is above 95% [2], [3], [9] for all the studies previously analyzed which gives evidence of the technology being improved since the oldest study found dated in 2011. This study further proposes that RBE alone could provide energy savings in the station and EV charging (part of metro station) between 30% and 38% back then. It could be claimed that as time has passed, electrical energy requirements have increased, and from study [1] we know that the most recent calculated savings with only an ESS and RBE is of only 16%, which is evidence of the claim.

An interesting study is conducted in [5], where the approach to improve energy savings is to design an ESS by using supercapacitors and back-to-back converters (BTBC) to efficiently recycle recovered RBE. The ESS from this study was designed with a rated power of 60 MW and rated capacity of 0.3 MWh, to yield the most efficient result of 9% daily energy savings. This is interesting because PV is not considered in this study, and the savings with only the designed ESS provides a higher percentage of savings than those reported in study [1], which was only 3% for the same configuration. The designed ESS is also interesting because along with the BTBC, they balance the energy flow between two phases, which allows for efficient handling of high traffic and energy distribution. This system designed in study [5] maintains stability of DC bus voltage throughout different modes of operation (charge, discharge, transfer and standby) as well as a seamless transition between such. The study [5] has an important advantage in that it has tested and validated the system in a down-scale version. It is also important to point out that the SC based ESS was particularly fit for high-speed railway applications due to the rapid switching between braking and traction, which creates fluctuating energy demands. Figure 1 shows a schematic of the SC-based ESS with BTBC. The schematic shows the interaction between the energy phases α and β, which is an interesting concept to consider when you have trains traveling in opposite directions on the rail. The experimentation in study [5] describes how the BTBC transfers 0.15 MW of RBE coming from the β phase into the SC, and after the SC reaching its Upper charge limit (SoC= 70%), the BTBC transferred 0.075 MW to α phase. During the duration of the aforementioned process, the DC bus voltage was reported to maintain stable, which is attributed to the BTBC. Aditionally, the system reports recyclying 14.9 MWh of RBE per day

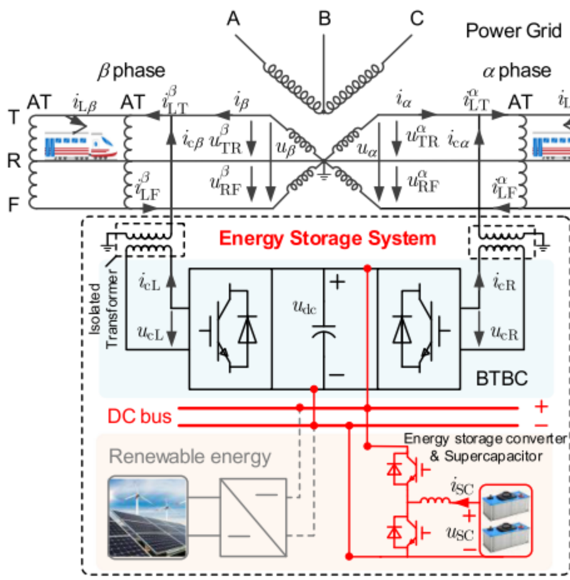

Fig. 1. Layout of the ESS developed in paper [5].

through the supercapacitor, while 32.8 MWh was transferred between phases for traction consumption per day as well. The schematic in figure 1 also proposes a way to implement renewable energy collection, which is of interest to the thesis at hand.

In a very similar way, the study analyzed in [6] also uses a Ground-based SC as an ESS. Compared to [5], the study at hand focuses on Urban rail, and the energy management is based on DC grid voltage regulation, opposed to the BTBC system incorporated in the ESS. In [6], the SC is the ESS and it charges or discharges according to the increase or decrease of the grid DC voltage respectively. This study takes into consideration the train intervals to model the charge and discharge capabilities of the SC, and based on the different headways it calculates the daily savings. The study concludes that using a ground-based SC yields more savings as the frequency of trains increases. A headway of 270s allows for savings up to 21.8% of the maximum energy. That implies a 12% daily energy savings for an urban rail line.

The study performed in [7] deviates from the other studies by exploring the comparison between way-side (stationary) ESS and on-board (mobile) ESS. The study finds that different traffic levels affect the savings of both stationary and mobile ESS's. Stationary ESS yields a lower savings respective to traffic levels compared to mobile ESS, however the mobile ESS requires more SC to store RBE. Mobile ESS can give daily savings of up to 27.3% at high traffic and 36.3% at low traffic, while stationary ESS can save up to 18.7% and 36.4% respectively per day. This can be compared to the results from study [1], where just the way-side ESS and PV is used, yielding a 19% energy savings. The study concludes that mobile ESS benefits from peak power shaving, voltage drop reductions in DC bus and reduced losses better than stationary ESS. Even though the mobile ESS seems to be better, it limits the size of the future research, as PV and Energy Management Strategies (EMS) don't play an important or sensical role. For this reason, the research is inclined towards stationary ESS rather than mobile.

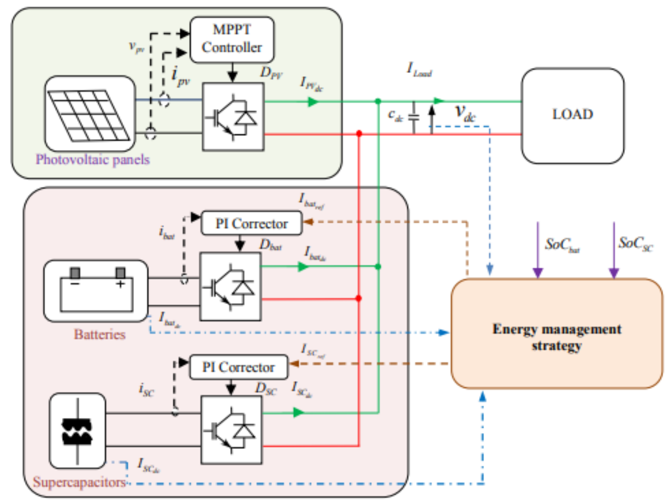

Fig. 2. PV HESS developed in study [8].

The study performed in [8] analyzes the integration of SCs and batteries along with PV generation. The Hybrid Energy Storage System (HESS) devised in this study can be seen in figure 2, and it connects a SC to a battery by using a DC bus, which coincides with the designs of other studies previously analyzed [5], [7]. In this study the authors are able to recognize some limitations of SCs, which are its low energy density and high costs. This leads to the assumption that an SC alone will not be sufficient to deal with PV and RBE, therefore the solution proposed in study [8] of the HESS looks like a promising lead on enery efficiency considering the findings of studies [2], [3], [5], [6], where an element like a SC can regulate high power fluctuations from RBE. The system designed by this study also implements an EMS using a PI controller, which regulates the voltage of the DC bus (400V in this study) by distributing energy between the SC and batteries. In the study, the model built analyzed the performance of a PV ESS with and without the integration of a SC. The study concludes that without SCs, batteries are solely responsible for stabilizing DC bus voltage and responding to load variations. PV alone can produce significant current peaks during changes in irradiation [8], and so can load changes, or energy recovered from RBE, which leads to high electrical stress and potentially shorter battery life. The study also concludes that there is a significant peak current reduction on the batteries when SCs are incorporated, and the current reaction coming from the batteries is smoother as the SC handles rapid energy demand changes. Its important to point out that the study performed in [8] concludes that the SoC of the battery is more stable with the use of SCs, which reduces energy consumption from batteries and results in a more balanced energy distribution, which in turn could potentially extend the batteries' lifespan.

Considering all the information gathered, it can be concluded that the best combination of technologies for train stations include PV and a battery ESS for renewable storage, a SC or some other component in another domain that can handle high power fluctuations in short periods of time like that of RBE or solar irradiance changes, and a metered utility point access to deliver power demand from loads if there is no power available in storage. Following this, an appropriate and simple model needs to be procured in order to experiment and answer the research question: Is it feasible financially to implement a SC-Battery HESS along with RBE and PV generation to reduce operating costs, grid dependency and as a result, reduce CO_2 emissions of railway stations?

III. Modeling

The model obtained was found in the Mathworks community file share [11]. It was first made by Jonathan LeSage and can be seen in figure 3.

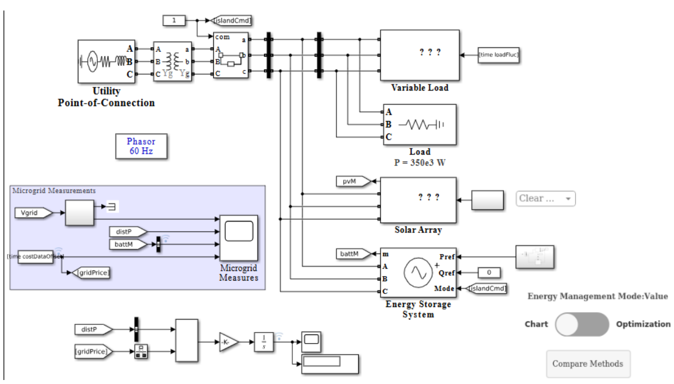

Fig. 3. Model procured from Mathworks by Jonathan Lesage [11].

The initial purpose of this model was to implement a three-phase AC microgrid that is fed by a utility point access to meet load demand at all cost, but it distributes power coming from PV to a variable load, like a household. The excess power is then stored in a battery ESS, which follows a charge and discharge profile calculated by an EMS. The model also was intended to implement an optimization algorithm that was used to drive the EMS based on grid pricing.

Three-phase AC systems use three power lines that replicate with a 120 degree phase shift to ensure balanced and continuous power flow at high reliability. This AC system is an ideal and common grid application for transportation systems, and that ensures that the modeling and available simulation components are reliable in the results they yield. In the case of the model in figure 3, the components that can be seen correspond to a three-phase utility access point, converter and switch combination for the grid component, a three-phase dynamic load and constant loads for the loads, a three-phase solar inverter for PV generation, and a three-phase ESS for the battery. It is important to note that the three-phase AC system components correspond to signal domains within Simulink, and it cannot correlate with DC components, therefore the need surges to approximate that to DC operation by the use of every component's parameters.

The choice for this model was made purely out of the completeness and simplicity that the solution brings. It is important to point out that the specifics of train systems in the Netherlands (DC, 1-1.5 kV, Catenary) are different than the system in the model. However, it can be assumed that AC operation can be approximated to that of DC systems if the AC frequency is minimal, and only active power (P) is acting in the system. More specifically, the reactive power (Q) must equal to zero. This is possible within the model since most of the parameters, including component-wise dynamics parameters, can be adjusted to whatever is needed. For our case the parameter of the system's frequency was set to 1Hz, assuming that is the lowest attainable frequency for the model's correct operation. Then for every component, the reactive power (Q) was set to 0, as well as the phase angle to avoid transients, and ensure the assumption that we are only looking at the steady state of the system.

As mentioned before, the operation of trains in the Netherlands are based on DC systems at 1-1.5 kV. In order to approximate that, the voltage was picked to be 1.5 kV DC which is comparable to 1.5 kV AC, but in three-phase systems that is comparable to 1.5 kV_{L-N} (Volts line to neutro. The model requires a V_{L-L} (Volts line to line) parameter which is given by:

$$V_{L-L} = V_{L-N} * \sqrt{3} \tag{1}$$

This results in a V_{L-L} of approximately 2.6 kV.

With these parameters set, some further assumptions that are made throughout the length of the study need to be addressed:

- We assume the train station already has an RBE system installed.
- Total weight of each train (number of carts, also number of passengers) affects the total power recovered and delivered to every train. We assume that all trains are the same weight all the time, that way the energy recovered and delivered can be constant for every train in the timetable.
- We are looking at steady-state of the system, not at the dynamics of the physical system. We avoid transients throughout the project by keeping only P in the system and setting Q=0 for every component.
- We assume that the approximation of DC to AC is possible under the conditions mentioned before.

- We assume the average rating of the load for regional train stations can range from 50 - 100kW; assuming that 60kW for the Enschede train station is the right ballpark.
- We assume that every element works at 100% efficiency to make the dynamics of power more comprehensible.
- We assume that the Enschede train station can structurally withstand a measured $1236m^2$ of PV on its roof.

With that clear, let us evaluate every component:

A. RBE Load

From some initial experimentation, it was determined that the load initially used for the variable load of the household is a dynamic load that can follow a predetermined load profile in which power can be injected or absorbed from the system. This means that if a load profile was fabricated in which the behavior of trains coming in and out of the Enschede train station was approximated, and a base load was selected for the minimum operation rating of the train station throughout the day, then the whole system would react correspondingly to the base load and the loads of the trains throughout the day.

The load profile was fabricated by analyzing the data that came with the model and determining the number of data points the input vector had by using the buildTrainloads script seen in Appendix A. The number of data points was determined to be 1441, which corresponds to a day evaluated in minutes (24 h/day * 60 min/h). This meant that by looking at the timetable of the trains arriving and leaving the Enschede station [23], the exact time an event happens can provide a data point that either absorbs power or generates power. Then under the assumption that Dutch trains operate in a similar manner as metro systems in different parts of the world, the study in [1] provides a comfortable approximation drawing from the study's conclusion that the amount of energy obtained from RBE recovery was the same as the energy used in traction for one day of operation, which was found to be 4.1 MWh/day on a single metro line. It seems illogical that the same amount of energy was calculated for recovery and traction, until the realization that more trains arrive throughout the day than the ones that leave. In the case of the Enschede train station the number of trains arriving throughout the day is 20, whereas 18 trains leave the station every day.

Following:

$$E_{RBE} = \frac{RecoveryEnergy}{ArrivingTrains} \tag{2}$$

$$E_{Trac} = \frac{TractionEnergy}{LeavingTrains} \tag{3}$$

and the assumption that for every hour that the station operates there is maximum one train that leaves and arrives, the power for recovery and traction are calculated to be 205 kW and 228 kW respectively. The Recovery Energy and Traction Energy in equations (2) and (3) are the same value previously found for traction in study [1]. This is feasible under the assumption that all trains arriving and leaving the station have the same number of carriages, and the same number of people. This is because the amount of energy recovered by RBE is affected by the weight of the moving object.

The script buildTrainLoads was then written to construct the input vector of the dynamic Load component. Another approximation is then made for a base load consumed throughout the day for the operation of the train station. For Regional Train stations, according to different sources analyzed by a GPT tool [12], [13], [14], typical base power ratings can range between 50-500kW. So we assume that for the Enschede train station, the consumption rating lies on the lower end of the range due to there not being any HVAC units or any high power demand equipment that runs all day, which leads us to comfortably pick 60kW as a good ballpark approximation.

The components that make up the load can be seen in figure 4.

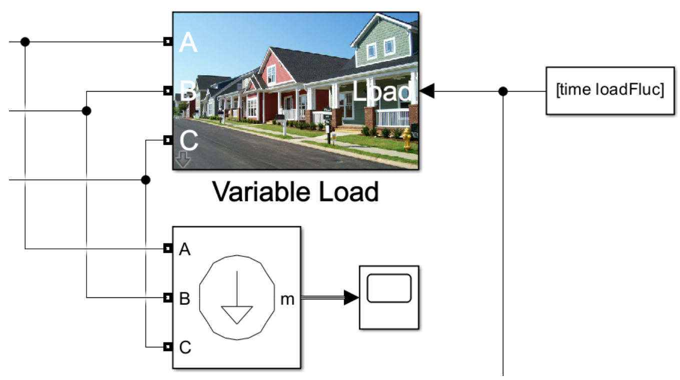

Fig. 4. Components that make up the RBE & base load

Now having the input vector and a base load, then it can be expected that the power consumed from the grid would follow the sum of the load input and base.

B. Photovoltaic

The PV initial functionality works in a similar way than the dynamic load of the previous subsection. A daily irradiance profile is used as an input, and in the initialConditions script that irradiance data is used to obtain a vector where the power is calculated using the following equation:

$$Ppv(n) = A * irr(n) * eff \tag{4}$$

where A is the surface area covered by PV, $irr(n)$ is the irradiance profile used as input which is discrete-time vector of variable n, and eff is the efficiency of the solar panels.

For the PV implementation we use in the model, the same components and irradiance data were used from the model's intended operation. This was because the data easily provided a selection between a clear day and a cloudy day in minutes, comparable to that of the dynamic load input.

To approximate this to the case of the Enschede train station, the surface area of the panels was adapted to a realistic sizing by evaluating the rooftop of the train station, and using google maps scales and a ruler, a clear usable area was determined. This was evaluated in $1236m^2$ initially, however after some initial experimentation, it was decided to lower the area to $750m^2$ using the logic that the more PV being installed, the higher the investment cost would be. The efficiency is then selected to be 0.3 to match the best available solar panels as of 2024 [15]. This selection is done under the assumption that it will take time for a solution like the one proposed to be realizable, and as the efficiency of solar panels increases each year, by the time this solution is feasible, a 30% efficiency solar panel should be commercially available.

The component for PV in the model can be seen in figure 5.

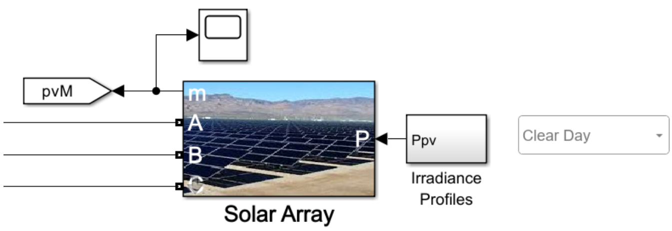

Fig. 5. Components that make up PV

C. Battery ESS

The battery in the model was initially intended to supply a household and charge using the power generated by PV. Initially the battery had a capacity of 150 kWh and a power rating of 150 kW, meaning the battery can be fully discharged in one hour, that is 1C. Additionally, the battery is meant to supply the base load of the household when PV is not available. That said, the battery follows a charge and discharge profile that is calculated using an EMS, which we shall explore later on.

Since sizing the battery for any specific case can be a whole study on its own, a ballpark value was selected based on recommendations from advisors and one source that mentions typical capacity for train applications can easily be above 500 kWh [16]. Based on this, the capacity of the battery is selected to be 600 kWh and the advice to keep the battery at 0.5C leads us to pick the power rating at 300 kW such that the battery can be fully discharged in 2h.

The battery and EMS system components in the model can be seen in figure 6

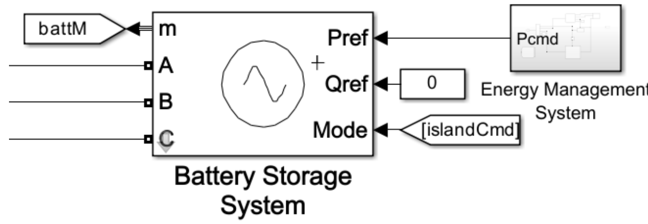

Fig. 6. Components that make up the battery and EMS system

D. Energy Management System

The EMS is intended to calculate the operation of the battery's charge and discharge throughout the day. This system is built using Simulink condition charts, and based on the system's inputs and an algorithm, it builds a vector that is used as an input for the battery. The algorithm originally used in the model follows four main states: Idle, Absorb from PV, Peak supply, and Night Recharge. The inputs for the intended operation of the EMS are: power from PV, power of the load, the battery state of charge (SOC), a battery on/off toggle, and a 24h clock. The original chart for the EMS can be seen in figure 7.

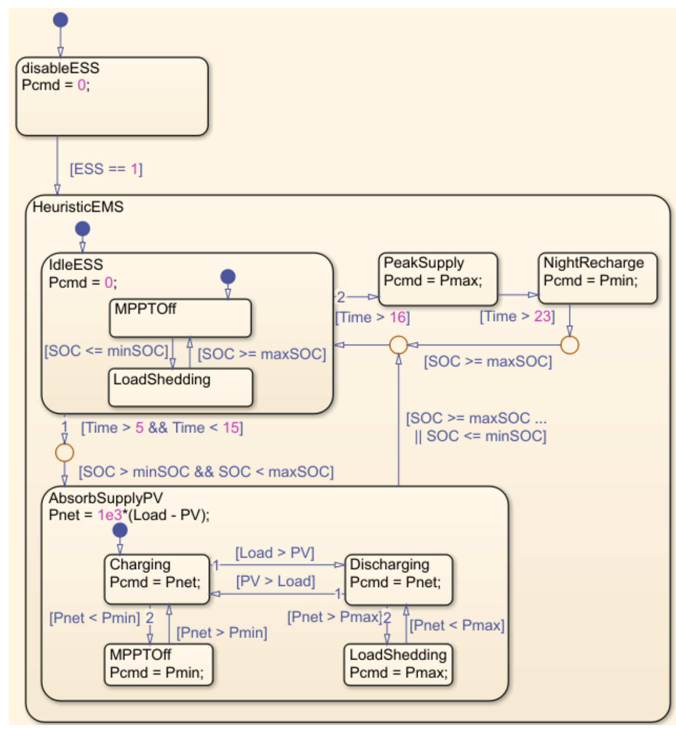

Fig. 7. Original EMS algorithm done by Jonathan LeSage.

Taking a closer look into the system in figure 7, it can be seen that the battery is allowed to charge from the grid when PV is not available. For the goals to be achieved by this study the function of charging from the grid is unwanted, as the objective is to reduce grid consumption as much as possible. The EMS should calculate the battery's function as: absorbing energy when available from PV and discharge to meet the load's demand. Additionally, the EMS can be programmed to maximize profit during the times of high cost, and sell the energy stored when prices energy are high.

The algorithm to achieve the function previously described can be seen in figure 8.

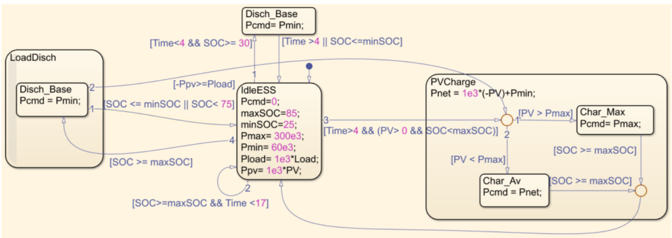

Fig. 8. EMS adapted to PV absorption and base load demand discharge.

The component for the EMS in the model can also be seen in figure 6.

E. Supercapacitor

The SC implementation is an added technology apart from the intended operation of the model. Its need was derived from the studies analyzed in the literature review section, where it can be seen that most implementations of RBE recovery use a technology that can support large fluctuations of power in short periods of time. In the case of the model at hand, it was ideal to just copy the battery component and adjust its dynamics to approximate that of a SC, that is a small capacity with large power rating. The purpose of the SC is to successfully absorb the power coming from the RBE load, and deliver the power to support traction of the same.

From study [6] ballpark values can be obtained for the aforementioned parameters resulting in a capacity of 5.1 kWh and a power rating of 2000 kW. However, after initial testing, the capacity of the battery was chosen to be 10 kWh. This is done to solve the issue of multiple trains arriving into the station at the late hours of the night without any trains departing to deliver power stored in the SC. This way, the SC can hold the energy of three or more trains, which is expected to be kept and delivered when the first trains depart in the morning.

The component that makes up the SC in the model can be seen in figure 9.

F. Grid

The utility access point is a metered point of connection with the high voltage grid. It is intended that this component would supply power to the microgrid system if the generating sources and storage systems can't supply the load's demand. This metered point allows us to calculate, based on the power absorbed by the system and a pricing profile in unitary money, the costs of operation for the train station during the day.

It is important to point out that costs of energy throughout the day change, where at specific times of the day power

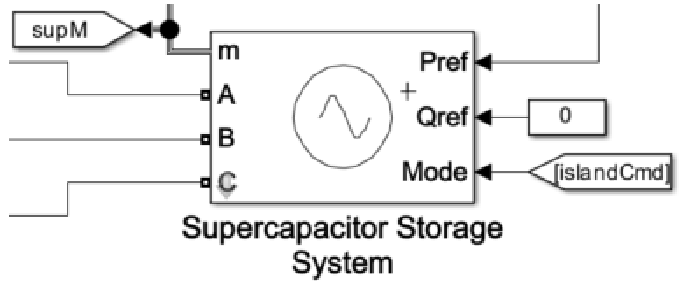

Fig. 9. Component used for SC emulation.

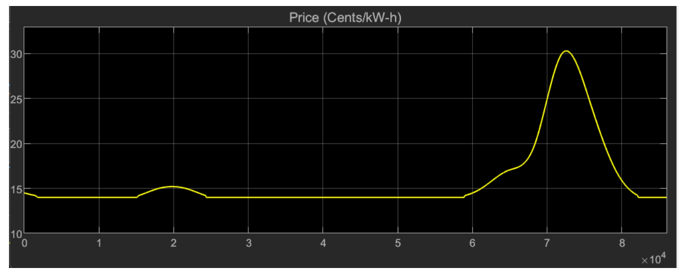

Fig. 10. Price of energy throughout the day provided by the model. The x-axis is time for 24h and the y-axis corresponds to the price of energy (cent/kWh).

can cost significantly higher. These times are specifically in the morning and the early hours of the night (late afternoon) as seen in figure 10. We use a cost profile measured in unitary money, where the cost per day is a key indicator to the performance of the system designed. The objective is to calculate the total energy that is consumed by the grid every day. The focus is only on the energy consumed from the grid when calculating the energy throughout the day, and not the energy generated as the point is to calculate how close the consumption can get to zero throughout the day. Adding generated energy to the energy consumed would be counterproductive, and in turn would not allow for accurate approximation of the amount of CO_2 consumed by the train station during the day.

The components that make up the grid access in the model are a three-phase transformer and a three-phase switch, and can be seen in figure 11.

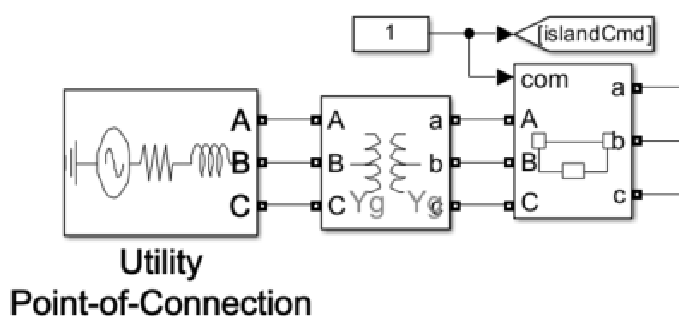

Fig. 11. Components that make up the Grid access point.

IV. SCENARIOS

There are four test scenarios that are proposed in this paper to be able to quantify data in a basis of Key Performance Indicators (KPIs). Said KPI correspond to overall cost, energy consumed from grid throughout the day, and the weight in tonnes of CO_2 consumed throughout the day. All these indicators will then be calculated for all scenarios using both clear and cloudy day datasets to have a broader data range to compare. The four scenarios are chosen as follows:

A. Base Case

The base case is analyzed as only the load and the grid access point are active. This is the case in which no technology is added to store energy, or additional PV generation. In this scenario we assess how much is the energy consumed by the station every day and the cost of said consumption. For the cost calculation, it is assumed that the station can recover braking energy from trains, and that the energy recovered can be sold at the same rate as that of the purchase rate described by the cost profile in unitary money provided by the model's resources.

It is expected that this scenario will yield the highest cost per day, but at the same time, it is the most economic solution. However, there is no improvement to the systems used today.

B. PV Only

In this scenario we analyze the effect of adding some PV generation to the system. This enables a separation between sunny and cloudy days and the effect on the KPIs for each variation. It is expected that the energy consumed per day, as well as the amount of CO_2 are higher when its cloudy compared to when its a clear day, as more energy is collected by PV in a clear day than in a cloudy day. It is also expected that PV meets the load demand when the power of PV is higher than the base load.

It is important to keep in mind that PV generation, similar to RBE, will also add earnings when calculating the costs per day, but only the energy consumed is considered for the energy KPI. That means that when calculating the costs of operation per day PV and RBE will generate profit that will influence the operation cost per day KPI, but are not included in the sum of power consumed from the grid throughout the day to get the energy KPI.

C. PV & ESS

For this scenario, the inclusion of a battery ESS is tested such that comparable results can be determined for the aforementioned KPI. The battery allows for storage of power coming from PV as well as a source to supply the base load of the station. Due to the high fluctuation of power coming from RBE, the battery can't handle storage and supply of such. The train load in this scenario is therefore met using power from the grid. The EMS that calculates the profile of the battery doesn't allow for the battery to recharge from the grid, so the battery is designed to be fully reliable on the power coming from PV.

It is expected however that during most of the day the base load demand is met using the power stored in the battery. This raises the expectation that the energy consumed throughout the day and the amount of CO_2 are lower in this scenario compared to that of the previous scenarios.

D. PV, ESS, & SC

In this last scenario a SC is added to the system such that RBE can be efficiently recovered and stored. The SC is expected to charge with the power delivered of up to three consecutive incoming trains, and is therefore expected to deliver the stored power to aid in traction of departing trains. With the SC solution, the energy consumed per day and the amount of CO_2 are expected to be significantly lower due to the amount of power redistributed from RBE recovery to traction. The power once consumed from the grid would significantly reduce without the big peaks of power that traction consumed, and in turn the disturbances on the microgrid voltage would become smaller.

The hypothesis of this research claims that this scenario is the best combination to reduce power consumption from the grid, however it is the most expensive solution when looking at the total cost of operation, where cost of investment needs to be evaluated as well.

Post-simulation Calculations

With the experiments described and the components of the model evaluated, individual simulations shall be performed for every scenario where KPI results should be comparable and make sense between scenarios. For this, the code postCalc was made to be run after the simulation in Simulink is complete, which can be seen in Appendix B. This code was made to calculate the different KPIs in the following ways:

1) Energy Consumed from Grid: Every single data point on the resulting grid power vector coming from the simulation is evaluated on whether it consumes or generates, if the point corresponds to generation, then we skip it, otherwise, we add the value to a sum. This would however be a sum of power and to convert it to energy, we multiply with time. Since the power vector corresponds to 24h of operation, then the sum is multiplied by 24h to get energy in Watt-hour.

2) CO_2 Created by Consumption: The grid energy previously calculated is then multiplied by the carbon intensity of the origin of the consumed energy. In the case of NS in the Netherlands, they claim that 100% of the energy consumed by their train stations is supplied by wind farms

[10]. Wind energy despite being renewable, does have a carbon intensity corresponding to 14 g/kWh.

3) Cost of Scenario: The total cost indicator is a combination of the daily operation cost and the investment cost of the technologies involved in each scenario. The investment costs shall be evaluated by using the web, whereas the daily cost of operation is a feature included in the original Simulink model and can be seen in figure 12. This however it is measured in unitary money since the currency is different than the euro, but most likely USD.

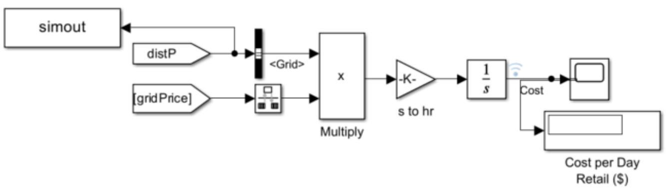

Fig. 12. Cost per day feature included in the original model.

It is important to notice that for every scenario not only the same KPIs are evaluated, but due to the method of analysis and the fact that more complex systems yield more precise datasets with more data points, the same number of data points needs to be evaluated for every scenario. If more data is added for every scenario, then the results would be opposite to those expected, where the energy consumed per day would increase every scenario. That is why the base case shall be evaluated first and the number of data points is to be determined. Every scenario following the base case shall then be divided by a decimating factor given by the division of each scenario's data points with the number of data points of the base case when calculated the energy consumed by the grid.

V. Results and Discussion

The results from the simulations performed using Simulink will be presented ahead. We shall first address the model designed and discuss the chosen sign convention to make the graphs in the results from the scenarios more comprehensive. Following this, an evaluation of every scenario and its relevant data shall be performed, as well as the KPI data will be arranged in a table. A discussion of the data collected will follow as well as discussion on the experimentation and further research.

A. Model & Sign Convention

The components previously outlined are arranged in the model designed for experimentation as seen in figure 13.

Comparing the model in figure 13 to that of figure 3, it can be appreciated that aside from the added component of the SC, there is a different structure under the power scope and its input arrangements. This structure seen in figure 14 is built with the intention of being able to rearrange the data coming from the distinct power signal that carries the data for all the powers in the system. This way the data

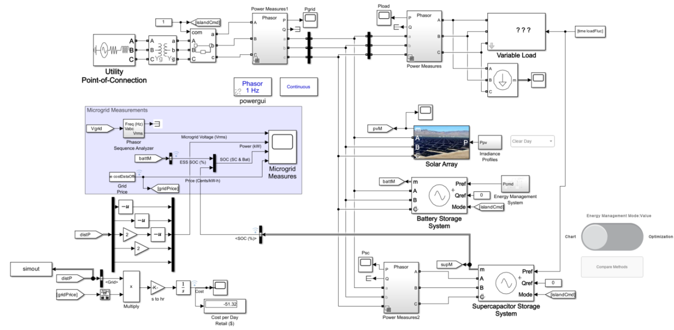

Fig. 13. Model designed for experimentation by adapting the model in figure 3.

could be flipped in order to make a sign convention that is understandable and follows physical rules like the conservation of power. The five signals being manipulated correspond to the powers of PV, Battery (ESS A), Grid, Loads, and SC. These signals are retrieved from a from-marker in such a way that its manipulation would only affect how we see the data whereas the operation would remain the same.

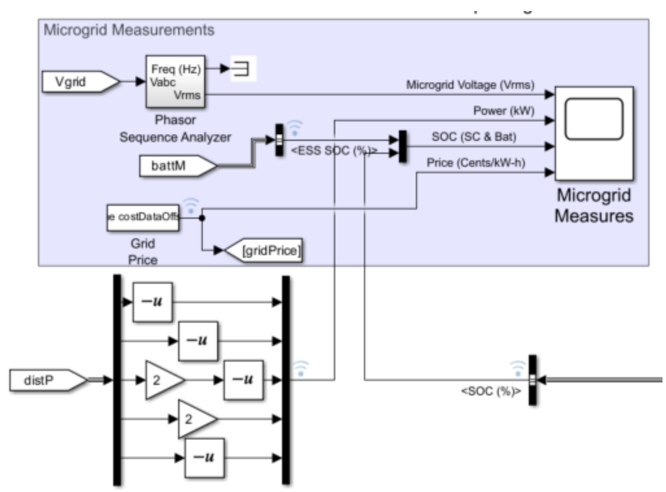

Fig. 14. Structure built in the model to flip and adapt signals to desired sign convention and gain.

The sign convention is then chosen as the following:

- PV - less than 0 is Generation.
- ESS A & SC - less than 0 is Discharging, more than 0 is Charging.
- Grid - less than 0 is Consumption, more than 0 is Generation.
- Loads - less than 0 is Generation, more than 0 is Demand.

The sign convention for the graphs is chosen following the logic that universally, generative sources are comonly displayed as negative, indicating power flowing out of the system. The storage systems like the battery and SC were chosen such that a logical interpretation of power flowing in and out of those devices as positive for charging and negative for discharging. The Grid and Loads sign conventions will be by nature confusing, since initially and by logic, the power consumed by the grid should follow the power of the loads throughout the day. The sign convention for this case is picked opposite, such that the curve for the power of the grid to be more comprehensive.

It can also be seen on figure 14 that the signals for the power of the grid and the power of the load have a gain of 2. This is added after solving for an initial problem found where these signals would not display correct values due to their RMS calculation. Within the model the power for the loads and grid specifically are calculated as the product of each component's voltage and current, which in RMS are expressed as:

$$V_{RMS} = \frac{V_P}{\sqrt{2}} \tag{5}$$

$$I_{RMS} = \frac{I_P}{\sqrt{2}} \tag{6}$$

The voltage and current that are comparable to DC correspond to the peak-peak formulation of these variables such that AC and DC power can be comparable. So combining equations (5) and (6) to calculate power yields the following:

$$Power = V_P * I_P = V_{RMS} * I_{RMS} * 2 \tag{7}$$

With these instructions to understand the data provided by the graphs, the results for the scenarios presented ahead shall be a seamless read.

B. Scenarios

1) Base Case: Represented by only the combination of RBE recovery, the base load, and the grid access point, it provides the lowest investment cost from all scenarios. There is no added technology that would represent additional costs other than the RBE recovery system, but this seems unimportant if we assume that train stations would have them already, and that we are considering added investment costs as a metric either way. The total costs of operation for the day in this scenario is recorded by the feature in figure 12, which marks 113.1$. This means that the way the station is allowed to consume from the grid every day would further cost the station about 113$. If we consider that value in the long term and thinking that train stations are open and operating 365 days of the year, that adds up to 41.25k$ in a year, 412.45k$ for 10 years.

The grid power vector has 1480 data points. All following scenarios would have to be decimated with respect to the number of data points in this scenario. The graph for the power dynamics of the grid (red) and the loads (green) throughout the day in this scenario can be seen in figure 15. From this, we can see the expected behavior of the load following the grid, but to maintain correct physical laws, the power of the grid is flipped to perceive the sum of powers equal to zero.

From the grid power curve seen in figure 15 we determine that the total energy consumed by the grid throughout the

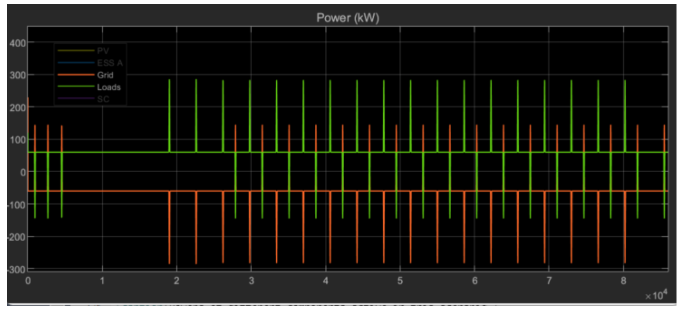

Fig. 15. Powers of different components active in the Base Case scenario. The x-axis is time for 24h and the y-axis corresponds to Power (kW).

day is 2.39 GWh for this scenario. This makes sense when considering the high costs of operation calculated throughout the day.

The amount of CO_2 calculated in this scenario from the energy consumed out of the grid is 33.45 tonnes produced during the day.

2) PV Only: In this scenario we consider a $750m^2$ array of PV cells that would generate power to meet the demand of the base loads and the traction of trains. First we shall evaluate this scenario when there is a clear day. All excess power would be sold at the same rate that is defined by the cost profile of the day supplied by the model. For that reason the cost of consumption of energy for the day in this scenario is recorded as a negative value, which is -28.45$. If the cost is negative, this can be considered that for the day of operation, profit from the sale of the solar power overcomes the costs of consumption leading to a daily profit of about 29$. When a cloudy day is found in this scenario, the total cost of the energy is recorded as 14.87$. This means that for cloudy days, the system is not so good at making enough energy to be profitable, in which case would cost instead of earn.

When assessing the solar panels, a high efficiency solar panel was considered, which corresponds to mono-crystalline panels of 750 W max. power rating per panel and an area of $3.24m^2$/panel [24]. The cost for these specific panels is about $200\$/m^2$ [17], so for $750m^2$ this would amount to an investment cost of about 150k$ just for obtaining the solar panels, which doesn't include labor and materials.

The number of data points that correspond to the grid power vector for this scenario when its a clear day is 2089, so this means that the resulting energy consumed from the grid shall be decimated by a factor of about 1.41. The graph for the power dynamics of the system for this scenario can be seen in figure 16. There it can be seen how the grid responds to the injection of power coming from PV (yellow), and how the response of RBE follow the same spikes, just larger when trains are coming into the station. The energy consumed for the clear day variation of this scenario was calculated based on the grid power curve in figure 16, which was 1.04 GWh. This result is as expected due to the supply of the base load for a big portion of the day. This in turn suppresses the traction peaks that demand consumption.

In this $750m^2$ area, the max. power can be derived using the data given for the area per panel and the max. power rating per panel. The number of panels that fit in this area is 231, which gives a max. generated power of 0.052 MW if 30% efficiency is considered. This is different than the max. point in the PV power curve of figure 16, where it can be seen to be about 0.2 MW. This discrepancy is given by the irradiance profile used, which is the same as the one that came with the model. The power of PV is calculated in the model by using equation (4) where the irradiance is not a vector calculated for the chosen of panels. More about this will be addressed in the Points of Improvement, subsection V-E.

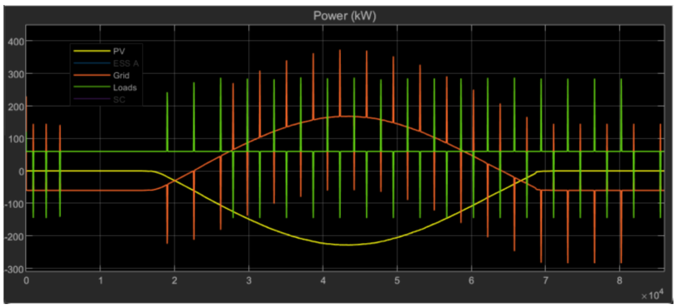

Fig. 16. Powers of different components active in the PV Only scenario, when its a clear day. The x-axis is time for 24h and the y-axis corresponds to Power (kW).

For the cloudy day variation of this scenario, the number of data points for the grid power curve is 2584, which yields a decimation factor of about 1.75. The graph of the power dynamics for this variation can be seen in figure 17. There it can be seen the effect of clouds in the environment and how the power of the grid responds to the disturbances. The energy consumed from the grid throughout the day was calculated to be 1.11 GWh. It can be seen from figure 16 and 17 that the power generation differs significantly between a clear day and a cloudy day, so that poses the concern that through extended cloudy periods the autonomy of the station would reduce, causing the costs of operation to increase. This however, could be mitigated by the addition of an ESS to store power, and ensure autonomy for extended periods of time when PV is not available.

Fig. 17. Powers of different components active in the PV Only scenario, when its a cloudy day. The x-axis is time for 24h and the y-axis corresponds to Power (kW).

The amounts of CO_2 calculated on this scenario per day are 14.53 tonnes produced when its clear, and 15.44 tonnes produced when its cloudy. This makes sense considering that the energy consumed when its clear is less than when its cloudy.

3) PV & Battery: For this scenario, a battery with a capacity of 0.6 MWh and a rated power of 0.3 MW is incorporated to absorb and store the power coming from PV. The EMS that comes with the battery that was previously outlined is also used to calculate the behavior of the battery. The most appropriate battery system for the application at hand is likely to be a Lithium-Ion (Li-Ion) battery pack, due to the high power density and commercial availability for ESSs. Acording to an article on Bloomberg Business, as of 2024 the price of Li-Ion dropped to 115$ per kWh [18]. For 0.6 MWh, the cost for the battery pack surpassess the 60k$, and adding the costs of electronics and installment, a ballpark value of 200k$ is analyzed on top of the investment for PV. The costs of operation for a clear day in this scenario is measured to be -51.80$, whereas when its a cloudy day, the cost is measured -8.94$. This means that with this technology combination the train station is making money every day regardless of there being a clear or cloudy day.

The number of data points of the grid power vector in the clear day iteration for this scenario is measured as 28063, which means that the decimation factor calculated is of about 18.96. The power dynamics for the clear day iteration can be seen in figure 18, where the curve for the battery (blue) can be seen responding to the power coming from PV. As the sun rises, the battery can be seen following the line where the grid would be receiving the power of PV in the last scenario, showing that the battery charges from the power coming from PV as intended. The State of Charge (SoC) curve is added to show the activity of the battery in terms of the energy stored, and its intended to make sense of the power curve from the battery. It can be seen how at the start of the simulation the battery discharges whatever is left from the night before (Start charge 50%) and fully discharges until the minimum limit at the rate of the base load. It can also be seen how the battery goes into idle state when its full, that is 0 power movement, and the grid takes on to sell the excess power coming from PV. It is important to point out the spikes coming from the trains are still present, this is as expected since the power fluctuations are too large for the battery to handle. This also means that the loads will keep consuming from the grid to meet the demand of the train's traction. For the clear day iteration, the resulting energy consumed by the grid throughout the day is 153 MWh. This is as expected since the grid power line is now most of the time located at 0 throughout the day. This allows for the observation that most of the power consumed from the grid is still largely caused by traction of the trains.

For the cloudy day iteration of this scenario, the measured number of data points jumps to 65758, which is understand-

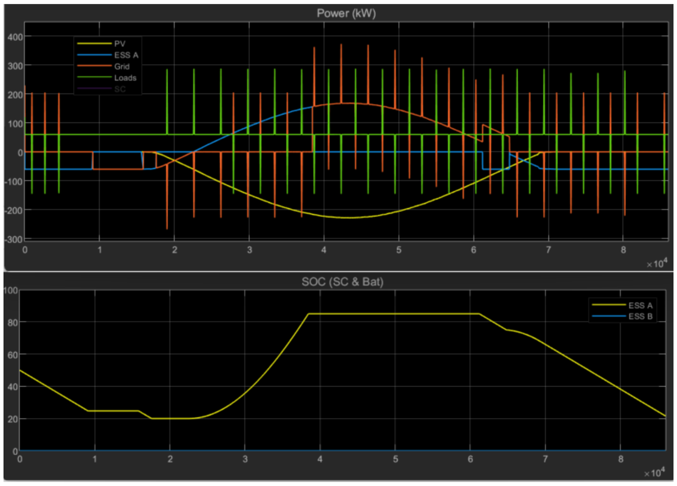

Fig. 18. Powers of different components active in the PV & Battery scenario, when its a clear day. The x-axis is time for 24h and the y-axis corresponds to Power (kW).

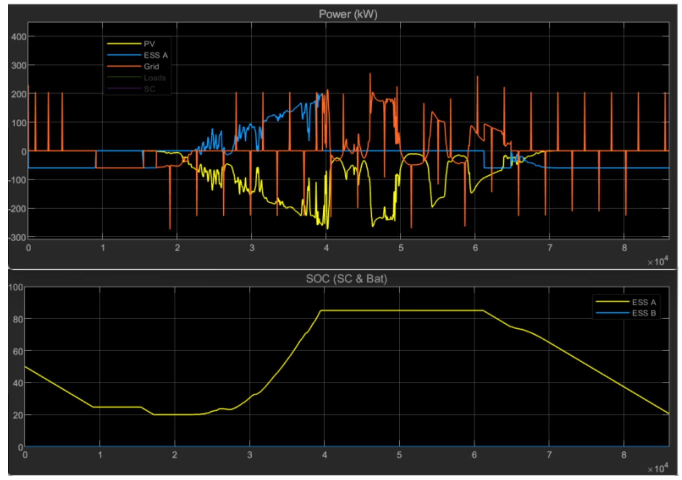

Fig. 19. Powers of different components active in the PV & Battery scenario, when its a cloudy day. The x-axis is time for 24h and the y-axis corresponds to Power (kW).

able considering the higher complexity of the model and the variability of the cloudy day scenario. The power dynamics for the cloudy day in this scenario can be seen in figure 19. By now the behavior of the grid power following the load should be evident, and we know that the base load is 60 kW, so to better visualize the behavior of the battery, the load curve is turned off in figure 19. Here we can see how the curve for the battery follows the high varying curve of PV with precision until the moment it gets full, however it follows the same behavior calculated by the EMS when compared with the clear day iteration. It can be also seen for both iterations the offload function when the price of energy is higher closer to 17:00 PM, that way the profit is maximized and the slope of PV can be used in favor for continuing with the supply of the base load. The energy consumed in the cloudy day iteration of this scenario was calculated 166 MWh, which follows the trend of higher consumption of every scenario when compared to the clear day iterations. Compared to the clear day iteration, it can be perceived that the effect of the cloudy day affects the SoC of the battery by delaying the time in which the battery reaches its full state by only a few minutes. The battery then stays idle for most of the day once the battery is charged to its limit. Prolonged cloudy periods will affect the autonomy if its multiple days, but only in the time it takes to charge the battery relating to the effect previously addressed.

When its a clear day in this scenario, the amount of CO_2 consumed is calculated to be 2.14 tonnes, whereas for a cloudy day it is calculated to be 2.33 tonnes. The difference shows that the energy consumed between variations is somewhat similar, so the observation can be made that the EMS is sufficiently good to pick up the power from PV when its available, and its optimal for meeting the base load's requirement throughout the day.

4) All Technologies: In this last scenario, a SC is added with a rated power of 2 MW and a capacity of 0.01 MWh to absorb and distribute the power spikes coming from RBE and traction. For that reason the input profile given to the SC is the same as the train load, that way the SC follows the power focused on the train loads. When looking at the investment that corresponds to a SC, it is important to keep in mind that this is the most expensive piece of technology. High fidelity SCs can cost between 5000-10000$ per kWh [19]. Assuming that the higher end of the spectrum is needed to ensure quality and efficiency, just the SC would cost 100k$. The expensive thing to make is the electronics and peripherals needed to handle the high power demand, which can cost 100-200$ per kW, and with 2 MW of power that would add up to 400k$. With everything combined and with installation costs considered, an appropriate ballpark value for the total investment cost of the SC is about 600k$. Along with PV and the battery proposed, the total cost of investment for this scenario is about 950k$. The clear day iteration of this scenario has a daily operation cost of -51.32$, and the cloudy day iteration has such of -8.47$. These values are slightly lower than those on the previous scenario, which would mean that there is less profit. The reason behind the lower profit will become evident later on.

The clear day iteration of this scenario recorded 51042 data points for the grid power curve, so the decimation factor used in this case is 34.49 due to the complexity of the system increasing by the addition of the SC. The power dynamics graph for this scenario can be seen in figure 20, and it can be seen how the SC curve (violet) follows the same curve of the load, but inverted and without the 60 kW offset coming from the base load. This shall be analyzed as trains coming into the station would make a generative peak (negative), for which the SC curve shall respond with a peak charging (positive) the device. This shall be vice-versa for trains departing the station, where a train leaving creates a peak demanding (positive) from the load and to which the SC shall respond with a discharging (negative peak). From the graph in figure 20 shows all the

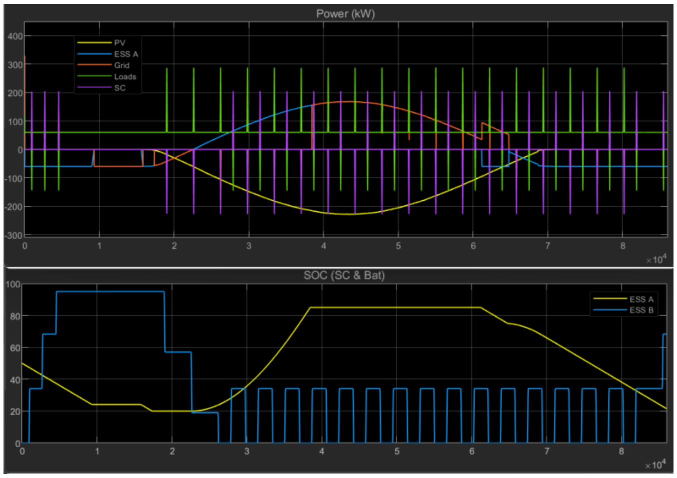

Fig. 20. Powers of different components active in the All scenario, when its a clear day. The x-axis is time for 24h and the y-axis corresponds to Power (kW).

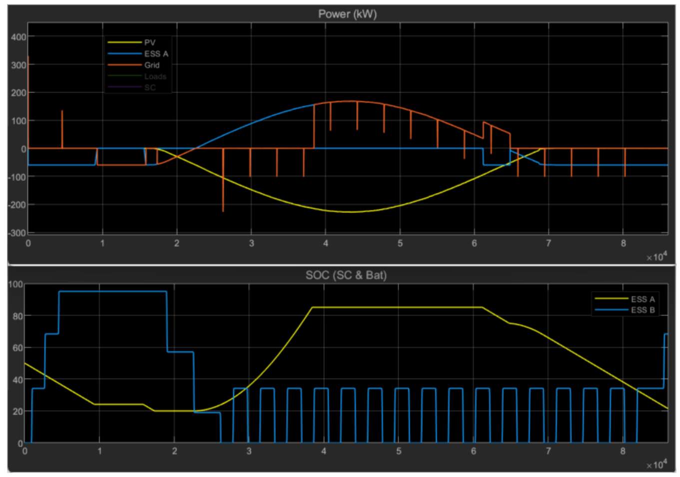

Fig. 21. Same graph as the one in figure 20, but with the SC and loads curves turned off. The x-axis is time for 24h and the y-axis corresponds to Power (kW).

curves, and the effect of the SC on the grid power is not very noticeable, so let us look at figure 21. Here the load and SC curves are turned off, but its the same graph as figure 20 and understanding how the SoC curve describes the behavior of the SC over time, the effect of the SC on the grid power should be intuitive. The grid power in figure 21 is notably different than the other scenarios evaluated, where it can be seen that the peaks corresponding for RBE recovery are gone in the most part. The SC behaves as expected by fully absorbing the power of more than two incoming trains. In the same way, the peaks corresponding to the traction of trains leaving are visibly lower than that of the previous scenarios. It is safe to say that the SC behaves as expected, however there seems to be a problem with the precision of the power consumed by traction, where the value is calculated to be higher than it should be by 0.0791 MW. This is odd since even with the efficiency parameter of the SC set to 100%, the difference is still there. This would in turn affect the energy consumed per day, and would in fact be lower than the value calculated of 52.5 MWh throughout the day.

In the cloudy day iteration of this scenario, 134882 data points are recorded, and that means a decimation factor of 91.14. This jump shows how this is the most complex system in the most variable scenario. As before, the loads and SC curves shall be turned off to better appreciate the grid power curve in figure 22. Here, the same behavior seen on the grid curve for the clear day iteration can be seen, where the peaks corresponding to traction are significantly reduced and the peaks of RBE for the most part disappear. The energy consumed in the cloudy day iteration of this scenario added up to 203 MWh troughout the day, which is about 50 MWh higher than the energy consumed in the cloudy day iteration of the previous scenario. This could be in part an effect of the same discrepancy previously found, which would in fact reduce the energy consumed from the grid in both iterations.

The amount of CO_2 produced per day of operation in

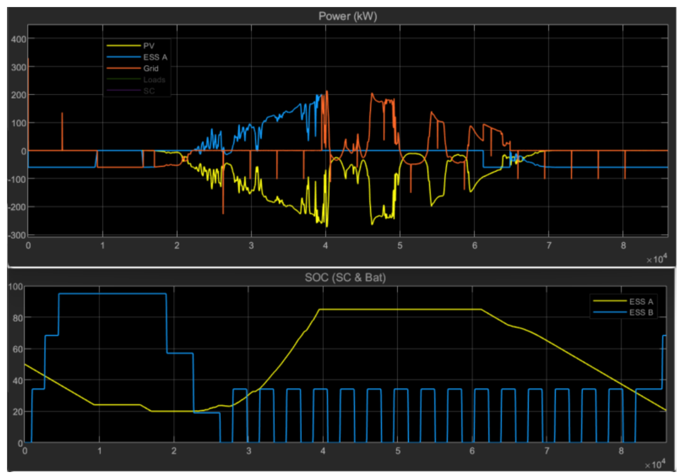

Fig. 22. Powers of different components active in the All scenario, when its a cloudy day. The x-axis is time for 24h and the y-axis corresponds to Power (kW).

the clear day iteration was recorded to be 0.735 tonnes. This makes the clear day iteration the less polluting solution found. The cloudy day iteration recorded 2.84 tonnes of CO_2 produced throughout the day, which is corresponding to the higher energy consumed, and is also higher than the comparable iteration of the previous scenario.

C. KPI Data

In Table I, we can find the results from the simulations for every scenario arranged in a more clear and concise fashion. It is important to point out that all data collected corresponds to a single train line so when we say that the train station consumes x energy per day, we mean for a sinlge line. Reality would be 3 train lines in the case of the Enschede train station, which are handled by the company NS.

TABLE I

KPI VALUES RECORDED THROUGH EXPERIMENTATION

Scenario	E_g (kWh/day)	Cost ($/day)	CO_2 (Ton./day)	Data Points
Base Case	2.39x10^6	113.1	33.45	1480
Pv Only (Clear)	1.04x10^6	-28.45	14.53	2089
Pv Only (Cloudy)	1.11x10^6	14.87	15.44	2584
PV & Bat. (Clear)	1.53x10^5	-51.8	2.14	28063
PV & Bat. (Cloudy)	1.66x10^5	-8.94	2.33	65758
All (Clear)	5.25x10^4	-51.32	0.735	51042
All (Cloudy)	2.03x10^5	-8.47	2.84	134882

D. Discussion

Results: The base case scenario provides a look into the system with no added technology. This system shows the highest daily energy consumption and CO_2 emissions, with values of 2.39 GWh and 33.45 tonnes respectively. In this scenario the loads' demand is purely met by using power from the grid, which explains the staggering amounts of energy consumed and CO_2 emitted. In this scenario there is no daily profit, every day the operation of the station will cost 113.1$, so with the objective to reduce costs in mind, this solution is counterproductive. If long term is considered, close to 500k$ would be spent in a 10 year span.

The PV only scenario improves the system with the addition of $750m^2$ of high efficiency solar panels. This scenario, adds a weather factor that determines the amount of power that can be generated throughout the day, which must be mentioned that can be a limitation when there is no irradiation. In this scenario however, the system designed reduces the energy consumed from the grid by half compared to the base case regardless of the weather conditions. This system provides adequate profitability when its a clear day, with daily profit of 28.45$, but when clouds roll in the system's profitability diminishes with an operating cost of 14.87$. This solution comes with an investment cost of over 150k$, where if the assumption is made that the weather is cloudy 60% of the time in the Netherlands (and 40% of the time its sunny), then an average cost/profit per year can be derived by using equation (8). For this scenario the annual cost is calculated to be -897.2$/yr and this would consider both evaluated weather iterations throughout the year. The negative value represents profit, and using that the Payback Period (PbP) can be derived using equation (9). With this profit margin it would take longer than 300 years to recover investment from the sale of power alone.

$$Cost_{av.}/yr = Cost_{Cle} * 365 * 0.4 + Cost_{Clo} * 365 * 0.6 \quad (8)$$

Where $Cost_{Cle}$ is the cost of the clear day scenario and $Cost_{Clo}$ is the cost of a cloudy day.

$$PbP = \frac{InitialInvestment}{AnnualProfit} \quad (9)$$

It is important to point out however, that compared to the base case, the PV only scenario is indeed profitable. Over a 300 year span, the base case would have spent close to 12M$, whereas in that time the investment made on the PV system would have been made back and profiting would start. However, this is a surrealistically long time.

For this scenario, the emission of CO_2 is significantly reduced by almost half of the emission of the base case, meaning that the solution at first glance is greener than purely consuming energy from the grid all day.

The PV & Battery scenario further improves the system with the addition of a Li-Ion battery pack with a capacity of 0.6 MWh and a rated power of 0.300 MW. With this scenario, the battery provides a method to store the power generated from PV only, as the battery cannot handle the high power peaks caused by RBE and traction. From the data collected in Table I, it can be calculated that the power consumed by both iterations of this scenario is more than 6 times lower than that calculated for the PV only scenario, and at least 14 times lower than the base case for both iterations. In the same way the emissions calculated respond to the same factor of reduction. The daily cost of operation for the clear and cloudy day iterations are respectively -51.8$ and -8.94$, and using this to calculate the yearly profit the same way using equation (8), it is calculated to be 9.52k$/yr. This solution comes with a ballpark investment cost of about 350k$, so in such way as it was calculated the previous scenario, the time that would require to return the investment is calculated to be closer to 52 years using equation (9).

When analyzing the profitability, this system shows great potential to reduce costs and the fact that the initial investment of that magnitude can be recovered in 52 years by just the sale of power alone. Its interesting to see that the investment cost for this scenario is comparable to the cost of operation for 10 years calculated in the base case. If the same 52 years elapsed in the base case scenario, this would correspond to a total cost of 2.15M$. This shows that the PV & Battery scenario could be the best option for implementation so far, but its important to point out that this solution does nothing to approach the storage of energy coming from RBE, which is one of the targets of this study as well.

The emissions of CO_2 for this scenario are further reduced compared to that of the previous scenario. Similar to the calculated consumed power, emissions are reduced by a factor of 6, and compared to the base case by a factor of 14.

The last improvement done in the All scenario is the addition of a SC with capacity 0.01 MWh and a rated power of 2 MW. This scenario gains the sought capability of absorbing and distributing the power of RBE and traction, and it does so for the most part. From Table I, the results of the energy consumed from the grid, the emissions, and the operation costs don't show major improvement from the previous scenario. When in a clear day, the energy consumed from the grid is only 3 times lower than the last scenario, whereas for the

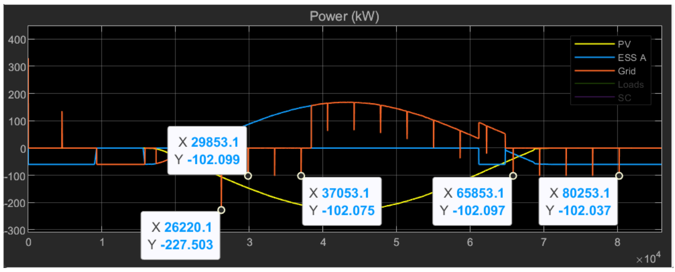

Fig. 23. Same graph in figure 21, but with data points marked to show constancy of the discrepancy found.

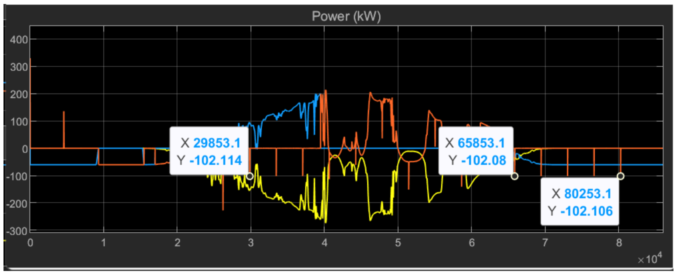

Fig. 24. Same graph in figure 22, but with data points marked to show constancy of the discrepancy found.

cloudy day scenario the energy consumed is calculated to be close to 0.04 MW higher than that of the last scenario. As previously mentioned, there seems to be a discrepancy on the peaks corresponding to traction in the grid power line, where the results obtained differ from what was expected by 0.0791 MW. It can be observed in figures 23 and 24 that in the same graph obtained in figures 21 and 22 are tagged with different data points to allow us to see that the value found for the discrepancy in the traction surges remains constant. This is a shortcoming in the process that didn't have the time to be investigated and more about it can be found in the Points of Improvement, subsection V-E. This however does affect every KPI value calculated for this scenario, as the calculation of the energy consumed from the grid will be higher than what is expected in both iterations, and the operation cost would also be higher (or less profit) as more energy is being consumed than it should.

The operation costs recorded by Table I for this scenario shows -51.32$ for a clear day and -8.47$ for a cloudy day. Compared to the last scenario, both iterations of the All scenario perform slightly worse at generating profit with a difference of at least 0.5$ per day. With the addition of the SC to the system, the investment costs jump up to approximately 950k$, which is a significant amount higher than that of the previous scenario. Using equations (8) and (9) the annual profit is calculated to be 9.35k$/yr, and with that the PbP is calculated to be 102 years. Comparing to the base case scenario, 102 years would mean expenses of 4.19M$, which is more than 4 times the cost of investment.

When evaluating the CO_2 emissions in this scenario, it can be seen from Table I that similar to the energy consumed throughout the day, the improvement done in reducing emissions follows the same trend. For the clear day there is an improvement of almost 3 times lower emissions, but for the cloudy day iteration the system performs worse than that of the PV & Battery scenario.

Overall the analysis of every scenario provides a clear picture on the feasibility of the proposed solution. It is evident that the cost of investment of the All scenario is too large for the improvement the SC adds to the system based on the results obtained. It is important to mention again however, that the error in the traction found in the All scenario would significantly change the results, but further research should be conducted where all these issues are addressed, and a more realistic study can be conducted, but in the case of this study there was not enough time. In any case, the feasibility of this scenario would have been subjected to evaluation relating cost and improvement, but the investment costs appear to be too high either way.

Using the base case as a common point of comparison, it can be seen that the PV & Battery scenario poses the highest energy savings, cost of operation, and the least CO_2 emissions with the most reasonable initial investment. From the 350k$ that the investment poses, a big portion corresponds to power electronics and installment, which is estimated in today's prices for power electronics and labor. With this considered, and the fact that power electronics are bound to reduce in price as time passes [20], the PV & Battery solution significantly increases feasibility if applied a few years down the line. The PV & Battery solution does not succeed in reducing grid dependency however, which is the target of this study.

Furthermore, it was discovered while doing some final research that the company responsible for the technical maintenance and infrastructure of the Dutch train system is a company called ProRail, when it was assumed that it was NS itself (they just handle everything passenger related). When digging deeper into the company, it was discovered that the government provides subsidies for their operation and infrastructure work, and in 2023 the cash flow of the company amounted to 249M€ [21], which is higher if converted to USD. It is mentioned that the amount of money that the company moved doesn't only go into station and track renovations, but it is a big part of their yearly budget. It was also found that the government is not shy to upgrade rail systems when there is business to be made as seen in the article in [22]. With this in mind, the limitation posed by investment cost loses pressure when the fact that the company that handles this, at least in the Netherlands, is aware and able to handle the high investment costs.

E. Points of Improvement

The biggest point of improvement found for this solution is found in the data used for the PV generation. Since the beginning of this research, the data used for the irradiance profile of PV was the data that came along with the model, without realizing that that data set provided is definitely not from Enschede and most likely, not from the Netherlands at all. For better approximation to local application, a data set of the irradiance of the zone would have been better to yield more realistic results. For this, an online program called PVGIS was found that could provide a dataset of exactly the location where the panels would be installed on the roof. This program can provide a 24h irradiance vector as a .csv file but the limitation is that the vector measures the day by hours, when the input of the component in figure 5 takes a vector of a day in minutes. This could have easily been solved by up-sampling the vector provided by PVGIS such that it would include the number of points of a day in minutes. The use of PVGIS for a more realistic irradiance profile would also solve the discrepancy found with the power generated from PV compared to what was calculated, as the online tool provides a way to input numerous parameters like the max. power rating and panel area.

Another point of failure that can be determined was the error previously mentioned with the spikes from traction of the grid power curve. The source of this error is still unknown, but an educated assumption can be made on the source if we consider the addition of data points that the model goes through as the complexity of the model increases. Because of this, it is possible that the surges felt by the grid were slightly shifted in time, and the activity of the SC should follow the train load, so this would mean that the short duration of the pulse done by the SC attempting to follow the load falls out of synchrony with the grid, and the surges wont match in time anymore. This does pose the question of what happens to the power charged into the SC however, if the SC shows it fully discharges? If that could be justified, then a correction process can be done on the peaks related to traction, as it can be seen from figures 23 and 24 that the peaks are constant for both weather iterations, and the peaks are the only place where discrepancy is found. With that, the KPI values for both iterations of the All scenario can be recalculated and the performance would show significant improvement for both weather iterations.

Aside from errors on the model, a point of improvement is found on the reality, or rather the approach of reality for the system. Throughout this study, many assumptions are done in order to make an approach to reality, yet both the battery and SC are programmed with an efficiency of 100%. This was done initially to verify the correct operation of both these components, but in reality, neither of these components can have such efficiencies on physical systems. Another significant point of improvement on the reality of the system lies on the difference between AC systems and DC systems which this model tries to emulate. Even though an approximation can be made to the DC system, it is not fully the same. The AC implementation used in this model was chosen due to the simplicity it provides, but the system in essence should be a DC system for correct approximation to train systems in the Netherlands.

As a further improvement on the system, the use of predictive algorithms could mitigate the issue with extended cloudy periods and handling the battery SoC. The original model has a way to toggle a day-ahead optimization that uses a predictive algorithm, but due to the lack of time this feature couldn't be looked into. This however could be key to improving the EMS of the system by making predictive calculations and adjusting the behavior of the battery such that grid autonomy can be further improved. Predictive algorithms could also be beneficial in the price profile used to calculate costs, as energy doesnt only have different costs throughout the day, but it also differs from day to day.

VI. Conclusion

The system created shown in figure 13 successfully accomplishes the targets set out to reduce the energy consumed from the grid, reduce operation costs, and reduce CO_2 emissions, but due to the number of approximations and assumptions made for this model, implementation in the real-world would require more rigorous studies where a system that approaches reality is used. Throughout this paper, different scenarios are evaluated where different technology combinations are tested and analyzed for the aforementioned metrics. The results show how the PV & Battery scenario, where the technologies added are only PV and a battery from a base case (Grid and Loads only) shows the best performance compared to investment cost. For the energy consumed from the grid per day, 24 MWh was calculated when its a clear day and 175 MWh when its cloudy. With negative values recorded for both iterations of the weather, costs per day turn to profit per day with 57.57$ for a clear day and 14.72$ for a cloudy day. The amount of CO_2 emitted from the daily consumption of energy from the grid for a clear day is calculated 0.336 tonnes and 2.44 tonnes for a cloudy day. Although the solution proposed by the last scenario assumes a high investment cost, this paper concludes that if not now, in a couple of years when the cost of power electronics have reduced, it will still be a feasible option.

Acknowledgment

A special thanks to Dr. Nataly Bañol and Dr. Prasanth Venugopal for the attentive help, tender teaching and comprehensive motivation throughout the duration of this study. A special mention to ChatGPT, for the help condensing the studies used to write this paper and their results.

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APPENDIX A
CODE FOR BUILDTRAINLOADS.M

```
RBEload= readmatrix("LoadTrain.xlsx");
veclengy= size(RBEload(:,1));

rbe=205e3;
trac=228e3;

for i=1:1:7
    if i<=4
        for j=1:1:veclengy
            if RBEload(j,i) == 1
                RBEload(j,i)= RBEload(j,i
                    )*trac;
            elseif RBEload(j,i) == -1
            RBEload(j,i)= RBEload(j,i)*
                rbe;
            end
        end
    elseif i==5
        RBEload(:,i)= 0;
    elseif i==6
        RBEload(:,i)= -300000;
    elseif i==7
        RBEload(:,i)= 300000;
    end
```

APPENDIX B
CODE FOR POSTCALC.M

```
Pgrid=0;
Pload=0;
Pgrid = simout.Grid.Data;
sumGrid=0;
Egrid=0;
CarInt_win= 0.014;    % kgCO2/kWh     Wind
    Carbon Intensity
baseLen=1480;
l=0;
l = length(Pgrid);
```

```
for i=1:1:l
    Pgrid(i) =Pgrid(i);        % factor 2
       multip. for p-p instead of RMS
    if Pgrid(i) <= 0
        sumGrid = sumGrid;
    else
        sumGrid = sumGrid + Pgrid(i);
    end
end

decfac=l/baseLen;
Egrid= sumGrid*24/decfac;      %kWh
Co2= Egrid*CarInt_win;  %kg
```