MASTER

Designing a Battery Energy Management System for Minimizing Energy Costs in Local Energy Community

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by

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Designing a Battery Energy Management System for Minimizing Energy Costs in Local Energy Community

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Abstract— **Solar power plays a vital role in addressing environmental challenges caused by fossil fuels. Nowadays, many households, office buildings, and communities are installing photovoltaic (PV) panels on their rooftops to harness green electricity and, more importantly, reduce electricity expenses. Despite its benefits, solar power supply is unpredictable, and sometimes generating more energy than is needed, resulting in wastage. To address this issue, a combination of renewable resources and battery energy storage (BES) proves to be an effective solution. BES allows surplus solar energy to be stored during periods of high supply, ensuring its availability when needed. Moreover, it is essential to not only consider the integration of BES and renewable energy sources in alignment with sustainability goals, but also recognize its economic advantages for building owners. By optimizing the performance of BES, it becomes possible to reduce electricity operating costs. Therefore, this study focuses on developing an energy management system (EMS) designed to enhance cost savings for PV owners. Conducted in Bunnik, the Netherlands, the case study aims to explore the impact of integrating RES with BES. The findings of this research provide valuable insights and highlight the substantial potential of such integration in achieving economic savings.**

NOMENCLATURE

ARIMA - Auto Regressive Integrated Moving Average

ANN - Artificial Neural Networks

BES - Battery Energy Storage

EMS - Energy Management System

EU - European Union

KNMI - Koninklijk Nederlands Meteorologisch Instituut

LEC - Local Energy Community

LP - Linear Programming

MLR - Multiple Linear Regression

NWP - Numerical Weather Prediction

PV - Photovoltaic

R^2 - R-squared

RES - Renewable Energy Sources

RMS - Root Mean Square

SE - Standard Error

SVR - Support Vector Regression

SoC - State of Charge

TSI - Total Sky Imager

TROEF - Transparent Reducing CO2 and Optimizing Energy in an Ecosystem of Flexibility

I. INTRODUCTION

In its pursuit of the ambitious goal to achieve climate-neutrality by 2050, the EU is actively promoting the energy transition. To expedite this transition and reach the set target, the establishment of local energy communities is strongly encouraged. These communities consist of prosumers, which include households, or office buildings equipped with small-scale renewable energy production technologies, such as rooftop photovoltaic (PV) panels. Beyond the evident environmental consciousness, prosumers are increasingly motivated to install PV panels on their rooftops by the desire to curb electricity expenses. Embracing solar power not only aligns with their sustainability goals but also offers tangible economic benefits in the form of reduced electricity costs.

However, a key drawback of solar power lies in its intermittent nature. The unpredictability of solar power supply often leads to situations where surplus energy is generated, exceeding immediate demand and resulting in wastage. To overcome this challenge and fully leverage the potential of solar energy, the integration of renewable resources with battery energy storage (BES) has emerged as an effective solution. BES offers the ability to store excess solar energy during periods of high supply, ensuring its availability for consumption during times of increased demand.

To facilitate the seamless integration of BES with renewable resources, the implementation of an energy management system (EMS) becomes essential. An EMS empowers owners to optimize BES performance and achieve their objectives, such as load shifting, financial savings, grid independence, and more. Researches have already been conducted on this topic.

The authors of references [1] and [2] have conducted comprehensive analyses of various methods for microgrid EMS. These methods encompass classical approaches like linear and nonlinear programming, dynamic programming, and rule-based methods. They also explore meta-heuristic approaches such as genetic and swarm optimization, as well as artificial intelligent methods like fuzzy logic, neural networks, and multi-agent systems. The studies further consider stochastic and robust programming approaches, model predictive control, and optimization algorithm types, including linear programming, non-linear programming, and stochastic programming. Both references provide comprehensive overviews of solution approaches, including heuristic approaches, neural network approaches, and other tools employed for energy management in microgrids.

In [3], the focus is on a day-ahead operational planning method for a grid-connected local energy community (LEC), consisting of some prosumers, battery storage systems, and local loads. The primary objective is to achieve cost minimization for power transactions with the utility grid on the following day. A distributed procedure is utilized to calculate energy resource schedules, limiting grid balancing actions and allocating network losses. Results from various case studies are compared with those obtained from a centralized optimization approach. Both approaches yield comparable results, indicating that each prosumer within the LEC experiences cost reductions or increased revenues by participating in the LEC compared to transacting solely with an external energy provider.

Furthermore, there is a study that presents an optimization model aiming to schedule energy transactions within a LEC of prosumers with PV production and BES [4]. The primary goal is also to minimize the total cost of the energy community. The model incorporates both peer-to-peer transactions and grid transactions. Findings demonstrate that implementing a battery system can yield energy savings of 11-13%, and when combined with peer-to-peer transactions, an overall cost reduction of up to 25% is achievable for community members. This approach fosters efficient energy management and cost savings within the LEC setting.

Prior to operating the EMS, precise forecasting of RES is crucial. Reference [5] focuses on solar forecasting methods and evaluation metrics, categorizing them into three main categories: physical, statistical, and hybrid methods. The physical method incorporates numerical weather prediction (NWP), satellite or Total Sky Imager (TSI) cloud observations, and atmospheric data such as temperature, pressure, humidity, and cloud cover. Statistical methods involve historical data and are divided into statistical and learning approaches. Examples of statistical methods include regression analysis, Auto Regressive Integrated Moving Average (ARIMA), while machine learning techniques include artificial neural networks (ANN), support vector regression (SVR), random forests, and gradient boosting. It is observed in this reference that statistical methods, both traditional and machine learning-based, are more suitable for smaller areas and shorter-term forecasts.

The referenced study [6] also conducted an in-depth investigation into predicting PV power generation. This review encompassed a comprehensive performance analysis of various forecasting models for PV power, categorized by different methodological approaches. Furthermore, the study critically assessed both the strengths and limitations associated with these models. Within the domain of regression modeling, the study identified multiple linear regression as a particularly effective technique, surpassing the predictive accuracy of simple regression analysis. Additionally, the study highlighted the significance of ANN, especially when dealing with intricate, nonlinear data relationships. Unlike conventional statistical methods, ANN excel in managing complex data interdependencies without relying on pre-established assumptions.

In [7], similar to [5], the study presented diverse variable generation forecasting models. Employing MLR analysis, it examined significant variables, identifying solar irradiance, relative humidity, and temperature as primary influencers of solar power generation. The outcomes demonstrated robust performance.

Further, another study [8] explores the utilization of day-ahead forecasted weather parameters from a weather station to predict RES using a feedforward neural network method. Additionally, reference [9] presents a multiple linear regression (MLR) analysis model for solar power prediction. This model generates probabilistic forecasts of solar energy by considering crucial variables like solar irradiance, relative humidity, and temperature, which have a significant impact on solar power generation. The model exhibits strong performance in forecasting solar power and can further enhance accuracy by incorporating additional historical data.

In the study [10], weather data and regression analysis were employed to enhance forecasting accuracy. The research revealed that utilizing current, precise weather parameters as inputs led to more accurate generation forecasts, with same-day corrections proving more precise than predictions made a day in advance. Additionally, the study highlighted the potential of accurate weather predictions to enhance the precision of power forecasts.

The primary objective of this study is to achieve the electricity operating cost savings of a LEC. This will be attained by considering the uncertainty of PV generation through day-ahead scheduling and implementing optimized BES operations. To assess this, the case study conducted in Bunnik, the Netherlands, examines the impact of integrating an EMS to efficiently schedule energy usage and storage in BES along with the existing PV panels. To address this, the EMS optimization problem takes into account day-ahead predictions for RES, utilizing regression analysis of weather forecasts and data from the Transparent Reducing CO2 and Optimizing Energy in an Ecosystem of Flexibility (TROEF) [11] research. Additionally, the study includes an evaluation of the battery sizing as part of its analysis.

The research is organized as follows: Part II provides an overview of the project description and data collection. Part III describes the PV power generation prediction method. Part IV covers the sizing of the community's BES. In Part V, the discussion and methodology of the EMS for BES are presented. The results and conclusion are then presented in Part VI and Part VII, respectively.

II. OVERVIEW OF PROJECT DESCRIPTION & DATA COLLECTION

A.Project Description

Currently, sustainability objectives remain unfulfilled due to extended payback periods for sustainable measures in homes and utilities. Users pursuing sustainability also encounter limited benefits due to conflicting incentives within the traditional energy system. Additionally, the surge in renewable energy generation complicates grid balance at reasonable costs.

In the TROEF project, the consortium strives to forge a novel layered energy ecosystem, incorporating systems, tools, and business models to optimize energy exchange across Dutch buildings, aiming to minimize CO_2 emissions. Within the TROEF project, TU/e's role centers on creating a Digital Twin of the energy ecosystem. This involves a virtual testing environment for design and a digital twin for control, critical for evaluating energy community value, optimizing system design, and formulating control strategies.

This study sources data from the Bunnik community in the TROEF project, there are four buildings, with PV panels installed on the rooftops of buildings A, B, and C, shown in Fig. 1. In total, there are 424 PV panels, with each panel having a capacity of 270 watt peak (Wp). In the Netherlands, a standard specific energy yield of 875 kWh/kWp can be expected for solar panels [12]. Given that there are 424 PV panels, each with a capacity of 270 watt peak (Wp) in the community, it can be estimated that these devices are expected to generate approximately 100,170 kWh of energy per year. Remarkably, the actual energy generated by the PV panels in 2021 was 102,122 kWh, which closely corresponds to the expected value based on the product specifications. Later in section 4 will present an introduction to the prediction of the PV generation formula, which is derived from the one-day ahead weather forecasting. As a result, the energy generation of a single PV panel can be accurately calculated.

Figure 1. A configuration diagram for the building community (located in Bunnik)

B.Data Collection

Weather Data

The Koninklijk Nederlands Meteorologisch Instituut (KNMI) is a leading weather agency known for its reliable data and rigorous validation process. Hourly data for 2021 was collected from KNMI's De Bilt location, including parameters such as air velocity, relative humidity, temperature, and global radiation. For day-ahead weather forecasting, KNMI's weather data was used due to its superior accuracy and efficiency compared to prediction algorithms. In Figure 2, it shows plots of some of the mentioned weather parameters.

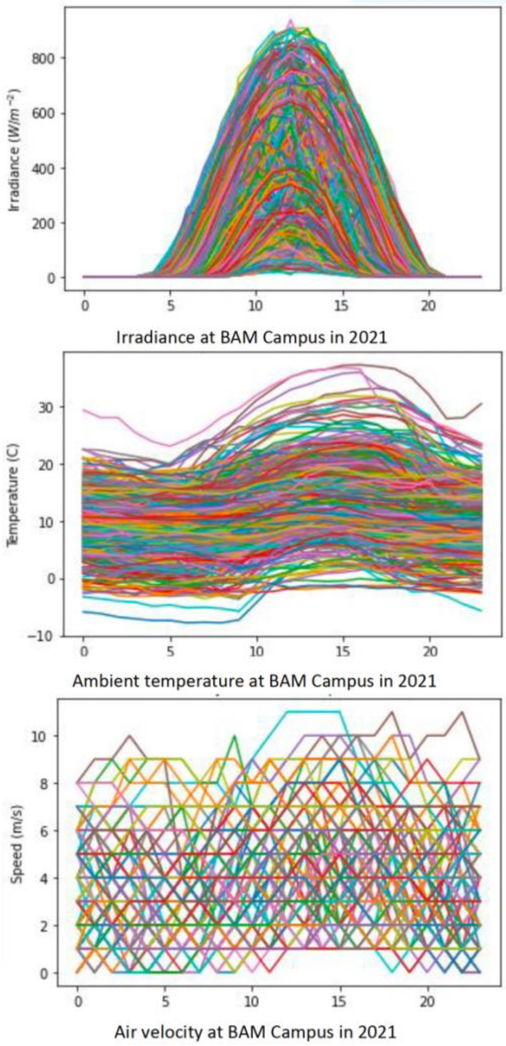

Figure 2. Weather data records from 2021 at the BAM campus located in Bunnik [13]

Historical PV Production

Throughout the entirety of 2021, data on historical PV power generation in the community was collected at one-hour intervals.

Day-Ahead Forecasted Community's Demand

The case study in this research focuses on a business community, where the energy demand exhibits a consistent pattern and remains relatively stable over time. Therefore, the demand is assumed to be predictable as it remains constant throughout the study. The day-ahead forecasted data for the community's energy demand is obtained from the TROEF project and is based on hourly intervals throughout the year 2021.

Day-Ahead Forecasted Electricity Price

Additionally, the day-ahead forecasted data for electricity prices is also obtained from the TROEF project for each hour throughout the entire year of 2021.

The above-mentioned historical PV production, day-ahead forecasted community demand, and day-ahead forecasted electricity price data for the entirety of 2021 are shown in Figure 3 (see Appendix).

III. PV GENERATION FORECASTING

The prediction of PV generation is a crucial aspect of determining the optimal battery size and energy management strategy. In this study, a thorough analysis was conducted to examine the relationship between historical weather data and PV generation data, with hourly analysis conducted throughout the entirety of 2021. After conducting a comprehensive literature review of various research papers that predict PV generation [5-10], as mentioned in the introduction, it was determined that regression analysis was a suitable tool for this study's purpose. In this case, based on previous studies, the selection of significant weather parameters for the model is already established. Thus, adapting the Regression method for forecasting is deemed sufficient and effective.

Building upon the insights presented in the aforementioned reference [9], the regression equation resulting from this method allows for the quantification of the relationship between multiple variables that have the most significant impact on PV generation, including temperature, relative humidity, air velocity, and solar radiation. This equation provides an estimate of the expected PV generation, which can be utilized to inform the design and operation of BES.

To ensure the accuracy of the regression analysis, a thorough yearly data analysis was conducted, involving the identification and removal of missing and outlier data. The resulting MLR equation is presented below:

$$\Upsilon = \alpha_1 \mathcal{X}_1 + \alpha_2 \mathcal{X}_2 + \cdots + \alpha_k \mathcal{X}_k + \beta \quad (1)$$

Here, Υ represents the response variable, signifying the projected PV generation in kilowatts (kW). The predictor variables $\mathcal{X}_k$ correspond to different factors, with $\mathcal{X}_1$ denoting Air Velocity (m/s), $\mathcal{X}_2$ representing Relative Humidity (%), $\mathcal{X}_3$ indicating Temperature (℃), and $\mathcal{X}_4$ symbolizing Global Radiation (W/m²). The term β stands for the error or fluctuations in Υ.

For the current study's case, encompassing 424 PV panels, each with a 270-watt peak (Wp) capacity, the equation's coefficients can be expressed as shown in (2):

$$\Upsilon = 0{,}079125\mathcal{X}1 + 3{,}364651\mathcal{X}2 - 0{,}08611\mathcal{X}3 + 2{,}9187e^{-5}\mathcal{X}4 - 2{,}718835 \quad (2)$$

In the event that the community seeks to introduce additional PV panels for an expected generation of 270Wp per panel, the coefficients in the equation would be as presented in (3):

$$\Upsilon = 0{,}000187\mathcal{X}1 + 0{,}007935\mathcal{X}2 - 0{,}000203\mathcal{X}3 + 0{,}006844e^{-5}\mathcal{X}4 - 0{,}006412 \quad (3)$$

To ascertain the accuracy of the equation (2), diverse statistical metrics were utilized to evaluate the model's performance. These metrics encompass Multiple R, Adjusted R-squared, Root Mean Square, and standard error. The resulting findings are summarized as follows.

The Multiple R, also referred to as the multiple correlation coefficient or coefficient of multiple determination, assesses the strength of the linear relationship between predicted values (Y) and actual values of the dependent variable (Y), accounting for all independent variables (X1, X2, X3, X4) together. Its formula can be represented mathematically as:

$$R = \sqrt{R_1^2 + R_2^2 + \cdots + R_k^2} \quad (4)$$

In this equation R signifies the multiple correlation coefficient. $R_1, R_2, \ldots, R_k$ represent the individual correlation coefficients between the dependent variable and each independent variable. This formula gauges the collective linear relationship between predicted and actual dependent variable values when considering multiple independent variables. The calculated multiple correlation coefficient (Multiple R) was 0,974691, indicating a robust positive correlation between the dependent variable and the entire set of independent variables. This suggests that the model effectively explains a significant portion of the variation in PV generation.

In addition, R-squared (R^2) was employed to quantify the proportion of variance in the dependent variable that is accounted for by the independent variables. The formula for R-squared is:

$$R^2 = 1 - \frac{SSR}{SST} \quad (5)$$

Where SSR is the sum of squared residuals, SST is the total sum of squares. However, a R^2 value of 0,9 typically indicates a model that fits about 90% of data points. Yet, it's important to recognize that as more independent variables are introduced, R^2 may increase even if these extra variables don't significantly enhance the model's performance. To mitigate this, the Adjusted R-squared was adopted, factoring in the number of independent variables. Its formula is:

$$Adjusted\ R^2 = 1 - \frac{(1-R^2)\times(n-1)}{n-p-1} \quad (6)$$

Where n represents the number of data points, p denotes the number of independent variables. In this study, the computed adjusted R^2 was 0,949999, signifying that roughly 95% of the variability in PV generation is explicable by the incorporated independent variables. This substantial adjusted R-squared value reaffirms the model's remarkable fit and overall effectiveness in the context of regression analysis.

Root Mean Square (RMS) is a mathematical concept widely employed to assess the average magnitude of a set of values. It proves especially valuable when addressing fluctuations or differing magnitudes within a dataset, allowing for an understanding of the overall magnitude of values while accounting for both positive and negative disparities. The formula for calculating the RMS value is:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \quad (7)$$

Where n signifies the quantity of values in the dataset and x_i represents each individual value within it. The RMS value serves to illuminate the effective or equivalent magnitude of the value set, assisting in the comprehension of diverse data trends and fluctuations. In this investigation, the calculated RMS value amounts to 4,436816.

Furthermore, the standard error (SE) was calculated as 4,507800. This value is indicative of the model's high prediction accuracy, with an average separation of approximately 4.51 between actual data points and the regression line. The formula for calculating the SE is:

$$SE = \sqrt{\frac{1}{n-p-1}\sum_{i=1}^{n}(Y_i - Y'_i)^2} \quad (8)$$

Where n represents the number of data points, p denotes the number of independent variables. Y_i is the actual value of the dependent variable for data point i, Y'_i is the predicted value of the dependent variable for data point i. The relatively low SE value enhances the model's dependability and accuracy in forecasting PV generation.

In conclusion, these critical metrics played a pivotal role in assessing the quality and accuracy of the regression model in predicting the PV generation of the existing PV panels based on the provided independent variables. The results indicate the model's admirable performance, with a high multiple correlation coefficient, substantial adjusted R^2 value, and small SE (see Table 1). These findings validate the model's effectiveness in effectively explaining and predicting variations in PV generation using the weather parameters from KNMI forecasts.

Additionally, the seasonal variations of Actual vs. Predicted PV Production are presented in Figures 4 to 7, available in the appendix. These visual representations further underscore the model's robustness and its ability to capture diverse patterns across different seasons.

Table 1. Regression Model Evaluation and Coefficients

Statistical Metrics	Values
Multiple R	0,974691
Adjusted R Square	0,949999
Root Mean Square	4,436816
Standard Error	4,507800
Coefficients	**Values**
Intercept	-2,718835
X Variable 1	0,079125
X Variable 2	3,364651
X Variable 3	-0,086110
X Variable 4	0,000029

IV. BATTERY ENERGY STORAGE

To optimize the utilization of solar energy, given its intermittent nature, a dependable BES becomes essential. By integrating PV generation with BES, surplus energy can be stored and utilized during periods of low solar output. Moreover, this BES can charge when the electricity price is low and discharge when the price is high, enabling more efficient energy management and achieving the desired objectives. In this context, determining the suitable battery size and technology holds utmost importance in ensuring optimal performance and cost-effectiveness.

A. BES Selection - Comparing Parameters and Cost

When selecting a BES, several parameters such as cost, performance, and reliability must be taken into consideration. The Energy Storage Technology and Cost Characterization Report by the U.S. Department of Energy [14] presents the latest data collected across a wide range of parameters and performance metrics for different storage types in 2025. The report includes several critical performance metrics, such as round-trip efficiency, response time, depth of discharge, lifespan, cycle life, volume, and safety, which are essential for determining the most suitable energy storage technology for a particular application. Tables 2 (see Appendix) provides a side-by-side comparison of different BES, offering valuable insights into the advantages, disadvantages, and cost implications of each option, thus aiding in the selection process.

B. Selection of a Short-Term BES: Lithium-Ion Battery

According to [14], a lithium-ion battery emerges as the ideal short-term BES for building communities, aligning perfectly with the parameters outlined earlier. Its superior cost-effectiveness and remarkable performance metrics make it the top choice. On average, a lithium-ion battery can last up to ten years with 3500 life cycles at 80% Depth of Discharge and boasts an incredibly short response time of just one second. Moreover, the high specific energy of the lithium-ion battery [15] allows it to store a substantial amount of energy per unit of battery weight or volume. This feature translates to a smaller battery space requirement, making it an efficient and practical choice for short-term energy storage in building communities.

Furthermore, based on the data gathered until 2021 from the National Renewable Energy Laboratory's website [16], the capital cost of Li-ion batteries has indeed shown a decreasing trend. Depending on their storage duration, the cost ranges from \$135 to \$211 per kilowatt-hour (kWh). Considering these attributes, the lithium-ion battery stands as a particularly compelling solution for short-term energy storage for the building community within the scope of this study, as highlighted in Table 3.

Table 3. Performance, Cost, and Sustainability of Lithium-ion Batteries [14][16]

Li-ion Battery	Value
Capacity Cost (\$/kWh)	135-211
Lifespan (yrs)	10
Response Time (sec)	1
Circles at 80% Depth of Discharge	3500
Specific Energy (Wh/kg)	100-265

C.Battery Size for the Community

After thoroughly analyzing historical data on community demand and PV production, it became evident that the year 2021 witnessed a total of 4,733 hours of sunshine, resulting in a substantial energy generation from the PV devices. Notably, during the period spanning from mid-April to mid-August, characterized by ample sunshine and intensified solar activity (as depicted in Fig. 8 in the Appendix), the electricity status consistently remained positive. The term "electricity status" represents the disparity between PV generation and community demand, with a positive value signifying surplus power generation within the building community during those periods.

Given these findings, the central objective of sizing the battery is to efficiently fulfill the operational needs of the community's energy management system. Additionally, the battery's design must take into account the potential future increments in PV generation to ensure its capability to effectively meet the escalating energy storage requirements.
Consequently, based on the analyses and considerations, a 300 kWh Li-ion battery storage system with 95% efficiency and an 80% depth of discharge is recommended. This system strikes an optimal balance between cost-effectiveness and

energy storage demands, taking into account the community's specific energy consumption patterns. Moreover, the battery's modular configuration facilitates future scalability, enabling seamless expansion to cater to the community's evolving energy needs. By opting for this battery size, the community can ensure a reliable and sustainable energy storage solution, while simultaneously minimizing costs, making it a prudent and advantageous long-term investment for enhanced energy security.

V. ENERGY MANAGEMENT SYSTEM FOR LEC

To enable the smooth integration of BES with renewable resources, the adoption of an EMS is crucial. This research emphasizes a well-functioning EMS, which plays a pivotal role in effectively optimizing BES performance, ultimately leading to minimized energy costs for the LEC.

The EMS utilizes an LP method, effectively addressing the optimization problem by considering the objective and fulfilling system constraints during LEC operation. This research employs an offline LP approach in the EMS, requiring a day-ahead forecast of RES and load demand for optimization purposes. This forecast enables the management of energy transactions between the LEC and the utility grid.

The EMS flow chart, shown in Fig. 9, demonstrates the system's logic, where historical data, including weather parameters and RES, is analyzed using MLR to understand their relationship. An equation is then derived to predict RES generation based on one-day ahead forecasted weather parameters. Finally, incorporating the day-ahead prediction, the EMS formulates and solves an optimization problem for the BES.

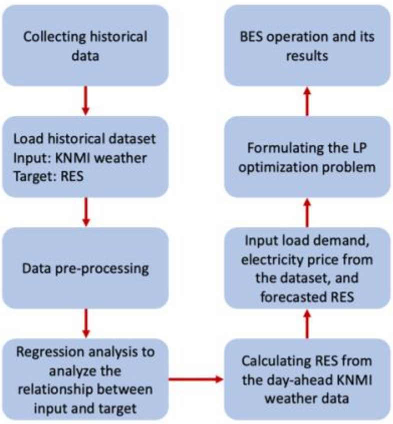

Figure 9. Energy Management System Flowchart

Optimization Problem

In this research, the energy system comprises PV panels for power generation ($PV(t)$ $[kW]$), consistently producing non-negative energy ($PV(t) \geq 0$). The system also includes a power demand ($PD(t)$ $[kW]$) component, representing the electricity required by the community, which is always non-negative ($PD(t) \geq 0$). Additionally, a BES is integrated into the setup, governing the transition between charging and discharging processes ($Pess(t)$ $[kW]$). When $Pess(t) < 0$, it indicates that the battery is discharging, whereas $Pess > 0$ signifies that the battery is charging. The net power exchanged with the utility grid ($PE(t)$ $[kW]$) is determined by the difference between the power demand ($PD(t)$), the battery operation ($Pess(t)$), and the PV production ($PV(t)$). When $PE(t) > 0$, it indicates that the system imports power from the utility grid, and when $PE(t) < 0$, it indicates that the system exports excess power to the utility grid. The schematic diagram of the energy system can be seen in Figure 10.

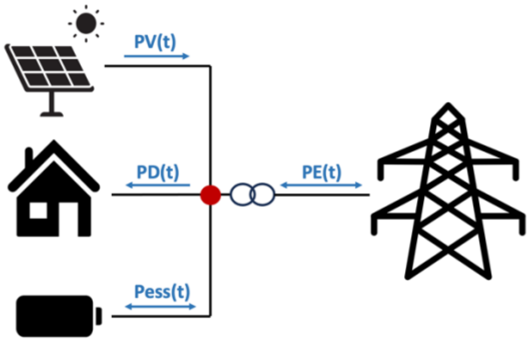

Figure 10. Power Flow Schematic Diagram

The primary objective of this study is to minimize the operating cost (OC $[EURO]$) associated with energy consumption in day-ahead scheduling. This expense is determined by subtracting the expense of purchasing energy from the utility grid from the income generated by selling surplus energy back to the grid. It can be expressed by:

$$Min\ OC = \sum_{t=1}^{24}(PE(t) \times \Delta t \times C(t)) \quad (9)$$

In this representation, the index ' t ' ranges from 1 to 24, signifying each hour in a day. As mentioned earlier, $PE(t)$ $[kW]$ represents the power flow value from/to LEC to/from the utility grid. Δt $[hr]$ denotes the time interval, indicating the duration over which the battery charging or discharging occurs (in this study, the time interval is consistently set to 1 hour). $C(t)$ $[EURO/kWh]$ represents the electricity price at that specific moment.

Constraints

During the optimization process, several crucial constraints must be considered. First and foremost, maintaining a power balance is of utmost importance. This involves calculating the net power by subtracting the community demand from the combined power generated by the PV panels and the battery. If additional energy is needed, it can be obtained from the utility grid, whereas any surplus energy can be exported to the grid as shown:

$$PE(t) = PD(t) - PV(t) + Pess(t) \quad (10)$$

The State of Charge (SoC) at time 't' represents the current energy level stored in the battery [%], which plays a crucial role in maintaining the energy balance within acceptable limits. It is subject to the following constraints:

$$SoCmin \leq SoCt \leq SoCmax \quad (11)$$

The function for SoC is defined as follows:

$$SoC_t = SoC_{t-1} + (Pess_{t-1} \times \Delta t)/BC \quad (12)$$

In the equation, ' SoC_t' represents the SoC of the battery at a given time ' t ', and ' SoC_{t-1}' denotes the initial SoC of the battery at the beginning of the time interval before ' t '. '$Pess_{t-1}$' represents the battery charging and discharging flow at the beginning of the time interval before ' t '. 'Δt' denotes the time interval, which is always 1, as mentioned before. ' BC ' represents the total capacity of the battery $[kWh]$.

In summary, the state of charge at any time ' t ' depends on the previous state of charge, the charging/discharging rate ($Pess(t)$), and the battery capacity. This relationship allows tracking and controlling the energy levels in the battery to ensure they remain within acceptable limits.

The battery charging and discharging flow, denoted as $Pess(t)$, is a crucial aspect of this research. Ensuring that the charging and discharging rates of the battery remain within the predefined limitation P $[kW]$ is imperative to guarantee their smooth operation, as illustrated:

$$|Pess(t)| \leq P \tag{13}$$

This constraint ensures that the battery operates safely and efficiently, preventing it from being overloaded during the charging or discharging processes. Adhering to this constraint is essential in maintaining the battery's performance and prolonging its lifespan.

Furthermore, to ensure the battery operates in a healthy manner, it is assumed that in the study case, the battery should only fully charge and discharge once per day. This assumption is based on the lifecycle being assumed to be 3500 cycles for operating over 10 years, which averages to almost 1 cycle per day. And the constraint can be presented as:

$$\sum_{t=1}^{24}(|Pess(t)| \times \Delta t) \leq BC \tag{14}$$

Finally, the rated power of the transformer, denoted as $Ptr\ [kW]$, represents its maximum capacity or power handling capability. In the context of the research, it is imperative to ensure that the transformer's loading does not exceed 100% of its rated power to guarantee safe and efficient operation. To adhere to this requirement, the following constraint is applied:

$$\frac{|PE(t)|}{Ptr} \times 100\% \leq 100\% \tag{15}$$

Here, $|PE(t)|$represents the absolute value of the total power flowing through the transformer. The above constraint ensures that the transformer operates within its safe limits, avoiding overloading that could lead to overheating and potential damage. By following this constraint, the efficiency and reliability of the transformer within the electrical system can be maintained.

The optimization problem introduced in (9) to (15) is solved using a deterministic LP formulation. Based on the day-ahead scheduling results, the LEC can control the BES to achieve savings in electricity operating costs.

VI. RESULTS

In this study, the optimization problem is formulated in Python, and the SolverFactory class from the Pyomo library is utilized for its solution. Specifically, the CBC solver is employed to address the formulated mathematical optimization model, enabling the efficient operation of the BES. The input data includes day-ahead predicted values of RES obtained through regression analysis, and load demand and electricity prices as described in part II B. The BES chosen for this study is a lithium-ion battery, and the simulation incorporates the parameters specified in Table 4.

Table 4. The parameters of considered BES

Parameters of Considered BES					
Battery Capacity (kWh)	P (kW)	Ptr (kW)	Initial SoC (%)	Minimum SoC (%)	Maximum SoC (%)
300	200	700	20	20	80

The simulation is performed for one day each for both weekdays and weekends, and it is further extended to across all seasons. This comprehensive approach enables us to observe and analyze the variations in energy scheduling between weekdays and weekends under different seasonal conditions.

Scenario 1: Existing Number of PV Panels

In the first scenario, the optimization considers that the EMS is operating with the current number of PV panels and the BES.

In Figure 11, the blue line represents the power demand, while the yellow line depicts the corresponding electricity generation from PV sources. The pink line indicates the electricity price, exhibiting fluctuations throughout the day and peaking during nighttime hours. Notably, power demand is significantly higher during working hours, whereas PV generation peaks around noon.

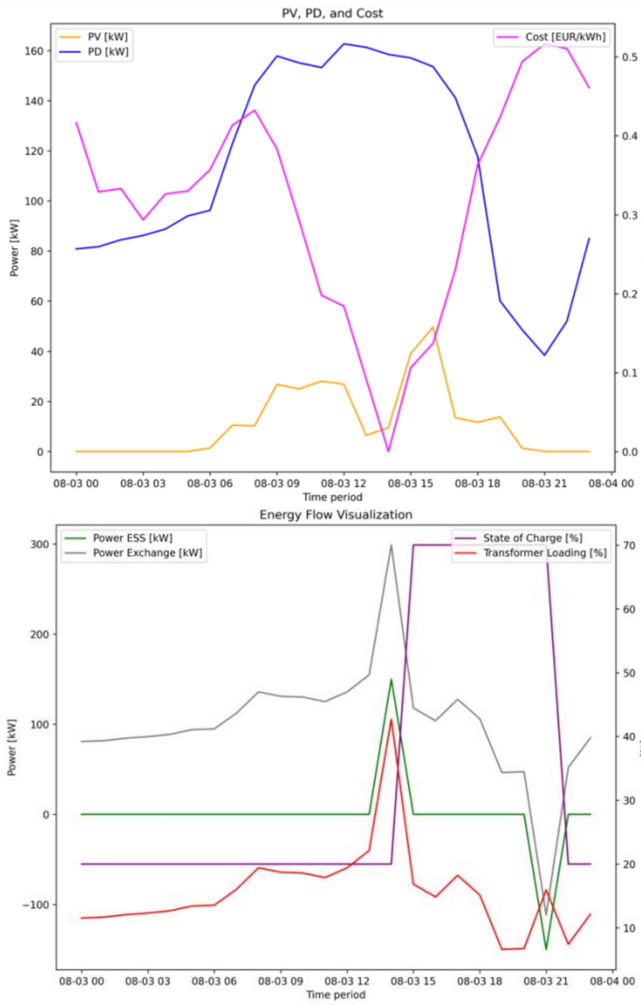

Figure 11. Energy Profile for BES on Weekday in Summer with the Original Number of PV Panels

However, on weekdays, the aggregate power demand exceeds the output from PV generation. To address this energy deficit, the EMS orchestrates the BES. The gray line signifies the power exchange between the utility grid and the LEC. This involves importing power from the grid during the day to meet the demand, with a focus on stockpiling extra energy in the battery during midday when electricity prices are relatively lower. Subsequently, the stored excess energy is sold back to the grid during high-priced nighttime hours.

Within the graph, the purple line delineates the SoC of the battery. Notably, the battery charges around midday, causing the SoC to rise, and then discharges during the night after selling power to the utility grid. The green line reflects the battery's charging or discharging status, showcasing charging during midday and discharging at night in alignment with the described scenario. Lastly, the red line signifies the transformer loading, where a lower value is desirable to ensure the safety of the grid.

In Figure 12, the scenario portrays a subtle variation, where all color lines hold identical significance. As it's the weekend, the demand maintains a consistent and low level throughout the day, distinct from the fluctuations seen on weekdays. This results in a surplus of PV generation, capably fulfilling the community's needs, especially around noon.

However, it's crucial to acknowledge the strategic adaptation executed by the system in this scenario. The excess power generated promptly returns to the utility grid when electricity prices are relatively high. Afterwards, the system continues to operate and obtains some energy from the grid during periods of lower electricity prices. This acquired energy combines with the surplus PV energy stored within the BES. Eventually, during the nighttime hours when electricity prices reach their peak, this stored energy is effectively returned to the grid.

Scenario 2: Assumption of Future PV Panel Expansion, Resulting in a 3.5 Times Increase in PV Generation

In the second scenario, the optimization takes into account the possibility of future expansion in the community's PV panel capacity. Therefore, the EMS is operating with 3.5 times the PV generation compared to the current capacity, along with the BES.

In Figure 13, representing a weekday, all color lines continue to hold consistent significance. Notably, the power generated by PV sources has increased by a factor of 3.5 compared to the initial scenario. However, even with this considerable increase, PV generation continues to fall short of fulfilling the power demand during most of the daytime.

Consequently, the EMS opts to address this energy shortfall by procuring power from the utility grid within these time periods. Additionally, as the previous scenario, it strategically purchases surplus energy for storage in the battery during times of lower electricity costs. Subsequently, in alignment with the usual pattern, during periods of elevated electricity

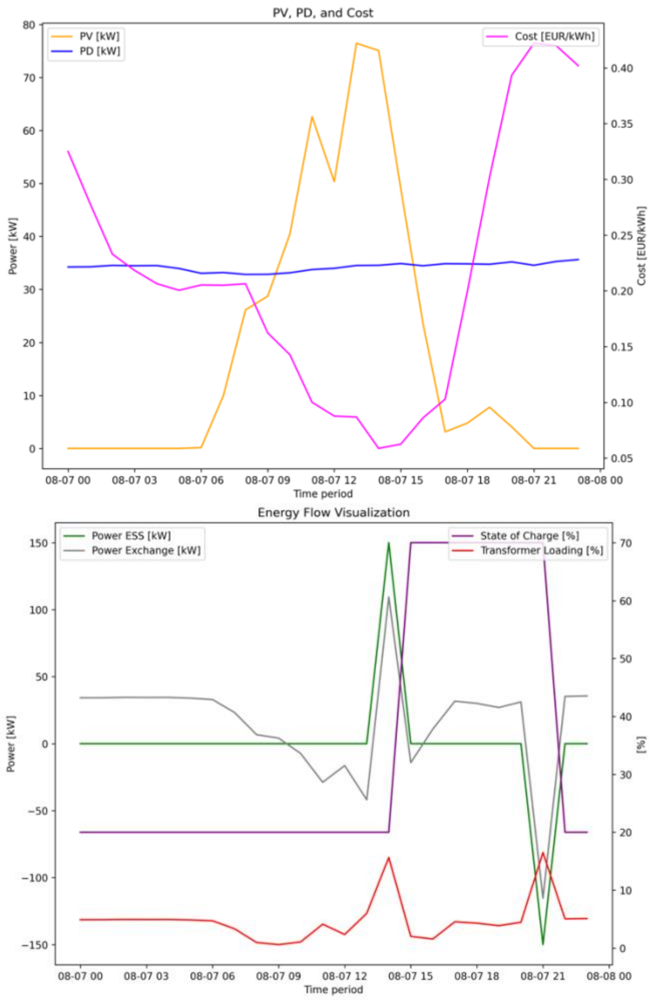

Figure 12. Energy Profile for BES on Weekend in Summer with the Original Number of PV Panels

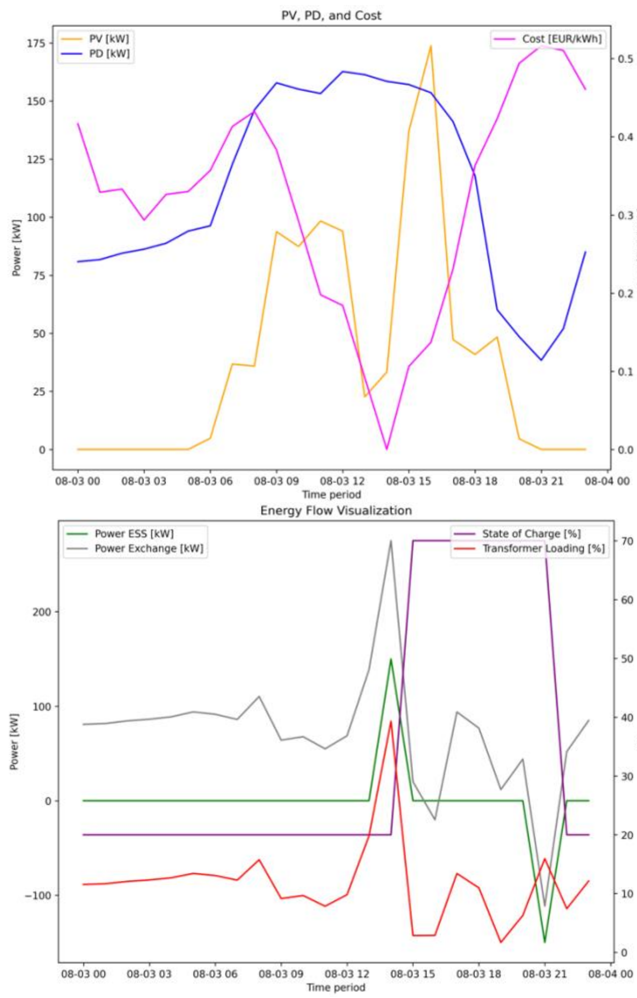

Figure 13. Energy Profile for BES on Weekdays in Summer with Assumption of Future PV Panel Expansion

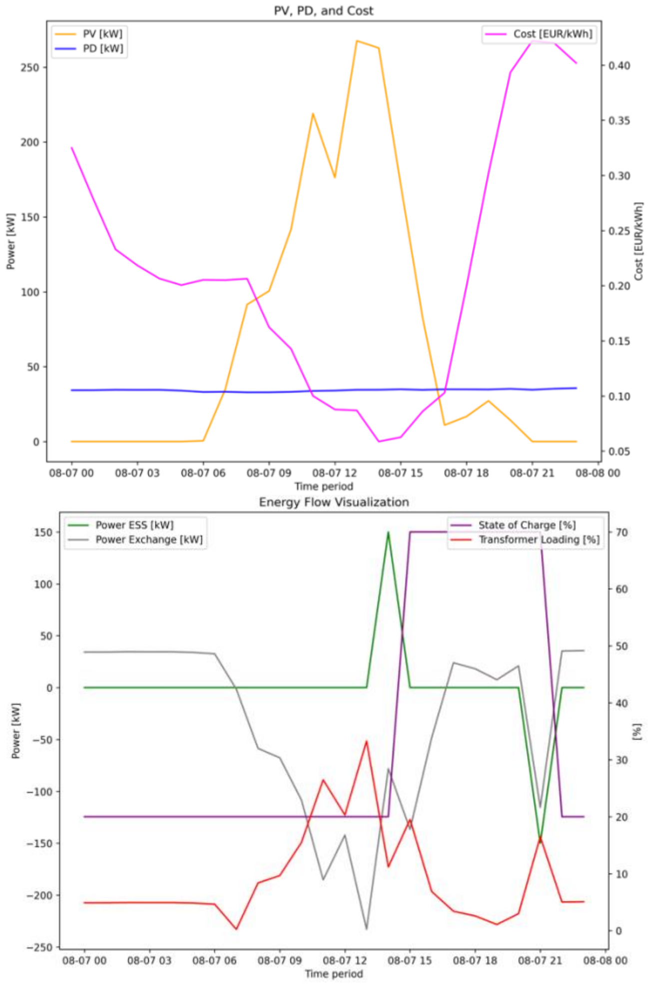

Figure 14. Energy Profile for BES on Weekends in Summer with Assumption of Future PV Panel Expansion

prices later in the night, the EMS efficiently sells back the stored excess energy to the grid, capitalizing on favorable price conditions.

In Figure 14, which represents a weekend, the substantial increase in power generated by PV sources (3.5 times greater than the initial scenario) brings about a significant transformation. Abundant PV energy generation is observed throughout the daytime, enabling the EMS to efficiently sell energy to the grid for extended periods. This outcome notably benefits the community, resulting in substantial revenue from the surplus PV energy sold back to the grid.

Of particular note is the noon period, during which surplus energy is not only sold to the utility grid but also stored within the BES. This strategic energy storage is influenced by electricity prices, as they are not very high. Subsequently, BES operation resumes during the high-priced nighttime hours, further enhancing profit generation. This scenario vividly exemplifies the EMS's prowess in optimizing energy resource utilization and revenue generation.

Table 5. The parameters

	Operating Cost (EURO)		
	No BES	*Scenario 1*	*Scenario 2*
Spring	26259,13	23808,49	9377,90
Summer	52486,45	48929,87	21435,71
Autumn	39871,58	37024,91	26738,49
Winter	34507,34	32401,35	28108,42
Yearly	153124,50	142164,62	85660,52
	Comparing Reduction in Energy Costs with No BES		
%		7,2	44,1

Table 5 presents the operating cost results across various scenarios: No BES, Scenario 1, and Scenario 2. These scenarios are evaluated across all seasons and the entire year. In Scenario 1, there is a 7,2% reduction in energy costs compared to the No BES condition. Notably, in Scenario 2, where the PV panel capacity is expanded, the energy cost reduction is even more remarkable, reaching 44,1% compared to the No BES scenario.

VII. CONCLUSION

The European Union (EU) has set ambitious goals to significantly decrease its carbon footprint, aiming for net-zero greenhouse gas emissions by 2050 and a 55% reduction by 2030 compared to 1990 levels. To achieve this, the EU is promoting renewable energy adoption and energy efficiency to pave the way for a future marked by sustainability and diminished carbon footprint.

One of the key strategies is to encourage households, office buildings, and communities to embrace renewable energy resources, such as PV panels and other renewable energy systems. These installations not only contribute to a sustainable energy future by reducing reliance on fossil fuels but also offer an attractive opportunity for cost savings.

In this research, the integration of BES with RES is examined to optimize the EMS for energy cost savings. A case study in Bunnik, the Netherlands, explores the economic viability of installing BES, and even expanding PV panels in the future. The optimization process utilizes LP techniques, with day-ahead values of RES determined through regression analysis, incorporating critical weather forecast parameters from KNMI.

The findings of this study suggest that the integration of BES and the optimization of the EMS can yield energy cost savings. Particularly, these results emphasize that the inclusion of additional PV panels in the future has the potential to significantly enhance the achieved energy cost reductions.

While these results showcase the potential advantages of integrating BES and EMS, it is crucial to acknowledge that the outcomes are based on the data from the TROEF project. Therefore, the actual energy cost savings in real-world applications may vary depending on various factors and uncertainties. Nonetheless, the findings emphasize the considerable potential and benefits of adopting BES and EMS technologies, especially when considering potential future renewable energy expansions.

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APPENDIX

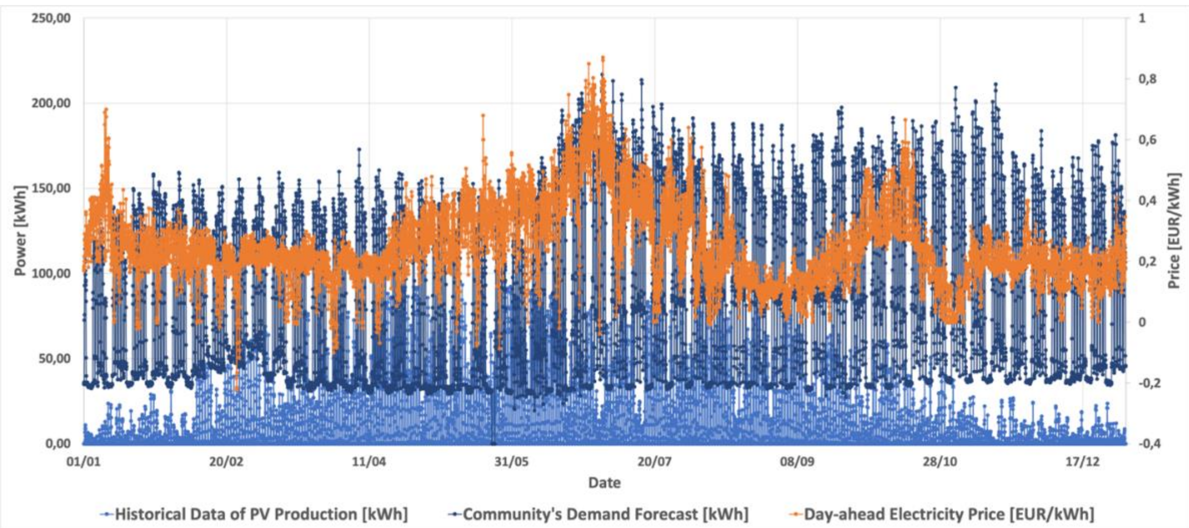

Figure 3. PV Production, Community's Demand, and Electricity Price in 2021

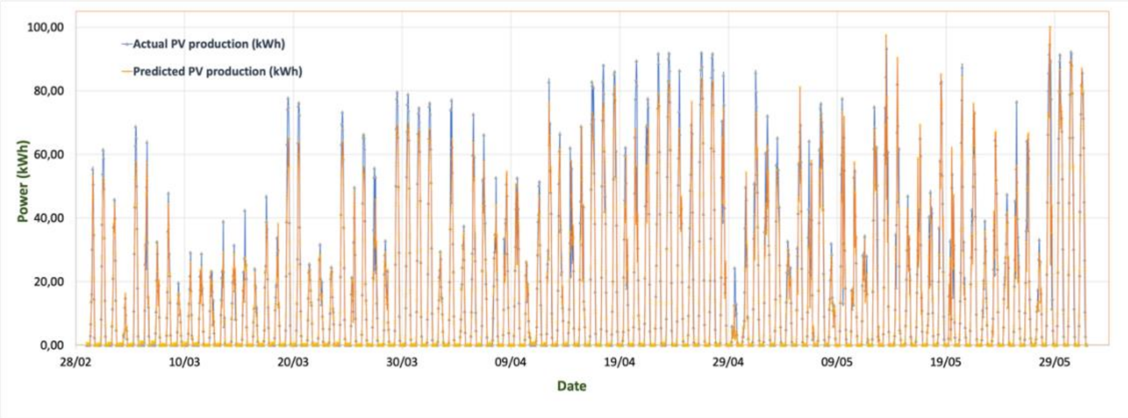

Figure 4. Actual vs. Predicted PV Production in Spring

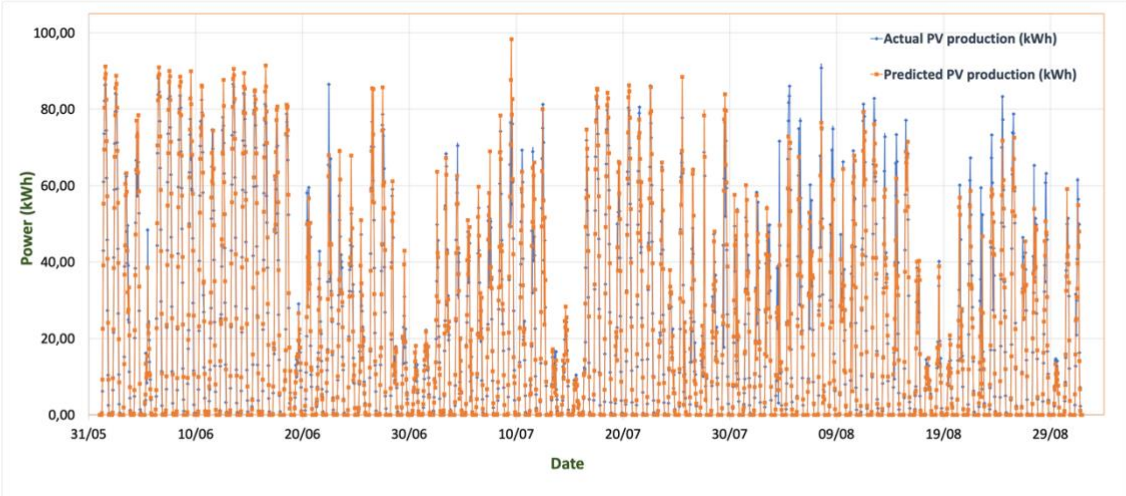

Figure 5. Actual vs. Predicted PV Production in Summer

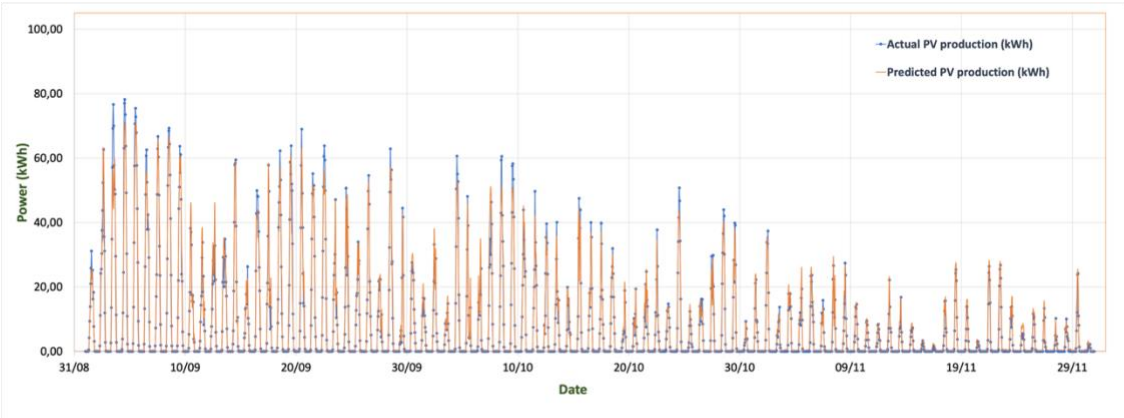

Figure 6. Actual vs. Predicted PV Production in Autumn

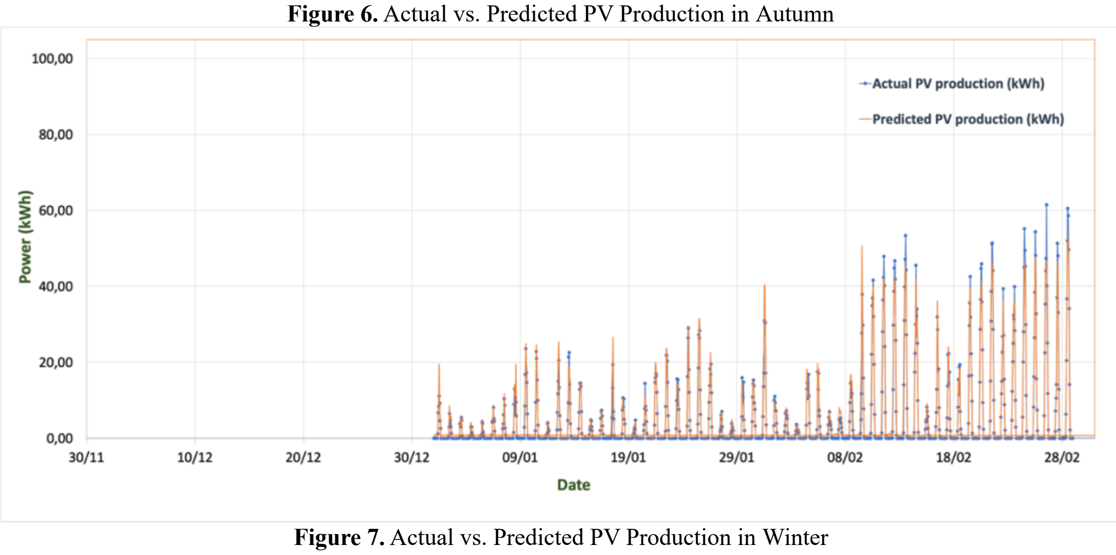

Figure 7. Actual vs. Predicted PV Production in Winter

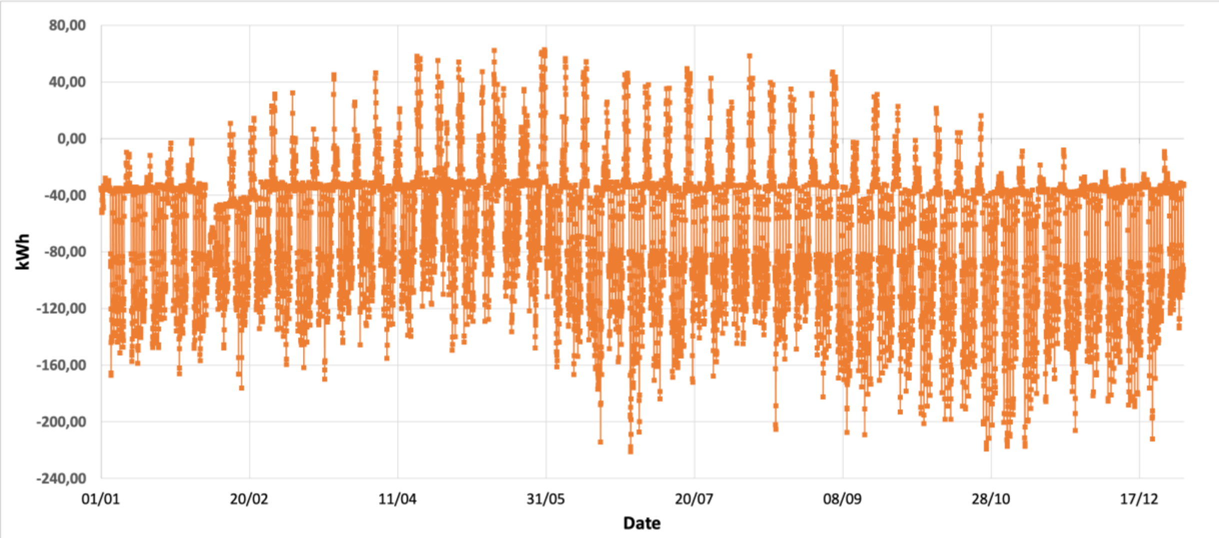

Figure 8. Electricity Status in 2021

Table 2. Summary of 2018 findings and 2025 predictions for BES cost and parameter ranges by technology type [14]

Parameter	Sodium-Sulfur Battery		Li-Ion Battery		Lead Acid		Sodium Metal Halide		Zinc-Hybrid Cathode		Redox Flow Battery	
	2018	2025	2018	2025	2018	2025	2018	2025	2018	2025	2018	2025
Capital Cost – Energy Capacity ($/kWh)	400-1,000 **661**	(300-675) **(465)**	223-323 **271**	(156-203) **(189)**	120-291 **260**	(102-247) **(220)**	520-1,000 **700**	(364-630) **(482)**	265-265 **265**	(179-199) **(192)**	435-952 **555**	(326-643) **(393)**
Power Conversion System (PCS) ($/kW)	230-470 **350**	(184-329) **(211)**	230-470 **288**	(184-329) **(211)**	230-470 **350**	(184-329) **(211)**	230-470 **350**	(184-329) **(211)**	230-470 **350**	(184-329) **(211)**	230-470 **350**	(184-329) **(211)**
Balance of Plant (BOP) ($/kW)	80-120 **100**	(75-115) **(95)**	80-120 **100**	(75-115) **(95)**	80-120 **100**	(75-115) **(95)**	80-120 **100**	(75-115) **(95)**	80-120 **100**	(75-115) **(95)**	80-120 **100**	(75-115) **(95)**
Construction and Commissioning ($/kWh)	121-145 **133**	(115-138) **(127)**	92-110 **101**	(87-105) **(96)**	160-192 **176**	(152-182) **(167)**	105-126 **115**	(100-119) **(110)**	157-188 **173**	(149-179) **(164)**	173-207 **190**	(164-197) **(180)**
Total Project Cost ($/kW)	2,394-5,170 **3,626**	(1,919-3,696) **(2,674)**	1,570-2,322 **1,876**	(1,231-1,676) **(1,446)**	1,430-2,522 **2,194**	(1,275-2,160) **(1,854)**	2,810-5,094 **3,710**	(2,115-3,440) **(2,674)**	1,998-2,402 **2,202**	(1,571-1,956) **(1,730)**	2,742-5,226 **3,430**	(2,219-3,804) **(2,598)**
Total Project Cost ($/kWh)	599-1,293 **907**	(480-924) **(669)**	393-581 **469**	(308-419) **(362)**	358-631 **549**	(319-540) **(464)**	703-1,274 **928**	(529-860) **(669)**	500-601 **551**	(393-489) **(433)**	686-1,307 **858**	(555-951) **(650)**
O&M Fixed ($/kW-yr)	10	(8)	10	(8)	10	(8)	10	(8)	10	(8)	10	(8)
O&M Variable (cents/kWh)	0.03		0.03		0.03		0.03		0.03		0.03	
System Round-Trip Efficiency (RTE)	0.75		0.86		0.72		0.83		0.72		0.675	(0.7)
Annual RTE Degradation Factor	0.34%		0.50%		5.40%		0.35%		1.50%		0.40%	
Response Time (limited by PCS)	1 sec		1 sec		1 sec		1 sec		1 sec		1 sec	
Cycles at 80% Depth of Discharge	4,000		3,500		900		3,500		3,500		10,000	
Life (Years)	13.5		10		2.6	(3)	12.5		10		15	
MRL	9	(10)	9	(10)	9	(10)	7	(9)	6	(8)	8	(9)
TRL	8	(9)	8	(9)	8	(9)	6	(8)	5	(7)	7	(8)

(a) An E/P ratio of 4 hours was used for battery technologies when calculating total costs.
MRL = manufacturing readiness level; O&M = operations and maintenance; TRL = technology readiness level.