Towards an Open Energy Management System for Integrated Energy Storage and Electric Vehicle Fast Charging Station

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Abstract

SINTEF's solar energy infrastructure, which integrates photovoltaic (PV) panels, meteorological instruments, inverters, and data pipelines, enables real-time data acquisition and visualization. Building on this infrastructure, we developed AI-based algorithms for forecasting PV power output and analyzing the performance of the system and various PV panel types. The potential of this system is significantly enhanced by integrating battery storage, electric vehicle (EV) charging stations, external energy market pricing, advanced meteorological forecasting, and demand forecasting. These integrations support the development of a comprehensive open energy management system (EMS) that facilitates localized energy production and adaptive demand response. In this paper, we outline the key elements of an open EMS that includes PV, batteries, and EV charging station. We describe a prototype and discuss further developments needed in this area. Our approach leverages machine learning to optimize energy flow decisions, with the inclusion of rule-based models to guide and explain these decisions. This work addresses the gap in applying theoretical open EMS models to practical residential and commercial settings, aiming to provide a dynamic platform where forecasting and optimization methods are refined and implemented in real-world scenarios.

Keywords

photovoltaic power, energy storage, electric vehicle charging station, forecasting, optimization

1. Introduction

The rapid growth of renewable energy sources, particularly solar and wind, has significantly transformed the global energy landscape. As highlighted in [1], global annual renewable capacity additions surged by nearly 50% to approximately 510 gigawatts (GW) in 2023, marking the fastest growth rate observed in the last two decades. As the share of these variable energy sources increases, so does the complexity of managing energy systems that must balance supply and demand in real-time. Traditional energy management systems, which were designed for more predictable and centralized power generation, are increasingly inadequate for the dynamic and decentralized nature of modern energy grids. To address these challenges, there is a growing movement towards the development of open energy management systems (EMS) that leverage advanced forecasting, optimization algorithms, and real-time data integration to enhance the resilience, efficiency, and flexibility of energy networks.

An open energy management system is characterized by its ability to integrate diverse energy sources, including distributed renewable generation, and to accommodate the fluctuating demand profiles of

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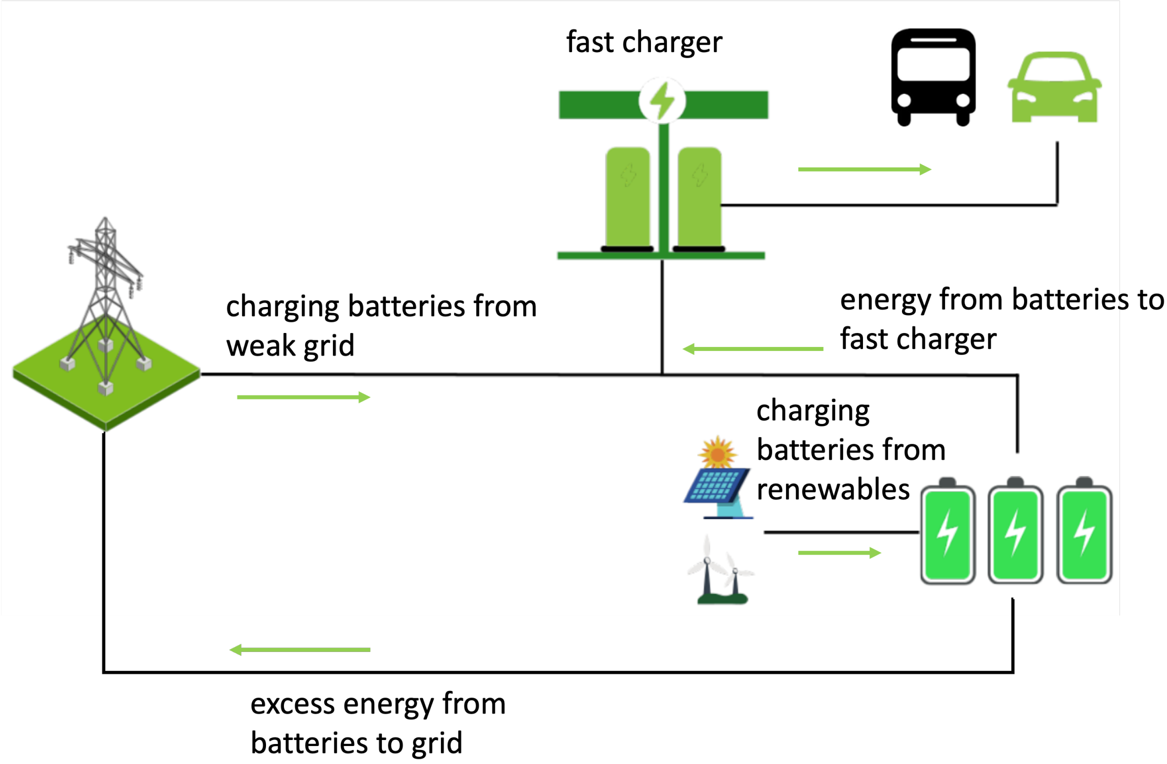

Figure 1: SINTEF Prototype for an Open Energy Management System.

new energy consumers such as electric vehicles (EVs) [2]. Such a system must be capable of processing vast amounts of data in real-time, including meteorological data for renewable energy forecasts, market prices, and consumption patterns. By using machine learning algorithms and other advanced analytics, these systems can optimize energy flows, reduce costs, and improve the reliability of the grid.

Recent research has highlighted the potential of these systems to bridge the gap between theoretical models and practical implementations in residential and commercial settings [3]. For example, the integration of machine learning techniques for forecasting and optimization in EMS has been shown to significantly enhance the accuracy and efficiency of energy management [4, 5]. Furthermore, the use of synthetic data generation for scenario analysis and the incorporation of rule-based machine learning models for operational decision-making are emerging as key components of these open systems [6].

In this paper, we present our current open EMS prototype and discuss further developments. Our goal is to bridge the gap between current theoretical approaches and practical applications in both residential and commercial fields. By leveraging advanced forecasting methods, optimization algorithms, and real-time data integration, we aim to create a flexible and resilient EMS that can effectively manage the complexities introduced by the integration of renewable energy sources.

2. SINTEF Prototype for an Open Energy Management System

A diagram of SINTEF prototype for an open Energy Management System, including Photovoltaic (PV) system, electric vehicle (EV) charging station, grid connection, and battery storage system is given in Figure 1.

2.1. Photovoltaic (PV) System

The PV system, located at the top of the SINTEF building at Forskningsveien 1 in Oslo (coordinates: 59°56’41.4”N, 10°42’46.1”E), consists of 43 solar panels, along with a data logger, pyranometer, optimizers,

Table 1
PV system layout with panel types

Manufacturer	Model of Panels	Count
Manufacturer 1	Mono-facial	5
Manufacturer 1	Bi-facial	4
Manufacturer 1	Innovation 2	5
Manufacturer 2	Bi-facial	4
Manufacturer 2	Innovation 2	4

Figure 2: An image of the PV system.

inverters, and a DustIQ Soiling Monitoring System. These panels are distributed across three distinct sections on the L-shaped roof, as detailed in Table ??. The site includes installations of ten different solar panel varieties. A photograph of the demo site is provided in Figure 2. Real-time monitoring at the demo site facilitates the observation of various data, including power measurements from optimizers and inverters, as well as weather-related data. This includes power, voltage, current, radiation, dust-related parameters, wind speed, environmental temperature, panel temperature, and other relevant metrics. At the moment, the PV system can deliver up to 10 kW peak power to the grid, which can be used to charge the EV charging pile, thereby efficiently utilizing the generated solar energy.

2.2. Battery Storage System

The battery storage system has a total capacity of 193 kWh, comprising of four battery packs, each with a capacity of 315 Ah and an energy rating of 48.4 kWh, operating at a nominal voltage of 153.6V. This system is crucial for balancing supply and demand within the network. It allows for the storage of excess energy generated by the PV panels or obtained from the grid during periods of low demand or high generation. The stored energy can then be used to power the EV charging stations, particularly during times when PV generation is low (such as at night) or when grid power is insufficient.

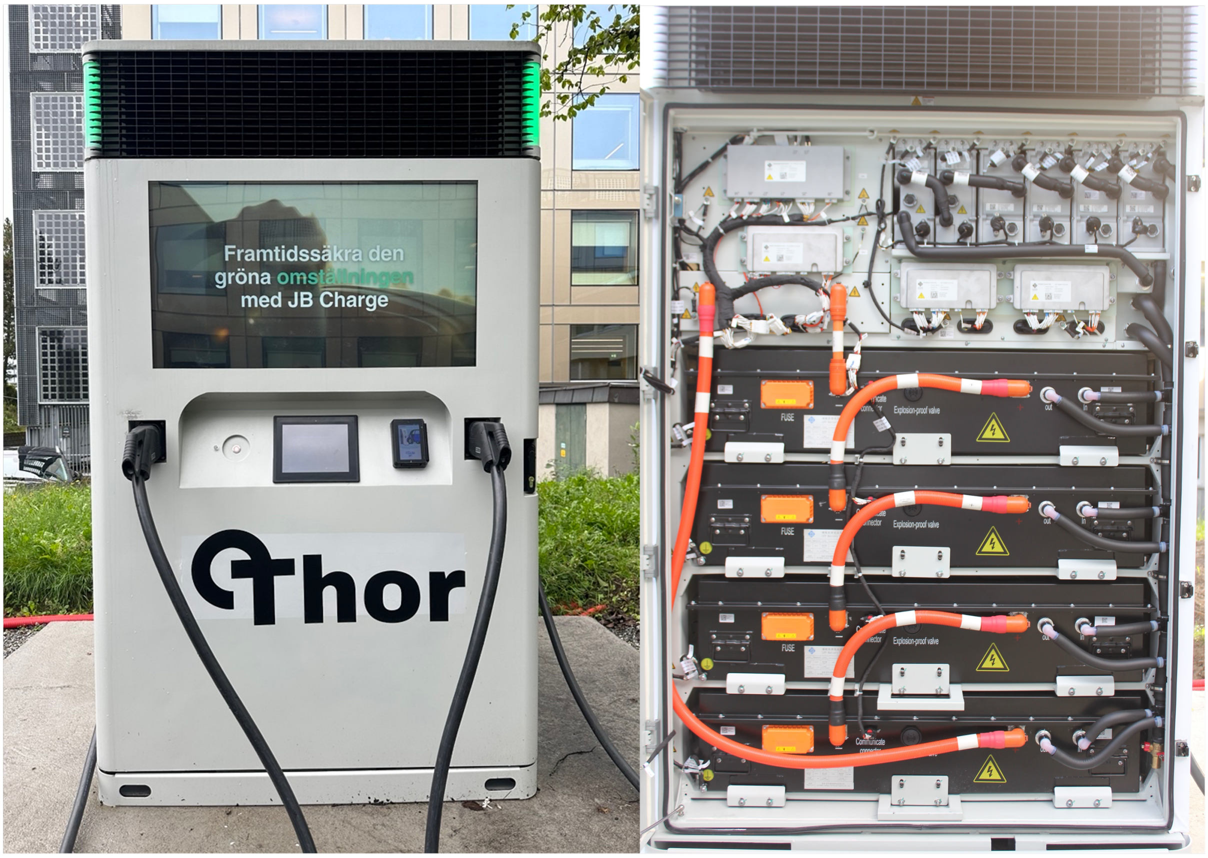

Figure 3: An image of the EV charging station

2.3. Grid Connection

The system is connected to the electrical grid, allowing for the exchange of energy. There are two main flows of energy involving the grid, as follows.

2.3.1. Charging Batteries from Weak Grids:

When the PV panels are not generating sufficient power, the system can draw energy from the grid to charge the batteries. This ensures a reliable power supply for the EV charging stations.

2.3.2. Excess Energy from Batteries to Grid:

If the batteries are fully charged and there is excess energy (especially from the PV panels), this surplus can be fed back into the grid, supporting grid stability and potentially generating revenue or reducing costs through net metering.

2.4. EV Charging Stations (Fast Charger)

The system includes a DC (direct current) double-gun fast charger for electric vehicles, provided by High North Quality AS (HNQ) with a rated power of 160 kW [7]. An image of the EV charging station is given in Figure 3. The charging station can draw power from two sources, as follows.

2.4.1. Direct Energy from PV Panels or Grid:

When the solar panels are producing energy, it can be directly supplied to the fast chargers for immediate use. The charger operates with an input voltage of AC 380 V and can output a voltage range of DC

200–920 V, supporting fast charging of EVs with a current of up to 250 A for a single-gun or 500 A for double-gun operation.

2.4.2. Energy from Batteries:

The fast chargers can also draw power from the battery storage system, which has a capacity of 193 kWh. This ensures that EVs can be charged quickly even when solar power is not available or when grid power is insufficient, thereby maintaining reliable and efficient charging operations.

2.5. Integrated Energy Flow and System Capabilities

The energy flow within this system is designed to efficiently manage and utilize renewable energy, specifically solar power, to meet varying energy demands. During periods of peak PV generation, the energy produced is primarily used to charge the battery storage system. This stored energy can then be utilized by the fast chargers to quickly power electric vehicles (EVs), ensuring availability even during low solar production or peak usage times. Additionally, when the battery storage reaches its maximum capacity, any excess energy is exported back to the grid. This not only enhances overall energy efficiency but also provides potential benefits to the grid by contributing surplus power, particularly during high-demand periods.

The system's capabilities extend beyond simple energy storage and distribution. It maximizes the use of locally generated renewable energy, thereby reducing dependence on grid electricity, especially during peak hours when electricity costs and demand are high. The battery storage system also offers grid independence by providing backup power during outages or periods of high demand, ensuring a stable energy supply for EV charging and other critical needs. Furthermore, the ability to feed excess energy back into the grid plays a crucial role in stabilizing the electrical grid, enhancing its resilience during times of fluctuating energy production and consumption.

3. Integrating PV Power Forecasts, Energy Demand Forecasts, and Energy Market Prices

Integrating PV power forecasts, energy demand forecasts, and energy market prices into this system is crucial for optimizing energy flow decisions. By accurately predicting PV output and aligning it with anticipated energy demand, the system can efficiently manage energy storage and distribution, minimizing waste and ensuring that energy is available precisely when it is needed. Additionally, by incorporating energy market prices and forecasts, the system can make informed decisions about when to draw energy from the grid or when to sell excess energy back, thereby maximizing cost savings and revenue generation. Rules can be used to guide these decisions, ensuring that the system operates within predefined parameters while maintaining flexibility. Furthermore, the use of explainable models in this process enhances transparency, allowing stakeholders to understand the rationale behind each decision.

3.1. PV Power Forecasts

Photovoltaic (PV) generation forecasting is a crucial aspect of optimizing solar energy systems, allowing for more accurate predictions of energy output under varying environmental conditions. Weather forecasts provided by the Norwegian Meteorological Institute [8] have been integrated into the PV power prediction models. The forecasting models are built using several key inputs, which have been carefully selected based on their correlation with power generation and weather forecasts. These inputs include hourly forecasts of air temperature at 0 meters, relative humidity at 2 meters, solar irradiance (measured as surface downwelling shortwave flux in air), and the power generated in the previous hour, the month, and the hour of the day.

Recognizing that different PV panel types respond uniquely to environmental factors, the system forecasts power generation for each panel type separately. This approach ensures that the models account for specific characteristics of different PV technologies. The forecasting is conducted using advanced machine learning techniques, such as Long Short-Term Memory (LSTM) networks, Random Forest, and XGBoost. These methods are particularly effective in handling the complex and nonlinear relationships between the input variables and the resulting power output.

Despite the use of sophisticated algorithms, predicting peak power values remains challenging due to the inherent variability of solar irradiance and other influencing factors. To improve the accuracy of these forecasts, further analysis incorporating sun angle and shading information is recommended. By refining these aspects of the forecasting models, the system can achieve more reliable and efficient energy management, ultimately supporting the broader integration of renewable energy into the grid.

3.2. Integration of Energy Market Prices

To enhance system performance, we aim to incorporate energy price data from several sources into the system. One of the intended data sources is ENTSOE (European Network of Transmission System Operators for Electricity) [9], which provides an overview of market prices. However, this platform currently lacks an API for accessing real-time data, which poses a challenge for immediate integration. To address the need for more granular and up-to-date information, the system plans to leverage price data from NORDPOOL [10], which offers detailed hourly area prices, although this data requires a subscription to access. Additionally, the integration of daily electricity prices from the Strompris API[1] [11] is anticipated. By incorporating these varied sources of energy pricing data, the future system will be capable of optimizing the timing of energy usage and storage, aligning energy consumption with periods of lower prices, and potentially selling excess energy back to the grid during peak price periods. This future development will significantly enhance the system's economic efficiency and overall performance.

3.3. Integration of EV Demand Forecasts

The system will integrate electric vehicle (EV) demand forecasts to further enhance its predictive capabilities and optimize energy management. Accurately forecasting EV charging demand is essential for balancing energy supply with consumption, especially as the adoption of electric vehicles continues to rise [4]. By incorporating EV demand forecasts, the system will be able to anticipate periods of high and low charging activity, allowing for better alignment of energy generation, storage, and distribution. This integration will enable the system to manage peak loads more effectively, reduce the risk of grid overloads, and ensure that sufficient energy is available to meet the needs of EV users. Moreover, by predicting EV demand in conjunction with energy market prices, the system can optimize the cost-effectiveness of energy usage, potentially charging vehicles during periods of lower electricity prices. This future enhancement is expected to play a critical role in creating a more resilient and economically efficient energy ecosystem that supports the growing demand for EV infrastructure.

3.4. Generation of Synthetic Data for Power Flow Optimization

The system will incorporate the generation of synthetic data to optimize power flows more effectively. This synthetic data will be crucial for simulating various scenarios, including extreme and rare events that may not be well-represented in historical data. To achieve this, we plan to utilize traditional probabilistic-based approaches [6, 12]. In addition to these methods, we will explore the use of large multi-model frameworks for time series data generation [13, 14], which are well-suited for modeling uncertainty and variability in power generation and demand. These advanced techniques will enable the creation of complex, realistic datasets that reflect the intricate temporal dynamics of power flows. By generating and integrating synthetic data, the system will be better equipped to predict and manage

[1]https://www.hvakosterstrommen.no/strompris-api

power distribution, ensuring more robust and resilient energy management strategies. This approach will enhance the system's ability to optimize energy usage and storage, particularly in scenarios where real-world data is limited or where future conditions deviate significantly from past trends.

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