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A Rule-based Control Approach Using Neural Network and Optimized Battery Energy Management to Efficiently Integrate Renewable Energy Sources in Data Center

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ABSTRACT :

The rapid growth of data center energy demand, combined with the urgency to decrease carbon footprint, has led to the development of new energy management systems. The thesis aims to optimize energy management in data centers using a rule-based control framework which considers renewables, battery storage and local grid power. The proposed framework also uses a Neural Network forecasting model capable of predicting solar PV generation and integrates two distributed rule-based controllers for dynamic energy sourcing management. The grid-side controller maintains power usage from the grid according to dynamic electricity prices and PV forecast values. The controller on the battery-side manages and optimizes the operation of a battery storage system based on their state-of-charge. The proposed system was simulated using MATLAB R2024B software and the control logic is simplified and verified through various scenario-based analysis and Karnaugh mapping.

The outcomes satisfy the capabilities of the proposed framework in terms effectively prioritize renewable energy usage, minimize grid power dependency and ensure secure operations under different conditions based on – PV generation, load demand, peak hours and emergency blackout scenarios. The framework combines hybrid energy sources and battery storage using rule-based control, which aligns the sustainable development goals[1][2] for carbon emission reduction and acquisition of green energy practices in the domain of data center. In future work this study suggests a real-world implementation and the inclusion of advanced control strategies like fuzzy logic, reinforcement learning, model predictive control to better control the system. This research provides a scalable and cost-effective solution for optimizing energy management in data centers for ensuring a sustainable energy future.

KEYWORDS: Rule-based Control, Energy Management, Distributed Controlling, Battery Storage System, Renewable Energy Sources, Neural Network, Karnaugh Mapping, Data Centre.

[1] Ensure access to affordable, reliable, sustainable and modern energy for all.
[2] Take urgent action to combat climate change and its impacts.

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1 Introduction

The increasing demand for digital services and online applications has led to a significant growth in the number of data centers worldwide. According to Goldman Sachs Research (Masanet et al., 2020) it is estimated that data centers power demand will grow 160% by 2030. As data centers deal with rising energy needs and environmental issues, using renewable energy sources has become a key research focus in recent years. While these sources can significantly lower the carbon footprint of a data centers, their intermittent nature poses challenges in maintaining reliability and efficiency (Rostirolla et al., 2022). On the other hand, optimizing energy management in such systems remains a challenge due to the complexity of balancing energy supply and demand. Existing energy management systems mostly rely on intensive optimization techniques (e.g., LP, MPC) that require heavy computational resources (Ghorashi Khalil Abadi et al., 2022). However, while this is useful, these optimization approaches adds more complexity and computation overhead to the network where rule-based methods can offer greater transparency, as they are generally easier to interpret and validate than empirical or black-box optimization techniques. In energy conversion systems, this transparency supports better maintenance and troubleshooting (Becchi et al., 2024). This emphasizes an important research gap, the need for a low-complexity, easy to implement controls framework, which can enable maximized utilization of renewable energy sources while limiting carbon footprints. Thus, rule-based approaches are still relevant in spite of metaheuristic, machine learning and heavy optimization approaches. Hence, this chapter sets the needed background and context for the research and its attentive investigation via the proposed idea through this introductory framework. This chapter also includes the background, motivation to study, problem statement and the research question and objectives. In addition, it describes the scope, limitations and structure of the study. This chapter aims to establish a clear context of the proposed idea and its implications for sustainable energy management in data centers.

1.1 Background

The biggest contributor to climate change, greenhouse gas emissions is due to fossil fuels being burned for electricity generation. In 2015 alone, electric power sector has been the largest contributor to CO2 emissions in the United States, accounted for 36.5% of the total CO2 emissions (Grange et al., 2018). According to the same study, the data center total consumption was estimated to almost 270 TWh in 2012 only. In light of these, data centers are being designed with energy efficiency and sustainability in mind. Integrating Renewable Energy Sources is one way to achieve the goal. While this approach solves the initial concern about the environmental impact from data centers, but introduces a whole spectrum of new complexities. Theoretically data centers can reduce the carbon footprint through renewable energy sources, but before discussing further we need to set a solid background about the traditional energy sources and how they are controlled. The background of some optimization approach in existing EMS and the need for a rule-based approach for a data center. This section will cover the background of these topics in the following parts.

1.1.1 Traditional Energy Sources and Controlling

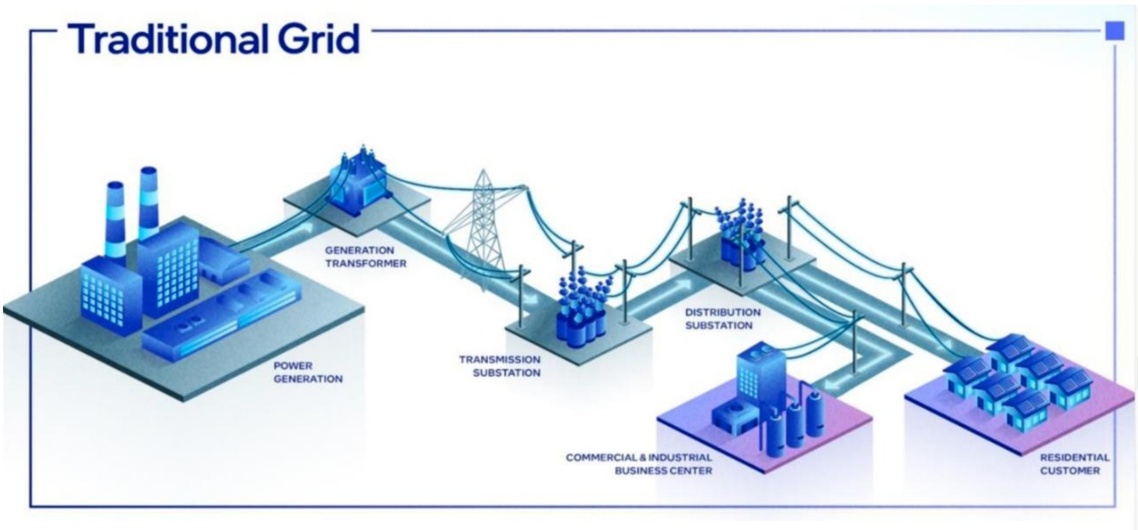


Figure 1. A traditional, centralized power grid (Bates, 2023)

Historically, the very foundation of global electricity supply has been traditional centralized energy systems, particularly fossil fuels — coal, gas and oil. Power generation is centralized and focused on producing large quantities of electricity, which is then transported through large transmission lines into the distance to supply power to clients. The control mechanisms of these systems are highly centralized — grid operators rely on increasingly advanced monitoring and control tools to balance supply and demand in real time (Espín-Sarzosa et al., 2020). This balancing is vital to keeping the grid stable, as any imbalance between supply and demand can result disruption in frequency, voltage oscillations and even blackouts. Conventional systems do balancing with the help of a combination of base-load power plants that run continuously and peaking power plants that are turned on in periods of peak demand (W. Guo & Wu, 2023). In addition, load forecasting, economic dispatch and automatic generation control are used by grid operators to optimally operate these plants and ensure reliable power (Nanda & Kaul, 1978).

Traditional energy systems are widely used but still face some substantial challenges. They depend heavily on fossil fuels, which are limited resources and key drivers of greenhouse gas emissions, which is one of their biggest problems. Burning of coal, oil and natural gas emits CO_2 and other pollutants, driving climate change and environmental degradation. Moreover, the centralized design of these systems can potentially suffer from disruptions, including natural disasters, cyberattacks and equipment or plant failures, resulting in blackout. Energy losses during transmission of electricity over long distances also reduce the efficiency of the system. These inefficiencies have accelerated a global transition to cleaner, more sustainable energy solutions. On the other hand, moving away from traditional systems is not so easy, as they are so closely embedded in the nations infrastructure and economies across the globe. This emphasizes the demand for a smarter mechanism of energy management that can provide a foundation between the traditional energy system vs its modern counterpart the distributed generation system and simultaneously tackle challenges.

1.1.2 Distributed Generation Systems and Data centers

Over the past couple of decades, the energy systems came a long way in their evolution, moving from the classic centralized system using fossil fuels to technically demanding advanced distributed generation (DG) systems, using renewable energy sources including solar panels, wind turbines and small hydroelectric power plants which are distributed by nature. DG System generate electricity close to the consumer as opposed to traditional systems to minimize transmission losses and improve grid robustness (Zahraoui et al., 2021). DG systems are based on decentralized systems that provide flexibility and scalability, functions for different applications ranging from homes to large scale industrial plants. Furthermore, the implementation of smart grid technologies, including advanced metering infrastructure (AMI) and real-time monitoring systems, has also significantly improved the efficiency and reliability of the DG systems (Rahmani-Andebili, 2021). This allows for real time monitoring of energy production and consumption according to demand and supply conditions.

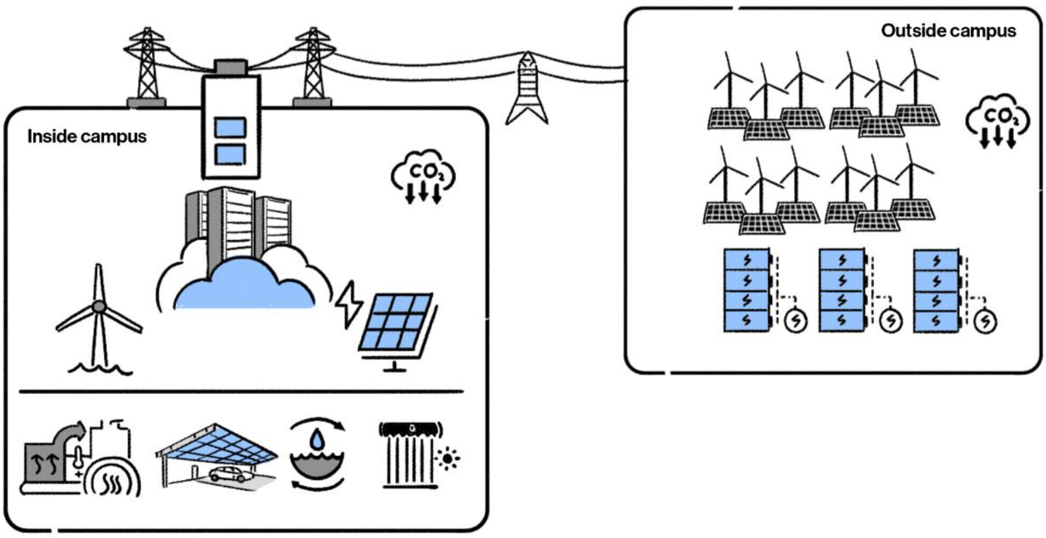


Figure 2. The distributed energy microgrid by Tencent's data center, saves 12 million kWh annually, enough to power 6,000 households[3].

[3] Running on Sunshine: How Tencent Is Powering Data Centers Sustainably

As one of the most energy-demanding infrastructures, data centers have been the primary center for implementing advanced DG systems (Chao Li et al., 2013). In fact, modern data centers have massive electricity requirements to run servers and other vital infrastructure and are a substantial portion of global energy demand and carbon emissions. On the other side, their high and continuous power requirements provide a unique opportunity for deploying novel energy management approaches. With the use of renewable energy sources together with BES (Battery Energy Storage), datacenters can have a positive impact by reducing carbon footprint significantly. For example, solar PV panels can be deployed on the site, or near, to produce clean electricity, while battery storage systems can respond to release energy during low generation periods or during peak demand (Amin et al., 2023). This contributes to better energy resilience for data centers, helping them to operate through interruptions (including grid failures or fluctuations) and enhancing their sustainability. But operating these systems successfully is dependent on advanced control systems that balance the supply and demand of energy, optimize the work of renewable energy sources and control battery storage systems.

1.1.3 Optimization Approaches in Energy Management Systems

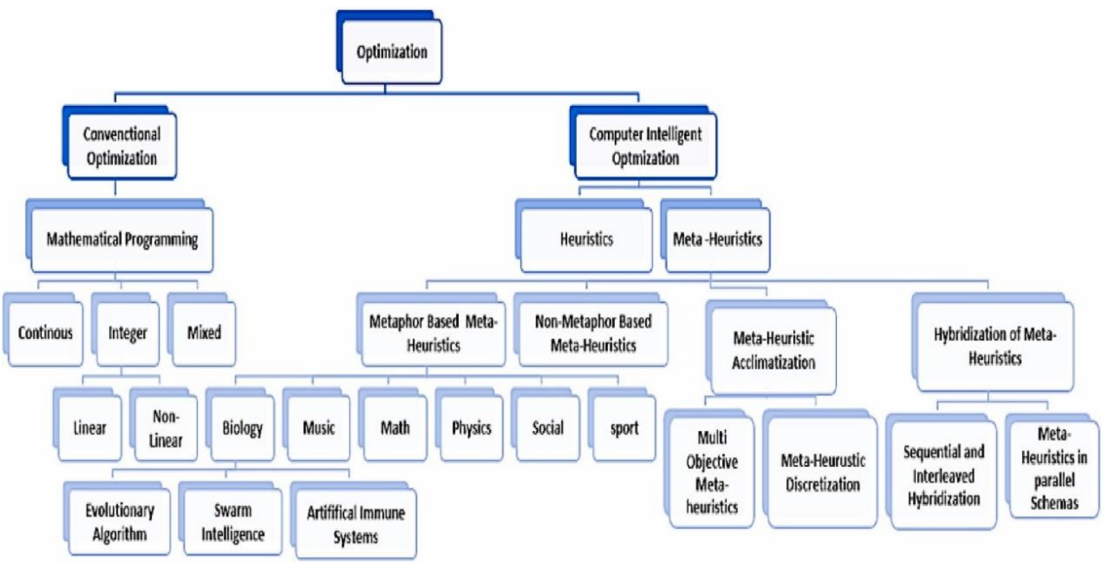


Figure 3. Classification of optimization techniques (Akkara & Selvakumar, 2023).

Modern energy infrastructures can benefit from Energy management systems (EMS), especially in optimizing DG systems and battery storage systems (BSSs). Advanced optimization methods are used to manage supply and demand of energy, optimize renewable energy generation and usage of storage systems. One popular optimization approach is known as Model Predictive Control (MPC), which means using predictive models to forecast energy demand and generation, adjusting control strategies in real time (Ghorashi Khalil Abadi et al., 2022). This is especially useful in dealing with the unpredictable nature of renewable energy sources, where MPC can adjust the control quantities according to real-time measurements. Linear programming (LP) and mixed-integer linear programming (MILP) are another common approach for solving complex optimization problems by minimizing costs or maximizing efficiency under a set of constraints. In their work Samsatli & Samsatli (2018) discussed that these methods are potentially useful for scheduling energy generation and storage operations over longer timeframes (i.e. days or weeks). Moreover, finding solutions for non-linear or non-convex problems, heuristic and metaheuristic algorithms like genetic algorithms and particle swarm optimization are suitable when traditional optimization methods fail (Arabali et al., 2013).

Although such optimization techniques are powerful, they have major drawbacks. One of their prime faults is that they are computationally expensive. MPC, for example, needs to solve a sequence of optimization problems at each time step, demanding considerable computational power and time. The larger the system and the more complex the models are, the more computationally expensive the approach becomes, which current limits its applicability in real-time situations and large-scale systems like data centers. LP and MILP methods are powerful but utilize too many computational resources and usually not used for real-time decision-making. Even though heuristic and metaheuristic solutions are flexible but do not guarantee the optimal solution. A second challenge is the intensive energy consumption of these optimizations. These challenges emphasize the necessity of alternative control strategies, enabling near similar performance levels, but with lower computational load, energy usage and implementation complexity. This has resulted in increasing interest in the RBC approaches that represent a less sophisticated and cheaper alternative for energy management in distributed generation systems.

1.1.4 The Need for Rule-Based Control in Energy Management

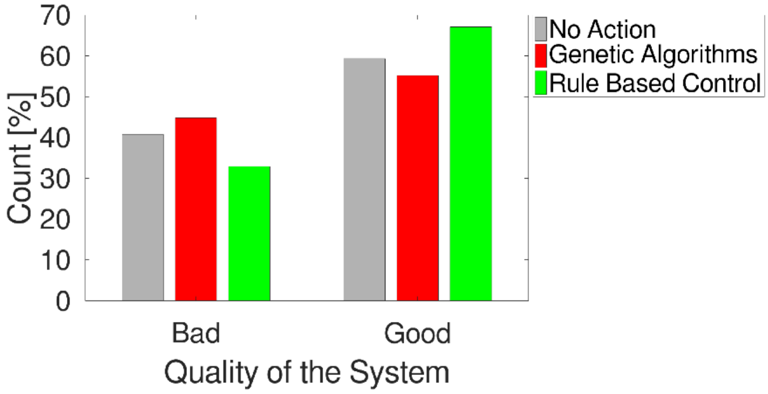


Figure 4. Performances comparison concerning the quality of a system (Ferrari et al., 2023).

Recognizing the shortcomings of conventional optimization methods, RBC has been proposed as an effective alternative for energy management systems. Instead of optimization algorithms, RBC uses rule-based logic, making it a simple, cost-effective and easy to design solution. Such an approach is especially useful for applications where responses have to be immediate and fast and sustainability is important. Its simplicity enables a relatively simple implementation and maintenance, especially in case of decentralized energy systems. According to a recent study by Ferrari et al. (2023), RBC shows more count in a optimization problem and able to reduce energy consumption while ensuring a good quality of the service compares with a more sophisticated genetic algorithm approach shows in figure 4. Adding real-time data analytics and machine learning will further improve it. This method combines the computational power of machine learning with the effectiveness of rule-based systems for better and faster decisions. We are in the era of cleaner energy transition, where leveraging rule-based control systems integrated with modern technologies will be crucial for energy saving and compliance with environmental goals.

1.2 Problem Statement and Research Questions

Integration of renewable energy sources (RES) and battery storage systems (BSS) in data centers is a potential solution to reduce carbon emissions and improve energy sustainability. But the fluctuations of RES with the difficulties in balancing energy supply and demand, make energy management complicated. This creates a critical need for a cost-effective, low-complexity control framework. This thesis addresses this gap by proposing a RBC approach integrated with neural network-based forecasting to optimize BSS energy management and maximize renewable energy utilization in data centers. **The purpose of this work is to develop a rule-based control for optimizing a battery storage system and integrate a hybrid energy sourcing for a data center.**

To tackle this, the research is structured around the following conceptual sub-questions:

- What are key design principles to consider when designing the rule-based control framework for a distributed energy management?
- How can the control strategies be optimized for using renewable energy and battery storage efficiently?
- How does flexibility help to integrate renewable energy sources with the local power grid?

1.3 Objectives of the Study

The objective of this study to adopts a "Design Science Research Approach" to implement a data-driven rule-based control framework for optimizing energy management in data centers. By integrating real-time electricity prices, peak-time data and neural network-based energy forecasts the framework intent to ensure efficient energy utilization. The overall performance of the framework will be evaluated then through scenario-based analysis, for a scalable yet easy to implement control system and ensuring simplicity against traditional optimization methods. The specific objectives of the study are:

Objective 1: Development of a neural network enhanced rule-based control

The primary objective is to create and apply a rules-based control system assisted by a neural network model. The neural network will be used to predict the amount of renewable energy generation based on real-time weather data and historical data. These predictions will be used by the framework to ensure data centers use proper energy sourcing, including real-time price and peak time and thus will not need to issue a heavy computational burden.

Objective 2: Design of control strategies for battery storage systems

This objective focuses on creating control schemes for the battery storage systems for efficient charging and discharging processes. The implications will be based on the state-of-charge (SoC) levels, energy demand and energy availability. The aim is to maximize the usage of renewable energy, minimize dependence on the grid and ensures the data center operates reliably.

Objective 3: Performing a simulation for the evaluation of the proposed framework

This objective aims to perform a comprehensive simulation-based evaluation of the proposed framework. The simulation will see how the framework performs in several scenarios ranging from different weather conditions, peaks in electricity prices and demands during busy hours. Karnaugh mapping will serve as an evaluation matrix to simplify and establish the boolean expression for the decision logic to achieve optimal control strategies in terms of energy source selection and battery operation.

With these goals in mind, the study can address the challenges facing data center energy management and renewable energy sources.

1.4 Significance and Limitations of the Study

This study holds significant importance in the field of energy management, particularly for data centers. The framework presented is applicable to real-world applications since it utilizes real-time data and forecasts. The assessment also improves the efficiency of framework interpretations as it simplifies the logic for decision-making and ensures the optimal control strategies. The contribution of this study will assist data centers in contributing to energy sustainability by providing a modular and practical approach. The study's findings can also be extended to other industries to promote widespread adoption of renewable energy and advanced energy management systems.

The limitation of the proposed framework is that, the overall efficiency depends on the NN model's forecasting for renewable generation. Any errors or redundancy leads the Grid side controller taking wrong decision. Secondly, the RBC itself a straight forward controlling method, comparing with optimization control RBC does not have the ability to gain peak optimality. This trade-off between simplicity and optimality is a key consideration. Thirdly, even though the framework evaluated thoroughly via a simulation environment, its capability to capture real world complexity is not adequate and satisfying only limited pre-defined scenario. Despite these limitations, the study provides a strong foundation for future research and implementation of the findings in the realm of sustainable energy management.

1.5 Structure of the Thesis

The thesis organized in total 5 chapter which follows the respective order - introduction, literature review, methodology, system implementation and evaluation, conclusion and future work. In this way, the study aims to provide a comprehensive overview of the research work. It ensures that the outline maintained the process and finding in an organized manner for future contribution to both academic and professional.

2 Literature Review

Historically alternating current (AC) is dominated the electrical domain of traditional data center. Even though on the server level the use of direct current (DC) is changing faster pace. DC power distribution have many advantages over AC, the high power density and quality achieved in the system makes the choice obvious (Gupta et al., 2019). According to the study by Prabhala et al. (2018), in terms of distribution DC power have high efficiency, fewer power loss and cost effective as DC power topology do not requires extra conversion steps. In this chapter, the literature review focus on some overview of previous relevant study and research related to EMS. Further it will discuss about different approaches and development has been done in this domain and highlight current issues and novel solutions and the relative research gap which needed to be addressed.

2.1 Overview of Energy Management Systems in Data centers

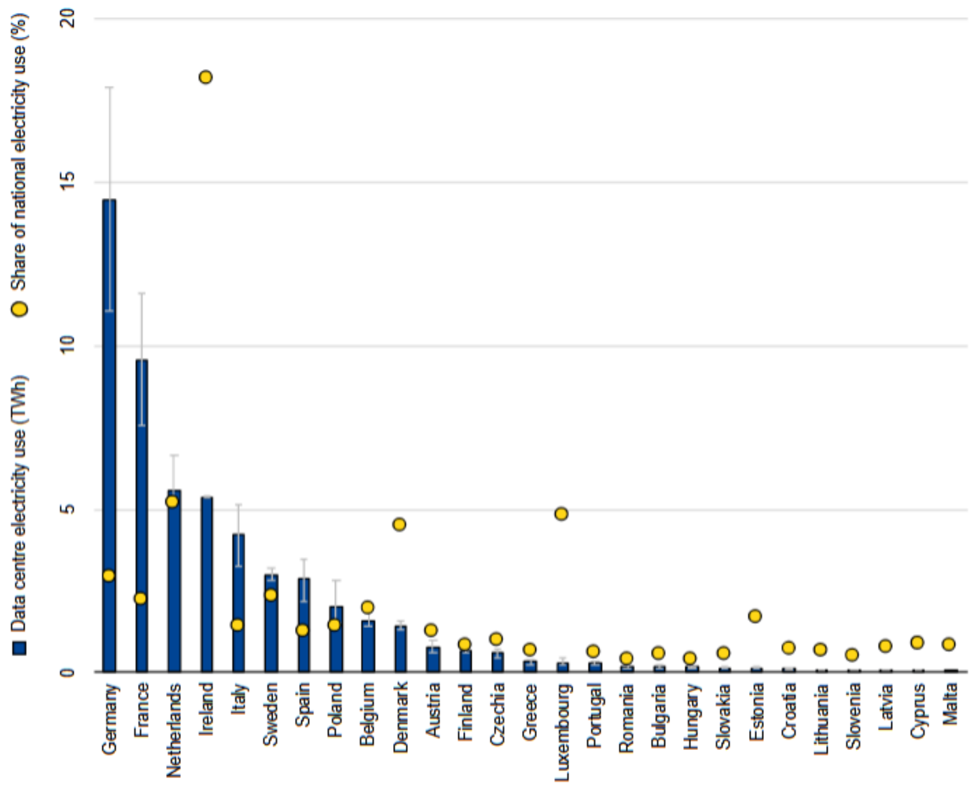


Figure 5. Data Center Energy Consumption by Country 2022

Data centers (DCs) becomes the most important energy consumer according to picture above in figure 5, DCs consume usually under 5% of country's electricity and energy is much more than just electricity, in this era of artificial intelligence and cloud computing which eventually increases the carbon footprint as well. The growing need for data intensive applications which leads to a more concerning topic, the efficient way to manage a data center and a more advanced sophisticated EMS. While the existing EMS are facing challenges like sudden power failure, high electricity cost, large carbon footprint and growing demand for managing global warming problems, it is high time to incorporate novel adoption. To tackle these challenges researchers are experimenting with different approaches to meet the quality of the service of a data center such as – using renewable energy sources (RES), automation in power distribution layer and incorporating advanced algorithms.

Yu et al. (2018), studied an EMS topology where multiple DCs were connected to microgrids. They aims to cost minimize for long term operation in terms of electricity prices, RES output and load demand. In another study by Aujla et al. (2016), optimization techniques have been used to aim similar cost reduction. They employ stochastic framework and distributed algorithm to improved energy efficiency. Further the study notes, with the integration of RES, the carbon footprint of DCs can be reduced. The same study notes about future social and economic benefits such as the rise of microgrid and the use of RES to integrate renewable energy, but it must grow based on efficient and effective algorithms for managing grid stability during increased uncertainty.

Dynamic power management technique is another important area of research that strives to maximize the usage of provided power in DCs. Facebook's (Meta[4] in present time) large-scale DCs in real time implement adaptive control systems, Dynamo, to avoid power outages and enhance performance (Wu et al., 2016). Such systems observe the whole power hierarchy and consolidate control decisions, allowing more aggressive use of allocated power within safe and efficient ranges.

[4] The Facebook Company Is Now Meta

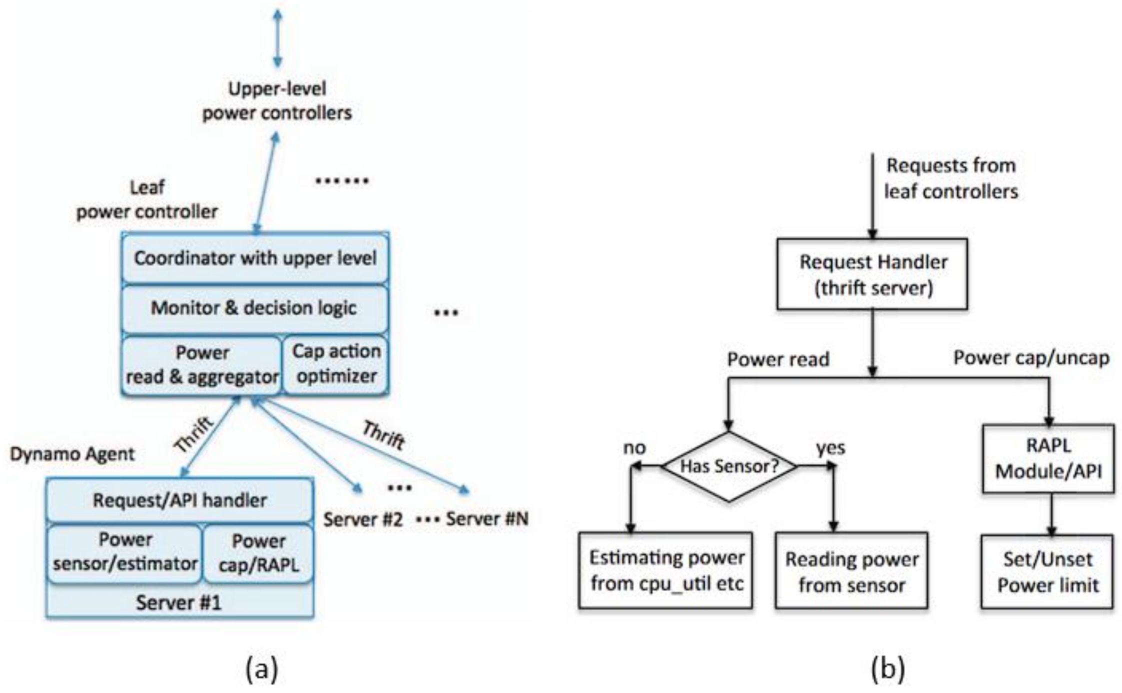


Figure 6. Illustration of (a) Dynamo's major components and (b) block diagram for overall workflow

DC microgrids are a promising domain as well, as they provide a high level of reliability and reduced energy losses. To power sensitive electronic loads and prevent power interruptions in the event of a grid failure, adaptive control systems for DC microgrids have recently been proposed (Salomonsson et al., 2007). These systems show that these decentralized microgrid systems can increase energy efficiency and reliability but also highlight the need for fast outage detection and switching mechanisms to minimize voltage transients. Although the substantial benefits associated with DC microgrids are evident, extensive research is needed on the control techniques as well as the smooth transition between various operational modes.

Energy management in DCs also involves task scheduling and resource allocation. In order to optimize energy utilization while satisfying performance constraints, a dynamic energy management systems are proposed by Pang et al. (2017) that bring together task scheduling, load balancing and voltage scaling modules. Innovative algorithms like LET-ACO have demonstrated efficient energy savings over classical scheduling approaches.

But there is a need to implement smarter, more adaptive algorithms that are capable of handling dynamic workloads and different resource requirements.

However, there are research gaps to be addressed related to data center energy management. First, although stochastic programming and optimization techniques have been suggested towards these ends, they cannot handle higher-order real-world variability nor are their solutions robust and energy-scalable. Second, the incorporation of new technologies, particularly EVs, RES and DC microgrids, appears to be promising, although more studies are needed to enhance their coordination with the grid and algorithm development to achieve stable operation at various circumstances. Third, existing control systems are usually not adaptable enough to cope with the ever-changing DC workloads and power requirements, making the development of intelligent control systems capable of adaptation on-line a priority. The absence of standardized energy management system frameworks has also contributed to the limited uptake of EMSs as it remains extremely important to develop interoperable and modular solutions.

2.2 Battery Storage Systems vs Renewable Energy Integration

Configuration of RES offers a solution to mitigate the cost of energy, environmental concerns and uncertainty of a grid. The large amount of renewables is still causing technical challenges due to the variability and irregularity of RES at the generation and demand side. Battery energy storage systems (BESS) have been presented as an effective solution for such challenges and facilitating the integration of RES through technical and economic advantages. This subsection discusses the role of BESS and compares its advantages and limitations.

Energy storage technologies are vital for providing an efficient solution to the temporal mismatch between generation and load due to the intermittency of RES. By storing surplus generation and releasing it once generation is low or demand is high BESS can solve the grid instability. It has the potential to increase the levels of energy from RES consumed in small-scale, decentralized renewable energy applications (e.g. commercial buildings, residential dwellings) while providing numerous technical and financial benefits. Nair & Garimella (2010), proposed a modeling framework to analyze technical and economic viability for different battery technologies in their work and software tools such as Simulink and HOMER have been applied. In their findings, BESS plays a significant role in improving small-scale renewable energy systems reliability and efficiency. BESS, in contrast, is economically feasible and appropriate up to a large scale, where technical limitations pose challenges.

Due to their flexibility, modularity and fast-response capability, ESS are considered the enabling technology of new generation power systems. Particularly, ESS can work effectively with or without integration with RES in the power grid, thus making them appealing for broad use (Rana et al., 2023). This comprehensive review lists several types of ESS technologies, including mechanical, chemical, electrical, electrochemical and thermogravimetric, each with unique contributions and applications depending on their pathways. Although ESS provides significant benefits as it creates better grid stability and the integration of RES, still there are some issues such as - high cost of maintenance, degradation of storage systems, waste disposal and environmental pollution remain. These challenges indicate the urgency for the further development of the ESS economics and technology for large-scale application.

In the work by Grillo et al. (2012), such advancement of the coupling of RES is shown with sodium nickel chloride batteries. A discrete-time model of the storage device has been created and validated using experimental tests in this work. Then a dynamic programming based optimal management strategy has been rolled out in order to take advantage of the arbitrage, in terms of energy cost. According to their study, this approach improved wind generation efficiency and made it responsive to load requirements, which leading to higher profits. These studies demonstrate the capacity of BESS to enhance RES integration with a focus on technical performance and economic impacts.

The interaction of using smart grid connected data center and their impact is discussed by C. Guo et al. (2021). In this work authors addressed integrated planning of interconnected Internet data center and BESS. They developed a multi-objective optimization model to identify the optimal locations and capacities of the framework. The model's optimizing metric cover computational performance also the operational criteria of the grid. The application of advanced evolutionary algorithm proved the effectiveness of the approach. The study highlight the need for coordinated planning between cyber and energy resource for optimal performance and sustainability.

To bridge the gap between the intermittent nature of energy generation and consumption, hybrid systems of RES integrated with storage elements have been suggested in another study by Iverson et al. (2013). A two-fold optimization routine was created to minimize both the levelized cost of energy (LCE) and zero loss of power supplied (LPS) for applications in data centers. The research studied scenarios with and without controllable power demand termination, finding reductions in lifecycle costs in when controllable demand was allowed. Such shows the potential of hybrid systems to improve the efficiency in energy management of data centers in regions where renewable resources are scarce.

While much progress has been made in integrating BESS and RES, many research gaps still exist. BESS has been successfully applied at a small level and there is still a need for developing module wise and scale solution for large scale data centers and power grids. Additionally, the complexity has called for the necessity to establish real-time optimization techniques and control algorithms to make BESS perform reliably.

2.3 Optimization Strategies in Energy Management

EMS are critical for making data centers more energy-efficient. Modern DCs consume large amounts of resources including energy and water, thus demanding optimization techniques in design and operation part, are applied for improving the energy consumption and cost and also better utilization of the components. These techniques can be classified in two groups: Traditional optimization techniques and Advanced optimization techniques, which are discussed in the following subsection.

2.3.1 Traditional Optimization Techniques

Traditional methods for EMS optimization include Linear Programming (LP), Dynamic Programming (DP) and Mixed Integer Linear Programming (MILP). Linear programming (LP) is a widely used optimization approach that defines the optimization problem as a linear equation and it allows to utilize linear programming algorithms to solve it. Dynamic Programming (DP), a very popular optimization technique, which is based on solving the same sub-problem recursively. MILP on the other hand an extension of LP applying integer variables to model the optimization problem (Putz et al., 2021).

Linear Programming: The historical and classical optimization methods for EMS had been developed nearly half a century ago, specifically LP was proposed as early as the 1960s. LP is a common optimization approach that formulates the optimization problem as a linear equation that can be solved through linear programming algorithms. The mathematical expression for the LP problem is given in expression (1):

$$min \sum_{i=1}^{n} c_i x_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

subject to:

$$\sum_{i=1}^{n} a_{ij} x_i \leq b_j, \qquad j = 1,2,\dots,m$$

$$x_i \geq 0, \qquad i = 1,2,\dots,m$$

where x_i is the decision variable, c_i is the cost coefficient, a_{ij} is the constraint coefficient, b_j is the right-hand side of the constraintand n and m are the number of decision variables and constraints, respectively.

LP can solve large-scale optimization problems efficiently. LP has been widely applied in the areas of energy management, finance and logistics. The disadvantages of LP include that it cannot handle non-linear optimization problems and its sensitivity to the choice of the objective function and constraints.

Dynamic Programming: DP another classic optimization method which solves the problem by dividing the optimization problem into smaller sub-problems and using recursive solutions to solve them. The DP problem can be represented in equation (2, 3):

$$F(t) = \min c(t) + \sum_{i=1}^{n} p_i F(t+1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

subject to:

$$\sum_{i=1}^{n} p_i = 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$p_i \geq 0, i = 1,2, \ldots, n$$

where $F(t)$ is the value function, $c(t)$ is the cost function, p_i is the probability of transitioning from state t to state $t+1$and n is the number of possible transitions.

Some properties of DP include non-linearity in case of optimization problem, It is also resilient with respect to objective function and constraints changes, etc. Nevertheless, DP can be slow and use quite a bit of memory to store the value function.

Mixed-Integer Linear Programming: MILP is an extension of LP that uses integer variables in defining the optimization problem. A mathematical representation of MILP represented in expression (4):

$$min \sum_{i=1}^{n} c_i x_i + \sum_{j=1}^{m} d_j y_j \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4)$$

subject to:

$$\sum_{i=1}^{n} a_{ij} x_i + \sum_{j=1}^{m} b_{ij} y_j \leq b_j, \qquad j = 1,2,\dots,m$$
$$x_i \geq 0, \qquad i = 1,2,\dots,n$$
$$y_j \in 0,1 \quad j = 1,2,\dots,m$$

where x_i is the continuous decision variable, y_j is the integer decision variable, c_i is the cost coefficient, d_j is the cost coefficient, a_{ij} is the constraint coefficient, b_{ij} is the constraint coefficientand n and m are the number of continuous and integer decision variables, respectively.

In summary, several optimization techniques such as LP DP and MILP have been used in EMS for optimizing energy consumption and minimizing cost. Some of the benefits of using these types of techniques are that, they can cope with very large instances of optimization problems and they are not sensitive to the changes in the objective function and constraints.

2.3.2 Advanced Optimization Techniques

On the other hand, besides the traditional optimization methods, we can choose from variety of latest techniques like - Machine Learning (ML), Artificial Intelligence (AI). They all are advanced optimization techniques used for EMS. In their work Li et al. (2020), describe the process of using advanced ML algorithms to pick patterns in the data so that the system can forecast energy consumption. In another work, AI technique used to optimize energy consumption and improve the overall efficiency of the data center (Yang et al., 2019). In this section we will discuss about the fundamental concepts about this advanced technology and their approach.

Machine Learning: ML is a very special optimization approach which utilize many algorithms that try to learn the patterns in data and then predict the next point of objective such as next hour energy consumption based on that given dataset. ML can be mathematically represented in equation (5):

$$y = f(x) + \in \cdots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (5)$$

where y is the predicted energy consumption, x is the input data (room size, number of appliances, outside temperature), $f(x)$ is the prediction, ∈ is the error term and f() is the machine learning method.

ML can be used in both linear and non-linear optimization situation. It is robust to the incremental changes in the objective function and constraints. Machine Learning is being used in various fields from energy management to finance to healthcare. ML also has its own limitations, as in its core ML's accuracy depends on the given data sets quality and quantity. Also different problem required different algorithm so choice of algorithm and hyperparametering that algorithm is a challenge itself.

Model Predictive Control: MPC is a sophisticated control technique which take future and past states in its consideration and predict next states based on some user defined constraint. In the context of EMS, MPC can predict future energy consumption and take optimize energy management decision. MPC can be mathematically represented in expression (6, 7):

$$min \sum_{i=1}^{N} (y_i - r_i)^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (6)$$

subject to:

$$y_i = f(x_i, u_i) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (7)$$

$$u_i \in U$$

where y_i is the predicted energy consumption, r_i is the reference energy consumption, $x_i$is the state of the system, u_i is the control action, $f(x_i, u_i)$ is the model of the system, U is the set of admissible control actions and N is the prediction horizon.

In conclusion, above mentioned advanced optimization methods have gained a lot of features in the power sector over the last few years. For their capability at managing complex and non-linear optimization problem they are becoming a obvious choice for nextgen EMS controlling.

2.4 Neural Networks for Renewable Energy Forecasting

Renewable energy forecasting using Neural Network (NN) is being in constant development phase in recent years. As this kind of forecasting improves energy management and optimization in this section we will explain the neural networks, its architecture and some application of NN incorporate in some recent works for renewable energy forecasting.

Architecture of Neural Networks: NN architectures generally include an input layer, some hidden layer and an output layer. The input layer takes the input data. In the context of EMS this input will use historical data for weather or energy production data or any other relevant factors. Then the hidden layer, which provide processing for the input data and learn complex patterns of the given data. Then the output layer try to predict the next possible state or in this case the forecasted energy production.

The neural network architecture can be mathematically represented in equation (8):

$$\boldsymbol{y} = \sigma(\boldsymbol{W} \cdot \boldsymbol{x} + \boldsymbol{b}) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (8)$$

where $\boldsymbol{y}$ is the forecasted energy production, $\boldsymbol{x}$ is the input data, $\boldsymbol{W}$ is the weight matrix, $\boldsymbol{b}$ is the bias term and σ is the activation function.

Training of Neural Networks: The training of neural networks involves the use of historical data, which optimize the weights and biases of the network. The training process typically involves the steps shows in figure 7 (H. Lin et al., 2020).

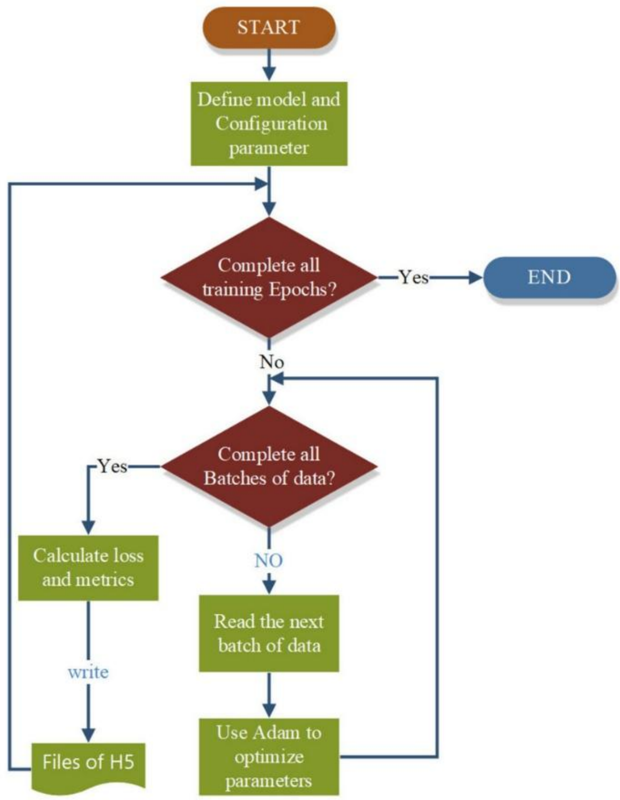


Figure 7. Flowchart for a trainning process of NN model

The method to estimate the squared error sum of the prediction can be mathematically represented in equation (9). The goal of the training is to minimize this error.

$$E = \frac{1}{2}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (9)$$

where E is the error, y_i is the actual energy production, $\hat{y}_i$ is the forecasted energy production and N is the number of training samples.

As we see the potential of NN model and the possibility of using it in different problems. Artificial neural networks (ANNs) have become a popular option to solve complex problems in renewable energy. According to the review work by Kalogirou (2001), ANNs provide many advantages, including learning from data, accommodating noisy and incomplete data and making high-speed predictions. Which make it useful for different forecasting agent. For example, solar energy applications of ANNs include modeling of solar steam generating plant, predicting the performance the system and estimating buildings heating load. The study suggests that ANNs expanded even further to solar and wind generation forecasting, PV system modeling and load forecasting and so on. This indicating the versatility of ANNs in renewable energy system and the prospective implementation.

In their work Y. Lin et al. (2020), focuses on a new neural network architecture, Temporal Convolutional Neural Networks (TCNNs), proposed for sequential modeling tasks such as solar power forecasting. TCNNs use a combination of causal and dilated convolutions with residual connections to capture long-term dependencies in time-series data better than traditional recurrent neural networks (RNNs). The paper addresses the relative strengths of TCNNs with respect to multi-layer feedforward neural networks and state-of-the-art RNNs. It reports that TCNNs yield higher accuracy and effective history length than these models. Such performance indicates the promise of convolutional architectures for renewable energy forecasting where long-term dependencies and accuracy at higher time scales are essential. But TCNNs require more computation for training and can rely on larger datasets to be trained.

The Marine Predators Algorithm (MPA) turned out to be a very efficient algorithm serves as an additional technique for optimizing neural network models in regards to energy demands within data centers. This algorithm is used to find the optimal weights and biases of an ANN model and minimize the prediction errors e.g., Mean Squared Error (MSE), Mean Absolute Error (MAE) etc. Using real-life datasets with ambient temperature, relative humidity and chiller output temperature as input variables, the MPA-based ANN model was utilized for the energy demand prediction of a data center (Ajayi & Heymann, 2021). The findings indicated its superior performance relative to other models in terms of accuracy and error metrics. That predicted energy demand was then solved with a dynamic economic and emission dispatch problem based on thermal and solar photovoltaic generation. It was shown that MPA-based approach is robust in optimizing the energy dispatch and it gave evidence for the preference of the solar photovoltaic energy usage instead of conventional thermal generators if available. However, the reliance on specific datasets and the need for further validation in diverse operational environments remain limitations of this approach.

2.5 Rule-Based Control in Modern Energy Management System

Among other optimization techniques, RBC has attracted great interest due to its simplicity, flexibility and effectiveness. Above mentioned advanced optimization techniques sounds fancy and optimal but they are complex and computationally hungry in terms of scalability and real world implementation. On the other hand, RBC work by some simple set of rules to make a control strategy used to control the EMS. RBC support incremental development and can represent problem-solving in conditional if-then rules (Hayes-Roth, 1985).

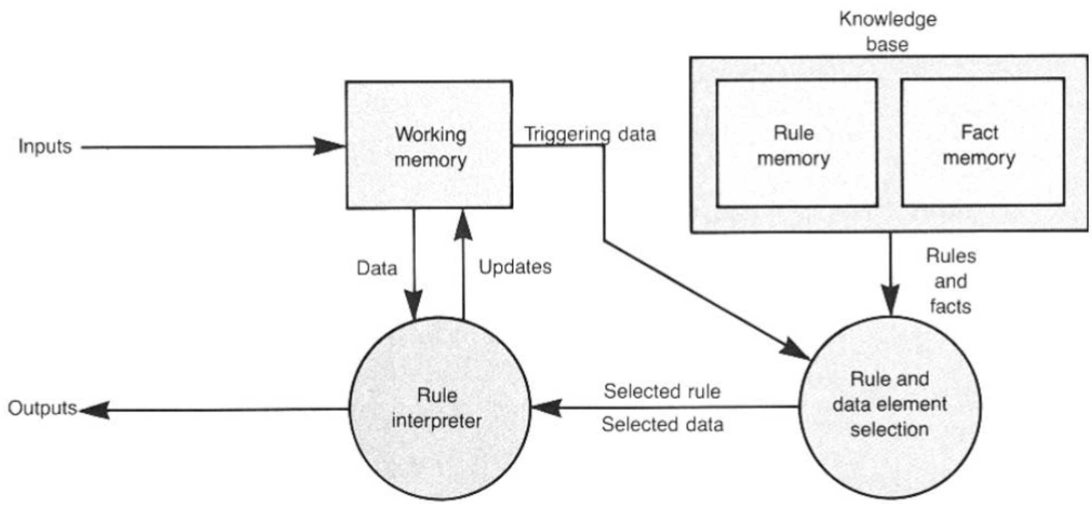


Figure 8. The basic features of a rule base system

The RBC in figure 8 can be mathematically represented in equation (10):

$$u = f(x, R) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (10)$$

where u is the control action, x is the state of the system, R is the set of rules and $f(x, R)$ is the rule-based control function.

The RBC consists of a set of rules that are defined based on expert knowledge and the characteristics of the system. Each rule is defined in the following expression in (11):

$$R_i : IF \ x \in X_i \ THEN \ u = u_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (11)$$

where R_i is the i^{th} rule, x is the state of the system, X_i is the set of conditions for the i^{th} ruleand u_i is the control action for the i^{th} rule.

In a recent study by Wang et al. (2019), a hybrid energy source system (proton exchange membrane fuel cells, lithium-ion battery and supercapacitors) are managed using a RBC in a distributed EMS. In the control strategy energy distribution is performed based on demand power, remaining capacity and power capability. This work implement a more sophisticated RBC, compared to traditional methods, where power capability limitations are not considered.

EV charging systems powered by PV energy and grid energy could also use Rule-based energy management schemes (REMS). A REMS developed by Bhatti & Salam (2018), for continuous charging during the day at a fixed-price shows how RBC balances the energy transfer between the PV, energy storage units and the grid. Specifically, the scheme includes the valley-filling operation at nighttime for reducing the load of the grid and improves the economic efficiency of the PV-grid system by taking advantage of vehicle-to-grid (V2G) technology.

In prosumer energy management, RBC are computationally efficient solutions for optimizing the energy flows between low-voltage distribution networks and prosumers equipped with PV systems and BESS. A data driven rule-based prosumer BMS is introduced which can maximizes economic revenue (Becchi et al., 2024). The study further notes, RBC algorithm achieves economic performance comparable to linear programming optimization while reducing processing time by 30 times.

3 Methodology

In this chapter, we provide details on the method that uses neural network to enhance RBC and how it is developed and tested. The process consists of four stages: Data Collection and Preprocessing, Neural Network forecasting model development, Rule-based control framework design, and Evaluation using Karnaugh mapping. For our part, we retrieve historical PV generation, weather and electricity price data and preprocess them to train the neural network model predicting solar PV generation with a high level of accuracy. The RBC framework integrates these forecasts to optimize energy sourcing and battery storage operations. After that Karnaugh mapping is used to simplify and evaluate the control logic for ensuring efficient and low-complexity decision-making. Then scenario-based simulations validate the framework's performance under varying conditions.

3.1 Overview of the Proposed System

This research uses a Design Science Research approach, a methodology that focuses on creating the innovations and evaluating them to solve a real-world problem (Venable et al., 2017). This type of research is particularly well suited for design science which emphasizes creating practical solutions and systematically assess their effectiveness. This method includes iterative cycles of design, development and evaluation, thus assuring the proposed framework is both theoretically grounded and practically useful.

Here, the RBC framework is designed incorporating these neural network based PV generation forecasts along with the real time electricity prices and peak-time details, for optimized management of energy in data-centers. The tools include the switch controller for collecting energy from the grid, breaker controllers for BSS management based on SoC and on energy demand. In the design phase, logical rules are defined for control decisions while keeping the implementation simple. Based on the design, the development phase conducts the implementation of the framework which including, training the neural network model by using historical PV and weather data and integrate it to the control logic. Subsequently the framework is then evaluated through Karnaugh mapping and in a simulated environment.

3.2 Requirements List for the Design of the RBC Framework

The design science research approach follows some predefined requirements. In this context, the requirements are categorized into functional requirements (FR) and non-functional requirements (NFR) to clearly distinguish between what the system must do (e.g., optimize energy sourcing) and how it should perform (e.g., scalability, reliability). The chosen requirements are listed below in Table 1.

Table 1. List of requirements for the RBC Framework.

Category	ID	Description
Functional Requirements	FR1	Prioritize renewable energy (PV) over grid power.
	FR2	Optimize current production using the PV forecast.
	FR3	Optimize for electricity price and peak-time and PV forecasts.
	FR4	Implement simple, transparent and modifiable rule-based control logic.
	FR5	Optimize energy sourcing and battery charging/discharging.
Non-Functional Requirements	NFR1	Reliable under varying conditions (weather, generation, prices).
	NFR2	Operate with minimal computational burden for real-time performance.
	NFR3	Scalable to larger systems and integrable with hybrid energy sources.

3.3 Data Collection and Preprocessing

Data collection and preprocessing are critical steps in developing the framework. This section describes the process of gathering, cleaning and preparing the data for analysis and modeling. The study relies on three primary datasets: weather data, actual solar generation data, both collected over a one-year period and 24-hour ahead energy price data from the energy market.

3.3.1 Data Collection

Weather Data: Weather data was collected from the **Finnish Meteorological Institute**[5] (FMI) from 29th November, 2023 to 28th November, 2024 at 10-minute intervals. This dataset given below in Table 2 includes key parameters such as:

- Global radiation mean [W/m2]
- Cloud cover [1/8]
- Air pressure mean [hPa]
- Relative humidity mean [%]
- Wind speed mean [m/s]
- Air temperature mean [°C]

Table 2. Sample of collected weather dataset from FMI.

Timestamps	Cloud cover [1/8]	Air pressure mean [hPa]	Relative humidity mean [%]	Wind speed mean [m/s]	Air temperature mean [°C]	Global radiation mean [W/m2]
29.11.2023 T 00:00	Cloudy (8/8)	1001.8	95	1.6	-1.1	1
29.11.2023 T 00:10	Cloudy (8/8)	1001.9	96	2	-1.1	0.8
29.11.2023 T 00:20	Cloudy (8/8)	1002	95	2.2	-1.2	0.9

[5] https://en.ilmatieteenlaitos.fi/download-observations

29.11.2023 T 00:30	Cloudy (8/8)	1002.1	93	2.4	-1.2	0.9
29.11.2023 T 00:40	Cloudy (8/8)	1002.3	92	2.2	-1.3	0.8
...	...	...	...	...	...	...
28.11.2024 T 23:00	Cloudy (8/8)	1019.7	96	2.1	3.7	1.1

Solar Generation Data: Actual solar generation data was obtained for whole Finland from the **ENTSO-E Transparency Platform**[6] from 29th November, 2023 to 28th November, 2024 at 15-minute intervals. This dataset in Table 3 provides the real-time power output (in kW) of solar PV systems, which serves as the ground truth for training and validating the neural network forecasting model.

Table 3. Sample of collected solar generation dataset from ENTSO-E.

Time [Local time]	Solar Actual Aggregated [MW]
11:45 - 12:00	30
12:00 - 12:15	25
12:15 - 12:30	19
12:30 - 12:45	13
12:45 - 13:00	7

24-Hour Ahead Energy Price Data: Energy price data was collected from **Oomi**[7] (Finland's local energy supplier), providing 24-hour ahead electricity prices at hourly intervals. This dataset given in Table 4, is crucial for optimizing energy sourcing decisions, as it allows the framework to prioritize low-cost grid power during off-peak hours.

Table 4. Sample of collected energy price dataset from Oomi.

Time [Local time]	Price c/kWh (with VAT)
12:00	0,96
13:00	1,00
14:00	1,03
15:00	1,02
16:00	1,55

[6] https://transparency.entsoe.eu/
[7] https://oomi.fi/en/electricity/electricity-contracts/active/spot-price-of-electricity/

3.3.2 Data Cleaning and Resampling

We can see from the data that there is a misalignment in terms of time intervals and they need to be resampled before feeding to the NN model. In this section, one important process applied to the solar generation data which is resampling the data to 10-minute intervals. Through Python, resampling was made by several steps - clean, align and interpolation. Here's a summary of the resampling process with code snippets.

1. **Data Loading and Cleaning**: The raw data was first loaded into a Pandas DataFrame. Metadata rows were skipped and columns were named appropriately for better readability. Rows containing only `NaN` values were dropped to clean the dataset.

```
data_cleaned = pd.read_excel(file_path, skiprows=4,
names=["Date", "Solar"])
data_cleaned = data_cleaned.dropna(how='all')
```

2. **Extracting and Aligning Dates with Time Intervals**: A new column was generated to hold the valid dates so that we can properly relate time intervals with their respective dates. A regular expression was used to identify these dates and then propagate down the column to where it now aligns to the time intervals. Rows with only date headers (without time intervals) were filtered out.

```
data_cleaned['Valid_Date'] = np.where(
    data_cleaned['Date'].str.con-
tains(r'\d{2}\.\d{2}\.\d{4}', na=False),
    data_cleaned['Date'],
    np.nan
)
data_cleaned['Valid_Date'] =
data_cleaned['Valid_Date'].fillna(method='ffill')
data_cleaned = data_cleaned[data_cleaned['Date'].str.con-
tains('-')]
```

3. **Parsing Timestamps**: The start time of each interval was extracted and a new `Datetime` column was created by combining the valid dates with the start times. This column was converted into a datetime object for easier manipulation.

```
data_cleaned['Start_Time'] =
data_cleaned['Date'].str.split(' - ').str[0]
data_cleaned['Datetime'] = pd.to_datetime(
    data_cleaned['Valid_Date'] + ' ' +
data_cleaned['Start_Time'],
    format='%d.%m.%Y %H:%M',
    errors='coerce'
)
data_cleaned = data_cleaned.dropna(subset=['Datetime'])
```

4. **Setting Datetime Index**: The `Datetime` column was set as the index of the DataFrame, enabling efficient time-based resampling.

```
data_cleaned.set_index('Datetime', inplace=True)
```

5. **Resampling to 10-Minute Intervals**: The data was resampled to 10-minute intervals using linear interpolation to fill in any missing values.

```
solar_data_resampled = data_cleaned.resample('10T').inter-
polate('linear')
```

6. **Defining the Complete Time Range**: To ensure uniformity in the dataset, a complete time range covering the desired period was defined. The DataFrame was then reindexed to match this time range, with any gaps filled using linear interpolation.

```
complete_time_index = pd.date_range(start=start_date,
end=end_date, freq='10T')
solar_data_resampled = solar_data_resampled.reindex(com-
plete_time_index)
```

```
solar_data_resampled['Solar Actual Aggregated'] = so-
lar_data_resampled['Solar Actual Aggregated'].interpo-
late('linear')
```

7. **Handling Missing and Duplicate Values**: Before finalizing the data, any remaining `NaN` values were replaced with `0`. The data was rounded to the nearest integer and converted to integer type for clarity and consistency.

```
solar_data_resampled['Solar Actual Aggregated'] = so-
lar_data_resampled['Solar Actual Aggregated'].fillna(0)
solar_data_resampled['Solar Actual Aggregated'] = so-
lar_data_resampled['Solar Actual Aggregat-
ed'].round().astype(int)
```

8. **Outputting the Final Dataset**: The processed dataset was exported to an Excel file, making it ready for further analysis shows in Table 5 and 6.

```
solar_data_resampled.reset_index(inplace=True)
solar_data_resampled.rename(columns={'index': 'Datetime'},
inplace=True)
solar_data_resampled.to_excel(output_file_path, in-
dex=False)
```

Table 5. Resampled solar generation dataset.

Time [Local time]	Solar Actual Aggregated [MW]
11:50	22
12:00	20
12:10	16
12:20	13
12:30	9

Table 6. Resampled energy price dataset.

Time [Local time]	Price c/kWh (with VAT)
12:30	0.96
12:40	0.96
12:50	0.96
13:00	1.00
13:10	1.00

By using OpenAI's model GPT-4 Omni[8], the solar generation and energy price data were resampled to the time intervals of the weather data and used with interpolation to fill in any missing data. We will explain how the neural network forecasting model is built using this prepared data in the next section.

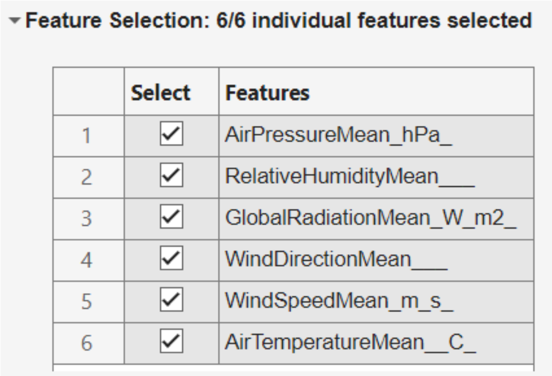
3.4 Neural Network Model for PV Power Generation Forecasting

NN model has been well used for forecast of PV power generation with many of its benefits that meets our dataset. The model is used to learn the relationships between given variables and predict future PV power generation from historical weather information. In the next section, we will present the model architecture, training and evaluation matrix of our proposed NN model for PV generation forecasting.

3.4.1 Model Architecture

In this study, an NN model was developed to forecast PV power generation in Finland. The model was trained and tested using historical weather data and PV generation data. The weather data was obtained from the Finnish Meteorological Institute's open data, specifically from the observation station of Helsinki Malmi Airfield, for a period of 1 year with a 10-minute interval. The variables used as inputs for the NN model are shown in figure 9.

[8] OpenAI's model GPT-4 Omni


▾ Feature Selection: 6/6 individual features selected

	Select	Features
1	☑	AirPressureMean_hPa_
2	☑	RelativeHumidityMean___
3	☑	GlobalRadiationMean_W_m2_
4	☑	WindDirectionMean___
5	☑	WindSpeedMean_m_s_
6	☑	AirTemperatureMean__C_

Figure 9. Feature selection for the proposed NN model.

These variables were selected based on their well-known effect on PV power production. An illustration of the importance of input variables is the analysis of solar irradiance, the main factor that has direct input on the performance of PV power generation, as it defines the amount of light energy that can be converted into electricity. The efficiency of the PV panels can be affected by air temperature. The atmospheric pressure can affect PV power generation due to the changing atmospheric density. As high atmospheric pressure will reduce solar irradiance and the efficiency of the PV panels.

3.4.2 Training and Validation Process

The training and validation process is a critical phase in developing the neural network model for forecasting solar PV generation. The preprocessed dataset is divided into three subsets:

Table 7. The training and validation of preprocessed dataset.

Training Set	70%
Validation Set	20%
Test Set	10%

Using the training set, the model is trained, so it learns how the input provided (for example, the Weather data) is related to the target value (solar PV generation). Validation set helps monitor model performance during training, to tune hyperparameters and avoid overfitting. The test set allows for an unbiased evaluation, under conditions that are similar to what will be encountered in the real-world, of the model's ability to generalize. To preserve chronological order of data a time-based split is used.

The NN model is trained using Mean Squared Error (MSE) as loss function between predicted and actual solar PV generation. As we go through further epochs, we apply the backpropagation algorithm that computes the gradient of the loss function and updates the weights of the model according to the error minimized. Weights are updated iteratively using an optimization algorithm (for example Adam or Stochastic Gradient Descent). The training process is repeated for a specified number of epochs to balance computational efficiency. Hyperparameters, like the learning rate and number of hidden layers, are tuned against validation performance. Then the model is evaluated on test set after training and validation.

3.4.3 Evaluation Matrix

The model performance was evaluated on the validation set at each epoch during training using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R-Squared (R^2). The MAE gives the average absolute difference between the predicted value and the actual value, which is easy to interpret in terms of the magnitude of the error of the model. While RMSE gives a measure of the size of the error, RMSE provides a measure of the average squared difference between actual and predicted values, penalizing larger errors more than smaller ones. The combined metrics ensure that the model's accuracy and reliability are assessed before integration into the RBC framework.

3.5 Rule-Based Control Framework Design

A DC power-based data center with a battery storage system is the type of data center we are discussing in this context. The battery storage system is charged with PV generation and also receives grid power; these supply inputs are combined to reduce reliance on grid by maximizing renewable power. A RBC framework is applied to fulfil this objective. The rule-based controller includes a control framework design which will be covered in this section.

A block diagram presented and figure 10 demonstrates the flow of data, decision making processes and control actions. It starts with input data sources, such as weather data, historical PV generation data and energy market data. Based on these features an NN model is trained to predict the solar PV generation in the next 24 hours. These forecasts and real-time electricity prices and peak-time data are input into the rule-based controller.

This entire system is divided into two subsystems instead of one centralized global controlling scheme. One is called the Grid Side Controller and the other as Battery Side Controller. The Grid Side Controller handles energy sourcing from the national grid and the Battery Side Controller optimizes charging and discharging of battery storage systems. Their outputs are the control for the use of the national grid, PV sources, batteries and data center (the main load).

It is crucial to justify this modular design of the framework both from practical and research perspective which will also be explained in further sections. Having a global controller at the center will increase model complexities along with computational burden. The modular approach enables each controller to focus on a dedicated aspect of energy management, thereby enhancing efficiency and accuracy compared to the other alternatives.

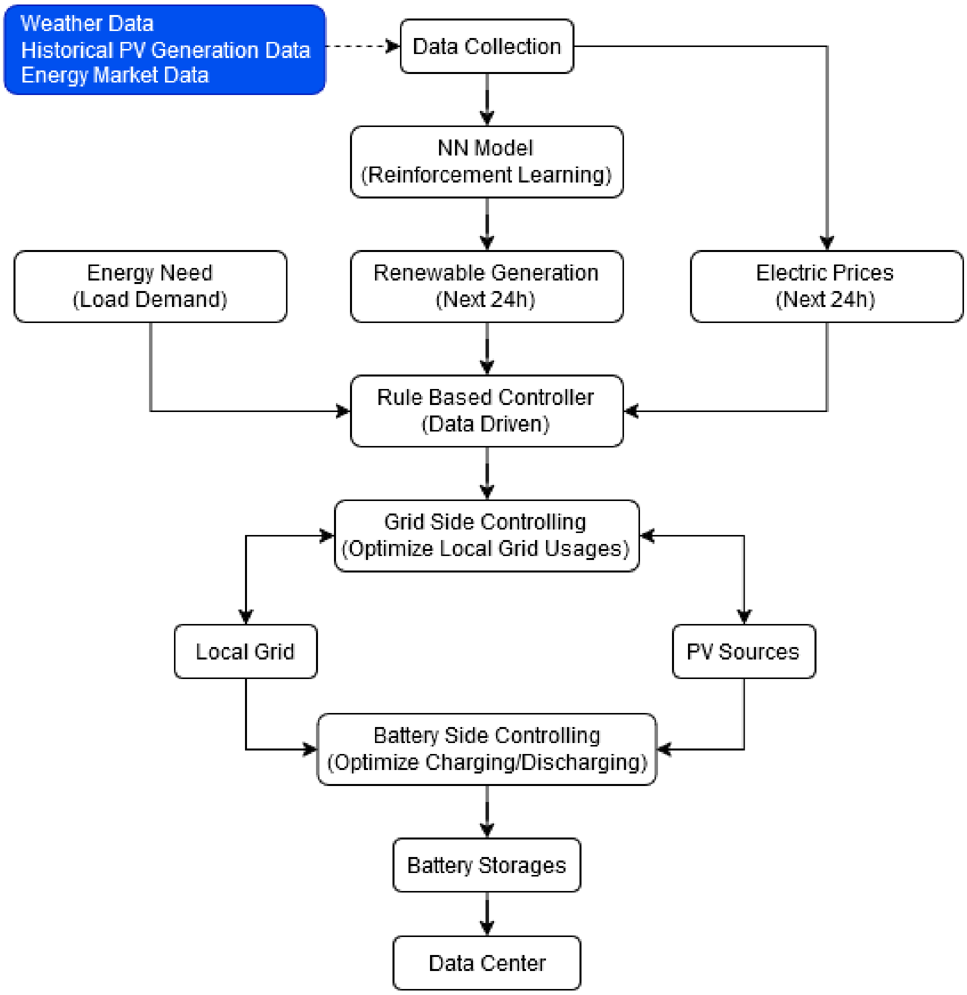


Figure 10. The block diagram of the proposed RBC framework.

Furthermore, the modular nature allows for easier implementation and maintenance: each controller can be developed, tested and updated independently. This minimizes error possibility and allows the system to be adjusted for future transformation such as - incorporation of more renewable energy sources or storage systems.

3.5.1 Control Logic for Grid Controller

The Grid Side Controller of the RBC framework that manages the energy sourcing from the grid to the primary DC bus while ensuring a continuous power supply. The grid and the PV system feed their power in at the point of common coupling (PCC) of the main DC bus. This controller's main focus is to consume the renewable energy from the PV system with minimal utilization of grid energy, particularly during peak hours when electricity prices tend to be high. The dynamic switching of PV power and grid power based on predefined rules like - droop control, where the voltage drops when there is more output than input. In that case the rule could be to maintain the voltage level, by providing suffient amount of power ensures the power/voltage stability of the main DC bus.

The flowchart and logical rules illustrated in figure 11, guide the operation of this Controller. The flowchart starts by initializing the output, which defaults to $grid\_breaker\_control = 0$, meaning that the grid is disconnected. The controller then calculate the availability of PV and how much demand is current. Mathematically, this is expressed as:

$$P_d = P_{d \cdot bus} - P_{Pv} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (12)$$

Where, P_d, is the power demand, $P_{d \cdot bus}$, is power demand in the bus and, P_{Pv}, is the solar power production.

If the remaining demand is less than or equal to zero, the PV system alone can meet the demand and the grid remains disconnected ($grid\_breaker\_control = 0$). If the remaining demand is positive, the controller evaluates the next hour's electricity price and PV generation forecast to determine whether to connect or disconnect the grid.

The rules for the Grid Controller are as follows:

- Default: Disconnect the grid ($grid\_breaker\_control = 0$).
- Rule 1: If PV meets the demand, disconnect the grid.
- Rule 2: If the grid is unavailable, disconnect the grid.
- Rule 3: If it’s off-peak and the price is low, connect the grid.
- Rule 4: If PV will meet the demand in the next hour, disconnect the grid.
- Rule 5: If the price is too high in the next hour, disconnect the grid.
- Rule 6: If none of the above conditions apply, connect the grid.

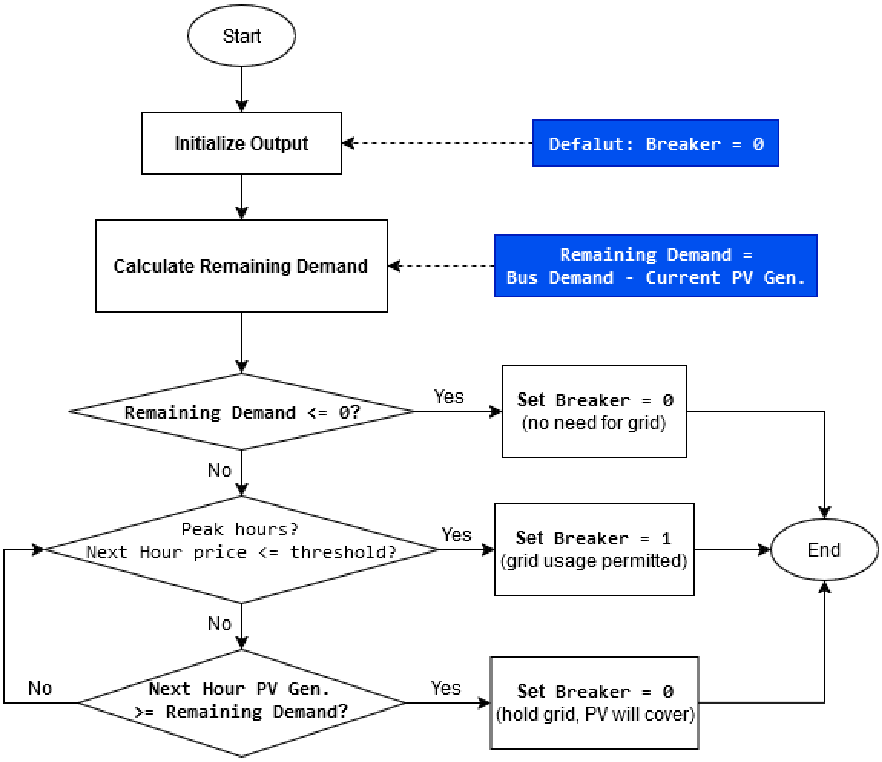


Figure 11. Illustration of the Grid side Controller's logical flowchart.

These rules ensure the controller prioritizes green energy sources, reduces reliance on the grid when rates are high and lowers energy costs. For instance, the controller connects the grid ($grid\_breaker\_control = 1$), when the electricity price of the next hour drops below a predefined value and the demand cannot be met with the PV system. On the other hand, if the PV system is anticipated to satisfy the demand in the coming hour, the controller will cut the grid connection to foster the use of renewables.

The pseudocode for the Grid Side Controller is as follows:

```
def grid_side_controller(bus_demand, current_pv_gen,
next_hour_price, next_hour_pv_gen, price_threshold):
    grid_breaker_control = 0  # Default: Disconnect grid

    # Calculate remaining demand
    remaining_demand = bus_demand - current_pv_gen
```

```
    # Rule 1: If PV meets demand, disconnect grid
    if remaining_demand <= 0:
        grid_breaker_control = 0
    else:
        # Rule 3: If off-peak and price is low, connect
grid
        if next_hour_price <= price_threshold:
            grid_breaker_control = 1
        # Rule 4: If PV will meet demand in next hour, dis-
connect grid
        elif next_hour_pv_gen >= remaining_demand:
            grid_breaker_control = 0
        # Rule 5: If price is too high in next hour, dis-
connect grid
        elif next_hour_price > price_threshold:
            grid_breaker_control = 0
        # Rule 6: If none of the above, connect grid
        else:
            grid_breaker_control = 1

    return grid_breaker_control
```

3.5.2 Control Logic for Battery Controllers

Battery Side Controllers in the suggested RBC architecture regulate the BSS's charging and discharging in terms of the SoC and energy demand. These controllers aim to maximize the use of renewable energy, optimize the operation of the battery system, and ensure that the data center receives a stable power supply. The rules dictate how the batteries charge and discharge, allowing optimal energy management.

The SoC (State-of-Charge) - A measure of how much capacity is left in a battery, expressed as a percentage of total capacity (Piller et al., 2001). It is a crucial performance indicator for BSS management. It controls the charging and discharging of batteries in energy management applications. SoC of a battery can be estimated by several methods depending on the data available and required accuracy.

The Coulomb Counting Method is one of the most popular techniques, which calculates the SoC by integrating the current flowing into or out of the battery over time. We can express the SoC at any time as follows in equation 13:

$$SoC(t) = SoC(t_0) + \frac{1}{C_n}\int_{t_0}^{t} I(\tau)d_\tau \dots\dots\dots\dots\dots\dots\dots\dots\dots (13)$$

where:

- $SoC(t)$ is the state-of-charge at time t,
- $SoC(t_0)$ is the initial state-of-charge at time t_0,
- C_n is the nominal capacity of the battery (in ampere-hours, Ah),
- $I(\tau)$ is the current at time τ (in amperes, A),
- The integral represents the total charge transferred into or out of the battery over the time interval $[t_0, t]$.

The SoC calculation based on Voltage uses the relationship between the battery terminal voltage to estimate the SoC. This approach is based on a battery's discharge curve, a graph that correlates a battery voltage with its SoC. The SoC can be estimated using the equation 14:

$$SoC(t) = f\big(V(t)\big) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (14)$$

where $V(t)$ is the battery's terminal voltage at time $t$and f is a function that maps the voltage to the SoC based on the battery's discharge characteristics.

A more advanced SoC estimation method is Kalman filter-based SoC Estimation, which combines the Coulomb Counting approach with voltage measurements to improve SoC estimation accuracy. This one utilizes state-space model to model the SoC with measurement noise and uncertainties, and estimates that model. The implementations of the Kalman filter for iterative SoC estimate updates are given by the following equations 15 and 16:

- State Prediction:

$$\hat{x}_{\bar{k}} = A\hat{x}_{k-1} + Bu_k \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (15)$$

where:

- $\hat{x}_{\bar{k}}$ is the predicted state (SoC) at time k,
- A is the state transition matrix,
- $\hat{x}_{k-1}$ is the previous state estimate,
- B is the input matrix,
- u_k is the input (current) at time k.

- Measurement Update:

$$\hat{x}_k = \hat{x}_{\bar{k}} + k_k\left(z_k - H\hat{x}_{\bar{k}}\right) \dots\dots\dots\dots\dots\dots\dots (16)$$

where:

- $\hat{x}_k$ is the updated state estimate at time k,
- k_k is the Kalman gain,
- z_k is the measurement (voltage) at time k,
- H is the measurement matrix.

The Kalman filter provides a more accurate and robust SoC estimation, especially in dynamic operating conditions.

The operation of the Battery Side Controllers is guided by a flowchart (Figure 12) and a set of logical rules. The flowchart starts by initializing the input parameters: SoC of Battery 1 (SoC1) and SoC of Battery 2 (SoC2). SoC thresholds are defined that dictate when to charge or discharge. The controllers then checks the SoC of both batteries and uses the following rules to control 4 separate breaker — the grid side breakers (GridBreaker1, GridBreaker2) connected to PCC & load side breakers (LoadBreaker1,LoadBreaker2) connected to the Data Center.

The rules for the Battery Side Controller are as follows:

- Default: Disconnect both batteries from the grid and load (GridBreaker1 = 0, GridBreaker2 = 0, LoadBreaker1 = 0, LoadBreaker2 = 0).
- Rule 1: If Battery 1 SoC < 50% AND Battery 2 SoC > 50%, charge Battery 1 and discharge Battery 2.
- Rule 2: If Battery 1 SoC > 50% AND Battery 2 SoC < 50%, charge Battery 2 and discharge Battery 1.
- Rule 3: If both Battery 1 SoC < 50% AND Battery 2 SoC < 50%, charge both batteries.
- Rule 4: If both Battery 1 SoC > 50% AND Battery 2 SoC > 50%, discharge both batteries.
- Rule 5: In an emergency scenario, charge both batteries and disconnect them from the load.

The rules about when to charge and discharge the batteries maximize the use of renewable energy and keep the power flowing in a reliable way. The controller will charge the low SoC battery while discharging the high SoC battery to satisfy the load demand, for instance. This configuration makes sure the batteries are on hand to support the data centre's energy requirements.

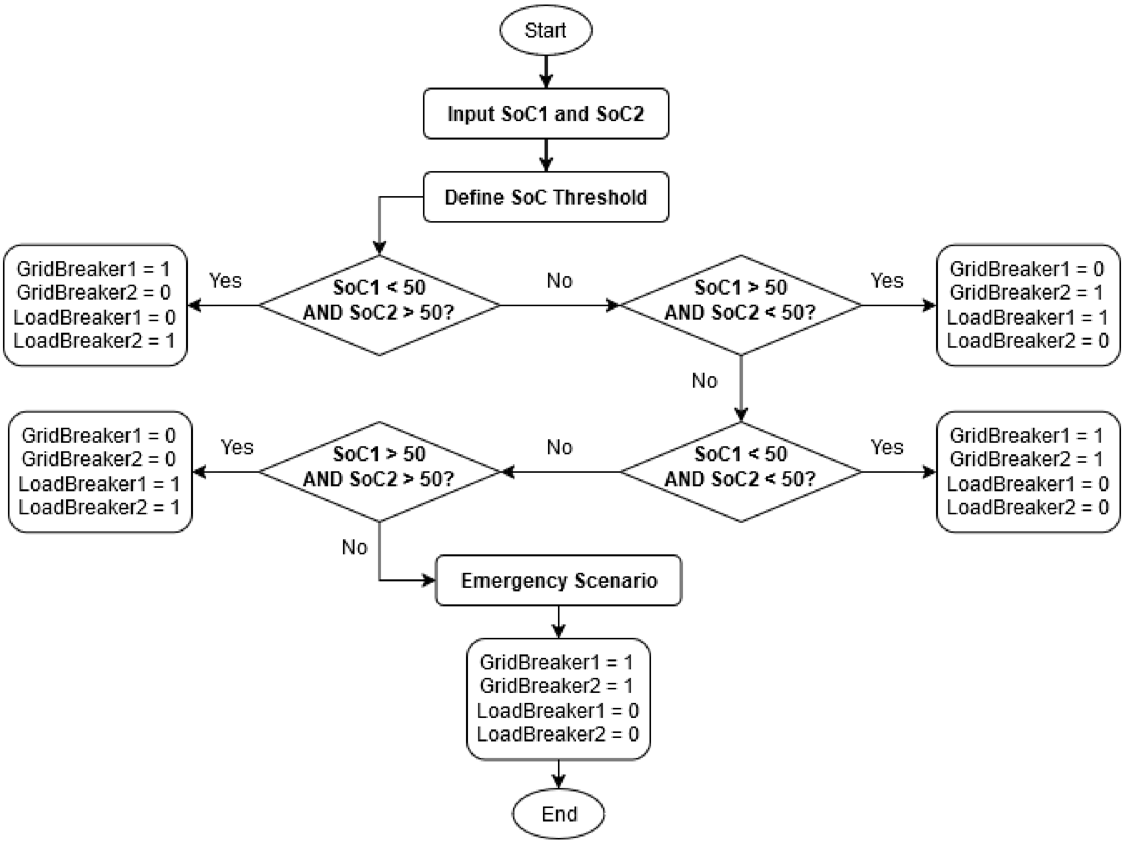


Figure 12. Illustration of the Battery Side Controller's logical flowchart.

The pseudocode for the Battery Side Controllers is as follows:

```
def bss_controller(SoC1, SoC2):
    # Initialize breakers
    GridBreaker1, GridBreaker2, LoadBreaker1, LoadBreaker2 = 0,
0, 0, 0

    # Rule 1: Charge Battery 1, discharge Battery 2
    if SoC1 < 50 and SoC2 > 50:
        GridBreaker1, LoadBreaker2 = 1, 1

    # Rule 2: Charge Battery 2, discharge Battery 1
    elif SoC1 > 50 and SoC2 < 50:
        GridBreaker2, LoadBreaker1 = 1, 1
```

```
    # Rule 3: Charge both batteries
    elif SoC1 < 50 and SoC2 < 50:
        GridBreaker1, GridBreaker2 = 1, 1

    # Rule 4: Discharge both batteries
    elif SoC1 > 50 and SoC2 > 50:
        LoadBreaker1, LoadBreaker2 = 1, 1

    # Rule 5: Emergency scenario (charge both, disconnect load)
    else:
        GridBreaker1, GridBreaker2 = 1, 1

    return GridBreaker1, GridBreaker2, LoadBreaker1, Load-
Breaker2
```

3.6 Karnaugh Mapping

In the context of this thesis, Karnaugh mapping (k-maps) is used to evaluate and optimize the decision-making logic of the proposed RBC framework. The framework involves multiple input variables, such battery's SoC, electricity prices, PV generation forecasts and load demand, which influence the control decisions for grid and battery operations. By applying K-maps, the complex logic rules can be simplified, reducing computational overhead and improving the efficiency of the control system.

K-map, is a tool for minimizing Boolean algebra expressions (Hassan & Hassan, 2016). It is also used as a well-known method for simplifying logic functions and equations of decision-making processes in digital systems. K-maps are a method of grouping adjacent 1's in a grid to minimize boolean expressions. This reduces complex logic expressions to their simplest form by identifying all adjacent cells that output the same result. It's a very effective method as it allows to build logic that can fine-tune.

The K-map is constructed by plotting the input variables along the axes and filling the cells with the corresponding output values. The grouping of cells follows specific rules:

- Group Size: Groups must contain 1, 2, 4, 8, or 2^n cells, where n is an integer.
- Adjacency: Cells in a group must be adjacent horizontally or vertically (diagonal adjacency is not allowed).
- Overlap: Groups can overlap to ensure the most efficient simplification.
- Coverage: All "1" cells must be covered by at least one group.

The simplified Boolean expression is derived by combining the input variables that remain constant within each group. For example, consider the Grid Side Controller, which decides whether to connect or disconnect the grid based on the following input variables:

- Remaining Demand (D): PV generation meets the load, ($D = 0$) or not ($D = 1$)?
- Next Hour Price (P): Electricity price meet threshold, ($P = 0$) or above ($P = 1$)?
- Next Hour PV Generation (G): PV generation meet the demand in the next hour ($G = 0$) or not ($G = 1$)?

The output variable is the grid breaker control (C), where $C = 1$ indicates grid connection and $C = 0$ indicates grid disconnection. The example K-map truth table for the Grid Side Controller given in Table 8.

Table 8. Example of K-map truth table.

D\PG	00	01	11	10
0	0	0	0	0
1	1	0	0	1

The simplified Boolean expression can be derived in equation 17:

$$C = D \cap \bar{G} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (17)$$

4 System Implementation and Evaluation

This chapter focuses on the practical implementation and evaluation of the proposed RBC framework for optimizing energy management in data center. Following the methodology outlined in Chapter 3, the system is implemented using a Single Line Diagram (SLD) to represent the integration of renewable energy sources, battery storage systems and grid power. The framework then simulated and tested in a simulation environment, where the framework is validated under various scenarios. The controllers are designed to dynamically manage energy sourcing and battery operations, ensuring efficient utilization of renewable energy and minimizing grid dependency. Finally, the system is evaluated using Karnaugh mapping to simplify and optimize the control logic, ensuring robust and reliable performance. This chapter provides a comprehensive overview of the system's implementation, simulation and validation.

4.1 Single Line Diagram (SLD) Overview

The SLD provides a detailed representation of the proposed energy management system (Figure 13). The goal of this system is to provide an EMS for the data center, which operates on DC power and is designed to minimize its carbon footprint by prioritizing renewable energy and battery storage. The SLD includes several key components that work together to ensure a stable and reliable power supply while maximizing the use of renewable energy.

The PV array serves as the primary source of renewable energy, generating electricity from solar power. All this energy goes into the main DC bus and connects to other energy sources and storage. The local AC grid provides backup power, delivering energy whenever renewable generation is lacking. A rule-based non-linear controller labelled "**Grid-side Controller**" designed to manage the interconnection between the grid and the main DC bus. This data driven rule-based controller use all the necessary information (such as, peak time, 24-hour ahead electricity prices, PV generation forecasts etc.) to ensure efficient grid power usage. The Grid-side Controller prioritizes low-cost off-peak hours and minimizes reliance on the grid during peak hours, further reducing the system's carbon footprint.

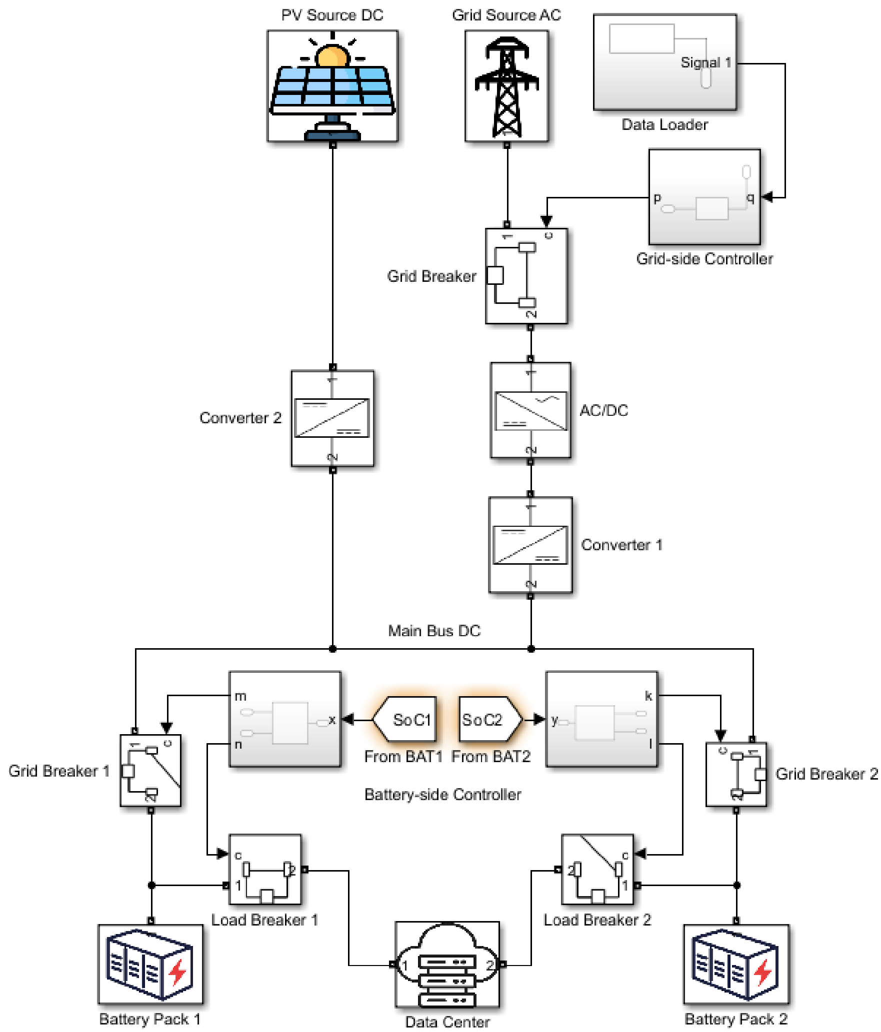


Figure 13. Illustration of the SLD for the proposed RBC framework.

On the other hand, the BSS includes two battery pack (Battery Pack 1 and Battery Pack 2), interfacing with the main DC bus as energy storage for the data center. Another Rule-based controller “**Battery-side Controller**” manages both battery pack charging/discharging based on the SoC. Such dynamic management guarantees a stable power supply to the data center while maximizing usage of renewable energy.

The main goal is to provide a stable supply of energy to the data center — putting renewable and battery storage energy ahead of grid power if possible. It aims to consume grid power only when absolutely necessary, for the data center to be as sustainable as possible. Both controllers implementing the RBC frameworks. With integrated control strategies, the SLD is a comprehensive EMS dedicating to carbon emissions reduction and renewable energy supply maximization for data centers.

4.2 System Simulation and Testing Environment

The proposed energy management system is simulated and verified in **MATLAB R2024B**, which provides the technical means for both neural network modeling and power system simulation. The NN model for solar PV generation forecasting is developed and trained using the **Regression Learner app**, ensuring precision in renewable energy availability forecasting. The control system integration is modeled in **Simulink** to simulate the power system. The RBC framework that includes both of the above-mentioned controllers is implemented as a **Matlab Function Block** in the Simulink environment to operate energy sourcing and storage operations in dynamics. This extensive simulation setup offers a comprehensive basis for testing the performance of the system under different conditions, thus ensuring that the framework performs in real-world situations.

4.3 Neural Network Forecasting Model Integration

As described in Chapter 3, after collecting, cleaning and resampling the data, the NN forecasting model was implemented using the Regression Learner app in MATLAB R2024b. At first multiple regression models were trained and tested using the above dataset which including - Regression Tree, Support Vector Machine (SVM), Ensemble of Trees and Neural Networks (with and without optimization). The performance of each model was evaluated based on metrics such as R^2, MAE and RMSE. The overall performance of each model summary given in the following table.

Table 9. The overall performance summary of each model.

Model Type	Status	RMSE MW (Validation)	MAE MW (Validation)	R-Squared (Validation)
SVM	Trained	88.07834	47.31485	0.835244
Ensemble	Trained	94.49775	57.36283	0.810353
Neural Network	Trained	83.74317	52.40000	0.851063

4.3.1 Best Performing Model Parameters

The best performance was achieved using a **Wide Neural Network**. The following are the parameters:

- Feature Selection: 8 input features were selected, including solar irradiance, temperature, cloud cover and historical PV generation data. Principal Component Analysis (PCA) was disabled to retain the original feature set.

- Iteration Limit: The training process was limited to 1000 iterations to balance computational efficiency and model performance.

- Model Hyperparameters: The hyperparameters included:
    - Preset: Wide Neural Network
    - Number of Fully Connected Layers: 1
    - Activation Function: ReLu
    - First Layer Size: 100 neurons

Test data was used to validate the model's performance, resulting in an R^2 score of 0.85, confirming its high accuracy in forecasting solar PV generation. The MAE and RMSE indicator values also proved that the proposed model was sufficiently precise and will be able to provide reliable forecasts for the rule-based control framework.

4.3.2 Predicted vs. True Response

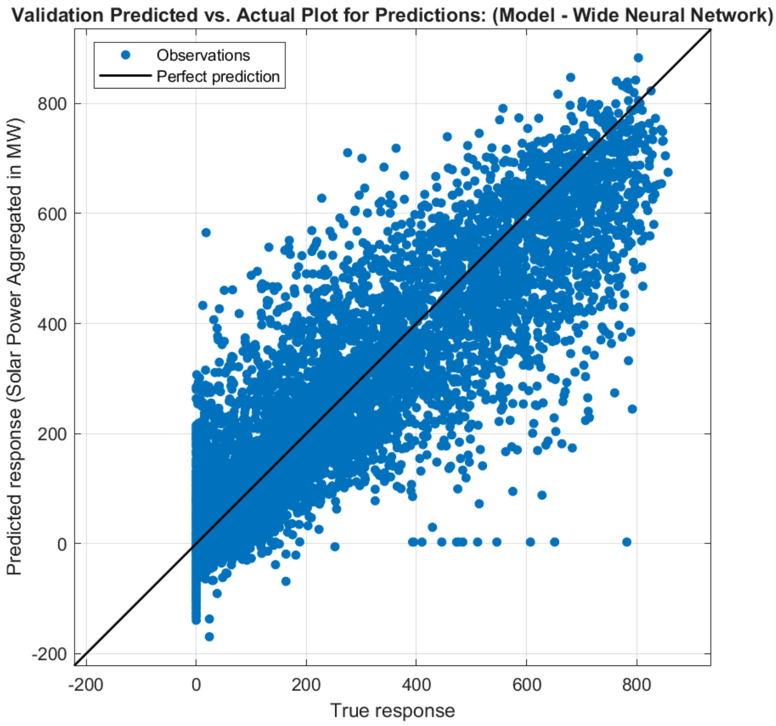


Figure 14. The Validation Predicted Solar Power (MW) vs. True Response Plot

Figure 15. The Test Predicted Solar Power (MW) vs. True Response Plot

Figure 14, 15 presents the Predicted vs. True Response Plot for the Wide Neural Network model, which is employed to forecast solar PV generation. As we can see in the plot, there is a strong correlation between the predicted and true values, as most points closely follow the diagonal line. This is a reflection that, the model is capable of successfully describing the underlying dynamics of the data for generating good forecasts needed for the RBC framework.

4.3.3 Training and Test Results

The results seen in Figure 16, gives an overview of model performance metrics. R^2 value of 0.85 indicates that, while testing the model, when it is fed on test data, 85% of the variance of the test data is explained by the model. With an RMSE (Validation) of 83.743 MW and MAE (Validation) of 52.400 MW validating the model precision. These metrics suggest that the model generalizes effectively to unseen data, providing reliable forecasts for use in real-world applications.

Model 4: Neural Network
Status: Tested

Training Results

RMSE (Validation)	83.743
R-Squared (Validation)	0.85
MSE (Validation)	7012.9
MAE (Validation)	52.400
MAPE (Validation)	Inf%
Prediction speed	~130000 obs/sec
Training time	1543.5 sec
Model size (Compact)	~60 kB

Test Results

RMSE (Test)	83.882
R-Squared (Test)	0.85
MSE (Test)	7036.2
MAE (Test)	51.506
MAPE (Test)	Inf%

Figure 16. NN model's performance summary.

The model provides high prediction speed, with around 130k observations per second, making it appropriate for real-time energy management applications. The training time is also optimized while the model size has been kept very compact at 60 kB so that it can be used very efficiently and integrated into the RBC framework.

4.3.4 Simulink Implementation of the NN Model

Once the NN model was trained, validated, and tested in the Regression Learner app, the optimized model was exported and integrated into the Simulink environment. This is important for deploying the NN model in the context of a comprehensive EMS embedded in the RBC framework.

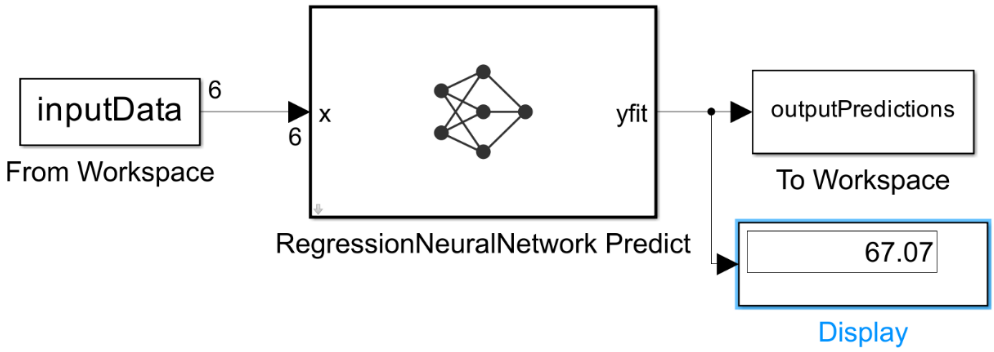


Figure 17. Simulink Implementation of the exported NN Model.

In Simulink, the exported NN model was implemented using the **Regression Neural Network Predict block** (see Figure 17). Simulink model has following key components.

- Input Data: Elements, such as solar irradiance, temperature, cloud cover and historical PV generation data, from the Workspace are provided as input to the model.

- Neural Network Predict Block: The predict input data being processed through the trained NN model produces forecasts of the PV generation.

- Output Predictions: The expected forecasted values are output to the Workspace for further analysis and integration into the rule-based control framework.

- Display Block: Used to visualize predicted values in real-time during simulation.

4.4 Rule-Based Control Framework

The RBC framework is implemented in **Simulink** to dynamically manage energy sourcing and storage operations in the proposed energy management system. This section discusses about the implementation of the proposed framework. The design of the Grid-side Controller and the Battery-side Controller both are first described then analyze further for the evaluation.

4.4.1 Grid-side Controller Design

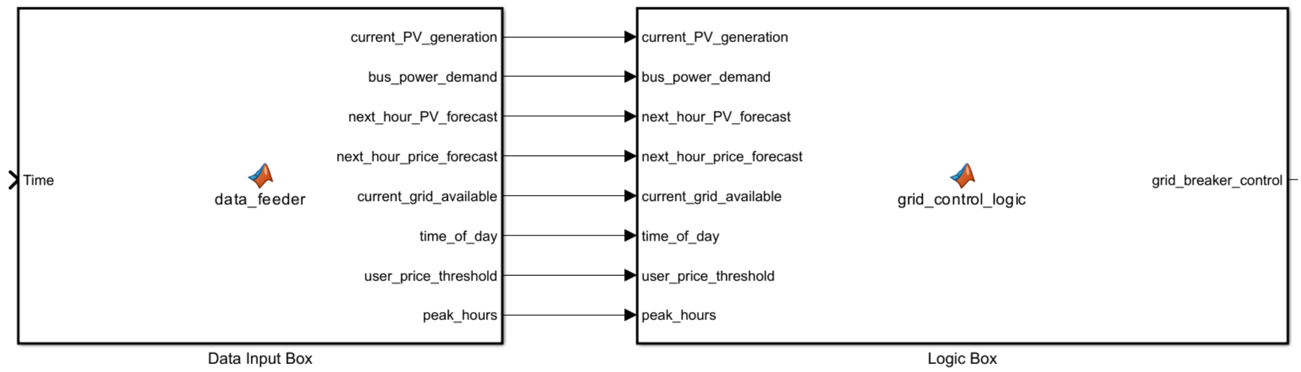


Figure 18. The Grid-Side Controller as a sub-system in Simulink.

The Grid-Side Controller is implemented as a subsystem in Simulink, as shown in Figure 18. The subsystem receive input data from various source such as, current PV generation, power demand from the main DC bus, next hour PV forecast, next hour electricity price and peak-time, user defined price threshold value and processed them in **Data Input Box**. These inputs then processed by the **Logic Box**, which contains the predefined rule based logic. Now the output of this logic box is the data **grid_breaker_control**, which based on the signal coming from the Logic Box is responsible for establishing (1) or disconnecting (0) the connection to the grid.

4.4.2 Battery-side Controller Design

A predetermined logic featuring the Battery-side Controller designed with rules to optimize renewable energy consumption and the balance of power supply illustrated in the Figure 19. The input data for the controller consists of the SoC of both Battery 1 and Battery 2. The Logic Box then analyzes these inputs through a set of pre-defined rules for the management of charging and discharging of the batteries.

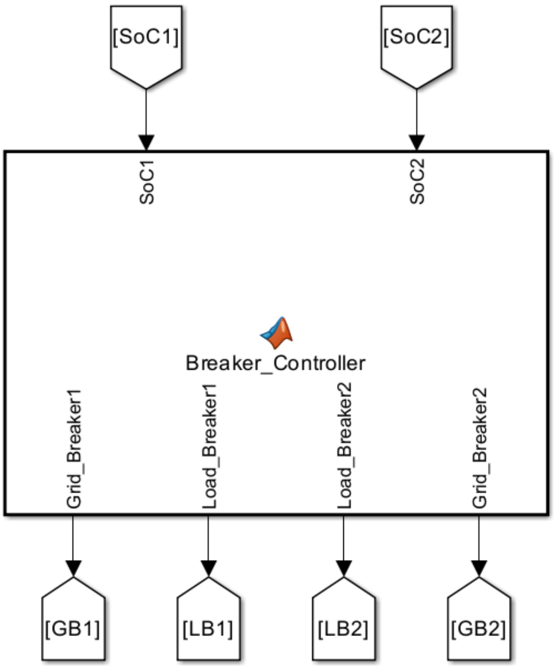


Figure 19. The Battery-Side Controller as a sub-system in Simulink

The output of the logic box includes control signals for the grid breakers and load breakers, which determine the charging and discharging behavior of the batteries. The Battery Controller dynamically adjusts the operation of the batteries based on real-time conditions, ensuring efficient energy storage and utilization.

4.5 Scenario-based Evaluation Using Karnaugh Mapping

In this section we will validate the effectiveness of the proposed RBC framework by introducing some scenario-based evaluation using K-map. By analyzing the system's behavior in different conditions, the evaluation ensures that the framework operates efficiently and reliably in real-world applications.

4.5.1 K-Mapping for Grid-side Controller

The Grid Controller Logic is designed to manage power flow between a photovoltaic (PV) system, the grid and the load based on various input conditions such as PV generation, load demand, electricity prices, time of day and grid availability. K-map is used to simplify the controller logic in evaluation. Then it evaluates the proposed framework correctness in various operational scenarios. A K-map of the controller is made in such a way that the output is derived in the form of the simplest expression. The simplification ensures that the controller continues to function in a dynamic manner while still retaining the ability to remain reliable in the face of changing pressure and temperature conditions.

Step 1: Define Inputs and Output

Inputs:

- PV Generation (A): (e.g., sunny weather, cloudy weather or PV blackout)
    - 0: Low PV generation.
    - 1: High PV generation.

- Load Demand (B): (Demand on the main DC bus)
    - 0: Low load demand.
    - 1: High load demand.

- Electricity Price (C): (Customer defined threshold).
    - 0: High price.
    - 1: Low price.

- Time of Day (D):
  - 0: Off-peak hours.
  - 1: Peak hours.

- Grid Availability (G):
  - 0: Grid unavailable.
  - 1: Grid available.

Output:

- Grid Breaker Control Signal (F):
  - 0: Disconnect from the grid.
  - 1: Connect to the grid.

Step 2: Define Cases

We'll define 6 cases based on different scenarios.

Case 1: High PV, Low Load, Low Price, Off-Peak, Grid Available

- Inputs: A=1, B=0, C=1, D=0, G=1
- Expected Output: F=0 (Disconnect from grid).

Case 2: Low PV, High Load, Low Price, Off-Peak, Grid Available

- Inputs: A=0, B=1, C=1, D=0, G=1
- Expected Output: F=1 (Connect to grid).

Case 3: High PV, High Load, High Price, Peak, Grid Available

- Inputs: A=1, B=1, C=0, D=1, G=1
- Expected Output: F=0 (Disconnect from grid).

Case 4: Low PV, High Load, High Price, Peak, Grid Available

- Inputs: A=0, B=1, C=0, D=1, G=1
- Expected Output: F=1 (Connect to grid).

Case 5: Low PV, High Load, Low Price, Off-Peak, Grid Unavailable

- Inputs: A=0, B=1, C=1, D=0, G=0
- Expected Output: F=0 (Disconnect from grid).

Case 6: High PV, High Load, High Price, Peak, Grid Unavailable

- Inputs: A=1, B=1, C=0, D=1, G=0
- Expected Output: F=0 (Disconnect from grid).

Step 3: Create Truth Table

Table 10. Truth table for the Grid-side Controller

Case	A	B	C	D	G	F
1	1	0	1	0	1	0
2	0	1	1	0	1	1
3	1	1	0	1	1	0
4	0	1	0	1	1	1
5	0	1	1	0	0	0
6	1	1	0	1	0	0

Step 4: Create Karnaugh Maps

Since we have 5 input variables, the K-map will have $2^5 = 32$ cells. To simplify, we'll focus on the most significant variables (A, B, C, D) and treat G as a condition. If G=0, which means Grid is unavailable, then every cell will be 0 in the K-Map. Here's how the grid is organized if G=1 (Grid Available):

AB\CD	C=0, D=0	C=0, D=1	C=1, D=1	C=1, D=0
A=0, B=0				
A=0, B=1				
A=1, B=1				
A=1, B=0				

Using the truth table from Table 10 in Step 3, now we fill the K-map with the output F:

Table 11. K-map for the Grid-side Controller

AB\CD	C=0, D=0	C=0, D=1	C=1, D=1	C=1, D=0
A=0, B=0	0	0	0	0
A=0, B=1	1	1	0	1
A=1, B=1	0	0	0	0
A=1, B=0	0	0	0	0

Here is the explanation of the Filled K-Map in Table 11:

Row 1: A=0, B=0 (Low PV, Low Load)

- If PV generation is low and load demand is low, the system can rely on PV and battery, so there’s no need to connect to the grid.

Row 2: A=0, B=1 (Low PV, High Load)

- This row represents scenarios where PV generation is low and load demand is high. The system connects to the grid unless the price is low and it’s peak hours. Cells are filled as follows:

- C=0, D=0: 1 (Connect to grid if price is high and it’s off-peak).
- C=0, D=1: 1 (Connect to grid if price is high and it’s peak).
- C=1, D=0: 1 (Connect to grid if price is low and it’s off-peak).
- C=1, D=1: 0 (Do not connect to grid if price is low and it’s peak).

Row 3: A=1, B=1 (High PV, High Load)

- If PV generation is high and load demand is high, the system can rely on PV and battery, so there’s no need to connect to the grid.

Row 4: A=1, B=0 (High PV, Low Load)

- If PV generation is high and load demand is low, the system can rely on PV and battery, so there's no need to connect to the grid.

Step 5: Simplify the K-Map

Now, group adjacent 1s in the K-map to simplify the Boolean expression for F.

For G=0: All outputs are 0, so $F = 0$.

For G=1: Group the 1s in the second row (A=0, B=1) for C=0, D=0, C=0, D=1 and C=1, D=0. So, the simplified Boolean expressed in equation 18:

$$F = \bar{A} \cdot B \cdot (\bar{C} + \overline{D}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (18)$$

Combining the conditions for G=1 and G=0, the final Boolean expression for the grid breaker control signal F is in equation 19:

$$F = G \cdot \bar{A} \cdot B \cdot (\bar{C} + \overline{D}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (19)$$

Which means connect to the grid ($F = 1$) when,

- Grid is available ($G = 1$).
- PV generation is low ($\bar{A} = 1$).
- Load demand is high ($B = 1$).
- Electricity price is low ($\bar{C} = 1$) or it's off-peak hours ($\overline{D} = 1$).

This matches the Grid-side Controller logic where controller will allow grid usage when PV generation is insufficient, load demand is high and either the price is low or it's off-peak hours, provided the grid is available.

4.5.2 K-Mapping for Battery-side Controller

The Battery-side Controller Logic manages the power between two battery packs, the grid, and the load, according to the SoC of each battery. The controller manages the distribution of energy to the breakers to make sure that every unit of energy is being put to good use — managing the two grid breakers (GridBreaker1, GridBreaker2) and the two load breakers (LoadBreaker1, LoadBreaker2). It includes how to simplify the controller logic using K-maps with verification of the logic in various operating scenarios, among other things.

Step 1: Define Inputs and Output

Inputs:

- SoC1: State of Charge of Battery 1
    - 0: SoC1 < 50%.
    - 1: SoC1 ⩾ 50%.

- SoC2: State of Charge of Battery 2
    - 0: SoC2 < 50%.
    - 1: SoC2 ⩾ 50%.

Output:

- GridBreaker1:
    - 0: Open (disconnect Battery 1 from the grid).
    - 1: Closed (connect Battery 1 to the grid).

- GridBreaker2:
    - 0: Open (disconnect Battery 2 from the grid).
    - 1: Closed (connect Battery 2 to the grid).

- LoadBreaker1:
    - 0: Open (disconnect Battery 1 from the load).
    - 1: Closed (connect Battery 1 to the load).

- LoadBreaker2:
    - 0: Open (disconnect Battery 2 from the load).

- 1: Closed (connect Battery 2 to the load).

Step 2: Define Cases

We'll define 5 cases based on the SoC of the batteries.

Case 1: SoC1 < 50%, SoC2 > 50%

- Inputs: SoC1=0, SoC2=1
- Expected Output:
- GridBreaker1 = 1 (Closed).
- GridBreaker2 = 0 (Open).
- LoadBreaker1 = 0 (Open).
- LoadBreaker2 = 1 (Closed).

Case 2: SoC1 > 50%, SoC2 < 50%

- Inputs: SoC1=1, SoC2=0
- Expected Output:
- GridBreaker1 = 0 (Open).
- GridBreaker2 = 1 (Closed).
- LoadBreaker1 = 1 (Closed).
- LoadBreaker2 = 0 (Open).

Case 3: SoC1 < 50%, SoC2 < 50%

- Inputs: SoC1=0, SoC2=0
- Expected Output:
- GridBreaker1 = 1 (Closed).
- GridBreaker2 = 1 (Closed).
- LoadBreaker1 = 0 (Open).
- LoadBreaker2 = 0 (Open).

Case 4: SoC1 > 50%, SoC2 > 50%

- Inputs: SoC1=1, SoC2=1
- Expected Output:
- GridBreaker1 = 0 (Open).
- GridBreaker2 = 0 (Open).
- LoadBreaker1 = 1 (Closed).
- LoadBreaker2 = 1 (Closed).

Case 5: Emergency Scenario

- Inputs: Any undefined combination (e.g., SoC1=0, SoC2=1 but treated as a fallback).
- Expected Output:
- GridBreaker1 = 1 (Closed).
- GridBreaker2 = 1 (Closed).
- LoadBreaker1 = 0 (Open).
- LoadBreaker2 = 0 (Open).

Step 3: Create Truth Table

Combined Truth Table for All Breakers in Table 12:

Table 12. Truth table for the Battery-side Controller

Case	SoC_1	SoC_2	Grid Breaker1	Grid Breaker2	Load Breaker1	Load Breaker2
1	1	0	1	0	1	0
2	0	1	1	0	1	1
3	1	1	0	1	1	0
4	0	1	0	1	1	1
5	×	×	1	0	0	0

Step 4: Create Karnaugh Maps

Since we have 2 inputs (SoC1 and SoC2) and 4 outputs (GridBreaker1, GridBreaker2, LoadBreaker1, LoadBreaker2). Each cell in the K-map will contain a 4-bit value representing the state of all four breakers. Here's how the grid is organized:

$SoC_1 \backslash SoC_2$	$SoC_2 = 0$				$SoC_2 = 1$			
	GB1	GB2	LB1	LB2	GB1	GB2	LB1	LB2
$SoC_1 = 0$								
$SoC_1 = 1$								

Using the combined truth table from Table 12 in Step 3, we fill the K-map with the 4-bit values for each combination of SoC1 and SoC2.

Table 13. K-map for the Battery-side Controller.

$SoC_1 \backslash SoC_2$	$SoC_2 = 0$				$SoC_2 = 1$			
	GB1	GB2	LB1	LB2	GB1	GB2	LB1	LB2
$SoC_1 = 0$	1	1	0	0	1	0	0	1
$SoC_1 = 1$	0	1	1	0	0	0	1	1

Step 5: Simplify the K-Map

From the previous analysis, we have the following simplified equation 20 for all four breakers:

$$[GB_1, GB_2, LB_1, LB_2] = [\overline{SoC_1}, \overline{SoC_2}, SoC_1, SoC_2] \dots\dots\dots\dots\dots (20)$$

Which means:

- GridBreaker1 (GB_1) is closed (1) if SoC_1 < 50% ($\overline{SoC_1} = 1$).
- GridBreaker1 (GB_2) is closed (1) if SoC_2 < 50% ($\overline{SoC_2} = 1$).
- LoadBreaker1 (LB_1) is closed (1) if $SoC_1 \geq 50\%$ ($\overline{SoC_1} = 1$).
- LoadBreaker2 (LB_2) is closed (1) if $SoC_2 \geq 50\%$ ($\overline{SoC_2} = 1$).

The K-map provides a compact representation of the behavior of all four breakers. By simplifying the K-maps, we can verify that the Battery-side Controller's logic is correct and reliable.

4.6 Dynamic Simulation-based Evaluation Using Python

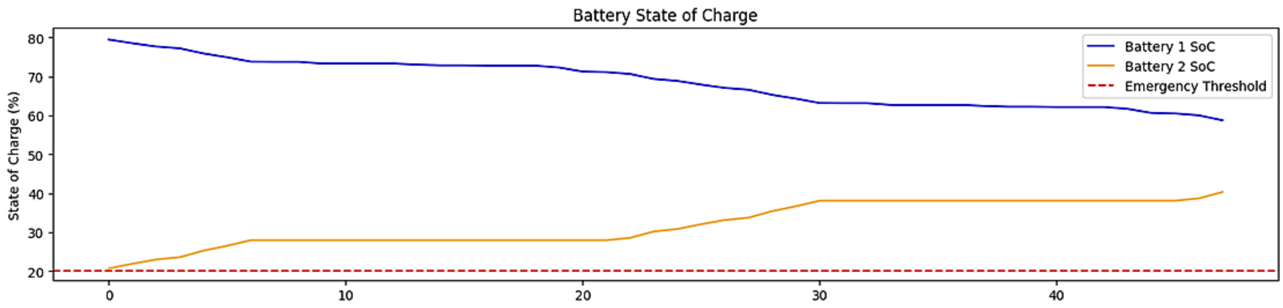


Figure 20. Battery SoC over 40h Dynamic Simulation

To analyze the dynamic behavior of the proposed EMS under real-world scenarios, a Python based simulator is developed based upon the validation of the RBC logic through K-map analysis in Section 4.5. Using hourly historical solar generation, electricity price and synthetic load demand data, a period of 40 hours were simulated in order to see the SoC of the battery, battery-side controlling and power flow for the grid-side controlling.

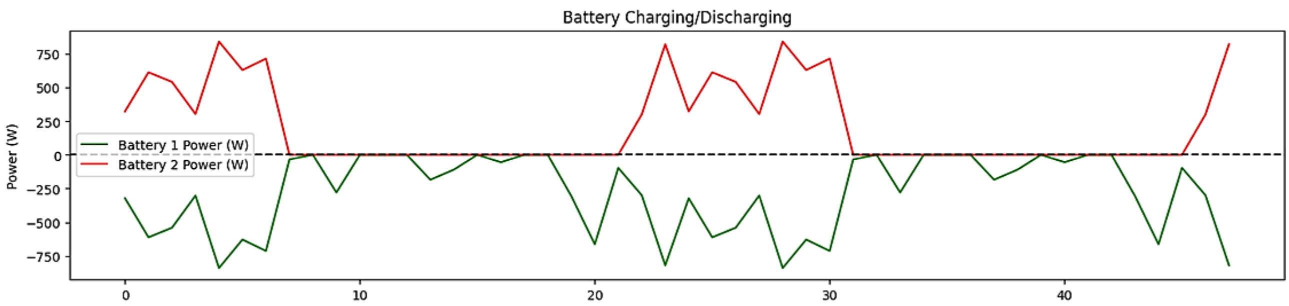


Figure 21. Battery-side Controlling over 40h Dynamic Simulation

The simulator, implemented in Python using Jupyter Lab, models battery charge/discharge dynamics using the Coulomb counting method. The SoC of the batteries is updated at each time step (1 hour) according to the equation 21:

$$\Delta Q = \frac{P}{U} \cdot \Delta T \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . . (21)$$

where, ΔQ change in battery charge(Ah), P is the power flow into/out of the battery (W), U is nominal battery voltage (V), ΔT is time step duration (1 hour).
The battery SoC is then calculated as shown in equation 22:

$$SoC(t+1) = SoC(t) + \frac{\Delta Q}{Q_{rated}} \times 100\% \ldots\ldots\ldots\ldots\ldots\ldots\ldots (22)$$

where, Q_{rated} is the battery's rated capacity (Ah).

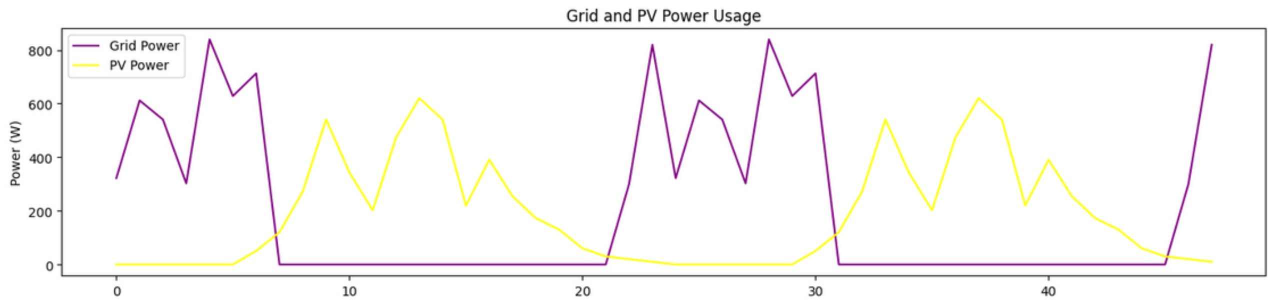


Figure 22. Grid-side Controlling over 40h Dynamic Simulation

The simulator outputs three key metrics, first the dynamic state of charge for both Battery 1 (green) and Battery 2 (purple). In figure 20-21, we can see that based on the SoC level both of the batteries charging/discharging. The system uses solar PV power (blue) instead of grid power (orange) if available during daylight hours (peak hours 7–22) based on pre-defined price threshold, shown in figure 22. For high solar generation periods, grid reliance is close to zero with the majority of the demand (low-PV generation hours) met by grid usage.

5 Conclusion and Future Work

This thesis focuses on the development of a RBC approach for hybrid energy management of data centers, specifically considering the usage of battery and renewable energy resources. The architecture utilizes a NN prediction model to forecast solar PV output, and features rule-based controllers for real-time energy sourcing and storage management. The Grid-side Controller is responsible for minimizing the amount of grid energy that can be utilized in real-time electricity prices and PV prediction, while the Battery-side Controller is responsible for charging/discharging battery storage systems according to their SoC. The system was then modeled and simulated in MATLAB/Simulink and its performance was analyzed using scenario-based study and K-mapping to optimized and verify the control logic.

The proposed framework promotes renewable energy usage and minimizes grid power dependence while remaining reliable under diverse conditions, and the results demonstrate this. This model was implemented and tested, with the NN forecasting model displaying an R^2 value of 0.88 on the validation dataset, generating predictions of the rule-based controller's output. This ensures efficient and sustainable energy management with grid support, as the framework evaluated through scenario-based simulations confirmed the framework was effective various scenarios. By integrating renewable energy sources, battery storage and rule-based control, the framework contributes to the global effort to reduce carbon emissions and promote sustainable energy practices in data centers.

5.1 Addressing the Problem Statement

Chapter 1 provided a problem statement about the need for more efficient models of energy management in data centers to mitigate their carbon emissions and avoid excess computational expenses, and the suggested framework directly manifests these concerns. When characterized, the RBC framework is an ideal systematic integration tool which integrates solar PV (Renewable Energy) and battery storage system in parallel to the grid supply. The framework uses a neural network forecasting model to forecast PV generation and helps in making more informed decisions about energy sourcing and storage. The Grid-Side Controller reduces dependence on grid power during peak hours, when electricity prices are high, while the Battery Controller prevents battery storage systems from improper charging or discharging caused by changes in the SoC. The framework control logic was also simplified and verified through scenario-based evaluation and K-mapping, indicating its efficiency in achieving low-carbon energy management. Consequently, the proposed approach helps to tackle the difficulties faced in integrating renewable energy sources, as well as in optimizing battery storage while providing a cost-effective and scalable solution for data centers to move towards sustainable energy practices.

5.2 Recommendations for Future Work

The proposed framework showed good results, but several elements need further investigation or improvement. The future work will be redirecting towards the real-world execution of the framework to confirm the performance in the actual operating conditions and integrating advanced control strategy like fuzzy logic, reinforcement learning and model predictive control. Perform a comparative study of these approaches to assess their effectiveness for the purpose of optimizing energy management with respect; improving system efficiency and mitigate carbon emissions. This will offer directly helpful knowledge regarding the various advantages and drawbacks of each method, and ultimately lead towards improving upon energy management systems in data centers and other applications where energy consumption is a major concern.

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