

**Machine Learning to Improve Microgrid Energy Management**

**ME420 Mechanical Engineering Individual Research Project**

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by

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# Declaration

I confirm that I have written this report without any external help and not using sources other than those I have listed in the report. I confirm also that this report or similar version of it has not been submitted to any other examination board and has not been previously accepted as part of an exam for a qualification. Each direct quotation or paraphrase of an author is clearly referenced.

Place, 28th Nov, 2023 \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

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# Summary

XXXXXX

# Acknowledgement

XXXXXX

# List of Symbols

Latin symbols

|  |  |  |
| --- | --- | --- |
| *A* | cross-sectional area | m2 |
| *a* | thermal diffusivity | m2s-1 |
| *B* | rotation constant | m-1 |
| *c* | speed of light *in vacuo* | ms-1 |

Greek symbols

|  |  |  |
| --- | --- | --- |
| ** | thermal conductivity | Wm-1K-1 |
| ** | lag time | s |
| **C | correlation time | s |

Abbreviations

|  |  |
| --- | --- |
| DLS | dynamic light scattering |
| MD | molecular dynamics |

Indices

|  |  |
| --- | --- |
| c | related to concentration fluctuations |
| i | initial state |
| t | related to temperature fluctuations |

# Table of contents

[Declaration i](#_Toc150378899)

[Summary ii](#_Toc150378900)

[Acknowledgement iii](#_Toc150378901)

[List of Symbols iv](#_Toc150378902)

[Table of contents v](#_Toc150378903)

[1 Introduction 1](#_Toc150378904)

[2 State of the art 3](#_Toc150378905)

[2.1 Introduction 3](#_Toc150378906)

[2.2 What is microgrid 3](#_Toc150378907)

[2.3 Energy demand 4](#_Toc150378908)

[2.4 Forecasting energy demand 4](#_Toc150378909)

[2.5 Machine learning 5](#_Toc150378910)

[2.6 Machine learning models used 6](#_Toc150378911)

[2.7 Optimization of microgrid operation 7](#_Toc150378912)

[2.8 8](#_Toc150378913)

[3 Methodology 9](#_Toc150378914)

[4 Data Evaluation & Optimization 11](#_Toc150378915)

[5 Results and discussion 12](#_Toc150378916)

[6 Summary 13](#_Toc150378917)

[Apdix (if required) 16](#_Toc150378918)

# Introduction

Microgrids are localized energy systems that integrate various energy sources and operate independently or in conjunction with the main power grid. They provide reliable and resilient power supply to specific areas, incorporating renewable energy technologies, energy storage systems, and conventional generators. Microgrids can disconnect from the main grid during outages and emergencies, ensuring uninterrupted power to critical facilities. They promote sustainability by integrating renewable energy, reducing carbon emissions, and optimizing energy generation and consumption.

When considering Microgrid energy demand it refers to refers to the amount of electrical power required by a microgrid to meet the energy needs of its consumers within a specific time period. It represents the total electricity consumption of the connected loads, including residential, commercial, or industrial facilities related to microgrid. Also, the demand for energy from microgrids might change depending on things like the time of day, the day of the week, seasonal fluctuations, weather, and consumer habits.

If we can accurately forecast the energy demand of microgrid it will be more effective for efficient operation of microgrid, when managing resource and in optimizing microgrid system. Also, it will be helpful in ensuring reliable power supply, manage load balancing inside the microgrid and optimize the generating and storage resources. So, understanding and predicting energy demand will help in using resources wisely, choosing demand response tactics and in optimizing energy usage and minimize cost.

In forecasting energy demand machine learning have advantage than traditional methods as they rely on pre-defined rules and assumptions. Machine learning has ability to handle complex relationships, adapt to changing conditions and leverage diverse data source. Also, it offers data-driven approach and scalability for accurate prediction. Machine learning models continuously learn and improve over time, ensuring accurate and reliable forecasts in dynamic microgrid environments. So, machine learning is providing more advance and effective approach to forecasting energy demand in microgrids.

This report aim is to forecast energy demand of microgrid and use optimization technologies to optimize microgrid operation. The project objectives include developing forecast models using machine learning techniques, evaluating the performance of these models on microgrid data, and developing a simple optimization model for microgrid operation according to that data. By achieving these objectives, the project seeks to enhance the understanding and application of machine learning in microgrids.

# State of the art

## Introduction

In past few years carbon emission and energy demand have been increased. This happens due to increase in energy-consuming equipment and population. So, due to growing concerns regarding the effects of fossil fuel emissions, the importance of renewable energy resources has grown markedly in recent years.[1] . Also, the power management is essential in industrial and local consumers because it is crucial for energy conservation, cost savings, environmental protection, technological advancements, and overall user satisfaction.

The industry standard for power management is a centralized power grid. Which is largely dependent on fossil fuels. There are two major problems in Centralized power grids. First, the rigid, inflexible centralized grid is unable to accommodate the unpredictable nature of current distributed energy resources (DERs). Second, energy is often lost when travelling large distances between energy generation and consumption locations [2] ,[1]. To overcome these problems Distributed, or on-site generation, has been proposed as a next generation smart grid solution. This method has advantages than other methods as its ability to generate energy locally, also it can reduce the energy lost in transmission, and due to its small scale and isolation it has superior reliability.[1] [3] .So, under these circumstances, small-scale grids operating in small areas as fully functioning energy systems have become an interesting solution.[4]. which is known as microgrids. Microgrids promote sustainability by integrating renewable energy, reducing carbon emissions, and optimizing energy generation and consumption. In following sections look more about microgrids in details.

## What is microgrid

Microgrids are localized energy systems that integrate various energy sources. A microgrid is a small-scale grid. However, it is fully functional, operating in a limited geographical area; it can operate independently or be connected to a larger grid [4]. Microgrids are mostly used in remote or off grid areas where it is difficult to connect to main grid. Now a days with the increasing of carbon emission microgrids have been as a solution to that. So now there are microgrids where they can operate independently or connected to main grid. Microgrids are using distributed energy resources (DERs) where it includes renewable energy sources. Such as wind turbines, solar panels, combine heat and power plants and energy storage systems like batteries, these energy resources can be categorized as adjustable or non-adjustable and storage systems The microgrid is the integration of several renewable energy sources with adjustable or nonadjustable loads and storage systems [5]. In the previous 10 years, a lot of research has come out on microgrids as a potential source of energy in the near future [6]. As mentioned in above this localized on-site generation method, is implemented due to their improved reliability and the ease of inclusion of renewable energy generation

## Energy demand

Energy strategy is extremely important for developing countries. The energy demand of a microgrid can vary depending on a number of factors, including the size of the microgrid, the type of loads it serves, and the availability of renewable energy sources. In general, microgrids are designed to meet the peak load demand when they are connected to loads.

This peak load demand is the maximum electricity that a microgrid must deliver at any one moment. A fundamental microgrid system’s load demand often fluctuates hourly [6]. So, this demand fluctuates depending on the time of day, the season, and the weather. For example, peak load demand of microgrid is higher in a hot climate. Energy demand is important in determining microgrids generating cost. The two most important factors that determine a microgrid system’s generating cost are load demand and energy market pricing [6].

So, to ensure that a microgrid can meet its peak load demand, it is important to accurately forecast the demand. This can be done by using historical data, as well as weather forecasts and other factors

## Forecasting energy demand

Energy demand forecasting is the process of predicting future energy consumption based on historical data and other factors. Energy demand forecasting is one of the most important tools that decision makers use (Ediger and Akar, 2007) [7]. As it can help to ensure that there is enough available to meet demand, and that energy resources are used efficiently. There are different methods that can be used to forecast energy demand. Techniques used in energy demand forecasting studies are mainly composed of BoxJenkins models, regression models, econometric models and neural networks (Jebaraj and Iniyan, 2006) [7].

In the studies of forecasting electric energy demand, there are many methods used in the literature including autoregressive integrated moving average (ARIMA), artificial neural networks ANN, time series methods, support vector machines and fuzzy logic method [7]. In time series analysis it uses historical data to identify trends and patterns in energy consumption. These trends can then be used to forecast future demand.

In 1960 Turkey’s Planning Organization realized a demand forecast study based on simple regression. Then they continue studies on energy demand. These early forecasts consistently predicted much higher values than the consumptions that actually realized. also, Short-term energy supply and demand forecasting are necessary to make informed and reliable decisions for distributed energy systems [8]. However, although there are many forecasting methods which take into account the advances in information, metering and control technologies in order to address the challenges of forecasting problems [9] ,[10].

Here are some challenges of energy demand forecasting. Energy demand is often volatile and difficult to predict. This is due to a number of factors, such as weather, economic conditions, and technological change. There is a lack of reliable data. This is especially true for long-term forecasting. Also, the models used for forecasting are often complex and difficult to understand. This can make it difficult to interpret the results of the forecast. Energy demand forecasting is a crucial instrument that may assist to increase the effectiveness and sustainability of energy systems despite these challenges. As the world becomes more interconnected and energy markets become more volatile, the need for accurate and reliable energy demand forecasts will only increase. Machine learning (ML) and deep learning (DL) based models are promising solutions for predicting consumers’ demands and energy generations from RESs [11]. let’s look forward to ML and ML models used in forecasting energy demand.Focus 2

## Machine learning

Machine learning (ML) is a type of artificial intelligence (AI) that allows computers to learn without being explicitly programmed. In ML algorithms that use available data for the training of a model, where the underlying system is more or less treated as a black box, are usually grouped under the term machine learning. Arthur Samuel was the one who coined the term ‘’Machine Learning’’ in 1959, defining it as “the ability to learn without being explicitly programmed.” Machine Learning, at its most basic form, is the practice of using algorithms to parse data, learn from them, and then make a determination or prediction about something in the world [9].

Machine learning tasks may be classified into three broad categories, namely supervised, unsupervised and semi-supervised. Another categorization of machine learning tasks is by the desired output. If the output of the model is a class, then it is a classification problem, if it is a number then it is a regression problem and if it is a set of input groups, it’s a clustering problem [9].

Machine learning techniques have been proven useful for short-term electricity load forecasting. Especially in microgrids where large variety of data should be included in the energy consumption prognosis. These Novel techniques and models are taking advantage of the advances in artificial intelligence algorithms. Where they allow for faster convergence, manipulating big data sets and solving more complex problems [9].

There are some challenges of using ML for energy demand forecasting. Such as it requires a large amount of data, it can be computationally expensive to train ML models and the results of ML models can be difficult to interpret. However, ML is a potential approach for predicting energy demand. As the technology continues to develop, it is likely to become even more effective for forecasting energy demand.

## Machine learning models used

Machine Learning has been shown to be effective for forecasting energy demand. According to researches it shows that ML was able to produce more accurate forecasts than traditional methods. As Electrical load forecasting algorithms are needed for prediction of the energy demand for the day ahead, a few weeks up to a year or a period of over a year [9]. so, the methods that are using have to be more accurate and efficient. The choice of ML model will depend on the specific needs of the energy planner or decision-maker. For example, if the planner is interested in forecasting short-term demand, then a SVR algorithm may be the best option. However, if the planner is interested in forecasting long-term demand, then an ANN may be more appropriate

In literature it has used many ML methods for forecasting energy demand. Enea Mele (2019) have given a review about short-term forecasting such as Support Vector Machines (SVM), k-Nearest Neighbors (kNN), Random Forest and Artificial Neural Networks (ANN) and compare their performance efficiency, capabilities and limitations.[9].

In [1] it shows that there have been proposed Multiple deep learning techniques in past. These include artificial neural networks (ANN), convolutional neural networks (CNN), recurrent neural networks (RNN), Long short-term memory networks (LSTM) and bidirectional long short-term memory networks (BLSTM).

Maciej Slowik and Wieslaw Urban has developed a universal forecasting tool for energy consumption by end-use consumers. This model allows the end-users to be equipped with an energy demand prediction, enabling them to participate more effectively in the smart grid energy market. A single, long short-term memory (LSTM)-layer-based artificial neural network model for short-term energy demand prediction was developed.[4].

Among these methods deep learning Deep Learning models are a good alternative to learn patterns from customer data and then forecast demand for different forecasting horizons. deep Learning uses multiple layers of neurons composed of complex structures to model high-level data abstractions [12]. most commonly used deep learning-based methods for energy management and power forecasting, namely, artificial neural networks (ANN), deep neural networks (DNN), convolutional neural networks (CNN), and recurrent neural networks (RNN) [13].

Another paper [14] considers a load forecasting problem in residential areas as well as in commercial buildings. A deep RNN is employed for medium to long term energy consumption forecasting. Simulation results show the effectiveness of the proposed deep RNN based model over MLP for load demand prediction of commercial buildings.

In research work [15] also adapts DL based methods for load forecasting. In there a hybrid forecasting method is developed by combining the best features of CNN and K-means clustering. The results show that their hybrid CNN–K-means forecasting algorithm has higher accuracy.

So, there are more research in forecasting energy demand of microgrid. And this existing literature suggests that machine learning techniques have significant potential to improve the accuracy of energy demand forecasting [10], [16]. Further research is needed to develop and evaluate advanced machine learning algorithms for energy demand forecasting, and to investigate their potential applications in microgrid management and optimization.

## Optimization of microgrid operation

Microgrids typically include a mix of renewable energy sources, such as solar and wind power, and conventional generation sources. The effective management and optimization of microgrid operation is essential for ensuring reliable and cost-effective power supply [17].

There are some different optimization techniques that can be used to optimize microgrid operations. Such as Linear programming which can be used to optimize the operation of microgrids by minimizing the cost of electricity generation or by maximizing the reliability of the system. Also mixed integer programming can be used in microgrid operations by considering the discrete nature of some of the decisions, and heuristic optimization can be used find quick solutions that are close to optimal.

By optimizing microgrid operations we can reduce the cost. Where forecasting data can be used in here. Also using that data, it can used to improve the reliability of the microgrid. This can be done by ensuring that there is always enough generation capacity to meet demand and by ensuring that the system is resilient to disruptions. There are some challenges that could occur when optimizing microgrid operations. The optimization problems that arise in microgrid operation can be complex. This is because the system is typically nonlinear and has a large number of variables. Also, the operation of a microgrid is subject to uncertainty, such as the amount of renewable energy that is available and the demand for electricity. This uncertainty can make it difficult to optimize the system. And the availability of data can be a challenge for microgrid optimization. This is because microgrids are relatively new and there is not a lot of historical data available. However, optimizing microgrid operation is a valuable tool that can help to improve the efficiency, reliability, and sustainability of these systems.

## 

xxxx. In Figure 2.1, a green square is illustrated.

*Figure 2.1: Green square [X].*

xxx. In Table 2.1, the letters appearing in different words are listed in alphabetic order.

*Table 2.1: Considered words and letters contained therein in alphabetic order.*

|  |  |  |  |
| --- | --- | --- | --- |
| word | letter 1 | letter 2 | letter 3 |
| for | f | o | r |
| and | a | d | n |
| per | e | p | r |

# Methodology

… A summary of the studied compounds and their properties required for data evaluation is given in Table 3.1.

*Table 3.1: Specification of the studied samples.*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| substance | source | specified mass fraction purity | molecular weight *M* / (g∙mol−1) | critical temperature *T*c / K | critical pressure *p*c / MPa |
| HFE-7000 | 3M | 0.995*a* | 200*a* | 438.15*a* | 2.48*a* |
| HFE-7100 | 3M | 0.995 | 250*c* | 468.45*c* | 2.23*c* |
| HFE-7200 | 3M | 0.99 | 264*e* | 482.95*b* | 2.007*b* |
| HFE-7300 | 3M | 0.99 | 350*g* | 516.45*b* | 1.877*b* |
| HFE-7500 | 3M | 0.99 | 414*h* | 534.15*h* | 1.55*h* |

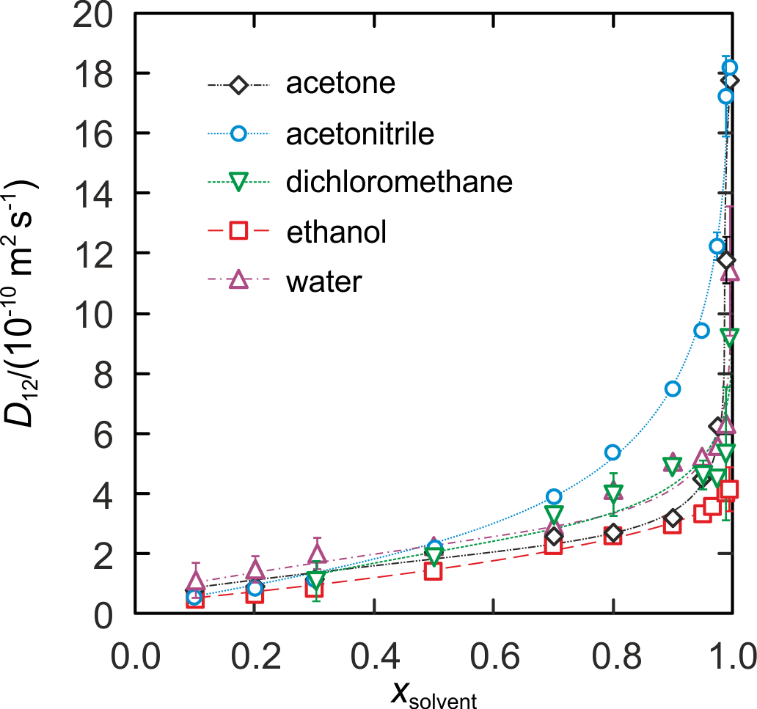
*a*ref [use reference link from the reference manager software]. *b*ref [use reference link from the reference manager software]. *c*ref [use reference link from the reference manager software]. *e*ref [use reference link from the reference manager software]. *f*calculated according to ref [use reference link from the reference manager software]. *g*ref use reference link from the reference manager software []. *h*ref [use reference link from the reference manager software].

# Data Evaluation & Optimization

# Results and discussion

dffd

Figure 5.1 shows …



*Figure 5.1: Mutual diffusion coefficients of binary mixtures of [EMIM][EtSO4] with different solvents as a function of the solvent mole fraction (lines are guide for the eye)..*

# Summary

In the present study, …

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**Appendix (if required)**

Apdix (if required)