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Masterarbeit

Feasibility analysis of using Model Predictive Control in Demand-Side Management of Residential building

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Abstract

The energy systems are becoming smart recently with an increase in communication capabilities between producer, distributor and consumer. Also, many distributed renewable energy producers both in large and domestic scale are adding to the system day by day. Executing Smart Demand-Side Management (DSM) programs can help in providing financial benefits and stability of the energy system without compromising the comfort of end-users. Model Predictive Control (MPC) is an advanced method of process control that is used to control a process while satisfying a set of constraints. Due to its ability to predict future events and generate optimal control, it is widely used in process industries since the 1980s [32] and in recent years it is introduced in power systems. This motivates to study the economic feasibility of using MPC in executing DSM for Residential building, to optimize the power consumption costs and stability of the energy system in the presence of local renewable energy sources (E.g., PV system). The main contribution of this thesis work is to measure the economic benefit of using MPC on DSM of household electricity consumption. A detailed study of modeling the demand side, i.e the appliances of a smart home, along with the domestic energy generators is done in the initial part. Apart from the physical properties of the renewable energy generators, the influence of external factors like weather, dynamic-pricing of electricity and changing user preference is also considered in the model. This formulated model is used to perform simulation of the residential building to generate an optimized energy consumption schedule and calculate the resulting economic benefits. The periodic changes in weather forecast and dynamic-prices are fed into the simulation to improve the prediction accuracy of the system. Lastly, the model is evaluated on a physical implementation to analyze its performance. There are multiple findings as part of the result of this thesis, like the economic benefit of using such a system will encourage many users to participate in Demand response programs, this in turn will help in the reduction of pollution originating from non-renewable energy generators.

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1 Introduction

The rapid climate change is a major factor pushing the energy sectors throughout the world to produce clean energy. For example, Europe has a target to cut greenhouse emissions at least 40% by 2030 compared to 1990 levels. It also targets to have a third of its energy produced from renewable resources and improve energy efficiency up to 32.5% [11]. Currently, buildings contribute to 40% of the overall energy consumption in Europe and 36% of greenhouse gas emissions in Europe.[12]. By making the buildings smart and by improving the energy performance we can try to help achieve the above goals.[13] Renewable energy is an alternative source for producing clean energy since they emit no CO2 during operation. But due to the non-reliability of these renewable resources, higher economic and environmental cost of operating non-renewable energy generation, there is a necessity to optimize the overall energy requirement from the consumer side as well. Demand Side Management(DSM) is a concept of encouraging the end consumer to participate in energy management. Also, many countries are adapting to a dynamic pricing scheme in the electricity market, a DSM technique, where the price of electricity varies based on the demand levels and the consumer gains incentives by scheduling their electricity usage accordingly. With the recent improvement in the technologies like Internet of Things(IoT), Smart Grid and Smart Homes, the entities like electricity producers, distributors and end consumers are all seamlessly connected. This communication capability helps to manage energy production and consumption efficiently. Model Predictive Control(MPC) is a popular advanced process control method. Since MPC has a model of the plant, in this case, a residential building, it can reliably predict the future behavior of the system. Easy implementation, robust against disturbances and guaranteed stability of the system are the main advantages of using MPC.

1.1 Problem Statement

Though DSM and MPC are in use in the industry for a long time, there is only limited research done on combining both these technologies and implement on Residential buildings. Many control techniques like Fuzzy Logic[20], Simulated-Annealing [30]

are used in DSM. Some of the existing works in using MPC in DSM deals with building climate control systems [8][27] and some on the stability of the energy system[25]. Although dynamic pricing is popular among researchers, there is still some hesitation from the industry and end consumers on the benefits over the large-scale implementation cost of this technology. [9]. The research study presented here is to analyze the economic and scheduling feasibility of using MPC on DSM of a residential building, while the building is equipped with local renewable electricity generators (For eg. Solar and Wind) and dynamic pricing of electricity. The economic benefits, in this context, is the cost saved by using this approach to generate a schedule for utilization of electricity by consumer load.

1.2 Assumptions

Below are the assumptions considered as part of this thesis work:

- Dynamic prices only from German energy market is considered.
- All the demand side loads are Electrical energy consuming devices

1.3 Document Structure

The remaining part of this document is organized as follows. Chapter 2 gives the background knowledge of concepts like DSM, MPC, Renewable energy generation, Smart Grid and Smart Home as it is needed to understand this thesis work. Chapter 3 shows the existing relevant latest works on these topics. Chapter 4 explains the architecture and approach to this thesis work. Chapter 5 shows the methodology used for simulating and practical measurements of data. Chapter 6 shows the discussion of the results obtained. Chapter 7 gives the conclusion and possible future works.

2 Background

2.1 Demand-Side Management(DSM)

Demand-Side Management(DSM) is defined as the planning and implementation of those activities designed to influence consumer use of electricity in ways that will result in changes in the utility's load shape. That is changes in the time pattern and magnitude of a utility's load [6]. The objective of demand-side management is to encourage users to consume less energy during peak times or to shift energy use to off-peak hours to flatten the demand curve or to follow the generation curve [28]. This allows the grid operators to improve the efficiency and stability of the grid. This will also help reduce the necessity to start non-renewable energy generations to meet the peak power demands. The types of possible load shaping with DSM are shown in Fig.2.1, by combining these shaping techniques DSM is implemented.

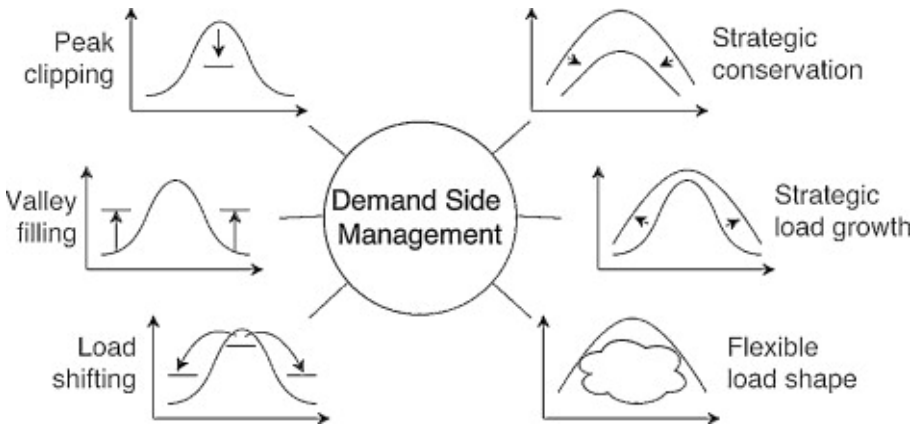

Figure 2.1: Load shaping techniques in DSM [6] [15]

Some of the load shaping techniques from the original DSM concept which are relevant to this thesis work and its explanation:

•Peak Clipping : Reduction of system Peak loads.

•Valley filling : Increase the demand off-peak daily or seasonal periods

•Load Shifting : Shifting the load from on-peak to off-peak

While DSM is a general term for energy management, with advancements in the field it has evolved into Energy Efficiency(EE) and Demand Response (DR) [4]. Energy-Efficiency is reducing the energy required for the provision of services or products. This is achieved by using the latest technology into the appliances which will reduce the energy requirement permanently. On the other hand, Demand-Response is the method used in this thesis work and is explained as follows.

2.1.1 Demand Response (DR)

Demand Response broadly refers to the actions of individual electricity end consumers to reduce or shift the electricity usage during peak hours based on price signal or when the grid reliability is deteriorating. [37] As part of this thesis work Price based DR is considered.

Dynamic pricing of Electricity

Dynamic Pricing is a DSM technique to charge a different price for electricity at different demand levels. The generation, transmission and distribution of electricity costs a certain price and charged per Kilo Watt-hour (KWh). This cost varies based on which method is used for electricity generation[9].
There are a few types of smart pricing schemes[19]:
•Time of Use (ToU) : Different prices in peak time and off-peak time. Usually, the prices are relatively higher in peak time.
•Critical Peak Pricing (CPP) : Same as ToU, but the peak price is higher and varies based on time of the year.
•Real-Time Pricing (RTP) : The cost of the retail price is charged nearest to the real price of generation at that time interval.

2.2 Model Predictive Control (MPC)

Model Predictive Control (MPC) is a widely used advanced method of process control. It is used to control a process while satisfying a set of constraints. It is also termed as Receding Horizon Control. MPC uses an explicit process model to predict the future response of a plant. At each control interval, an MPC algorithm attempts to optimize future

plant behavior by computing a sequence of future manipulated variable adjustments. [31] Currently, MPC is widely used in chemical, food processing and aerospace industry. MPC is also being considered for power systems for [29] : (i) MPC is based on future behavior of the system and predictions, this is useful as the systems are dependent on future energy demand and renewable energy generation; (ii) MPC provides a feedback mechanism, which makes the system more robust against uncertainty (iii) it can handle multiple/complex system constraints.

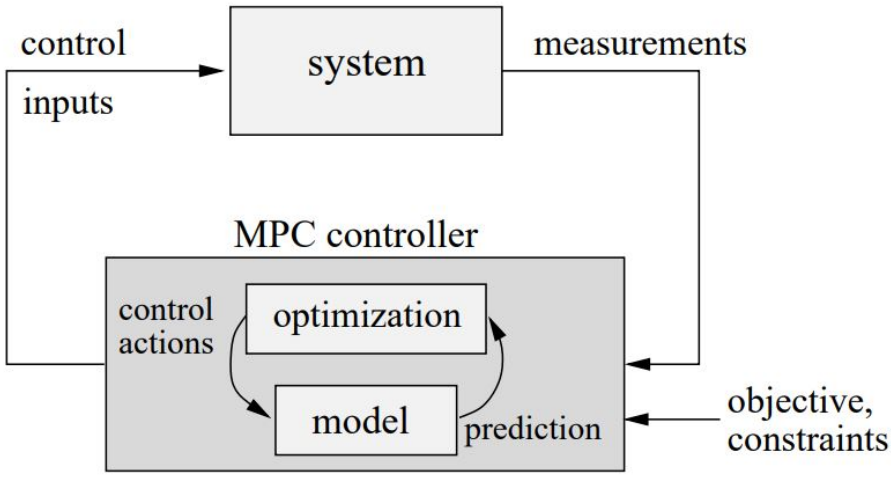

Figure 2.2: Model Predictive Controller illustration [3]

Schematic illustration of MPC is shown in Fig.2.2 and a sample of residing horizon concept of MPC is shown in Fig.2.3. The concept of MPC as explained in [3] - At each control step k, a MPC controller first measures the current state of the system, $\mathbf{x}(k)$. Then, it determines using optimization which control input $\mathbf{u}(k)$ to provide by finding the actions that over a prediction horizon of p time steps give the best predicted performance according to a given objective function. The control variables determined for the first prediction step are applied to the system. The system then transitions to a new state, $\mathbf{x}(k+1)$, after which the cycle starts all over again.

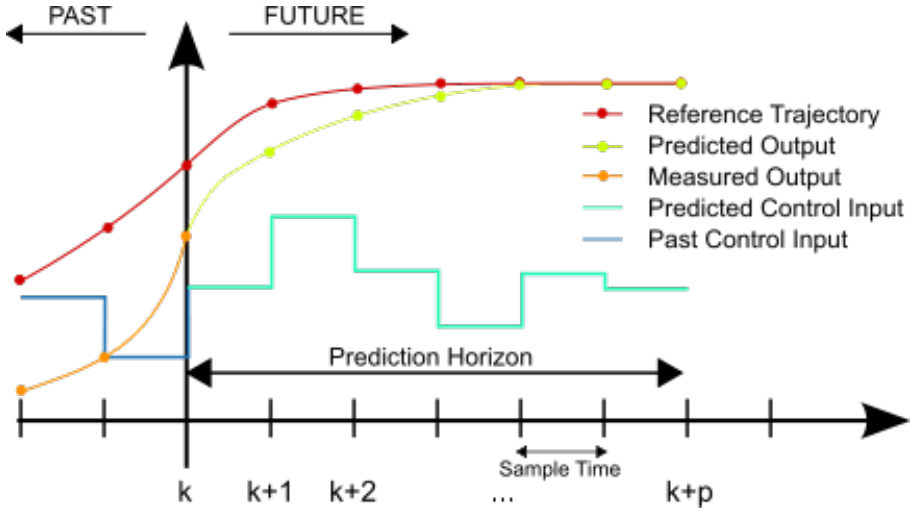

Figure 2.3: The receding horizon concept of Model Predictive Control (By Martin Behrendt, via Wikimedia Commons)

2.3 Home Renewable energy generation

Electricity generation for a long time has been from fossil fuels. Then came nuclear power plants. But in recent years, due to growing awareness of the environmental damages caused by these types of energy generators, many countries are moving towards renewable energy sources. For example, Wind, Photo-Voltaic, Hydro and Biomass. From Fig.2.4 we can see that renewable energy generation capacity for a country like Germany is on the rise. Also in 2014, 26% of final energy consumption in Germany is accounted for by households. [10]
Due to technical feasibility and low cost of installation/maintenance, some of these renewable energy generators based on Solar PV and wind are installed directly at the home. This enables the local production and consumption of electricity at a highly distributed fashion. The electric energy generated by solar and wind energy is always fluctuating and volatile. So the supply demand balance energy at all times is also an important factor to consider. The Home Energy Storage Systems (HESS) can help in these scenarios to store the energy and act as a buffer to provide stable and reliable power. [38]. Also if there are any problems with the grid, like outages, these renewable generators can along with HESS provide the necessary electricity for the house. Also with better weather forecast availability, it is easy to predict the production and plan ahead the usage schedule.

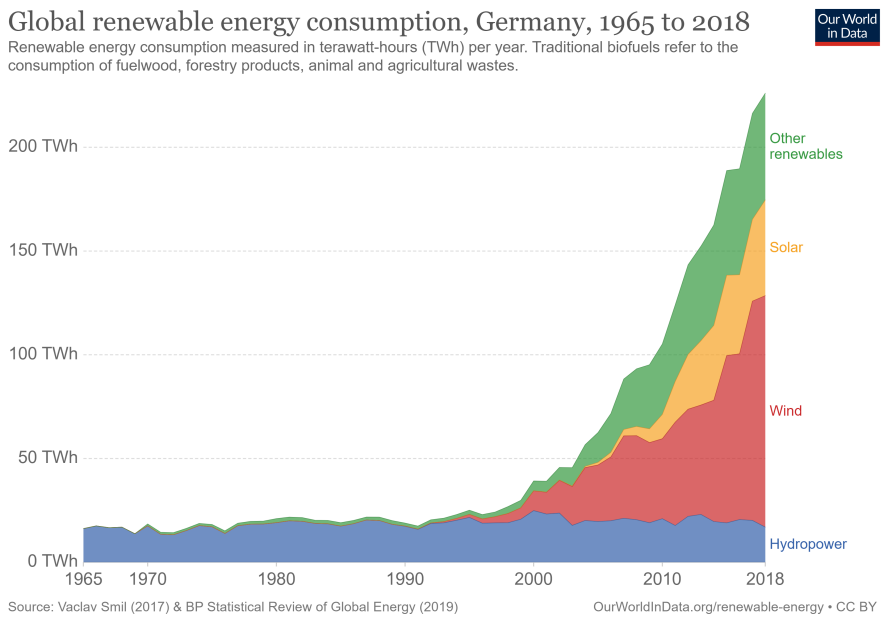

Figure 2.4: Renewable Energy consumption trend in Germany [33]

2.3.1 Solar PV

Electricity generation using the Photo-Voltaic system or Solar power system consists of an array of modular Solar cells and an inverter to convert the generated Direct Current(DC) in Alternating Current(AC). From Fig.2.5 it is apparent that the solar panel module prices per watt-peak have decreased 10 fold over the past 50 years span. The advantage of solar energy harvesting is the scalability and it is non polluting during operation. The PhotoVoltaic system can be deployed from a small size on roof top of a residential building to a very large scale solar farms.

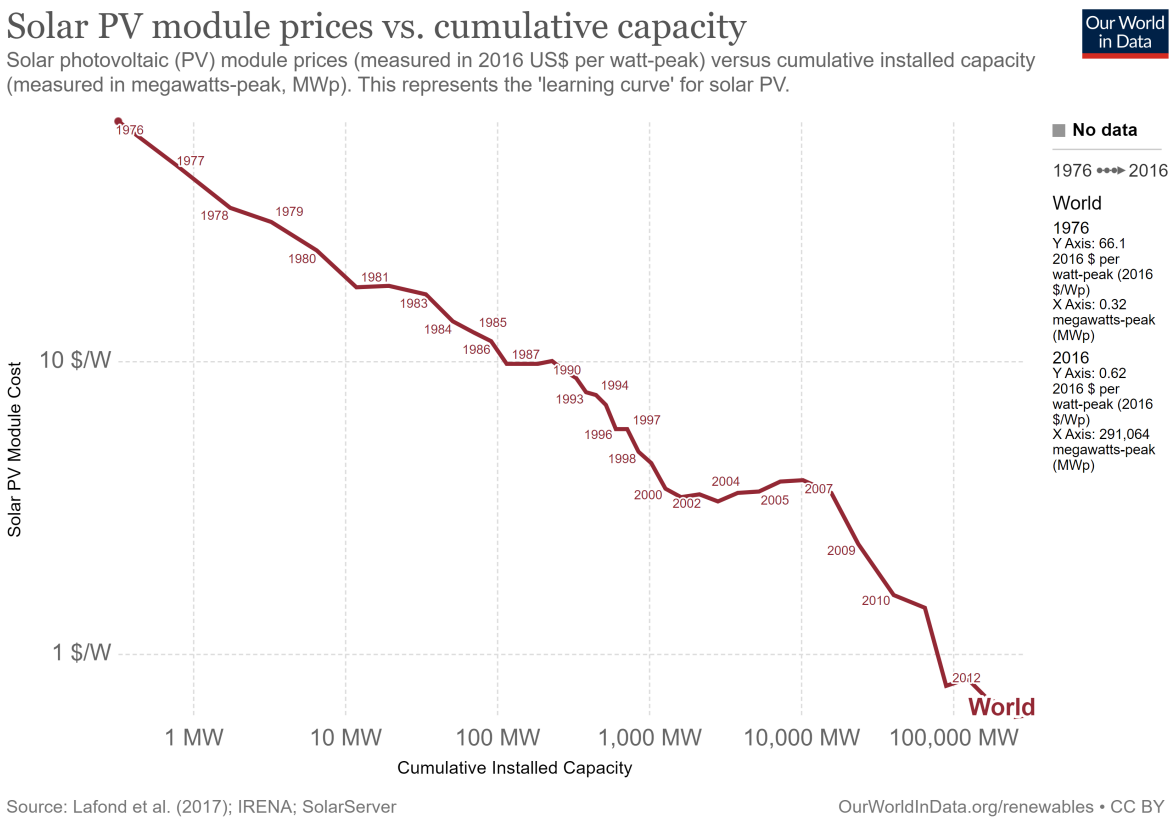

Figure 2.5: Solar panel price vs cumulative capacity [33]

2.3.2 Wind

If the residential building has the geographic advantage of having wind flowing across it most of the times in a year, a small Wind turbine can be installed to generate electric energy. Often the domestic wind turbine capacity less than 10kW and with a rotor size between 1 and 5 meters. [1]

2.4 Smart Grid and Smart Home

Advancements in communication and technology like Internet of Things (IoT) enables new ways of connecting different entities within the electricity gird in real-time. Now the producers, distributors and consumers of the electric energy market are connected and aware of the state of each other. Smart Meter is the overlapping entity between the Smart Grid and Smart Home.

2.4.1 Smart Grid

[7] defines Smart grid "as self-sufficient systems, which allows integration of any type and any scale generation sources to the grid that reduces the workforce targeting sustainable, reliable, safe and quality electricity to all consumers". Unlike traditional power grids which carry only electricity from generators to users, A Smart Grid can have electricity and information flow bidirectionally. This creates an automated and distributed energy delivery network.

2.4.2 Smart Home

There are multiple definitions of Smart homes. The one presented in Smart home energy web page [36] defines smart home as "A smart home, or smart house, is a home that incorporates advanced automation systems to provide the inhabitants with sophisticated monitoring and control over the building's functions. For example a smart home may control lighting, temperature, multi-media, security, window and door operations, as well as many other functions." With the help of a variety of sensors and connected appliances, it is easy to track the real-time state, usage patterns and control them remotely.

3 Related Works

This chapter discusses the related works done in the field of DSM and MPC. It discusses the various approaches followed by other authors. Also, the similarities and the differences of this thesis work with other works are explained.

3.1 Demand Side Management/Home Energy Management Systems

Existing works on Demand Side Management is found in a variety of places, like in smart buildings, smart home, smart office and retails spaces etc. The smartness in this context is making the building being aware of its occupants and facilitate automation of most of the tasks, like lighting control, HVAC and climate control.[26] Also meanwhile it should be optimizing the use of energy and help reduce pollution/CO2 emissions. Many works of DSM is dealing with the heating and cooling system of the building [22]. Also with penetration of Renewable energy into residential scale, there are a lot of works on Home energy management systems that can handle the bi-directional energy flow and local storage[24], also the concept of using Electric Vehicle as storage for grid [35] using HEMS are gaining attention. A detailed study on HEMS is done in the paper [38] and a detailed survey of energy management is presented in [13]. In this thesis work, most of the concentration is on HEMS and Demand response for electrical loads.

3.2 Model Predictive Control in Energy systems

Many research works have been done on using MPC in energy systems. Most of them involving the thermal modeling of the buildings to predict and precisely control the heating and cooling system. [21] [8] [27] [23]. Also, research works on combining the thermal and non-thermal loads to develop a model that can handle all types of energy consumed in the building. [5]. In the work of [16], On/Off control of PID and MPC are compared for Air Conditioning. On the other hand, this thesis work deals with On/Off control of electrical appliances.

4 MPC based DSM

4.1 Overview

This chapter discusses the approach to perform a feasibility analysis of Demand Side Management (DSM) using Model Predictive Control (MPC). The economic benefit of using an advanced proven control method like MPC on scheduling the electrical appliances in a smart home can be measured by comparing it with the same setup without using any scheduling algorithms. The architecture design is discussed first along with the description of each module. Then the MPC design is discussed in detail.

4.2 Architecture

The software architecture of this thesis work is shown in Fig.4.1.

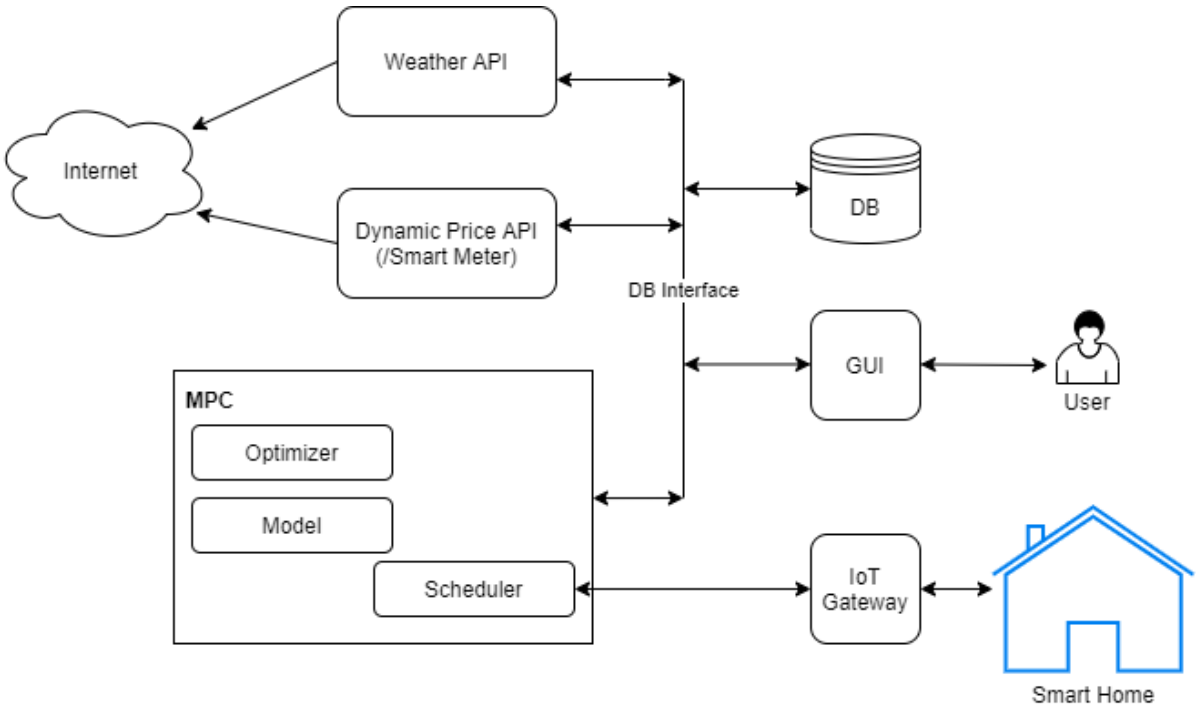

Figure 4.1: Architecture

4.2.1 Database (DB)

Since all the data collected and used in this thesis work are time-dependent, a time-series database, like influxDB is used. Different tables under the same database are used to store values from different entities. All the data in the DB is indexed in time order. So the data points between two timestamps can be fetched easily.

4.2.2 Weather API

The weather API fetches the latest weather forecast from the internet, parses and stores the data in weather table in the DB. Initially historic weather data from [34] is loaded into the database. This contains hourly information of temperature, relative humidity, wind direction/speed, pressure and so on for 6 months duration. This historic data can be useful to simulate the weather conditions of the past to validate the prediction accuracy of the system. Also useful when the current information cannot be fetched. For

current weather information and hourly forecast, data from WeatherBit[1] web page is collected using their API.

4.2.3 Dynamic Price API

The Dynamic price API is used to fetch the current and forecasted dynamic price of electricity for the Electric energy market in Germany. entso-e [2] API is used for fetching hourly Day-ahead Price. This data is also used as Dynamic Price for the upcoming hours. The historic data for the dynamic price is fetched from SMARD[3] and loaded into the database.

4.2.4 Graphical User Interface[GUI]

The visualization of all the collected and processed data is done using a Graphical User Interface. Grafana, an open-source interactive web application is used as a GUI. Multiple dashboards are created in the GUI for real-time data plotting. The data is directly fetched from the database. All the data points are plotted against time and different time ranges can be selected by the user.

4.2.5 IoT Gateway

The IoT gateway is the bridge between the computation environment and the actual smart home devices. It can measure the power usage and state of the appliances, and can also control the state. In this thesis work, a Raspberry Pi and a Plugwise zigbee dongle is used as a Gateway to communicate with all the smart home devices of the setup.

4.2.6 Smart Home

The smart home in the case of this thesis work is a student dormitory with a smart plug installed to control and measure usage of the electric appliances. The devices which are not available or not measurable in the current test environment, but are used

[1] https://www.weatherbit.io/
[2] European network of transmission system operators for electricity. Url: https://transparency.entsoe.eu/
[3] Bundesnetzagentur|SMARD.de

generally in all residential buildings are simulated based on data from Open Power Data Systems[4].

4.2.7 MPC Controller

The MPC controller functioning as a Home Energy Management System (HEMS) in this case, will find the optimal schedule for turning ON/OFF the household appliances. It is predefined with an objective function and user preferences. The objective function of the MPC controller in this the scope of this thesis work is to reduce the total cost of electricity spent on the residential building.

$$minJ = \sum_{t \in T} DyP(t).(\Sigma P^{Use}(t) - \Sigma P^{Gen}(t)) \tag{4.1}$$

The objective function in (4.1) shows that the total electricity cost J should be minimized. DyP is the Dynamic price of electrical energy during that time interval t. P^{Use} represents the energy needed to operate a household appliance between the time interval t. The total duration of the time horizon considered is T. P^{Gen} represents the amount of energy generated by local renewable resources in the time interval. In case if the energy utilized by the residential building is less than that of the energy produced by renewable energy the cost function J will be negative, assuming the DyP will be considered as the selling price.
Considering each time interval is 1 hour in length, Now the future horizon is considered for 24 time intervals, which is a day-ahead of scheduling. During the beginning of each time interval, the model runs for 24 iterations to obtain an optimum schedule for 24 hours, but only the decision made for the first time interval is considered for actuation. The Same procedure repeats every hour. During the next iteration, updated Weather forecast, new Dynamic electricity price and new customer preference, if any, are considered as shown in the flow chart 4.2

Apart from the objective function, there are multiple constraints that are to be considered while generating a schedule. The overall power utilized cannot exceed the peak power capacity. The storage of the produced energy in Home energy storage has to be considered, also the discharge of the stored energy. The State of Charge (SoC) of all battery operated appliances in the smart home environment shall be considered for schedule based on usage behavior.
The constraints of the system are formulated as follows:

[4]https://open-power-system-data.org/

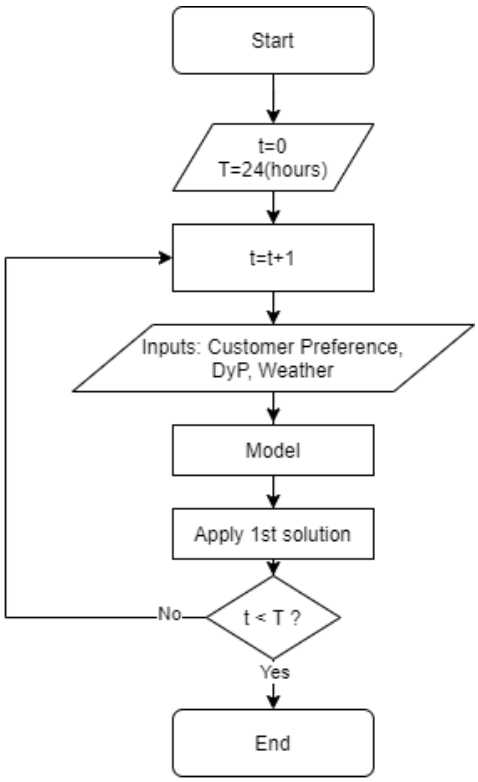

Figure 4.2: Process of MPC based Home Energy Management System [2]

•Power balance constraint (4.2). The generated and consumed power should always be balanced.

$$\sum_t (\Sigma P^{Gen}(t) - \Sigma P^{Use}(t) + P^{Grid}(t) = 0) \tag{4.2}$$

•Demand side power requirement (4.3). The $P^{StaticLoad}$ indicates the power requirement of all static non-schedulable electrical load during the time interval t. This is obtained from historic power consumption data. The $P^{DynamicLoad}$ is the amount of power required to operate a particular dynamic schedulable load.

$$\sum_t (P^{Use}(t) = P^{StaticLoad}(t) + \Sigma P^{DynamicLoad}(t)) \tag{4.3}$$

The objective function (4.1) along with constraints (4.2), (4.3) and the constraints for each controllable device's start, stop and status forms a mixed integer linear program for optimization. All t shown here are the time intervals within the prediction_horizon of the MPC controller.

5 Methodology

The methodology used to test the performance of Demand Side Management (DSM) using Model Predictive Control (MPC) in this thesis work is discussed in this chapter. Firstly the complete system is simulated to verify the working, later whatever practical smart home devices available were connected to the simulator acting like a hardware-in-the-loop setup.

5.1 Simulation

The simulation is written in Python since many of the required API and supporting libraries were readily available.

5.1.1 Modules of the simulator

Below are the modules of the simulator and description of each module:
• **db** - InfluxDB, time series database running on a docker instance.
• **gui** - Grafana, an open source data visualization tool running on a docker instance.
• **generation** - Local solar and wind energy generation is calculated based on weather and location data
• **load** - The electric loads of appliances and power required are calculated based on usage data.
• **optimizer** - The MPC and scheduler implementation. Calculates optimized schedule for the electric appliances in residential building
• **price** - The Dynamic-Price is fetched from Entso-e using API over the internet.
• **weather** - The weather forecast is fetched from weatherbit.io using API over the internet.

A description of the above modules are presented in following section of this chapter.

Table 5.1: Tables in Database

Type of data	DB table name	Stored measurements
Weather	weather	temperature, relative humidity, wind direction, wind speed, pressure
Day-ahead Price	day_ahead_price	Day-ahead price[EUR/MWh]
Solar Power forecast	solar_forecast	Forecasted Solar Power generation [kWh]
Wind Power forecast	wind_forecast	Forecasted Wind Power generation [kWh]
Forecasted power usage	power_usage	Forecasted power usage [kWh]
Saved energy	energy_saved	Energy saved using model [kWh]
Saved costs	cost_saved	Cost saved per hour [EUR]

Database (DB):

The Database is prepared to hold time series data of multiple entities. Above table shows the different tables created in the database. The influxDB serves a HTTP service in port '8686'. All the other entities of the simulator can communicate to the DB using this port.

GUI:

An instance of Grafana runs on docker to serve as GUI. It serves a HTTP based web interface in port '3000' to plot all the data stored in InfluxDB. Different dashboards can be created to keep track of a similar set of data on same page. A sample dashboard is shown in Fig 5.1

Figure 5.1: A sample screen shot of Grafana interactive Dashboard

Price:

The Day-ahead price from Entso-e is fetched using API and stored in DB periodically. This service is written in python. The price will be in EUR/MWh format. The history day-ahead price data from Smard.de is directly loaded into the DB initially.

Algorithm 5.1 Dynamic Price

```
Input: Day-ahead price from internet
procedure PRICE
    for Periodic_Interval do
        Fetch Day-ahead price from Entso-e and store in DB as day_ahead_price.
    end for
```

Weather:

The Weather forecast is fetched from weatherbit.io using API and stored in DB periodically. This service is written in python. The historic weather data for Stuttgart location from METEOSTAT is loaded into DB initially.

Algorithm 5.2 Weather forecast

```
Input: Weather forecast from internet
procedure WEATHER_FORECAST(
    for ) doPeriodic_Interval
        Fetch weather forecast for configured location from weatherbit.io and store
    in DB.
    end for
```

Generation:

The renewable electrical energy generators of the residential building are simulated by this python service. In the case of this thesis work, the solar and wind energy generators are considered. The total solar power generated by a panel for a particular duration of time is calculated based on the location from configuration and weather conditions from DB. Similarly, the energy produced by the wind turbine is calculated based on configuration and weather conditions.
The power generated by Solar panel is given by $P(t) = A.\eta.PR(t).S(t)$. Where A is Surface area of the solar panel, η is the Power coefficient. $PR(t)$ is Performance ratio and $S(t)$ is Solar irradiance at time t.[18]

The power generated by the Wind turbine is given by $P(t) = \frac{1}{2}.\rho.AU(t)^3C_p$. Where ρ is Air density, A is motor swept area, $U(t)$ is Wind Speed and C_p is aerodynamic efficiency of the rotor.[14]

Algorithm 5.3 Renewable energy generation

Input: Weather forecast from DB
Output: Forecasted Solar and Wind power

```
procedure SOLAR_FORECAST
    for Periodic_Interval do
        Fetch forecasted temperature from DB.
        Calculate forecasted power production of solar panel.
    end for
    procedure WIND_FORECAST
        for Periodic_Interval do
            Fetch forecasted wind_speed,pressure and temperature from DB.
            Calculate forecasted power production of wind turbine
        end for
```

Load:

The electric loads of the residential building are modeled in this module. The power needed for operating the load, the current state of the load, the preferred time window to operate the load is all considered. If the load has an energy storage facility, like an internal battery, then the State of Charge (SoC) is also considered during scheduling. The attributes of the controllable demand side appliances are shown in table below.

Table 5.2: Controllable Demand Model Parameters

Attribute	Detail	Unit
EST	Earliest Start Time	h
LET	Latest End Time	h
LOT	Length of Operation time	h
E	Power	W

Optimizer:

Based on the objective function, variables and constraints from eq.(4.1) to (4.1) and model of the load as shown in above section forms a mixed integer linear programming model, which is solved using GUROBI optimizer [17] in Python. The model is iterated through the prediction horizon to optimize the overall price paid for the electricity.

Algorithm 5.4 MPC Controller

Input: MILP MPC model of residential building
Output: Optimized schedule for smart home

```
procedure SCHEDULE OPTIMIZER
    Initialize input parameters - DyP, solar_forecast, wind_forecast from DB
    Read Dynamic_Load plan
    for Intervals in Prediction_Horizon do
        Solve the MILP MPC model and find optimized schedule for Prediction_Horizon
    end for
    Deploy the schedule of first Interval
```

5.2 Physical Implementation

IoT Gateway:

A Raspberry Pi 3B+ (RPi), compact single-board computer, is used to run the software for acting as a bridge between the Home Energy Management System (HEMS) and Smart home devices. The RPi runs on Raspbian, a Linux based light-weight operating system. The RPi runs multiple applications to perform the function of a gateway. A plugwise python utility and Plugwise USB Zigbee stick is connected to RPi to enable control of the smart home devices. A http based web server runs on RPi for the HEMS to actuate the appliances and also to collect the power consumption data over the network. The RPi is connected to the same network in which the HEMS system runs. The hardware setup of RPi is shown in Fig 5.2

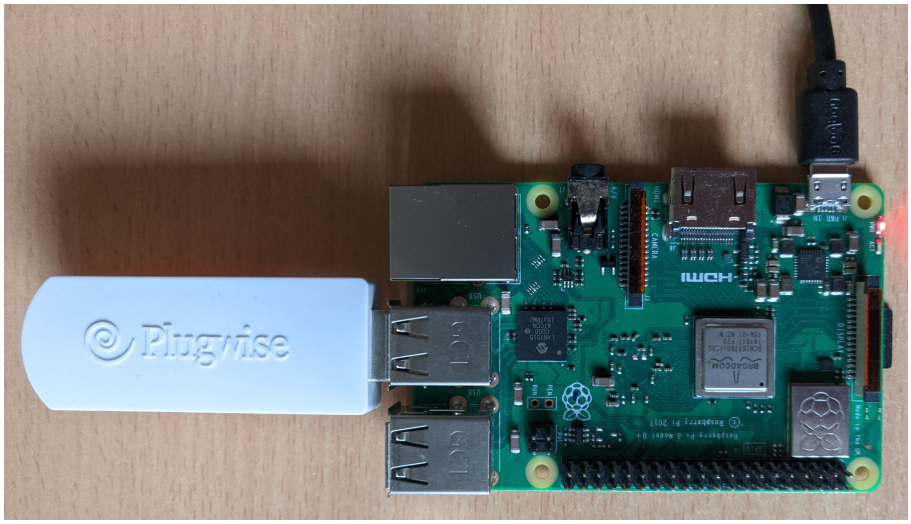

Figure 5.2: Raspberry Pi along with Plugwise USB stick connected to it

Smart Plugs:

For practical data collection, a smart home environment was created with the help of Plugwise devices [1]. Plugwise plug is a Zigbee based smart plug. It can create a mesh network among all the plugs and can be controlled using a Plugwise USB Zigbee stick. Unlike other smart plugs which only switch the state of the connected devices, Plugwise plugs have additional functionality such as measuring real-time power consumption and historic power consumption of the connected device. The plugwise hardware deployed in a home environment connected to appliances can is shown in Fig 5.3

[1] https://www.plugwise.com

Figure 5.3: Two Plugwise Circle smart plugs placed between power socket and load

6 Evaluation

This chapter discusses the evaluation study of the approach of using MPC in DSM as discussed in chapters 4 and 5. We start with a brief of how the simulation is setup and then discuss the results obtained.

Setup:

The program is run in two modes
•**Mode 1** - Simple DSM
In Mode 1, the MILP model eq.(4.1) of the system is optimized once per day at mid night. The optimized schedule is applied on the controllable loads to measure the overall power consumption, amount of energy exchanged bi-directional with the grid and the amount of money to be paid or received from the operator is measured.

•**Mode 2** - MPC based DSM In Mode 2, the MILP model is iteratively optimized for the complete prediction horizon (24 hours) and the control is applied only for the control horizon (1 hour in this case). The sampling time is also set to 1 hour, i.e. the program is run every one hour and a new schedule is generated based on latest changes in variables like weather forecast and dynamic-price changes. The power consumed by all devices, including power exchange with grid and payment are measured and accumulated in each time step.

The Database of the system is first loaded with historic data of weather and Day-ahead prices. Past values of power usage by non-controllable devices are used to initialize the model. The controllable demand side appliance model is initialized with a preference schedule, for example, as shown below.

Table 6.1: Controllable Demand Model Parameters Initialization

Device	Device code	EST(h)	LET(h)	E(W)	LOT(h)
Washing Machine	WM	9	17	2	2
Dish Washer	DW	9	18	1.5	2
Electric Vehicle	EV	1	9	2.5	5
Vaccum Cleaner	VC	9	18	0.5	1
Electric Lawn Mower	LM	0	10	0.5	1
Laptop	LP	9	18	0.1	7

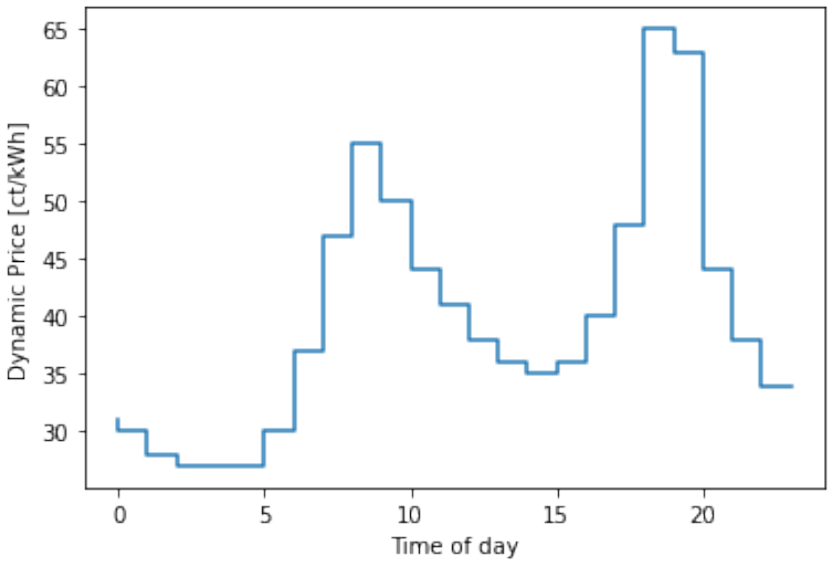

Figure 6.1: Day-ahead price of the day in simulation

The dynamic price shown in 6.1 is given as input to the simulator. The wholesale market price in German Electricity market is considered as such, the overhead of taxes and costs associated with the retail price is not considered as part of this work. Also the predicted wind and solar power generation for the day is shown in 6.2. An assumption here is that a Solar panel of 7kW capacity and a wind turbine of 5kW is capacity is considered for the simulation purpose. The energy forecast is based on the weather and model of the generators.

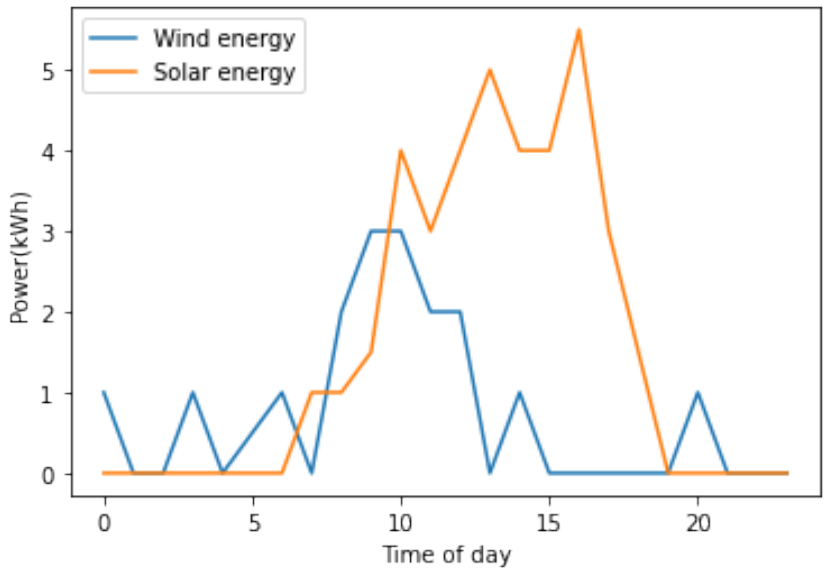

Figure 6.2: Forecasted Solar and Wind energy for the day in simulation

Simulation outcome:

•**Mode 1:** While executing the simulation in **Mode 1**, the schedule shown in 6.3 was generated by solving the equation once.

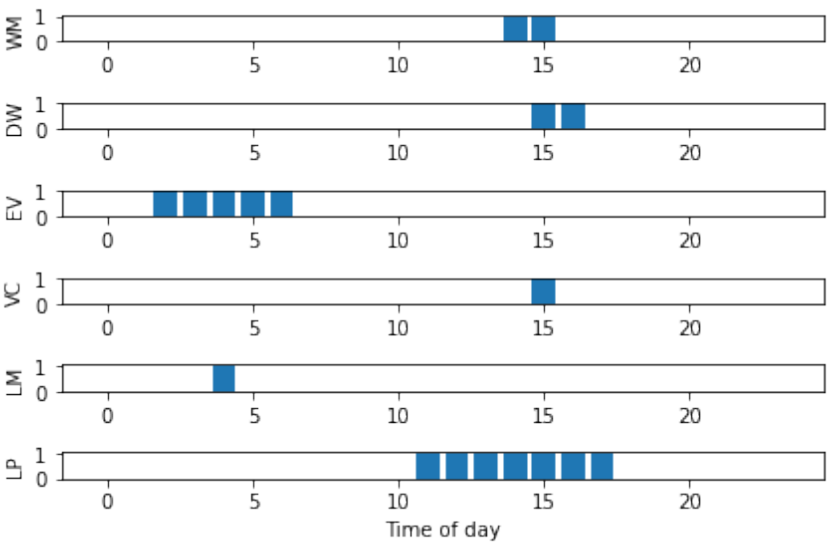

Figure 6.3: Schedule for the controllable load in Mode 1

The amount of energy exchanged with grid during this day is shown in 6.4. Positive value represents the energy purchased from the grid, the negative value represents the energy sold to the grid.

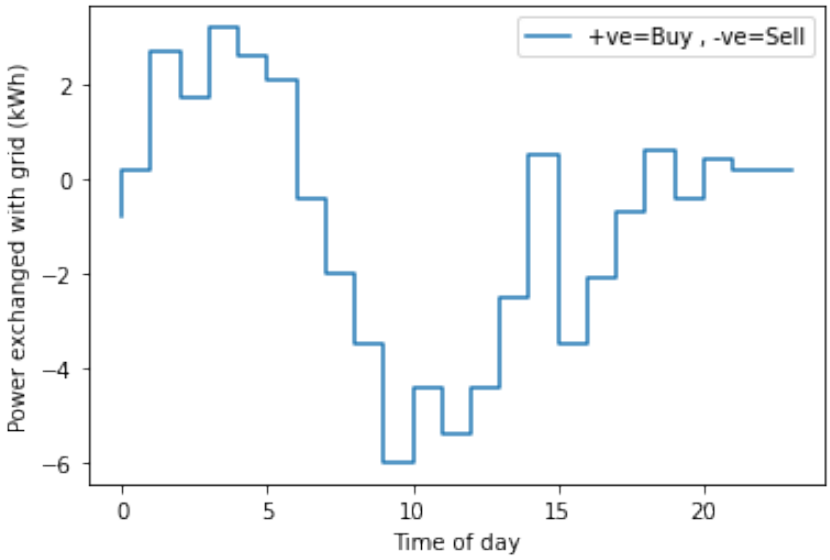

Figure 6.4: Energy exchanged with grid in Mode 1

By following this schedule and measuring the economic performance shows a profit of **EUR 11.315** for the consumer on the simulation day.

•**Mode 2:** While executing the simulator in **Mode 2** the schedule shown in 6.5 was generated. This type of control generated a profit of **EUR 15.048** to the consumer on the day of simulation.

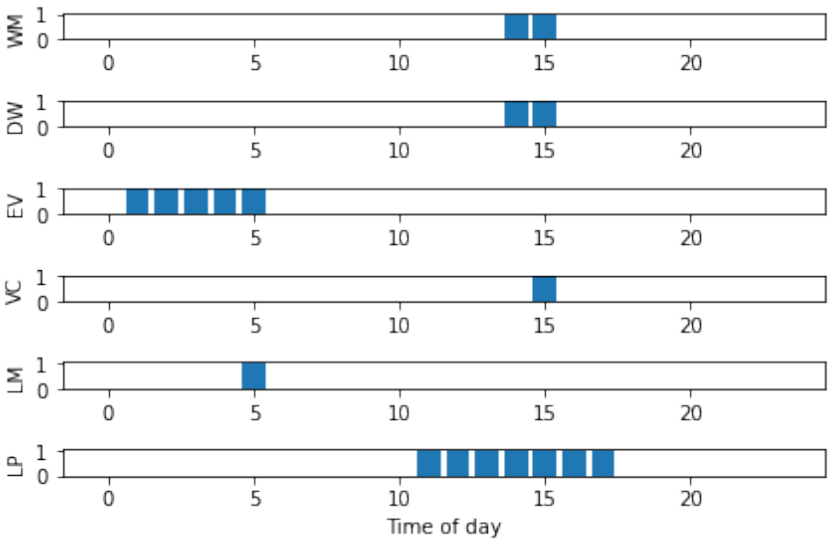

Figure 6.5: Schedule for the controllable load in Mode 2

The energy exchange with grid is shown in 6.6. Even though the schedule during the first iteration of Mode 2 was looking identical to 6.3 of Mode 1. After the all the iteration through prediction horizon was over, the energy exchange graph placement of schedule was different, and the use of updated forecast information in Mode 2 add an advantage of financial benefit.

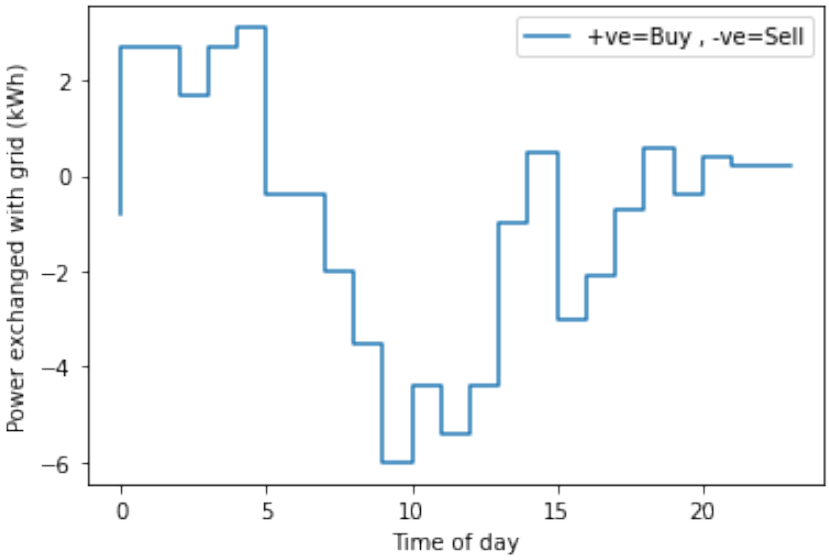

Figure 6.6: Energy exchanged with grid in Mode 2

Although this simulation considers only a short time duration of measurements and schedule, there is a significant difference in profit number. So by employing this approach for a significant amount of time on the system, the expected profit is higher than using a simple demand side management or not using one at all. The physical implementation setup was linked to the simulation via http protocol over the Local Area Network to control and measure the state of real world residential appliances.

7 Conclusion and Future works

7.1 Summary

In this thesis work, we studied the economic feasibility of using MPC on DSM. To achieve it, we modeled a residential building's electrical load into a mixed integer linear program. After that, we designed a simulation framework for testing the feasibility of solving and obtaining an optimized solution to it. The economic benefits calculated from this thesis work were from the model which takes dynamic price signals from German energy market and has real-time load information. Also to compare the MPC model's performance with other techniques of DSM, we designed another simple DSM program. Most of the profit estimated from this work is based on the excess renewable energy generated and sold to the grid when not used by the loads in the household. This also reassured that deploying renewable energy generators at a residential level not only reduces the risk of pollution by other sources of energy but also provides an economic benefit in the long term.

7.2 Limitations

The concentration of the work happened to be only on the electrical energy system and other sources of energy like thermal and gas were not considered during the modeling. Although the simulation has most of the real-world data considered during the work, the approach has to be implemented on a wide variety of actual home energy management systems, like in different areas of rural and urban households to validate the scheduling feasibility. Also, MPC is computationally complex compared to other type of control techniques.

7.3 Future Works

The present work can be improved by implementing techniques like Explicit MPC for DSM, so the computation complexity can be reduced and the necessity for powerful hardware can be avoided. This enables possibilities of deploying the models in low powered devices which are already part of many smart home devices. Furthermore, deploying this model and getting user feedback can help to tune the model in the MPC Controller to be more realistic.

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I hereby declare that the work presented in this thesis is entirely my own and that I did not use any other sources and references than the listed ones. I have marked all direct or indirect statements from other sources contained therein as quotations. Neither this work nor significant parts of it were part of another examination procedure. I have not published this work in whole or in part before. The electronic copy is consistent with all submitted copies.

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