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GRADUATE SCHOOL

MASTER THESIS

A PREDICTIVE CONTROLLER FOR EFFICIENT OPERATIONS OF HVAC SYSTEMS IN COMMERCIAL BUILDINGS: ALGORITHM DEVELOPMENT AND FIELD APPLICATION

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ABSTRACT

A PREDICTIVE CONTROLLER FOR EFFICIENT OPERATION OF HVAC SYSTEMS IN COMMERCIAL BUILDINGS: ALGORITHM DEVELOPMENT AND FIELD APPLICATION.

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January 2022

The global warming and energy security issues require a change in the way we generate, transfer and utilize energy. Buildings are among the largest overall energy consumers. People spend most of their time in buildings and therefore proper management of buildings are crucial for comfort, health and productivity. In buildings, heating, ventilation and air conditioning (HVAC) systems account for, on average, 40% of the overall energy use. Thus, proper and effective operation of HVAC systems is very important for energy efficiency and thermal comfort. Addressing this problem by merely installing new sophisticated equipment may not be feasible due to economic and technical reasons. In this case, advanced control techniques should be utilized to better operate existing infrastructure.

In this thesis, a predictive control technique (MPC) to optimally operate an HVAC unit is developed, implemented and tested in real-world environment. The control algorithm is implemented in Python and integrated into the embedded system that controls the HVAC unit. The performance of the predictive controller is compared against a PID controller, which is a commonly preferred method in the industry. Test results show that the MPC controller presented in this thesis outperforms PID in terms of reference tracking and energy consumption.

keywords: building energy management, heating-ventilation-air-conditioning systems, model predictive control, PID control, energy efficiency, telemetry platform, internet of things

ÖZ

TİCARİ BİNALARDA HVAC SİSTEMLERİNİN VERİMLİ ÇALIŞMASI İÇİN ÖNGÖRÜLÜ BIR KONTROLÖR TASARLANMASI: ALGORİTMA GELİŞTIRME VE SAHA UYGULAMASI.

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Ocak 2022

Küresel ısınma ve enerji güvenliği konuları enerjiyi dönüştürme, iletme ve kullanma yöntemlerimizde değişiklik yapmayı zorunlu kılmaktadır. Binalar, genel enerji kullanımı açısından üst sıralardadır. İnsanlar zamanlarının çoğunu binaların içinde geçirmekte; bu sebeple, binaların doğru bir şekilde yönetilmesi konfor, sağlık ve üretkenlik açısından kritik önem taşımaktadır. Isıtma-havalandırma-iklimlendirme sistemlerinin yükü (HVAC) binalarda kullanılan enerjinin yaklaşık %40'ına tekabül etmektedir. Bu sebeple, HVAC sistemlerinin doğru ve etkili yönetimi enerji verimliliği ve ısıl konfor açısından büyük önem taşımaktadır. Daha yeni ve gelişmiş ekipmanların kurulumu ile bu konuda iyileştirme yapmak Teknik veya ekoomic sebeplerden ötürü her zaman mümkün olmayabilir. Bu surumda, gelişmiş control tekniklerinden yararlanarak mevcut altyapı daha iyi işletilmelidir.

Bu tezde, bir HVAC sisteminin en iyi şekilde işletilmesi için öngörülü bir kontrol (MPC) tekniği geliştirilmiş, sahada uygulanmış ve test edilmiştir. Geliştirilen kontrol algoritması Python dilinde yazılarak sahada HVAC kontrolünü sağlayan gömülü sistem kartına entegre edilmiştir. Bu öngörülü kontrolörün performansı endüstride yaygın olarak kullanılan PID kontrolör ile karşılaştırmalı olarak test edilmiştir. Test sonuçları, MPC kontrolörün referans sıcaklık takibi ve enerji tüketimi açılarından PID kontrolöre göre üstün olduğunu göstermektedir.

Anahtar Kelimeler: bina enerji yönetimi, ısıtma-havalandırma-iklimlendirme sistemleri, model öngörülü kontrol, PID kontrol, enerji verimliliği, telemetri platformu, nesnelerin interneti

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Ali Selek

İzmir, 2022

TEXT OF OATH

I declare and honestly confirm that my study, titled " A PREDICTIVE CONTROLLER FOR EFFICIENT OPERATION OF HVAC SYSTEMS IN COMMERCIAL BUILDINGS: ALGORITHM DEVELOPMENT AND FIELD APPLICATION." and presented as a Master's Thesis, has been written without applying to any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.

Ali Selek

January 12, 2022

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SYMBOLS AND ABBREVIATIONS

HVAC	Heating, Ventilation and Air Conditioning
SP	Set Point
PV	Process Variable
MPC	Model Predictive Control
PID	Proportional Integral Derivative
BEMS	Building Energy Management System
NZEB	Nearly Zero Energy Buildings
BAS	Building Automation Systems
EMCS	Energy Management Control Systems
IoT	Internet of Things
VRV	Variable Refrigerant Volume
MQTT	Message Queuing Telemetry Transport Technical
IP	Internet Protocol
JSON	JavaScript Object Notation
GSM	Global System for Mobile
HTTP	Hypertext Transfer Protocol
MODBUS	Modicon Communication Bus
TCP	Transmission Control Protocol

CHAPTER 1
INTRODUCTION

Energy consumption is a significant issue in our time because of the leakage of fossil fuel energy sources and the ecological consequences of associated energy pollutants. In Europe, total energy consumption is increasing by 1.5% per year due to various factors such as economic growth, expansion of the construction sector and expansion of building services. As a direct result of this, the scientific community worldwide is making many efforts to improve the overall energy efficiency of human activities. In particular, European energy consumption presents the following energy breakdown: 34.6% in transport, 24.6% in household management, 27.9% in industry and 14.9% in commercial and others (Boyano et al., 2013). To summarize, these statistics show how both residential and commercial buildings account for around 40% of total energy consumption. Given these numbers, it's not surprising that academic and industrial research groups are working to achieve energy-saving improvements for buildings. The focus is placed on heating, ventilation, and air conditioning systems, i.e. the set of equipment that conditions and distributes a building's indoor air and is dedicated to maintaining its quality. In this texture, it is worth knowing that HVAC systems account for 50% of the energy consumption of buildings and about 20% of the total consumption.

It is also well known that HVAC systems use more energy than expected or desired, and potential energy savings are estimated to be between 5% and 30% (Chua et al., 2013). Because of this need, the concept of smart building is becoming more common today. The current trend is to equip buildings with tools and sensors that collect data that is then used by complex control techniques to improve energetic performances while maintaining comfort levels. Control algorithms have received much attention in recent years, especially for the control of buildings (Sturzenegger et al., 2016).

The Independent Statistics & Analysis of the U.S. Energy Information Administration in 2015 found that offices utilize approximately one-fifth of all commercial buildings' energy deliveries, making them a prime target for energy efficiency upgrades. It is estimated that commissioning an existing building may save 15 percent of the building's energy usage (Wall et al., 2008). The Building Energy Management System (BEMS) is responsible for lowering energy usage while maintaining user comfort. The creation of appropriate energy-efficient methods and their integration for interfacing with BEMS are now separated by a lack of methodologies. According to Aune et al. (2009), there is already a gap between sensor deployment infrastructure and facility managers' actual actuations in this context.

In office buildings, energy demand varies greatly depending on the time of day and week, which has a significant impact on energy usage. It follows that automating optimization methods that dynamically adjust the HVAC operating mode to the interior and outside circumstances is important in order to optimize energy savings in an office building's domain. Another essential human component in maintaining energy efficiency is the building's facilities manager. This person should monitor the BEMS at certain times to ensure energy efficiency.

A smart city uses technology to improve humanity by achieving the targets of every single human that contributes to society, such as government, inhabitants, and economy. Energy is the lifeblood of a city, and energy conservation is a global priority. Alternative energy sources, greenhouse gas emissions reduction, and the use of Internet of Things technologies to monitor and regulate energy performance are all crucial. Suppose that the smart city and energy efficiency targets are to be achieved. In that case, it is necessary to develop new smart buildings and convert existing structures to Energy Efficient Buildings and increase the reliability of Performance Certificates.

All energy certificates should ensure the performance of established or upgraded technical building systems, that all critical parameters are used to calculate energy consumption, and that all strict emission criteria are validated. The application of IoT technology to building certification and compliance audits may enhance evaluations. (Metallidou et al., 2020).

With this thesis, it is aimed to explain the optimum energy efficiency control of the HVAC system. PID and MPC methods are used to achieve this goal. The automation of these optimization methods integrated with BEMS was implemented in a real office building in Izmir, Turkey, and it was aimed to prove the energy saving possibilities. In order to perform the simulations, certain interior features of the office building in Izmir were taken into account in accordance with the Royal Decree 1826/2009 (Manjarres et al., 2017). In a nutshell, it states, among other things, that temperatures between 21 and 26 degrees Celsius (degrees Celsius) are preferred.

CHAPTER 2
LITERATURE REVIEW

There are many uncertainties in occupancy-building interactions, both internal and external, that make HVAC systems difficult to predict. Relevant research on topics such as distributed energy sources, building HVAC modeling, and building HVAC control utilizing MPC and PID in this thesis. Moreover, some studies underline that, in order to achieve a manipulated variable, MPC uses a process model, with the goal of optimizing an objective over time. Because it can foresee future occurrences and take control actions in response, MPC is a better alternative to PID systems (Iddio et al., 2020). MPC is named rolling or receding horizon because it takes initial measurements and then applies the first decision, refreshes the measurements, and solves the problem for the horizon again, which is why it is referred to as rolling or receding horizon. This procedure is repeated, and as a result, MPC switches from an open-loop to a feedback loop design and takes recent changes into account while solving the problem. (Bemporad, 2006). However, developing models that describe HVAC dynamics can be time consuming and require a lot of domain knowledge. Commercial buildings consume more than 35% of electricity in the United States. Around 15% of the electricity consumed in business buildings is for heating, ventilation, and air conditioning systems. HVAC systems are critical components of building HVAC systems because they deliver conditioned air from air handling units to individual rooms for heating and cooling the building's indoor temperature (Maasoumy et al., 2014). Several energy efficiency solutions can be used during the design phase; others can retrofit existing air conditioning systems. Still, others can be done with minimal modification to presently installed equipment. Several techniques are proposed (Al-Rabghi et al., 2004):

- Turning old HVAC programs into smart systems
- Cost-effective ways for dehumidifying the air.
- The establishment of conservation projects and initiatives.

The 1970s had seen a rise in popularity in adaptive control. The advancements in control theory over the last decade have resulted in a better understanding of adaptive control. Microelectronics' quick and innovative advancements have enabled the implementation of adaptive regulators cost-effectively (Åström, 1983). The field is currently undergoing rapid development at both the university and industrial levels. Using a feed-forward controller to account for meteorological uncertainty, (Wang & Ma, 2008) proposes an interior zone temperature prediction technique based on model predictive control. The authors, on the other hand, adopt a linear thermal model of in (Baldi et al., 2015; Ghiaus & Hazyuk, 2010), physics-based models were used to optimize HVAC system scheduling by reducing energy and thermal discomfort costs. Using model identification approaches, the authors of (Azuatalam et al., 2017) compare the outcomes of data-driven and physics-based A data-driven strategy leads to fewer prediction errors and model complexity, the study concludes. Liang et al. (2018) provides a detailed evaluation of HVAC system modeling alternatives. Due to major HVAC systems' non-linearity and time-variance features, tuning them is a difficult and time-consuming procedure. As a result, setting an HVAC system's PID controller to achieve optimal tracking control performance is a difficult challenge (Almabrok et al., 2018). A basic PID or ON/OFF control, which is common in older buildings, is inefficient due to the non-linear and complicated nature of HVAC systems (Zhou et al., 2017). Numerous researchers have improved the PID algorithm and provided innovative tuning rules since the well-known Ziegler-Nichols technique (Geng et al., 1993). The employment of supervisory (optimal) control methods in modern buildings equipped with building automation systems, on the other hand, can increase energy efficiency by optimizing energy usage while ensuring adequate interior thermal comfort (Amara et al., 2015). It has been shown that machine learning or optimization approaches may be used to both estimate and execute a building's demand response potential for regulated loads like HVAC and electric water heaters (Lazic et al., 2018; ATP et al., 1995; Kim et al., 2020).

Energy performance analysis tools are used to forecast an HVAC system's annual energy consumption. These tools execute (hourly or sub-hourly) simulations based on a system of equations that determine the thermal efficiency and techniques and with specified boundary conditions, operation strategy, and controls (Trčka et al., 2010). A comparison of simulated and actual heating demand and average interior temperature was made after their Algorithm was deployed in a real building. (Li et al., 2020). This is a broad framework used for much more than simple HVAC systems, so PID control is intended to be used to collect data for MPC and other approaches. (Han et al., 2018).

HVAC control has been a very active area of research and development, intending to optimize HVAC system functioning in cost savings, occupant thermal comfort, and indoor air quality. Numerous attempts in the control of building HVAC systems have often resulted in benefits at the local level (Wang et al., 2008). The advantages of MPC are shown to include the ease with which time depended restrictions could be calculated, such as adjusting the acceptable room temperature range based on occupancy or non-occupation and the use of weather and occupancy predictions. It proposes a stochastic MPC controller for dealing with uncertainty in weather forecasting (Oldewurtel et al., 2010). In this thesis, the effects of ambient sensors such as temperature are mainly examined. Also, there is a similar understanding with another research that decides which cooling system is more useful according to temperature, humidity, and various sensors with a control algorithm (Şahin et al., 2016).

The starting point in the creation of this thesis was to contribute to the literature by providing real-life applications of PID and MPC methods for HVAC management. The basis of the work carried out in line with this goal is the temperature set points that communicate with each other and collect information in an integrated manner. The MQTT approach is explained with communication between Matlab and a Linux device during the determination of temperature set points. According to the results for applications, it appears that is a convenient strategy for maintaining a suitable solution time.

CHAPTER 3
PROBLEMS AFFECTING ENERGY EFFICIENCY

3.1. Overview and General Efficiency Solutions

There is an increasing interest in creating solutions for low-energy buildings due to the growing concern about energy usage in buildings. By utilizing a two-level management framework, optimal HVAC system control tries to offer desired indoor comfort and atmosphere while using the least amount of energy. An actuator performs low-level local control of a single set point. For example, the supply air temperature from a coil. Adjusting the opening of a valve that provides cold water to the coil controls the coil. Surveillance control is a high-level control that aims to provide satisfactory indoor comfort and a healthy environment with the least amount of energy input or operating cost possible, while taking into account the constantly changing indoor and outdoor conditions as well as the characteristics of the HVAC system. Modern buildings with energy BAS and EMCS ensure that control for the HVAC system is adjusted to optimize set points and operating modes while maintaining the appropriate quality of the indoor environment at the lowest possible prices.

Recently, building commissioning and energy audits (Alajmi, 2012). Literature has reported on a large number of difficulties relating to energy. Every one of them come to same result: most buildings don't operate correctly and should be repaired (Balaras et al.., 2007). There are instruments for commissioning HVAC systems as well as techniques for assessing cost-benefit and the persistence of current building commissioning in the Annex 40 (IEA, 2004) and Annex 47 (Neumann et al., 2012) project study. As a result of these multinational research initiatives, commissioning approaches can be disseminated and used internationally. According to a recent research on commissioning (Castro et al., 2006), the majority of problems were observed in air handling systems, heating water plants, and chilled water plants during the commissioning process.

HVAC is an acronym for Heating, Ventilation, and Air Conditioning. Currently, the HVAC system is considered a component of the air conditioning system, which regulates the temperature, humidity in the air, outdoor air for ventilation, particle filtering, and air movement within a confined space. HVAC processes include the following:

- Heating – adding thermal energy to the air to maintain the zone's temperature
- Cooling - extracting heat energy from the air to keep the zone's temperature
- Humidifying – adding moisture into the air to preserve the area's humidity
- Dehumidifying – replacing moisture from the air to maintain the zone's humidity
- Ventilation – substituting outside air for inside air to keep the zone's air quality
- Cleaning – reduction of pollutants to preserve the area's air quality
- Air movement – the movement of air to keep the zone's temperature, humidity, and air quality

3.2. Factors Affecting Efficiency

Using a scale of 1 to 100, the U.S. Environmental Protection Agency's Energy Star program established an energy performance rating system as a way to measure a building's energy efficiency and evaluate its energy efficiency. In order to qualify for Energy Star certification, a score of 75 is necessary (Fuerst, 2009). Using the Energy Star Portfolio Manager APIs, City BES gets Energy Star scores for each selected building, visualizes the scores by color-coding 3D building forms, and filters the building stock based on the score. Buildings having an Energy Star score of less than a particular number, say 50, may be of interest to municipal authorities. Commercial and residential buildings' energy-related features are tracked by BPD, the biggest dataset of its kind in the United States. For the first time in the United States, it brings together and anonymizes data from federal, state, and municipal governments as well as utility providers and energy-saving initiatives. It is possible for City BES to benchmark building energy performance on a district basis by comparing the EUI distribution of chosen buildings with that of peer buildings in BPD.

Although humidity and latent heat play a crucial role in building temperature control, they are mostly ignored in present control models. The fundamental challenge in incorporating humidity and latent heat is that the factors that affect the building's temperature and humidity are a complex function of control orders that cannot be set independently. In some cases, the cooling coil is in one of three states: fully dry, entirely wet, or partially wet. Some are simple differential equations, while others are static models with a huge number of empirical relationships that change depending on coil geometry, setup, and manufacturer. Current rule-based controllers employ conservatively crafted rules that have been agreed at after decades of experience. In hot humid conditions, for example, a conventional rule is to keep the conditioned air set point around 12.8 ◦C (55 ◦F) (Klein et al., 2009). Even in worst-case scenarios, this lower number ensures that interior air is dry enough to keep humidity within recommended limits. The downside is that worst-case conditions rarely occur, resulting in higher energy cost.

Solar radiation alters the microclimate of modern urban development's surrounding land and has a substantial influence on the energy efficiency of high-rise structures. The intensity of solar radiation is affected by the atmosphere of a city. As much as 20% of solar radiation can be lost owing to turbidity in large industrial towns with densely built-up areas. During the summer, there is a 20-22 percent difference in direct solar radiation intensity among residential and industrial portions of the city. Near to any kind of large industrial companies, the intensity of direct sun radiation in a 3 km radius is waning and can approach 35-40 percent. Similar processes, along with a breach of the area's aerodynamic conditions, result in the formation of an urban heat island. It's a phenomenon in which the temperature in metropolitan regions is greater than in rural areas nearby. A controller that minimizes energy/cost without including moisture and latent heat in the problem formulation can have two potential problems. First, it can lead to poor moisture control. Second, because the objective function doesn't always account for the latent component of cooling, the energy usage projected by the controller may differ significantly from the actual energy use when the controller is utilized in practice.

CHAPTER 4
SMART HVAC MANAGEMENT

A new age of possibilities is opening up thanks to the Internet of Things, making it easier to work with partners and provide new goods. Other operational problems and adoption obstacles range from data exchange to data storage and security. Data gathering has no use if it cannot be used or interpreted by the end user. By enhancing system performance, manufacturers provide analytical algorithms for HVAC equipment to assist the operation and maintenance teams save time and money. For example, many systems provide reports on system performance that identify faults and provide solutions for them. These devices are equipped with failure analysis and system optimization logic that is built into their design from the ground up. They automatically detect the issue from the start, allowing maintenance downtime to be kept to a minimum. HVAC systems that function on a dynamic basis run more efficiently and consume less energy.

By monitoring, operating, and collecting data in real-time, experts and supervisors can make more certain diagnoses. Smart controllable devices provide remote monitoring and real-time alarms. You may monitor and gather data via an internet connection. Corrective measures may be taken anywhere and without the need to be in the building, thanks to real-time data. HVAC monitoring is particularly useful in hospitals and labs, where contamination risks are significant and exposure to contaminants must be minimized.

In order to monitor and enhance systems, IoT devices exchange information and analyze data. The information gathered may be used to automate, plan maintenance, and optimize a building's systems, among other things. In order to meet energy and efficiency targets, building managers and owners need more cost-effective and sophisticated solutions.

In the HVAC sector, IoT may be used to measure vibration, airflow, pollutants, the number of occupants, weather conditions, and other factors, among other things. Key stress indicators and remote analysis improve troubleshooting and preventative maintenance. The combination of smart HVAC and IoT enhances metering and feedback.

As a result, the system's functional needs are broken down into general functional requirements and system-specific requirements. There are basic needs for the system's functioning, and there are particular requirements for the individual business operations that will be supplied. Scalability, security and privacy are examples of non-functional needs.

- System should collect power usage and ambient condition data regularly, and communicate it to a centralized server.
- It's important that the server parses the information and sends the readings to a central database.
- The analytics engine should use the stored data to process it and produce reports, graphs, and charts from it.
- Clients should be able to see the produced graphs using a cross-platform mobile application.
- Users should be able to access different services based on their rights, such as reading reports, device status, remote control of devices, or bill payment.

According to the system's business operations, particular functional needs exist. To meet these requirements, six categories of business procedures have been identified: (Al-Ali et al., 2017).

- Analysis of Consumption for Monitoring
- Analysis of Asset Efficiency
- Analysis of the Root Causes
- Indicators of Predictive Performance
- The ability to control remote and local devices
- Utility for keeping track of your bills

They also show that the system is scalable and dependable, as well as safe and readily managed. It is also easy to install as well as remotely accessible. Elements like scalability, security, and privacy are significant non-functional aspects of the suggested systems.

A. In terms of scalability

A rapidly growing subject, Internet of Things (IoT) is thought to be made possible by scalability. A large number of linked devices or "things" must be supported, as well as a variety of users and application functionalities.

B. Securing the business

As a result, even a tiny mistake in the system might have serious consequences. It is possible for a system's design to cause catastrophic failures. Multiple safe web service calls using https must be established in order to ensure the protection of the connection between it is a system

C. Protecting the privacy

As a result of privacy, users or "things" might remain anonymous and unique. Since IoT requires that "things" or people's information not be disclosed, privacy is a major problem in the IoT world. Due to the fact that IoT objects may freely distribute data and communicate with one other, IoT objects also serve as part of a network of other "things." A network's interoperability is essential because it ensures that the various parts of the network can communicate with one another in a timely manner (Sarkar et al., 2014).

4.1. System Architecture

HVAC systems with the most efficient control actions for energy consumption and comfort over a certain period. These control operations are transmitted to the devices that operate the HVAC via a gateway that change the room temperature by the decisions made by the intelligent Algorithm. The pilot office room is shown in Figure 4.1.;

Figure 4. 1. Pilot office room

Additionally, the database server stores temperature and energy consumption readings. These measurements are displayed to the end-user through an IoT platform. Users can communicate with the control unit via the platform, selecting the ideal temperature range (Carli et al., 2020).

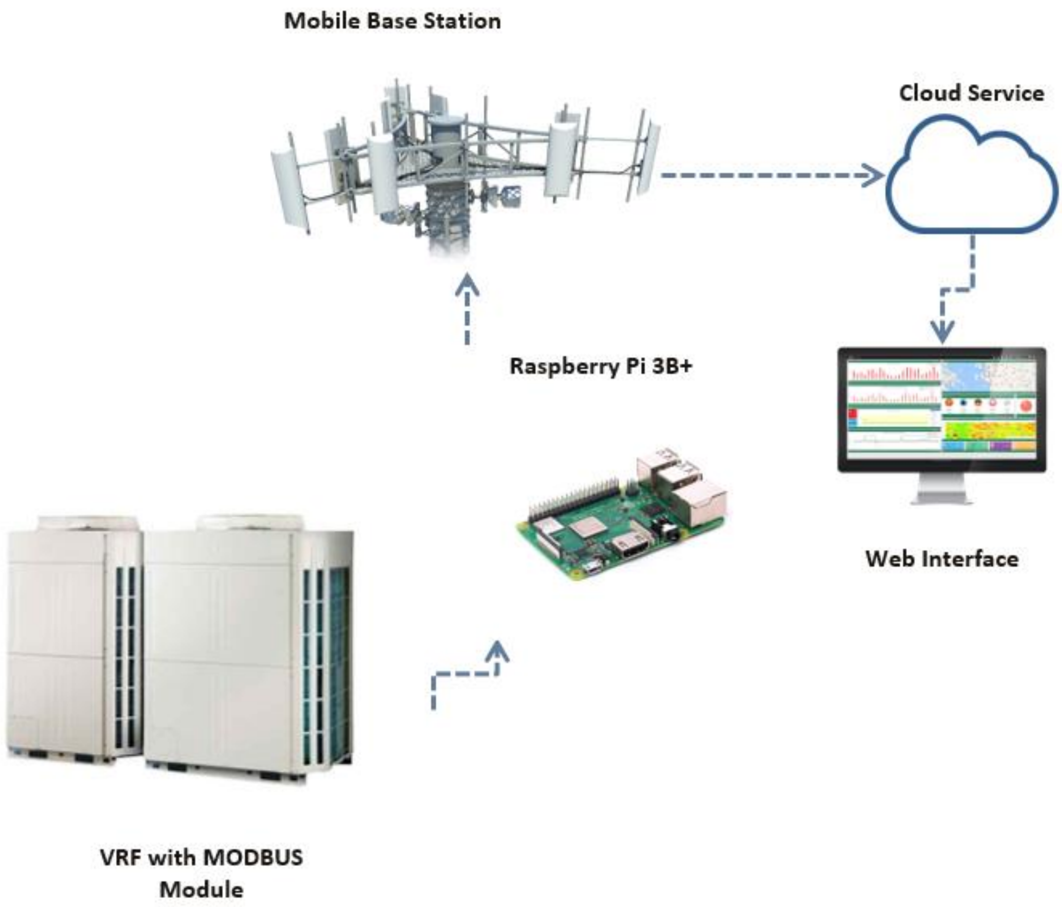

Figure 4. 2. System architecture

The Algorithm provides HVAC systems with the most efficient optimization decisions for electricity consumption and comfort over a certain period. These control actions are transmitted to the VRF system via a gateway. VRF module is communicating via RS-485 through the MODBUS just like the common PLC communication protocols which are RS-232, CAN-Bus and TTL UART (Kanmaz et al., 2018). Also, energy analyzer of the system is using the Modbus RTU protocol. Instant measurements from the AC unit are seen on the screen of the energy analyzer.

Figure 4. 3. Energy analyzer

The HVAC modules adjust the room temperature in accordance with the smart Algorithm's decisions. In addition, the database server saves temperature and energy usage measurements.

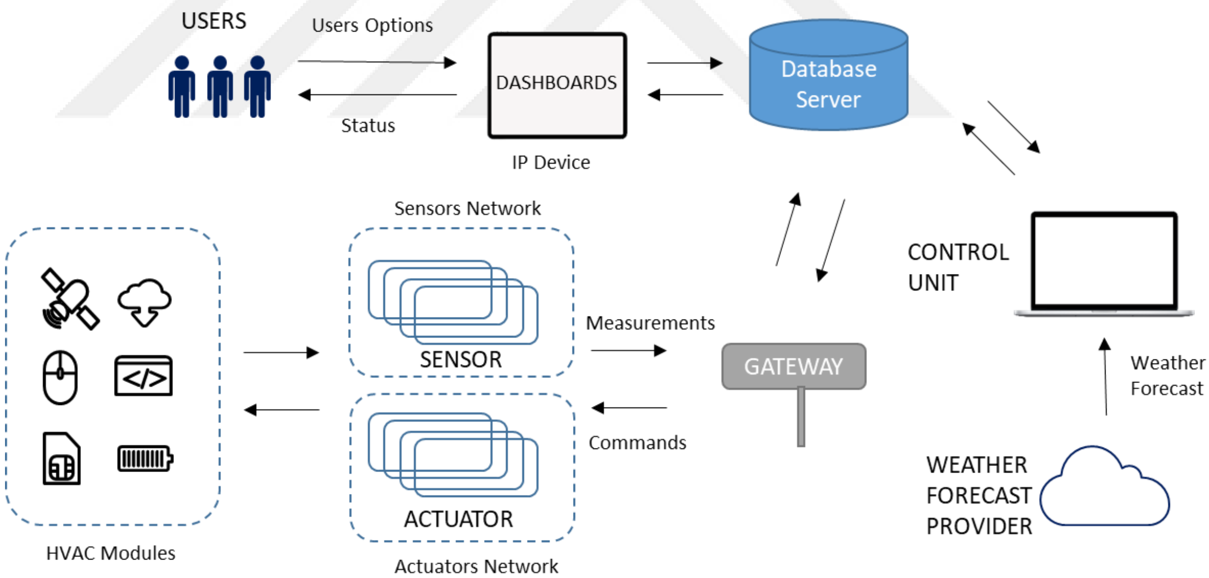

Figure 4. 4. Data flow diagram of the system

4.2. Software Architecture

A reference architecture for web platform is presented in this part. As shown in Figure 4.5, basically all data is collected from the gateway via the MQTT protocol. After that data is filtered as a JSON payload.

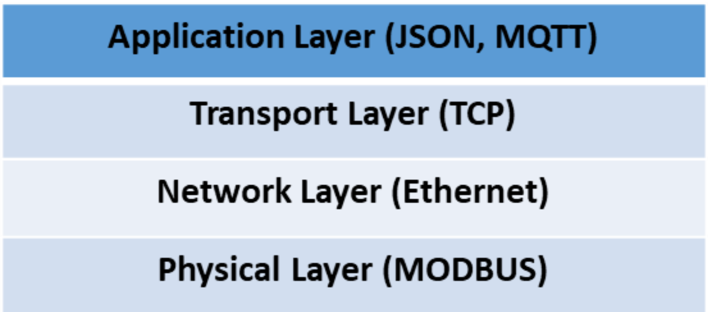

Figure 4. 5. Web platform layers

IoT Integration acts as an integration layer for various types of sensors and controllers as well as devices. In addition to receiving data from linked devices, it is also responsible for processing the received data, distributing it to web based applications, and controlling connected devices. For example, evaluating condition-action rules and sending commands to Thermostats.

Figure 4. 6. Thermostat web management widget

Device can connect directly with IoT Integration Middleware via IP over Ethernet or GSM, HTTP or MQTT. To interact with IoT Integration Middleware, Devices must use a Gateway. As an example, it might include a comparison charts like line or bar. It's also possible to manage the Devices and users and to aggregate and utilize the received data (Guth et al., 2017).

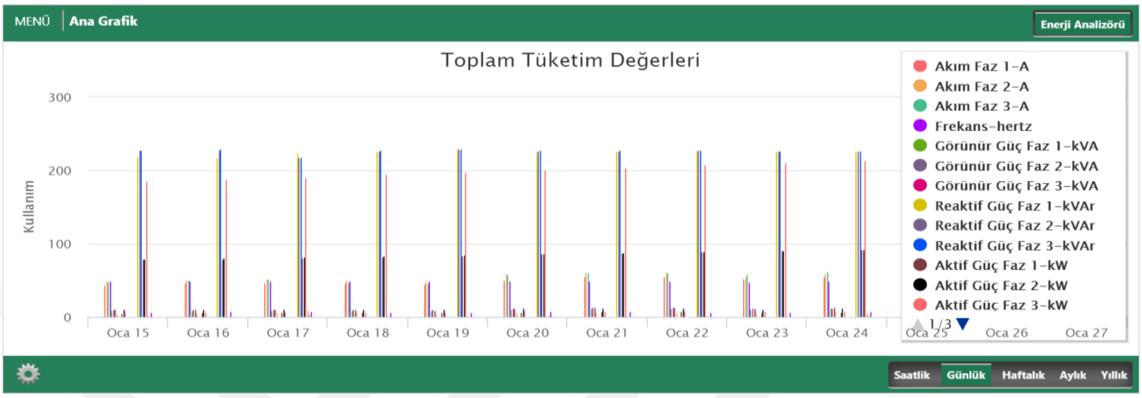

Figure 4. 7. Energy consumption trend of HVAC system

CHAPTER 5
METHODS AND APPLICATIONS

5.1. PID

Sensors are used to measure the variables in a process. To determine whether or not the measurement is in line with the set point value, a controller receives the sensor data signal. Process variables are continuously monitored with sensors to form the measured process variables. These values are evaluated by the PID controller and a set point value is created, thus ensuring stable operation of the system as shown in Figure 5. 1.

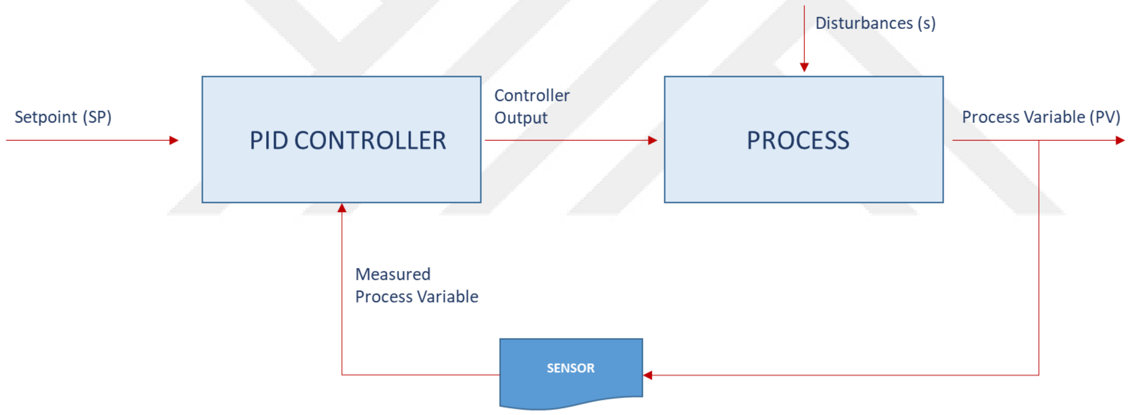

Figure 5. 1. PID control

Example for the PID control system, when a fan motor speed or water flow rate is changed, a controller tells the relevant equipment to take action. As new sensor measurements are received, the PID controller re-evaluates them, restarting the loop. In systems where the load changes often and the controller is required to adapt automatically owing to frequent changes in set point, energy available, or mass to be managed, PID controllers are suggested for precision and stability. For this reason, PID controllers are inappropriate for operations in which the measurement noise from sensors cannot be regulated. Automating HVAC systems with PID controllers has a variety of benefits. Temperature management in HVAC systems is dependent on a number of variables. Temperatures and pressures of cooling/heating fluids directly affect the system's ability to exchange heat. As an example, consider the following:

- Changing HVAC set point according to inside and outside temperature.
- Setting the maximum energy consumption according to energy efficiency target.
- Heating and cooling systems that use PID control are less prone to temperature fluctuations.

Within the scope of this study, a demo application area was created for the analysis of real data and the temperature set point control technique was used. Within the scope of this application area, an algorithm that can control the temperature according to the indoor and outdoor temperature has been developed, taking into account the Royal Decree No. 1826/2009 (Manjarres et al., 2017). In summary, it specifies, that temperatures between 21 and 26 degrees Celsius are preferred.

A PID controller is a mathematical expression that manages the Q(t) which is the controller's output. It is the difference between the setpoint and the process variable that is calculated. The controller gain and the controller reset time are all configurable parameters. A high gain or a small controller reset time results in a controller that rapidly reacts to a gap between the measured PV and desired SP. (Apmonitor, 2020)

$$\boldsymbol{e(t) = T_{SP} - T_{PV}} \tag{1}$$

In this study, the $\boldsymbol{Q_{bias}}$ was initially set to zero. It is assumed that the heater is turned off (2).

$$\boldsymbol{Q(t) = K_c e(t) + \frac{K_c}{\tau_I}\int_0^t e(t)dt - K_c \tau_D \frac{d(T_{PV})}{dt}} \tag{2}$$

The continuous integral is approximated as the total of the error multiplied by the sampling duration (3).

$$\boldsymbol{\frac{K_c}{\tau_I}\int_0^t e(t)dt \approx \frac{K_c}{\tau_I}\sum_{i=1}^{n_t} e_i(t)\Delta t} \tag{3}$$

The current slope is frequently determined by the difference between the present and former values of the PV (4).

$$\frac{d(T_{PV})}{dt} \approx \frac{T_{PV,n_t} - T_{PV,n_{t-1}}}{\Delta t} \tag{4}$$

The PID control equation is defined in discrete form (5).

$$Q(t) = K_c e(t) + \frac{K_c}{\tau_I} \sum_{i=1}^{n_t} e_i(t)\Delta t - K_c \tau_D \frac{T_{PV,n_t} - T_{PV,n_{t-1}}}{\Delta t} \tag{5}$$

PID parameters found with trial and error method as shown in Table 5.1. These parameters found according to the algorithm that explained below.

Table 5. 1. PID variables

Parameter	K_c	τ_I	τ_d
Value	8.111	182.5	7.191

If the heating level is between 0% and 15%, HVAC is working as used to as it seems in the below figure set temperature and present temperature variables are relatively close that's why HVAC set temperature does not increase by our controller working condition algorithm. As it seems from the Figure 5.2, according to the last 1-hour ambient temperature measurement, difference between set point and ambient temperature is less than 1 so that system did not change the set point of the HVAC system.

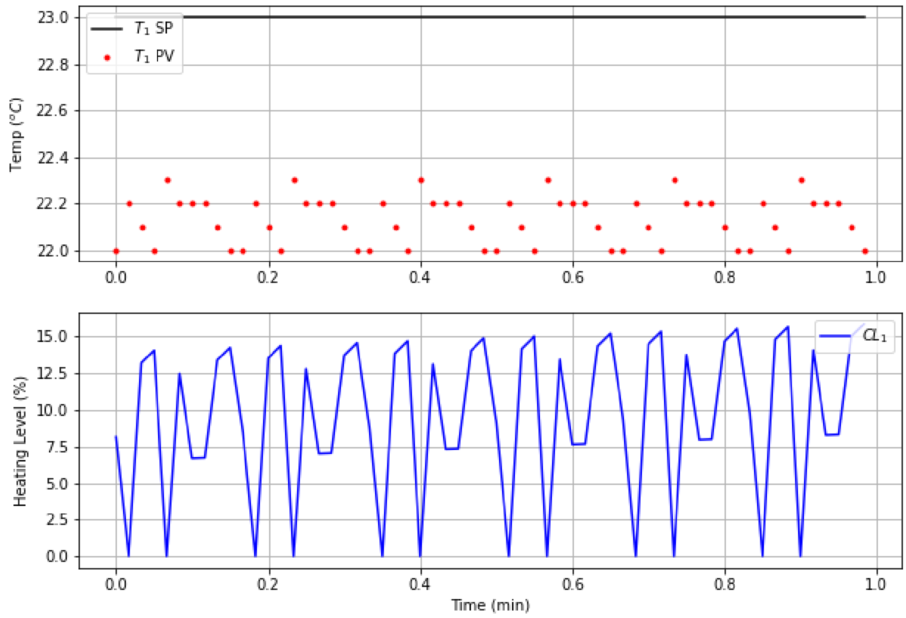

Figure 5. 2. PID control outputs for lower temperature differences

On the other hand, if the heating level is higher than the 15%, HVAC set temperature will be increased by the controller until the heating level will be below the 15%. As it seems from the Figure 5.3, according to the last 1-hour ambient temperature measurement, difference between set point and ambient temperature is much higher than 1 so that system increase the HVAC set point until the difference between ambient and set point is equal to 1.

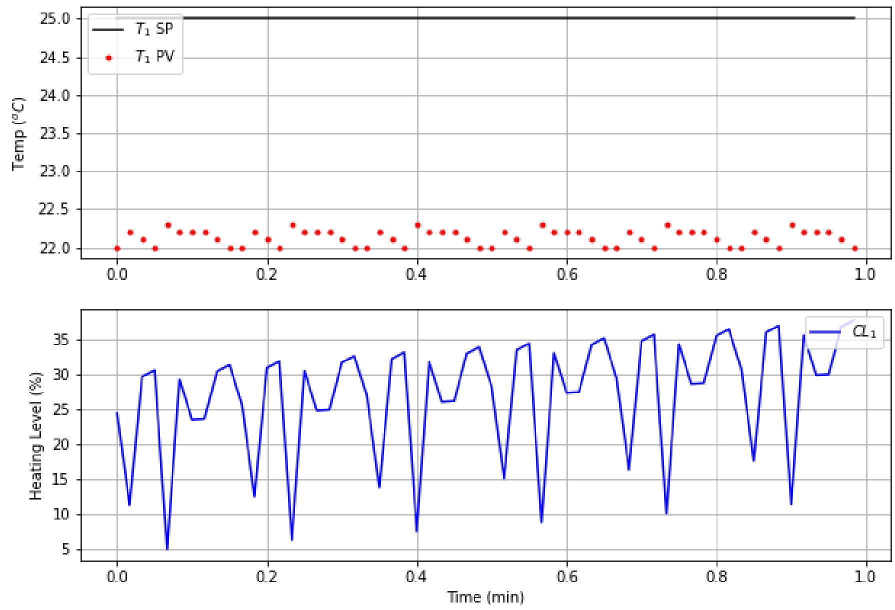

Figure 5. 3. PID control outputs for higher temperature differences

Mean absolute error and error analyses of the lower set point environment can be analyzed in Figure 5.4.

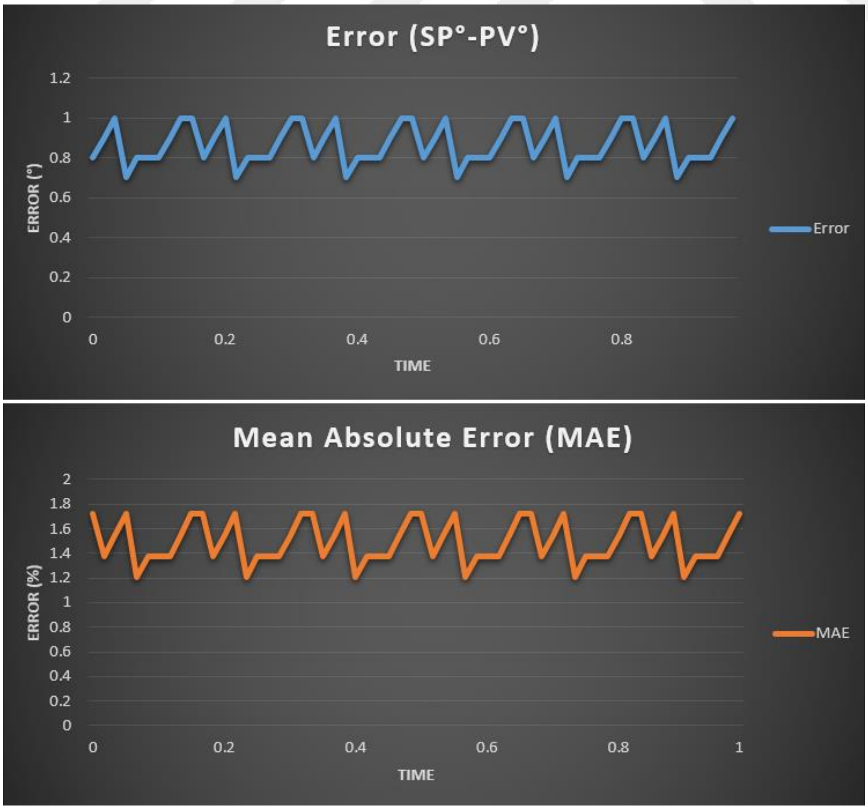

Figure 5. 4. PID control outputs for higher temperature differences

Mean absolute error and error analyses of the higher set point environment can be analyzed in Figure 5.5.

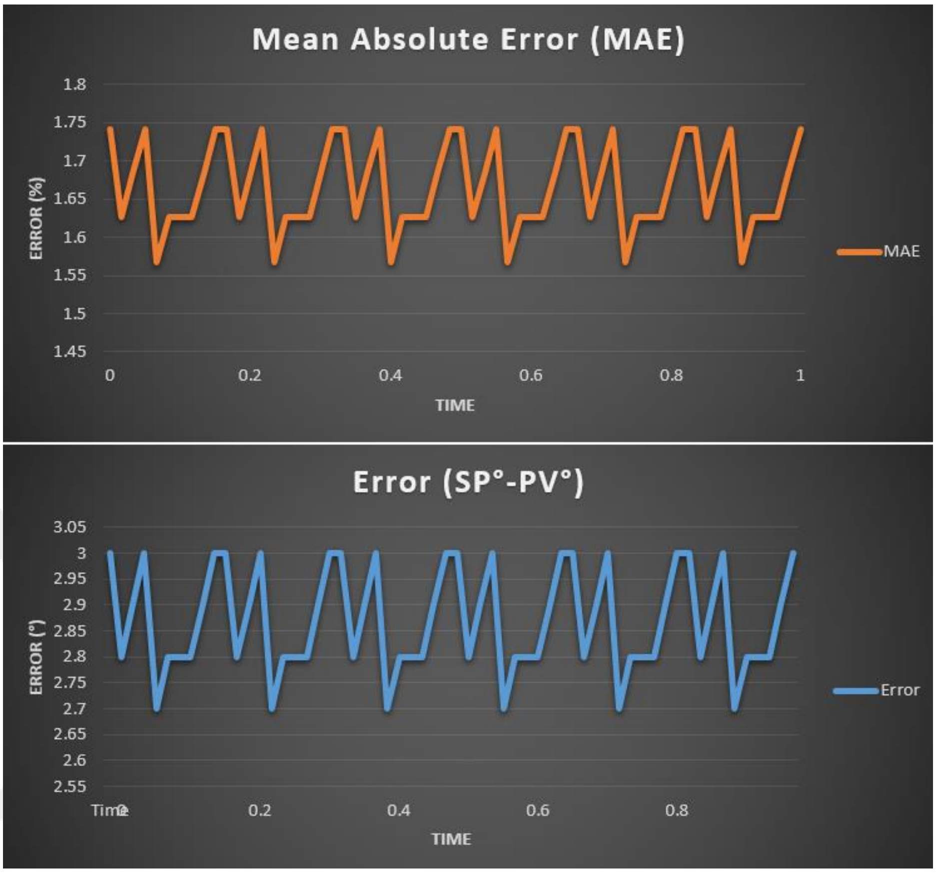

Figure 5. 5. PID control outputs for higher temperature differences

By looking at the result of the PID controlled system, PID results will be slightly different. Because, before day 1, system is uncontrolled and ambient temperature is controlled by human.

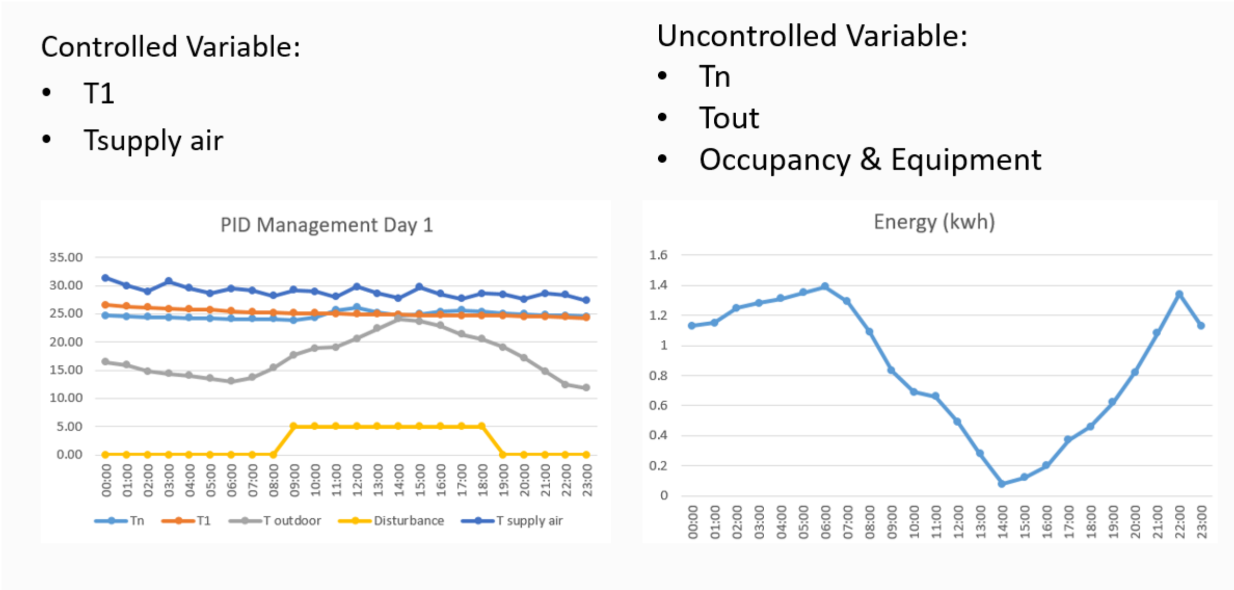

Figure 5. 6. PID controlled system day 1

On the other hand, in Figure 5.7, energy consumption is less than PID controlled day 1 in Figure 5.6. On day 2, ambient temperature is more stable, because it is controlled by the system automatically.

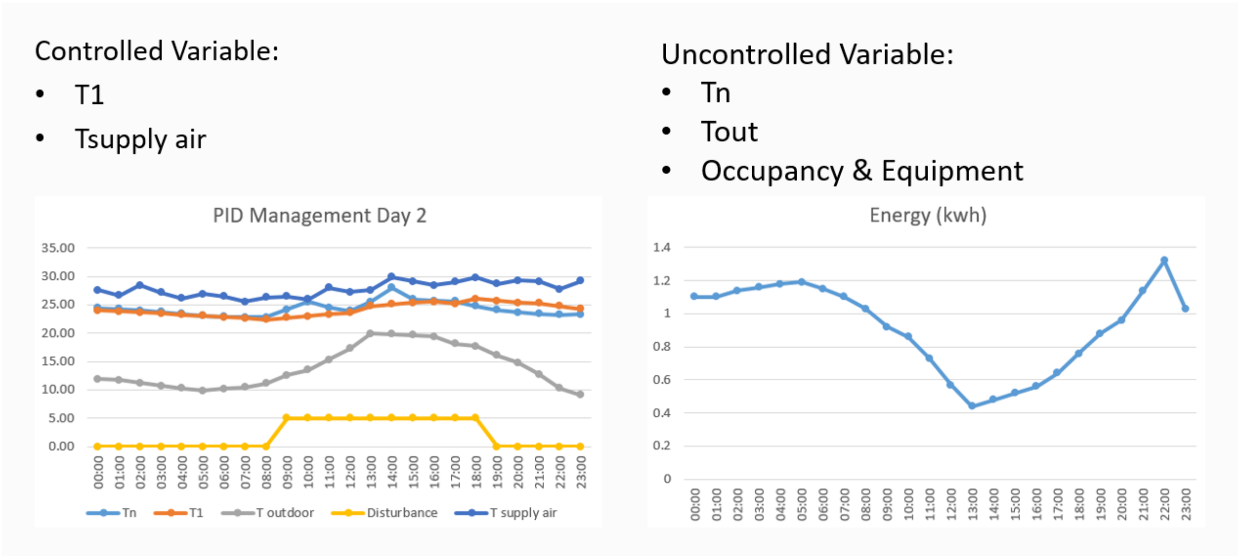

Figure 5. 7. PID controlled system day 2

5.2. MPC

MPC concept have gained widespread acceptance in industry and are being investigated in academics. This popularity is because MPC designs can result in high-performance control systems that can operate for extended periods without professional supervision. By definition, MPC integrates all components of decision-making process automation. Decision-making methods can be handled in stages as shown below; (García et al., 1989)

- Instrumentation: Gathering data from the process
- Control: This is often implemented in two layers: single-loop control via analog or rapid sampling digital controllers and real-time control using real-time computers.
- Optimization: It aims to achieve economic objectives for the plant. It is often applied at a rate that assumes the controlled plant is in stable condition.

As a result, the primary contrast between control and optimization is one of implementation frequency. These automation layers contribute something distinct and complementary to a system's ability to react fast to changes.

Numerous MPC typologies can be used when solving a building control problem, each with its prediction model. There are three main points that MPC system occur which are; Zone thermal model, predictive controller and the comfort model that can be seen in Figure 5.8. As a result, the optimization strategies used will vary according to the optimization problem's nature. The main purpose of the method called MPC tracking is to reach and closely follow a predefined reference trajectory for a controlled variable. The MPC problem might be linear or nonlinear, depending on the nature of the controlled system dynamics. Extending MPC to nonlinear situations is not straightforward because of the increased computing complexity, the dependability of nonlinear programming solvers, and the absence of general-purpose nonlinear systems identification approaches (Serale et al., 2018).

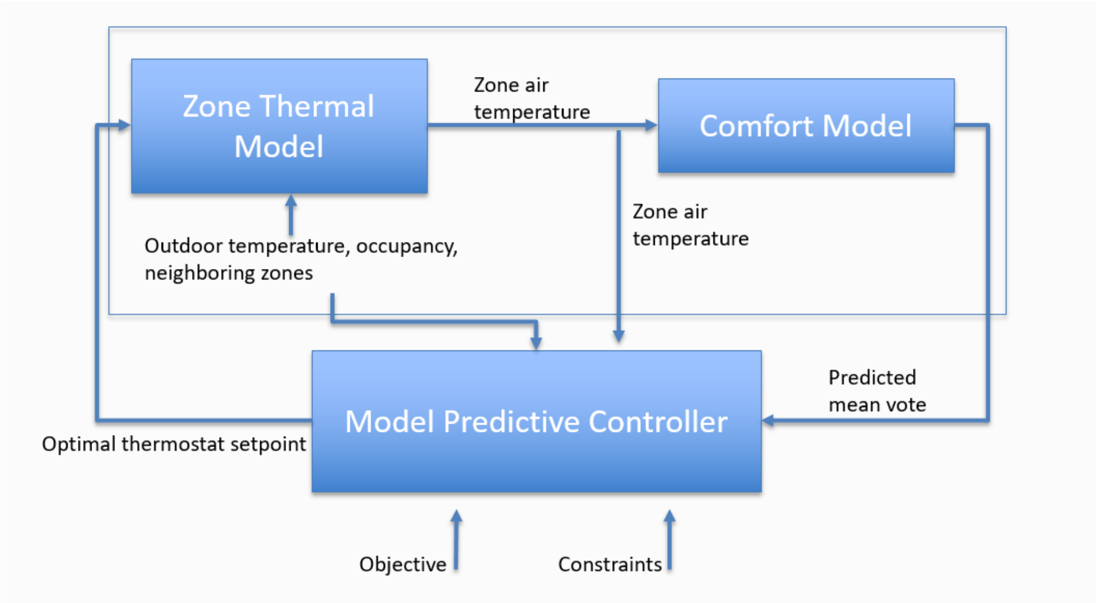

Figure 5. 8. MPC model

External and internal disturbances such as weather and tenant activities are also modeled, and their expected effects on the system are used to compute the control vectors. This work results in a durable controller to time-varying disturbances and system characteristics and firmly control the process within the specified constraints. MPCs are utilized in HVAC systems at both the administrative and operational levels of control. MPC also provides various chances for improving the energy efficiency of Heating, Ventilation, and Air Conditioning (HVAC) systems through its capacity to address restrictions, disruption prediction, and multiple conflicting objectives such as interior thermal comfort and building energy consumption.

The MPC predicts future states of the system using a system model and creates a control vector that minimizes a specified cost function over the prediction horizon in the presence of disturbances and restrictions. At each sampling moment, the first element of the computed control vector is applied to the system input, and the remainder is discarded. The entire procedure is repeated in the subsequent instant of time. Costs can be expressed as tracking inaccuracy, control effort, energy cost, demand cost, power consumption, or a combination of these elements. The rate and range limits of the actuators and the manipulated and controlled variables can be constrained (Afram et al., 2014).

In this thesis, the resistance-capacitance (RC) model is defined and the problem is formulated. The model of the system was extensively used in the literature (Mathieu et al., 2013). Considering the system described below, which is based on the dynamics of the room temperature, capacity, outside air temperature, neighboring air temperature, and disturbance (6), the thermal dynamics of the room can be modeled as

$$\dot{T}_1 = \left[\frac{-1}{R_0 C_1} - \frac{1}{R_n C_1}\right] T_1 + \frac{1}{C_1} Q + \frac{1}{R_0 C_1} Tout + \frac{1}{R_n C_1} Tn + \frac{1}{C_1} * P_d \tag{6}$$

The variables and parameters in (6) are explained in Table 5.2.

Table 5. 2. MPC definitions

Variables	Definition
Tn	Neighbour air temperature [◦C]
$Tout$	Outside air temperature [◦C]
T_1	Indoor air temperature [◦C]
C_1	Thermal capacity of the room
R_0	Thermal resistance between the room and outside
R_n	Thermal resistance between the room and outside
Q	Thermal heat input from the HVAC system
P_d	Disturbance (occupancy, equipment, solar gains)

To obtain the model in standard state-space form

$$\begin{aligned} \dot{x} &= Ax + \boldsymbol{Bu} \\ y &= Cx + D\boldsymbol{u} \end{aligned} \tag{7}$$

the following assignments are made:

$$x = T_1,\ \boldsymbol{u} = \begin{bmatrix} Q \\ Tout \\ Tn \\ P_d \end{bmatrix},\ \ y = T_1 \tag{8}$$

Using (8), the state space-model matrices are obtained as

$$\begin{gathered} A = \frac{-1}{R_0 C_1} - \frac{1}{R_n C_1}, \qquad \boldsymbol{B} = \begin{bmatrix} \frac{1}{C_1} & \frac{1}{R_0 C_1} & \frac{1}{R_n C_1} & \frac{1}{C_1} \end{bmatrix} \\ C = 1, \qquad D = 0 \end{gathered} \tag{9}$$

MPC incorporates both the control-oriented building zone and HVAC system models, considering the mutual interaction between the thermal behavior of the building zone and the HVAC energy components (Lee et al., 2015). MPC principle is defined in terms of an output-feedback model. State-space model of the MPC can be seen in Figure 5.9.

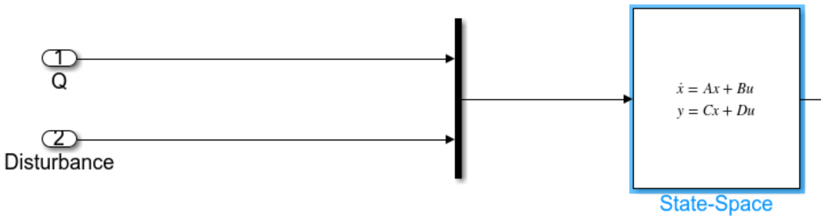

Figure 5. 9. State-space model in Simulink

The optimization problem determines the controlling variables, while the measured responses correspond to the major thermal parameters monitored by the available sensors deployed in the indoor environment. The accuracy of the model response is affected by the estimation of all variables affecting thermal comfort that are not monitored by sensors and the existence of disturbances (Carli et al., 2020).

MPC parameters found according to the cost function as shown in Table 5.3.

Table 5. 3. MPC variables

Parameter	C_1	R_n	R_0
Value	$3.0003*10^3$	$3.949*10^6$	10.009

The primary benefit of MPC is that the engineer or operator may directly enter constraints, and the algorithm will automatically identify the optimal solution that satisfies all of them. 1 zone model in Simulink as shown in Figure 5.10.

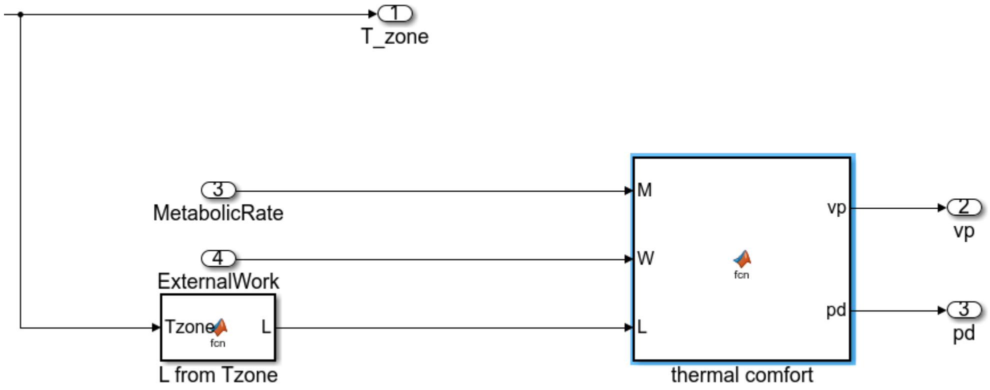

Figure 5. 10. Thermal comfort model in Simulink

While creating the thermal comfort model, predicted mean vote is used. It allows to assess the global thermal comfort and to predict the mean value of the votes of a large group of people that perform similar activities. The predicted mean vote model is

$$\mathrm{PMV} = (0.303 * e^{-0.036M} + 0.028) * L \tag{11}$$

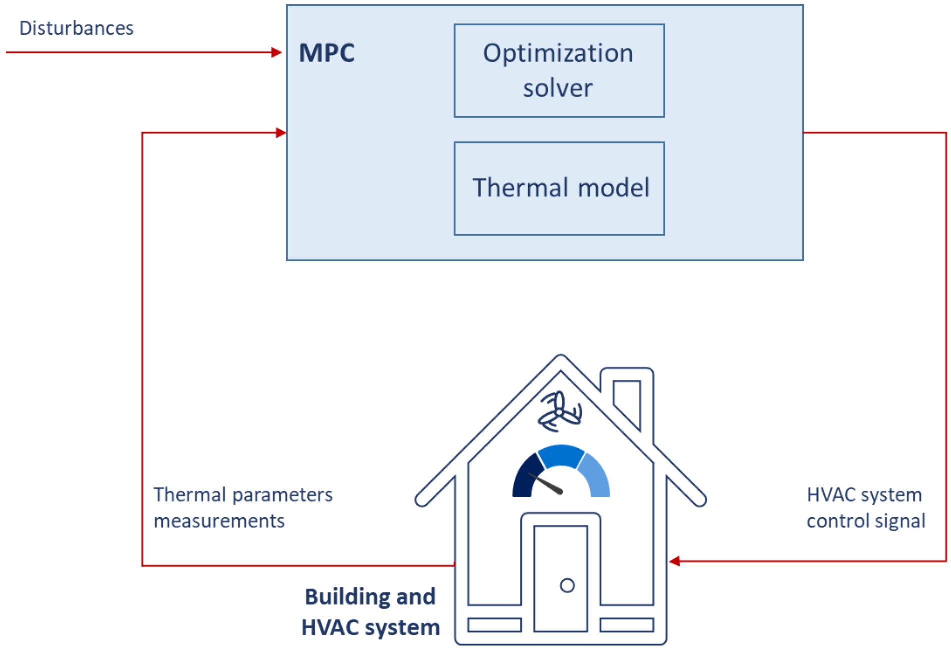

Figure 5. 11. MPC framework

Constraints imposed by MPC are always present in real-world process control situations. Constraints are handled in most of today's control implementations via split range controllers, overrides, and more general min-max selectors with some logic. These methods are challenging to design, debug, communicate to operators, and maintain. The primary benefit of MPC is that the engineer or operator may directly enter constraints, and the algorithm will automatically identify the optimal solution that satisfies all of them (García et al., 1989). The cost function and its constraint are shown in the equations below. Sampling period is 1 hour and the prediction horizon is 24 steps. The MPC controller solves the following constrained optimization problem:

$$\min \sum \alpha(\mathrm{T_{ref}} - T_1(k))^2 + \beta f(Q(k)) \tag{12}$$

subject to:

$$\dot{T}_1 = \left[\frac{-1}{R_0 C_1} - \frac{1}{R_n C_1}\right] T_1 + \frac{1}{C_1} Q + \frac{1}{R_0 C_1} Tout + \frac{1}{R_n C_1} Tn + \frac{1}{C_1} * P_d \tag{13}$$

$$21 \leq \dot{T}_1 \leq 26 \tag{14}$$

$$0 \leq Q \leq Q_{min} \tag{15}$$

MPC thermal model is working according to the cost minimization function that shown as above. An attempt is made to achieve a comfort temperature range of 21℃ to 26℃.

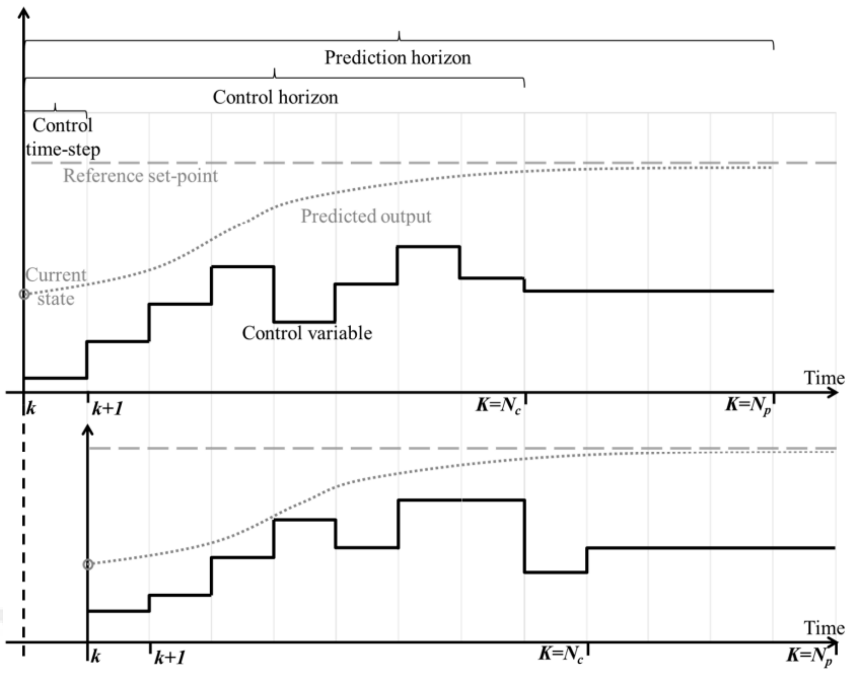

Figure 5. 12. Principle of receding horizon (Serale et al., 2018).

The graphic quoted above with reference can be explained in detail as follows.

- Current instant (k): Current sampling steps
- Control time-step (T_s): Time between control updates and iterative receding horizon optimizations.
- Prediction horizon (N_p): the number of control time-steps the controller looks ahead in the future to optimize the cost function under constraints.
- Control horizon (N_c): The number of possible different values the manipulated variables can take in the future that relate to the dimension of the optimization vector.

While building the simulation algorithm, grey-box model is preferred. Because the grey-box models provide some advantages in the buildings′ thermal modeling process, in particular, ease of their use and the possibility to link their parameters to global buildings′ physical characteristics, such as the heat resistance and the mass capacity. Simulink model and simulation result can be seen in Figure 5.13 and 5.14.

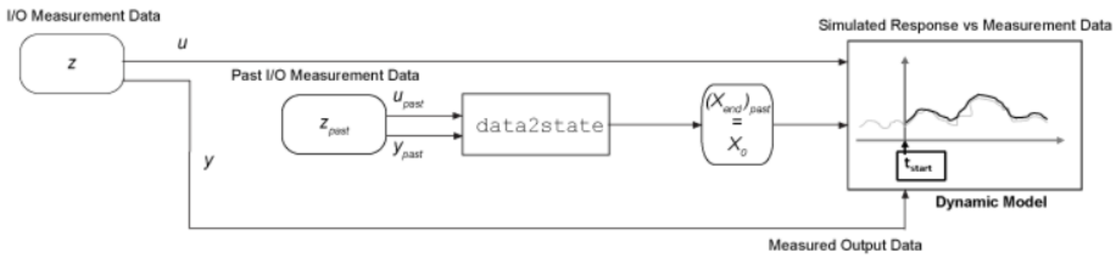

Figure 5. 13. Simulation simulink model

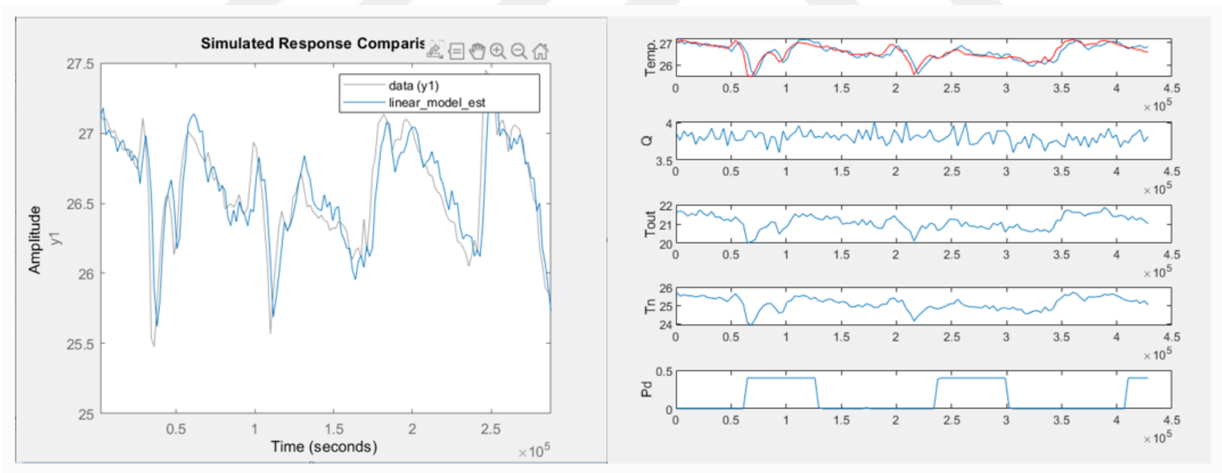

Figure 5. 14. Simulation comparison

If we look at the result of the MPC controlled system, MPC results will be slightly different. Because, before day 1, system is PID controlled.

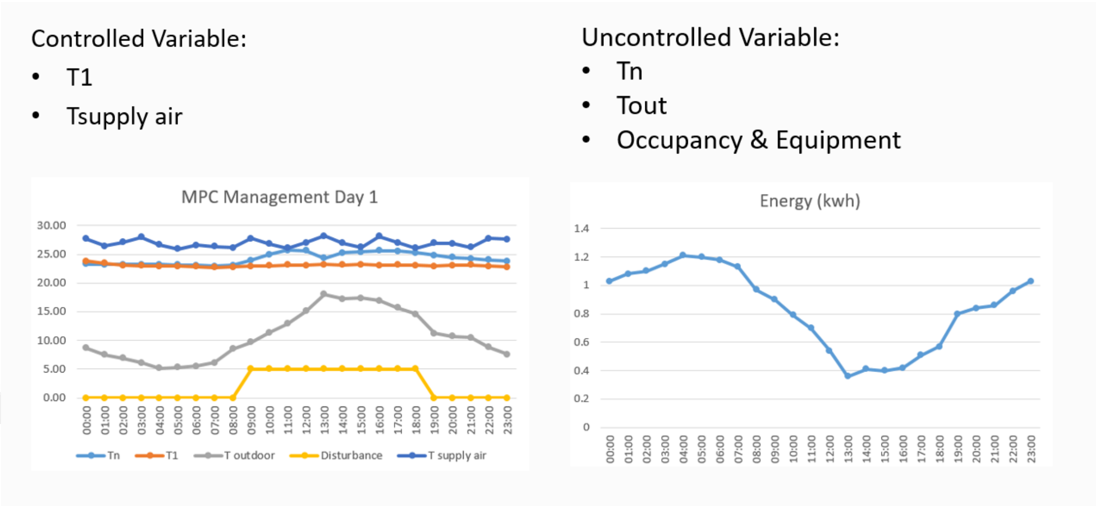

Figure 5. 15. MPC controlled system day 1

On the other hand, in Figure 5.16, energy consumption is less than MPC controlled day 1 in Figure 5.15. On day 1, ambient temperature and supply air are more stable, because it is controlled by the system automatically.

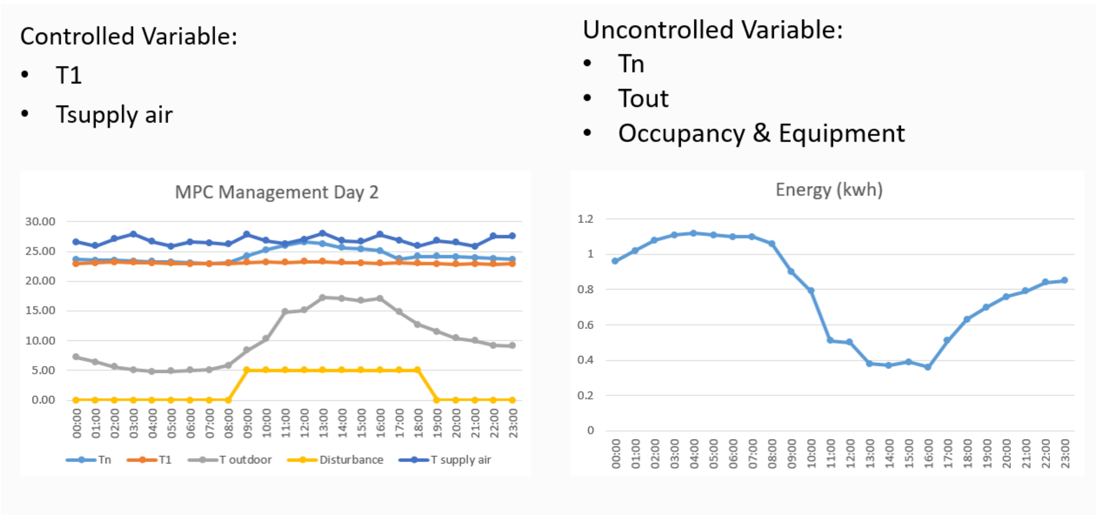

Figure 5. 16. MPC controlled system day 2

CHAPTER 6
CONCLUSION AND FUTURE RESEARCH

6.1. Conclusion

As a result, when it comes to converting inefficient buildings into smart and sustainable ones, the Internet of Everything and the Internet of Things can help.

On the basis of simulation-optimization techniques, a set point control scheme for the HVAC control system in fabric production facilities was devised. As a result of the complicated interaction between HVAC system characteristics, it is required to recommend optimal settings for different activities in response to dynamic cooling or heating demands and changing weather conditions throughout the year there has been a development of MPC (model predictive control) programming that can successfully handle discrete, nonlinear, and very restricted optimization It has been successfully developed and the dynamic model of the regulated zone produced for a building in Turkey to overcome this problem. In this thesis, PID and MPC control methods are analyzed so that the important points can be written as follows (Balaji et al., 2013);

- A PID controller is limited to one input and one output.
- MPC controllers are a more sophisticated form of process control that are utilized in MIMO (Multiple Inputs, Multiple Outputs) systems.
- There is no information of restrictions in a PID controller.
- MPC's key advantage is its capacity to handle restrictions.
- The PID controller is incapable of dealing with restrictions.
- PID controllers do not require a process model.
- MPC controllers require a process model.

The pilot office is closed on the weekend. Employees somehow forget about the HVAC return, so there is an uncontrollable power consumption seen in Table 6.1 below.

Table 6. 1. Weekend consumption before management

	Delta Active Energy (kWh)	Mean Indoor Temperature (C)	Mean Outdoor Temperature (C)
00:00	1.00	23.22	14.00
01:00	1.00	22.91	13.00
02:00	1.00	22.90	13.00
03:00	1.00	23.01	13.00
04:00	1.00	23.05	14.00
05:00	1.00	22.89	14.00
06:00	1.00	23.01	15.00
07:00	1.00	23.14	15.00
08:00	6.00	23.92	15.00
09:00	5.00	27.78	15.00
10:00	4.00	28.85	16.00
11:00	3.00	29.32	16.00
12:00	3.00	29.39	16.00
13:00	3.00	28.73	16.00
14:00	2.00	29.28	16.00
15:00	1.00	28.51	16.00
16:00	2.00	28.61	16.00
17:00	1.00	27.47	16.00
18:00	0.00	25.94	16.00
19:00	1.00	24.87	16.00
20:00	0.00	24.35	17.00
21:00	0.00	24.01	17.00
22:00	0.00	23.70	16.00
23:00	0.00	23.49	17.00

Table 6. 2. Weekend consumption after management

	Delta Active Energy (kWh)	Mean Indoor Temperature (C)	Mean OutDoor Temperature (C)
00:00	0.00	23.52	13.00
01:00	0.00	23.49	14.00
02:00	0.00	23.45	14.00
03:00	0.00	23.42	14.00
04:00	0.00	23.46	15.00
05:00	0.00	23.40	15.00
06:00	0.00	23.35	15.00
07:00	0.00	23.30	15.00
08:00	0.00	22.09	15.00
09:00	0.00	22.75	15.00
10:00	0.00	21.62	16.00
11:00	0.00	21.58	16.00
12:00	0.00	21.61	19.00
13:00	0.00	20.79	14.00
14:00	0.00	20.11	15.00
15:00	0.00	19.45	15.00
16:00	0.00	19.35	14.00
17:00	0.00	18.94	15.00
18:00	0.00	18.77	15.00
19:00	0.00	17.91	15.00
20:00	0.00	17.74	15.00
21:00	0.00	17.57	16.00
22:00	0.00	17.26	16.00
23:00	0.00	17.56	17.00

Looking at the difference between PID and MPC control methods, MPC can control HVAC for future reference, on the other hand PID need real time data. In this thesis, we analyze the PID and MPC from the different perspectives because for the PID method, we have used the trial and error method. If we use another method like

Ziegler-Nichols or Cohen-Coon, we could see higher performance for the PID. Eventually, when we look at the result of the controlled days, last day of the MPC is more efficient according to the other days. When we look at the result Figure 6.1 as shown in below, X axis shows the energy consumption value in kWh, y axis represents the control type of the day.

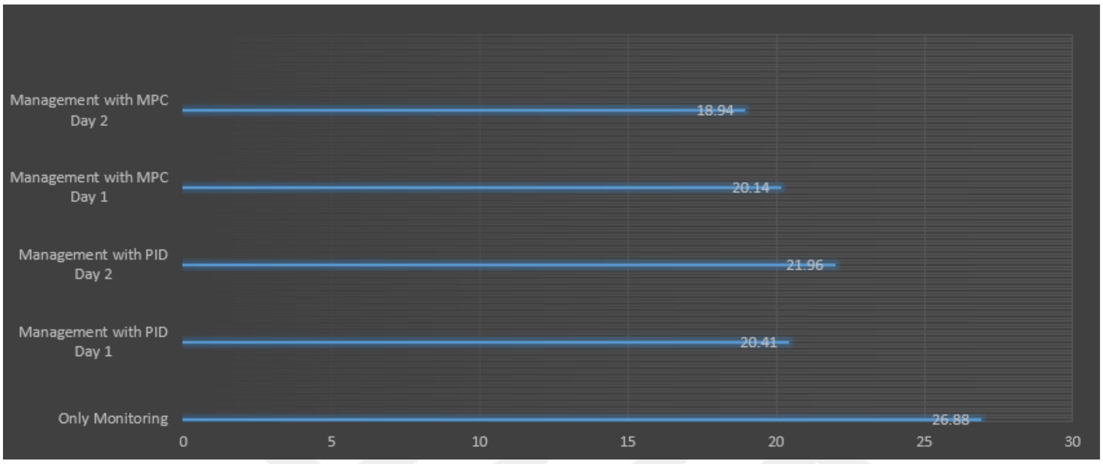

Figure 6. 1. Controlled days' results

Our research also includes an extensive literature study to identify all representative technological approaches that may be used to smart buildings. A smart template for the construction of energy-efficient buildings is then presented, based on IoT technology, for both the short and long term. We're ready and willing to make a further contribution to the gradual transformation of existing buildings into energy efficient buildings, by proposing a management system as well as solutions for addressing and controlling energy inefficiency in existing buildings. By providing remote and continuous measurements of all building's technical systems, the suggested management system may also contribute to Building Certification and Compliance Checking of buildings.

6.2. Future Work

To recreate both the smart technology building template and the management system that analyzes power consumption in existing structures, technological tools and equipment, as well as financial aid, are clearly necessary.

These finer details limited our investigation. As a result, a desirable and reasonable future goal of this research is the implementation and testing of both the management system that monitors and controls the smart building template and the management system that confirms the energy efficiency of a current structures and proposes solutions to transform the building into an e-building in accordance with current legislation. When all the energy data from other buildings are collected, the best control model for autonomous control of the building's HVAC system will be created.

The future centralized resource management system will enable the monitoring of detailed statistics and the ability to respond automatically to the building's demand requirements. Additionally, some machine learning models are being developed to forecast future scenarios based on existing measures. At the top of the hierarchy, an intelligent, automatic reaction will be created to monitor all available factors and advise steps to reduce energy use while maintaining user comfort. Additionally, condition monitoring and predictive maintenance are possible additions to the system (Blasco et al., 2012).

REFERENCES

Afram, A., & Janabi-Sharifi, F. (2014). Theory and applications of HVAC control systems – a review of Model Predictive Control (MPC). *Building and Environment*, 72, 343–355. https://doi.org/10.1016/j.buildenv.2013.11.016

Alajmi, A. (2012). Energy audit of an educational building in a hot summer climate. *Energy and Buildings*, 47, 122–130. https://doi.org/10.1016/j.enbuild.2011.11.033

Al-Ali, A. R., Zualkernan, I. A., Rashid, M., Gupta, R., & Alikarar, M. (2017). A smart home energy management system using IoT and big data Analytics approach. *IEEE Transactions on Consumer Electronics,* 63(4), 426–434. https://doi.org/10.1109/tce.2017.015014

Almabrok, A., Psarakis, M., & Dounis, A. (2018). Fast tuning of the PID controller in an HVAC system using the big bang–big crunch algorithm and FPGA technology. *Algorithms*, *11*(10), 146. https://doi.org/10.3390/a11100146

Al-Rabghi, O. M., & Akyurt, M. M. (2004). A survey of energy efficient strategies for Effective Air Conditioning. *Energy Conversion and Management*, *45*(11-12), 1643–1654. https://doi.org/10.1016/j.enconman.2003.10.004

Amara, F., Agbossou, K., Cardenas, A., Dubé, Y., & Kelouwani, S. (2015). *Comparison and simulation of BUILDING thermal models for effective energy management.* Smart Grid and Renewable Energy, 06(04), 95–112. https://doi.org/10.4236/sgre.2015.64009

Apmonitor. (2020). *Proportional Integral Derivative (PID).* Retrieved June 9, 2021, from https://apmonitor.com/pdc/index.php/Main/ProportionalIntegralDerivative

Åström, K. J. (1983). Theory and applications of Adaptive Control—A survey. *Automatica*, *19*(5), 471–486. https://doi.org/10.1016/0005-1098(83)90002-x

ATP, S., Chow T., Chan W., Tse W. (1995) Neural-network-based identifier/controller for modern HVAC control. *ASHRAE Trans.* 1995;101(2), 14–31.

Aune, M., Berker, T., Bye, R. (2009). Building operators and energy management in non-residential buildings. *Facilities*. 27, 44-55. 10.1108/02632770910923081.

Azuatalam, D., Mhanna, S., Chapman, A., & Verbic, G. (2017). Optimal HVAC scheduling using phase-change material as a demand response resource. *IEEE Innovative Smart Grid Technologies*, Asia (ISGT-Asia). https://doi.org/10.1109/isgt-asia.2017.8378315

Balaji, V., & Rajaji, D.L. (2013). Comparative Study of PID and MPC Controller Using Lab View.

Balaras, C. A., Dascalaki, E., & Gaglia, A. (2007). HVAC and indoor thermal conditions in hospital operating rooms. *Energy and Buildings*, 39(4), 454–470. https://doi.org/10.1016/j.enbuild.2006.09.004

Baldi, S., Michailidis, I., Ravanis, C., & Kosmatopoulos, E. B. (2015). Model-based and model-free "plug-and-play" building energy efficient control. *Applied Energy,* 154, 829–841. https://doi.org/10.1016/j.apenergy.2015.05.081

Bemporad, A. (2006, December). Model predictive control design: New trends and tools. *In Proceedings of the 45th IEEE Conference on Decision and Control* (pp. 6678-6683). IEEE.

Blasco, C., Monreal, J., Benítez, I., & Lluna, A. (2012). Modelling and PID control of HVAC system according to energy efficiency and comfort criteria. *Sustainability in Energy and Buildings*, 365–374. https://doi.org/10.1007/978-3-642-27509-8_31

Boyano, A., Hernandez, P., & Wolf, O. (2013). Energy demands and potential savings in European office buildings: Case studies based On ENERGYPLUS SIMULATIONS. *Energy and Buildings*, *65*, 19–28. https://doi.org/10.1016/j.enbuild.2013.05.039

Carli, R., Cavone, G., Ben Othman, S., & Dotoli, M. (2020). Iot based architecture for model predictive control of hvac systems in smart buildings. *Sensors*, 20(3), 781. https://doi.org/10.3390/s20030781

Castro, N., Friedman, H., & Frank, M. (2006). Cost effective commissioning for existing and low energy building. *ECBCS Annex 47: Cost-Effective Commissioning Research.*

Chua, K. J., Chou, S. K., Yang, W. M., Yan, J. (2013). Achieving better energy-efficient air conditioning – a review of technologies and strategies. *Applied Energy*, 104, 87–104. https://doi.org/10.1016/j.apenergy.2012.10.037

Iddio, E., Wang, L., Thomas, Y., McMorrow, G., & Denzer, A. (2020). Energy efficient operation and modeling for Greenhouses: A literature review. *Renewable and Sustainable Energy Reviews,* 117, 109480. https://doi.org/10.1016/j.rser.2019.109480

Fuerst, F. (2009). Building momentum: An analysis of investment trends IN LEED and ENERGY star-certified properties. *Journal of Retail & Leisure Property*, 8(4), 285–297. https://doi.org/10.1057/rlp.2009.18

García, C. E., Prett, D. M., & Morari, M. (1989). Model predictive control: Theory and practice—A survey. *Automatica*, 25(3), 335–348. https://doi.org/10.1016/0005-1098(89)90002-2

Geng, G., & Geary, G. M. (1993). On performance and tuning of PID controllers in HVAC systems. *Proceedings of IEEE International Conference on Control and Applications*. https://doi.org/10.1109/cca.1993.348229

Ghiaus, C., & Hazyuk, I. (2010). Calculation of optimal thermal load of intermittently heated buildings. *Energy and Buildings*, 42(8), 1248–1258. https://doi.org/10.1016/j.enbuild.2010.02.017

Guth, J., Breitenbücher, U., Falkenthal, M., Fremantle, P., Kopp, O., Leymann, F., & Reinfurt, L. (2017). A detailed analysis of iot platform architectures: Concepts, similarities, and differences. *Internet of Things,* 81–101. https://doi.org/10.1007/978-981-10-5861-5_4

Han, M., Zhang, X., Xu, L., May, R., Pan, S., Wu, J. (2018) A review of reinforcement learning methodologies on control systems for building energy. *Sustainable Cities and Society*. 51, 2210-6707. https://doi.org/10.1016/j.scs.2019.101748.

IEA (2004), *Energy Policies of IEA Countries: France 2004*, IEA, Paris https://doi.org/10.1787/9789264107984-en

Kanmaz, A., Orenbas, H., & Sahin, S. (2018). Android based PLC Data Monitoring Interface with Industrial Data Communication Port. *2018 26th Signal Processing and Communications Applications Conference (SIU)*. https://doi.org/10.1109/siu.2018.8404576

Kim, Y.-J. (2020). A supervised-learning-based strategy for optimal demand response of an hvac system in a multi-zone office building. *IEEE Transactions on Smart Grid*, 11(5), 4212–4226. https://doi.org/10.1109/tsg.2020.2986539

Klein, S.A., Beckman, W.A., Mitchell, J., Duffie, J., Duffie, N., Freeman, T., Braun, J., Evans, B., Kummer, J., (2009). TRNSYS 17: A transient system simulation program: mathematical reference. University of Wisconsin: Madison, WI, USA.

Lazic N., Boutilier C., Lu T., Wong E., Roy B., Ryu M. (2018) *Data center cooling using model-predictive control,* 3814–23.

Lee, Y. M., Horesh, R., & Liberti, L. (2015). Optimal Hvac Control as demand response with on-site energy storage and generation system. *Energy Procedia*, *78*, 2106–2111. https://doi.org/10.1016/j.egypro.2015.11.253

Li, H., Wan, Z., & He, H. (2020). Real-time residential demand response. *IEEE Transactions on Smart Grid*, 11(5), 4144–4154. https://doi.org/10.1109/tsg.2020.2978061

Liang, Y., Di, X., Chongxin, H., Tao, Jiang, T., Yulong, Z. (2018). Energy Optimization of HVAC Systems in Commercial Buildings Considering Indoor Air Quality Management. *IEEE Transactions on Smart Grid*. PP. 10.1109/TSG.2018.2875727.

Maasoumy, M., Sanandaji, B. M., Sangiovanni-Vincentelli, A., & Poolla, K. (2014). Model predictive control of regulation services from commercial buildings to the smart grid. *2014 American Control Conference*. https://doi.org/10.1109/acc.2014.6859332

Manjarres, D., Mera, A., Perea, E., Lejarazu, A., & Gil-Lopez, S. (2017). An energy-efficient predictive control for HVAC systems applied to tertiary buildings based on regression techniques. *Energy and Buildings*, 152, 409-417.

Mathieu, J. L., Koch, S., & Callaway, D. S. (2013). State estimation and control of electric loads to manage real-time energy imbalance. *IEEE Transactions on Power Systems*, 28(1), 430–440. https://doi.org/10.1109/tpwrs.2012.2204074

Metallidou, C. K., Psannis, K. E., Egyptiadou, E. A. (2020). Energy efficiency in smart buildings: Iot approaches. *IEEE Access,* 8, 63679–63699. https://doi.org/10.1109/access.2020.2984461

Mills, E., Friedman, H., Powell, T., Bourassa, N., Claridge, D., Piette, M.. (2004). The cost-effectiveness of commercial-buildings commissioning. Berkeley National Laboratory. Portland Energy Conservation Inc., Energy Systems Laboratory, Texas A&M University

Neumann, C., Jacob, D., Peitsman, H., Yoshida, H., Yuzawa, H., Watanabe, T., Kamitani, K., Kikuchi, H., Baumann, O., Choiniére, D., & Milesi Ferretti, N. (2012). Annex 47 report 2: Commissioning tools for existing and low ENERGY BUILDINGS. https://doi.org/10.6028/nist.tn.1744

Oldewurtel, F., Ulbig, A., Parisio, A., Andersson, G., & Morari, M. (2010). Reducing peak electricity demand in building climate control using real-time pricing and model predictive control. *49th IEEE Conference on Decision and Control (CDC)*. https://doi.org/10.1109/cdc.2010.5717458

Şahin, S., Alkuş, İ., Yağbasan, S. (2016). Automatic error detection and control of air conditioners placed in GSM base stations. *2016 National Conference on Electrical, Electronics and Biomedical Engineering (ELECO)*, 165-169.

Sarkar, C., Nambi, S. N., Prasad, R. V., & Rahim, A. (2014). A scalable distributed architecture towards unifying iot applications. *2014 IEEE World Forum on Internet of Things (WF-IoT)*. https://doi.org/10.1109/wf-iot.2014.6803220

Serale, G., Fiorentini, M., Capozzoli, A., Bernardini, D., & Bemporad, A. (2018). Model Predictive Control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities. *Energies*, 11(3), 631. https://doi.org/10.3390/en11030631

Sturzenegger, D., Gyalistras, D., Morari, M., Smith, R. S. (2016). Model predictive climate control of a Swiss Office BUILDING: Implementation, results, and Cost–Benefit Analysis. *IEEE Transactions on Control Systems Technology*, 24(1), 1–

12. https://doi.org/10.1109/tcst.2015.2415411

Trčka, M., & Hensen, J. L. M. (2010). Overview of HVAC system simulation. *Automation in Construction, 19*(2), 93–99. https://doi.org/10.1016/j.autcon.2009.11.019

Wall, J., Ward, J., West, S., Piette, M. (2008). Comfort, Cost and CO2 Intelligent HVAC Control for Harmonising HVAC Operating Principles, *IIR HVAC Energy Efficiecy Best Practice Conference*, Melbourne, Australia, 2008.

Wang, S., & Ma, Z. (2008). Supervisory and optimal control of building hvac systems: A review. *HVAC&R Research*, 14(1), 3–32. https://doi.org/10.1080/10789669.2008.10390991

Wang, S., & Ma, Z. (2008). Supervisory and optimal control of Building HVAC systems: A Review. *HVAC&R Research*, *14*(1), 3–32. https://doi.org/10.1080/10789669.2008.10390991

Zhou, D. P., Hu, Q., & Tomlin, C. J. (2017). Quantitative comparison of data-driven and physics-based models for commercial building hvac systems. 2017 American Control Conference (ACC). https://doi.org/10.23919/acc.2017.7963391

APPENDIX 1 – MPC Base Code

Demonstrates the basic MPC algorithm code used to develop our own MPC control software in MATLAB. The details of the reading area data are shown as follows;

```
cp = 1.005; %kJ/K
m = 0.54;
nz = 1; % number of zones
ns = 1*nz; %number of states (1 x nz number of zones)

fielddata = load('hvac.dat');

Tair    = fielddata(:,1);
Tn      = fielddata(:,2);
Tsa     = fielddata(:,3);
Tout    = fielddata(:,4);
Pd      = 0.08 * fielddata(:,5);

Tair2 = reshape(Tair,[30,240]);
Tn2 = reshape(Tn,[30,240]);
Tsa2 = reshape(Tsa,[30,240]);
Tout2 = reshape(Tout,[30,240]);
Pd2 = reshape(Pd,[30,240]);

Tair3 = sum(Tair2(:,1:160))'/30;
Tn3 = sum(Tn2(:,1:160))'/30;
Tsa3 = sum(Tsa2(:,1:160))'/30;
Tout3 = sum(Tout2(:,1:160))'/30;
Pd3 = sum(Pd2(:,1:160))'/30;


delta_T = (Tsa3 - Tair3);
Q = m * cp * delta_T;

Uvec  = [Q Tout3 Tn3 Pd3];
Ymeas = Tair3;

save field_data_systemID.mat Uvec Ymeas

ndata = length(Pd3); Ts = 1800;
Tvec = [0:Ts:(ndata-1)*Ts]';
dist_val = [Tout3 Tn3 Pd3];
md.signals.values = dist_val;
md.time = Tvec;

save mpc_dist md
```

The details of the single zone situation are as follows;

```
global xInitial
%% Original parameters

Ts = 1800;
load field_data_systemID.mat
ndata = length(Ymeas);
Tvec = [0:Ts:(ndata-1)*Ts]';
C1 = 3000;
Ro = 0.1;
Rn = 0.1;
data = iddata(Ymeas, Uvec, Ts);  %% If looking only at Tair
xInitial = Ymeas(1,:)';

%% Construct the linear model
linear_model_z = idgrey('singlezoneRC_1state',{C1,Ro,Rn},'c');

n_param = length({C1,Ro,Rn});

for kk = 1:n_param
    linear_model_z.Structure.Parameters(kk).Minimum = 0.0;
    linear_model_z.Structure.Parameters(kk).Maximum = 10;
end
% Modify C bounds
for nn = 1
    linear_model_z.Structure.Parameters(nn).Minimum = 1000.0;
    linear_model_z.Structure.Parameters(nn).Maximum = 500000;
end

opt = greyestOptions('InitialState',xInitial,'Display','on');
opt.EnforceStability = true;
opt.SearchMethod = 'fmincon';
%opt.SearchMethod = 'lsqnonlin';

opt.SearchOption.MaxIter = 200;

opt.DisturbanceModel = 'model';
%%%opt.OutputWeight = eye(size(Yc,2));
%opt.Regularization.Lambda = 100;
%% Specify initial  guess as Nominal.
%opt.Regularization.Nominal = 'model';

linear_model_est = greyest(data,linear_model_z,opt);

[param_est,dparam_est] = getpvec(linear_model_est,'free');

compare(data,linear_model_est)

save linear_model_1state_estimate.mat linear_model_est data

Aest = linear_model_est.A;
Best = linear_model_est.B;
Cest = linear_model_est.C;
Dest = linear_model_est.D;

RCmodel = ss(Aest,Best,Cest,Dest);
[Yrc,Trc,Xrc]=lsim(RCmodel,Uvec,Tvec,xInitial,'zoh');
```

Details of the single zone RC thermal model are as follows;

```
function [A,B,C,D,K,x0] = singlezoneRC_1state(C1,Ro,Rn,~)

global xInitial

A  = (-1/C1)*(1/Ro+1/Rn);

B  = [1/C1    1/(Ro*C1)   1/(Rn*C1)   1/C1];
% Q, Tamb, Tn, Pd

C  = 1;
D  = zeros(1,4);
K  = 0; % for modeling noise, nx-by-ny.
x0 = xInitial;

end
```