DEVELOPMENT OF A SUPERVISORY CONTROLLER FOR ENERGY MANAGEMENT PROBLEMS

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By
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July, 2011

I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

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Multi energy source systems, like hybrid electric vehicles in automotive industry, started to attract attention as a remedy for the greenhouse gas emission problem. Although their environmental performances are better than conventional technologies such as the case of gasoline vehicles versus hybrid electric vehicles in automotive industry, their operational management can be challenging due to their increased complexity. One of these challenges is the operational management of the energy flow among these multiple sources and sinks which in this context referred as the energy management problem.

In this thesis, a supervisory controller is developed to operate at a residential environment with multiple energy sources. First, dynamic optimization techniques are applied to the available mathematical models of the multi-energy sources to create a non-causal optimal controller. Then, a set of implementable rules are extracted by analyzing the optimal trajectories resulted from the dynamic optimization to create a causal supervisory controller.

Several simulations are conducted with Matlab/Simulink to validate the developed controller. The supervisory controller achieves not only a daily cost reduction between 6-7.5% compared to conventional energy infrastructure used in residential areas but also performs 2% better than heuristic control techniques available in the literature. Another simulation study is conducted, with different demand cycles, for verification of the controller. Although its performance reduces as expected, it still performs 1% better than heuristic control strategies.

In the final part of this thesis, the formulation used in the residential problem which was originally adopted from an example in automotive industry, is generalized so that it can be used in all types of energy management problems. Finally, for exemplary purposes, a formulation for energy management problem in mobile

devices is created by using the developed generic formulation.

Keywords: Energy Management, Dynamic Programming, Supervisory Control.

ÖZET

ENERJİ YÖNETİMİ PROBLEMLERİ İÇİN YÖNETİCİ TİPTE KONTROLCÜ TASARIMI

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Günümüzde, birden fazla enerji kaynağına sahip olan sistemlerin, örneğin hibrit otomobiller, popüleritesinin arttığı gözlemlenmektedir. Bu durumun altında yatan başlıca sebep ise çok kaynaklı enerji sistemlerinin çevresel yönden şu anda kullandığımız tek kaynağa bağlı enerji sistemlerinden, benzinli arabalar gibi, daha başarılı bir performans göstermesidir. Öte yandan bu tip birden fazla kaynaklı sistemler sundukları yeni operasyon modları sayesinde mevcut sistemlerden daha verimli çalışma potansiyeline sahiptirler. Fakat doğru operasyon modunu ve buna ilişkin güç seviyelerini belirlemek sorun teşkil etmektedir. Bu problem enerji yönetimi problemi olarak adlandırılmıştır.

Bu tezde çoklu kaynağa sahip bir yerleşim alanının enerji yönetimi problemini çözmek için yönetici tipte bir kontrolcü tasarlanmıştır. Bu doğrultuda öncelikle literatürde varolan matematiksel modellerden yararlanılarak sistem için bir dinamik optimizasyon formülasyonu oluşturulmuştur. Daha sonra dinamik optimizasyon çıktılarından yararlanılarak gerçek hayatta uygulanabilecek kurallar çıkartılmış ve kontrolcü oluşturulmuştur.

Matlab/Simulink ortamında yapılan simülasyonlar sonucu, tasarlanan kontrolcünün literatürde varolan sezgisel kontrolcülerden, seçilen tüm performans parametrelerinde, günlük olarak yaklaşık %1-2 daha iyi performans gösterdiği saptanmıştır.

Bu tez, daha önce otomotiv sektöründe uygulanmış bir çözümden yola çıkılarak ev ortamı için yaratılan kontrolcünün genelleştirilmesi ile tamamlanmıştır. Bu genel formülasyon kullanılarak farklı alanlardaki enerji yönetimi problemleri çözülebilmektedir. Yaratılan genel formun kullanımını göstermek amacıyla amacıyla mobil cihazlarda enerji yönetimi yapmak için bir formülizasyon

gösterilmiştir.

Anahtar sözcükler: Enerji Yönetimi, Dinamik Programlama, Yönetici tipte kontrolcü.

Acknowledgement

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Chapter 1

Introduction

In the first section of this chapter, the problem worked on in this thesis, energy management, is explained. In the subsequent sections, three industries that are facing this problem is introduced. Finally, this chapter concluded with motivation and contributions of this thesis.

1.1 Energy Management Problem (EMP)

In recent years, although our basic needs did not change much, the technology that provides them started to evolve. For instance, due to environmental concerns, hybrid electrical vehicles (HEVs) started to gain considerable amount of market share and in the future they are expected to replace conventional gasoline automobiles [26]. Another example can be given for the supply-side of the energy policy: Distributed Generation (DG) created the possibility to produce electricity where it is needed, instead of producing electricity in a big power plant and transport it for long distances, with a variety of technologies. These examples can be increased.

It can be deduced that, the technology evolution in the present and in the upcoming years is tend to create more than one energy source for a single demand. Such as, torque need of a driver in HEVs can be supplied by either an internal combustion engine (ICE) or electric motors (EM) or by combination of them. Likewise, with DG, electricity demand of a village can be gathered by photovoltaic's (PV) or a nearby wind farm or a combination of them. In conclusion, energy infrastructures started to become a multiple source and multiple sink (demand) systems.

European Commission's new report about future energy supply infrastructure, which is shown in Figure 1.1 [46], supports above conclusions.

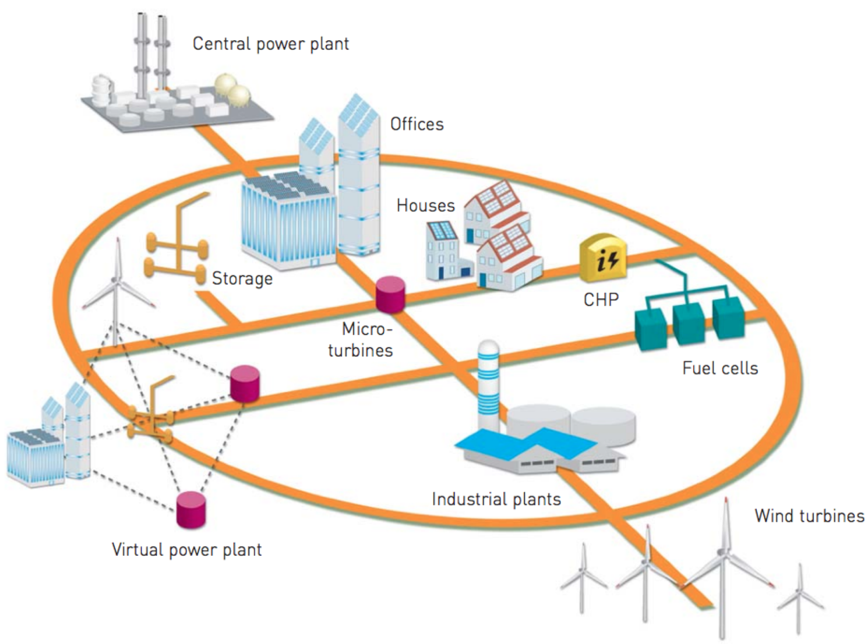

Figure 1.1: Multi-source Multi-Sink System

Figure 1.1 shows a good example of multiple source and multiple sink energy infrastructure or so-called the DG system. There are offices, industrial plants and houses which have two distinct demands: electricity and heating. This is mentioned as multiple sink or demand throughout in this thesis. In order to supply these demands there are micro-turbines, fuel-cells, wind turbines and a conventional central power plant. Additionally a storage device is also available for extra flexibility in terms of energy supply. These devices must be operated optimally otherwise potential of the system cannot be fully exploited; thus performance of the system may even got worse comparing to the current infrastructure.

The technology tries to create alternative energy sources for a single demand because at the moment there is no perfect solution for energy problems related to climate change. Fossil fuels will be depleted in the future and also machines using fossil fuels create unacceptable amount of harmful emissions. On the other hand, renewable energy provides a clean and unlimited energy source, however, their intermittent nature makes them unreliable. Also their energy conversion efficiencies still not comparable to systems that utilizes fossil fuels. In order to overcome these obstacles, using different kind of energy sources, multi-source, can be considered as a solution since, by this way energy supply flexibility can be increased which given an opportunity to operate devices on their most efficient zones or maximize usage of renewable energy sources.

In [22], different kinds of energy demands and sources are written as a set of equations coupled with an efficiency matrix of the devices. It can be seen that this matrix is non-invertible thus there is a potential for optimization. However, real energy systems are far from deterministic, as written in [22], and features a lot of stochastic parameters like unit cost of oil, energy demand of a house. Thus fully exploiting the potential advantages of a multi source system can be challenging.

In summary, the energy management problem involves finding mechanisms to manage devices included in the selected infrastructure at their optimal power levels based on a constructed performance index while satisfying the customer comfort level. These devices can vary from system to system and their numbers can increase or decrease but purpose of the energy management problem is the same: Finding the optimal power split between multiple sources to supply the demand.

1.2 Background and Literature Review

In this section, a background information is given on the energy management problem (EMP) from different industries.

First subsection starts with automobile EMP since it is a well-defined problem with more than a decade research. Following subsection includes definition of the residential EMP and research made on this area. Finally EMP discussion is extended for mobile devices.

1.2.1 EMP for Automotive Industry

Hybrid electric vehicles (HEVs) become popular and commercialized in recent years due to their environmental performance compared to conventional vehicles. Although there are various types of HEV powertrain configurations, a typical HEV powertrain generally consists of an electric storage device which can work bidirectionally and at least one electric motor apart from typical automobile technologies like internal combustion engine (ICE), transmissions.

By addition of storage devices and secondary sources, new operating modes become available for HEVs. For instance, during the so-called HEV specific power assist mode, the electric motor and the ICE can work together to provide the torque that is requested by the driver. Similarly, in the regenerative braking mode, some of the braking energy can be captured into the electrical storage device.

These new operating modes increased the energy supply flexibility of the vehicle system and made it possible to achieve certain performance parameters, such as reducing fuel consumption and harmful emissions, that cannot be achieved by conventional vehicles.

However, multiple source nature of HEVs resulted a new problem in automotive industry which is often called as the energy management problem. In a typical HEV, there is additional energy sources other then internal combustion engine. Energy management problem in automotive industry aims to find the optimal power split between these energy sources in every time step to achieve minimum fuel consumption without violating the problem constraints such as comfort of the driver. Additionally, reducing harmful emissions and maximizing battery life is also used objectives and/or constraints to the optimization problem [48, 18, 47].

Automotive energy management problem is a well defined, well studied problem with more than 10 years of history. The research done until now can be roughly categorized into two main approaches [48, 18, 47].

First approach is based on engineering intuition which is often called as heuristic methods. Rule-based control and fuzzy logic techniques falls into this category. Main aspects of the heuristic methods are, their ease of implementation and computationally efficient operation. However, they require substantial amount of time for tuning and whole potential of the additional energy supply flexibility of the vehicle cannot be fully exploited [23, 18].

Second research category is based on optimization techniques. This category can also be divided into two which are dynamic and static optimization methods. By adopting a dynamic optimization method, a global optimum can be found via dynamic programming (DP) methods or local optimums can be achieved by short-term drive cycle predictions. DP requires whole drive cycle in advance thus cannot be implemented real-time and local optimization techniques, that includes model predictive control (MPC), requires high computational resources. Static optimization methods on the other hand, does not consider future and make decisions at each time step instantaneously according to a pre-defined cost function. [23, 18].

According to [18], one of the best results for automotive energy management problem are obtained by applying dynamic optimization methods. By using these methods, performance results close to a global optimum can be obtained. However as a trade-off, computational burden and real-time implementation can be problematic. In this thesis, a residential energy management problem will be solved by using the dynamic optimization problem and method, previously done and successfully applied in the automotive sector [35].

1.2.2 Residential EMP

Household energy consumption is an area that can not be disregarded in planning the energy future. Only in US there is more than 105 million dwellings and their energy need covers a substantial amount in US energy consumption map [39].

Generally, a residential environment requires two kinds of demand which are electricity and thermal energy. This is one of the main differences with automotive EMP in which demand is single: the torque requested from driver. In a residential area, electricity is required to power household appliances used daily such as TV, hair-dryer or kettle. Thermal power is needed for space heating and hot water demands.

Current infrastructure that supplies the demands of a dwelling generally consists from a national electricity grid and a gas-fired boiler. Grid electricity is obtained from big central plants which generally uses an obsolete technology thus emits substantial amount of harmful gases. Also these big power plants are established far away from the settlements due to size issues, environmental concerns and desire to lower transport costs for raw materials. So electricity produced in these power plants have to be transported for long distances to reach residential areas which causes substantial amount of transportation losses. On the other hand, required thermal power from the occupants is generated inside the house by a boiler which uses natural gas connection to the building. However, the usage of a typical boiler started to become obsolete since since fossil fuel unit prices increased a lot recently and more efficient devices are developed. In this manner, it is clear that a new energy infrastructure, or at least an alternative, is needed for residential areas.

As mentioned in the beginning of this chapter, renewable energy technologies are emission free but intermittent nature of them are making these sources unreliable for residential production. For example if a dwelling is powered by solar energy, when the sun fades away there is a possibility for blackout. This problem cannot be prevented by electric storage devices because at the moment either they are not sufficient for powering consumption for long hours or satisfactory storage alternatives costs too much. In summary, the proposed energy infrastructure must also be reliable besides its efficiency and emission values.

At the moment distributed generation (DG) is the most viable candidate for household energy production. With DG there are many possibilities according to occupation type and geographical location of a dwelling. For example if it is a small family than Stirling type micro co-generation device, which is shown in Figure 1.2, can be used for electricity and thermal needs due to device's low capacity (produces 1 kW of electricity). And if the dwelling has an acceptable amount of sunny days, than PVs or passive thermal collectors can also be used.

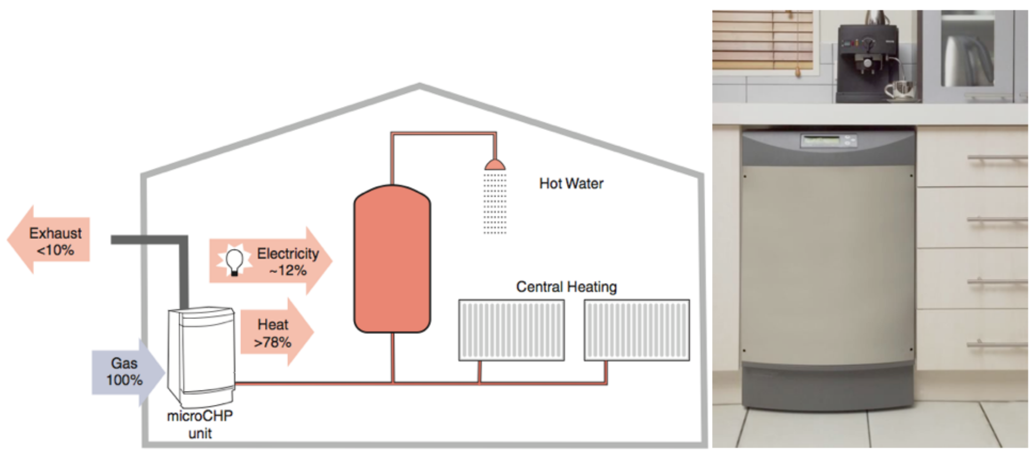

Figure 1.2: Micro Generation System

Figure 1.2 shows a micro co-generation system operated with Stirling engine prime mover [53]. These devices employ same principles as traditional combined heat and power cycles (CHP), which is simultaneous generation of electricity and heat. However these devices are at a size of a typical dish-washer and their output rates are scaled substantially (1-15 kW electricity production). Detail investigation of this device will be held in Section 2.

Although combining different types of technologies, as in DG, provides a great flexibility in terms of energy supply, they are harder to be efficiently operated by end-users. Thus a high level (supervisory) controller is required for optimal operation [24].

Optimal operation of the devices can be achieved by solving residential EMP which involves finding the optimal power split, according to a selected performance index, between DG sources and storage device while satisfying occupant comfort. In addition, DG sources and storage devices will likely to change a lot from one system to another since residential environment have no sizing or connection limitations like in vehicle problem. For instance, for a vehicle, size of the motor cannot be bigger than vehicle or once the vehicle is purchased no other energy sources, like another engine, can be added. So, apart from ensuring optimal operation of the energy sources, the supervisory controller must also be generic enough to be used with any device in a residential system.

Some valuable research made on operating the DG sources at residential scale in the literature. In this thesis, focus is especially on works that have used a controllable DG source, like a mCHP device. Since other devices, particularly renewable energy sources, has no prospect from the view of system dynamics and control. For instance, if the wind is available, then wind turbine is used otherwise it is turned off.

A small note before investigating current literature will be useful. In residential EMP literature and in this thesis, unless mentioned otherwise, comparisons are made according to the today's conventional case which includes a boiler for space heating and hot water demands and national grid connection for electricity demands.

Most of the systems that is investigated in the literature includes a mCHP device, an auxiliary boiler, a thermal storage and a grid connection. However most of these systems have extensions or missing devices from this configuration. Also occupancy times and climate conditions changes a lot. Thus making a healthy comparison is very difficult. However, an operational cost reduction between 5-20% is achieved with the introduction of mCHP device and a supervisory control strategy. Control strategies that have been used in the literature can be divided into two categories which are rule-based approaches and optimization approaches based on short term prediction.

Peacock and Newborough [43] used a rule-based approach based on hybridization of time-led and heat-led control logics, which will be introduced in Section 2, and achieved an approximate 13% operational cost reduction. Besides 10% reduction in CO_2 emissions also obtained. Alanne et all. [7] operated mCHP device based on pre-determined set-points. By this way 5% reduction in CO_2 emissions is achieved, however cost reductions are not given in percentage scale.

Collazos et all. [17] developed a predictive optimal controller based on mixed integer linear programming (MILP) to operate residential system. A 13% reduction in operating costs is achieved but no studies conducted for CO_2 emissions. Houwing et all. [25] used a model predictive controller (MPC) to minimize operational costs. A 5% cost reduction is obtained according to the case when no predictions are made and no further simulations are made for CO_2 emissions.

1.2.3 EMP for Portable Devices

Another energy management prospect example can be given for mobile devices. Rapid development in technology made computers available to almost everyone in recent years. This fact can be seen in national consumption maps. In U.S. more than 2% of total electricity consumed by computers and internet connected devices. And this percentage is expected to increase in the following years [16]. So an effective energy management scheme is needed to keep this percentage between acceptable ranges.

Currently, most common energy management approach in computers is entering these devices into sleep mode automatically while they are not used. These types of strategies generally called as dynamic power management (DPM) in the literature. By adopting DPM strategies, a power reduction between 15 to 65% is achieved in various mobile devices [12, 13, 5]. However, with this approach, normal operation of device changes and this could lead to decrease in usage comfort of consumers.

Nevertheless, there is a potential for increasing types of energy management strategies for mobile devices. In recent years, components of the mobile devices that are doing the same job started to increase. In Chapter 5 of [21], it is mentioned that a mobile system can choose between the components that have same functionality according to their energy efficiency for that certain moment i.e. workload. For instance, wireless communication uses 990 mW while bluetooth transmission can be made only with 81 mW but wireless transmission data rate is ten times faster than bluetooth [21]. Thus, aim of the energy management problem is to find optimal power split between these devices according to a desired objective.

Main objective of an energy management strategy is minimizing power consumption from the mobile devices, however, maximizing amount of work done in a certain time interval is also important for performance issues. So, as mentioned in [36], besides decreasing power consumption, how much time is saved or extended for a certain work should also be considered.

Another possibility in terms of energy management is arouses for plugged-in usage of the mobile devices. In this operation mode there is two energy sources, as oppose to mobile usage, for the power required from components which are battery and electricity grid. This extra this degree of freedom for energy supply can be exploited. For example, in the time of peak consumption zones, electricity need of the device can be covered by battery. After this battery can be charged in nights when the cost of electricity is low compared to peak-zones or it can be charged when renewable energy-mix of national grid is high. By this way while electricity cost to end user can be decreased also use of renewable energy can be boosted. These type of objectives can be achieved by employing a supervisory controller which adopts an energy management strategy.

1.3 Motivation

In this thesis, a residential energy management problem will be solved based on a previously applied strategy but in a very different area; automotive engineering. The objective of this thesis is to explain that energy management problems are similar and can be solved with a baseline strategy. Thus, final part of this thesis devoted to generalization of the procedure.

The strategy applied produces a sub-optimal rule based controller that can be used in real time to exploit possibilities presented by a multi-source multi-sink system. These possibilities can be reducing operational costs, harmful emissions or dependency to fossil fuels. In this thesis, performance of the controller is evaluated in residential system. However by modifying the formulation it can be applied to any system that fits to the definition, for instance mobile devices.

1.3.1 Contributions

Contributions of this thesis are listed below;

- For all types of energy management problems, a generic formulation is created for the development of a causal sub-optimal supervisory controller.
- Residential energy management problem is solved with the developed supervisory sub-optimal controller, which is a novel approach in this area.
- For residential energy management problem, typical energy demands cycles are used in the simulations and all of the important performance parameters are calculated. By this way, this thesis provides a healthy data for future comparisons, in which current literature lacks at the moment.

Chapter 2

Residential Energy Management Problem

In this chapter, first an introduction to residential energy management problem is given and possible energy supply infrastructures for the residential areas are discussed. In the following section, mathematical models and energy demand cycles used in this thesis for the selected residential system are introduced. In Section 2.3, by using these models, a dynamic optimization formulation is developed and solved. In the subsequent section, a real-time supervisory controller is developed based on dynamic optimization results. Finally this chapter concluded with the simulations conducted to verify and validate the developed controller.

2.1 System Definition and Possible Frameworks

Traditionally, residential occupation areas are considered as passive energy zones which means they consume energy without any production. However, this situation will likely to change with the introduction of technologies like micro combined heat and power (mCHP) [32] and decreasing capital cost of renewable energy technologies [4]. In near future, it is expected that households will produce majority of their energy needs locally and possibly use the national grid for only back-up purposes. With an optimistic perspective, *islanded* operation of residential sites will also be possible in the coming years [38].

A typical house have two distinct types of energy demands. These are a thermal demand which consists from hot water and space heating needs, and an electricity demand to power household appliances. Nowadays electricity demand is supplied from a national grid which consists of big power plants and requires transmission of electricity for long distances. And thermal demand is either supplied by district heating or a small boiler fed with a natural gas connection to the house. So household units depends on outside sources for their energy needs.

Alternatively, households can produce their own energy needs by a diverse set of technologies which is commonly mentioned in literature as distributed generation (DG). For example when the sun is available, by using passive solar collectors, hot water demand can be satisfied. If the thermal needs coincides with the electric demand then using mCHP device will be cost efficient. Or sometimes a combination of these technologies can give the best solution for a selected criteria. In conclusion, a residential zone with distributed generation falls into basic definition of the energy management problem that is defined in the Chapter 1 and thus requiring a supervisory controller to manage these energy sources optimally.

A list of commercially available technologies that can be used in residential area is given in Table 2.1.

Table 2.1: Possible Household Devices

Demand	PV	Sun Collector	mCHP	Wind Turbine	Grid	Boiler	Heat Pump
Thermal	-	+	+	-	-	+	+
Electricity	+	-	+	+	+	-	-

From Table 2.1 it can be seen that, a combination of these technologies must be used to cover both demands of a dwelling. Using only mCHP technology is possible but at the moment either operating costs more expensive than conventional case or capacity of the existing devices are not sufficient.

Apart from the energy converter technologies listed in Table 2.1, storage devices can be used to gain extra degree of freedom in terms of energy supply. For example by using an electro-chemical battery for electricity storage, one can supply the electricity demand from storage until unit price of the grid electricity decreases.

In this manner, a combination of these devices is selected for this thesis based on their availability in commercial market and their controllability. The proposed system is plotted in Figure 2.1, however the formulation that will be generated in the following sections is generic and can be applied to any residential system with the common distributed generation devices such as in 2.1.

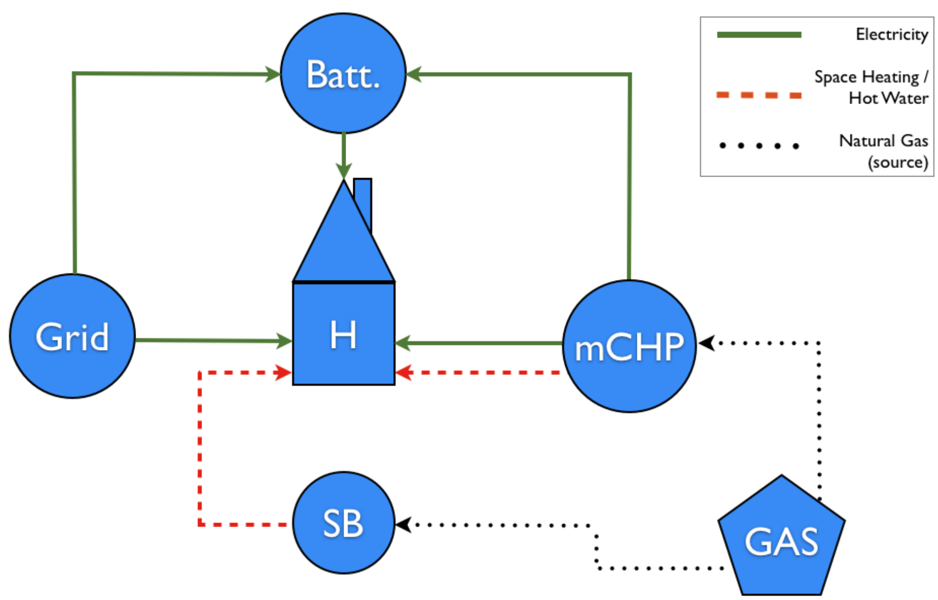

Figure 2.1: Graphical Representation of the System Worked

In the system shown in Figure 2.1, thermal demand of the dwelling is supplied by the mCHP device. In addition, a conventional gas-fired boiler is also present in the system for support purposes in case mCHP device is closed or its generation capacity is not enough for the demand. Because of this, it is called as support boiler (SB). Both devices use natural gas, which is a typical connection to a household, to create required heat. Electricity demand of the dwelling is covered by mCHP, national grid and lead-acid battery. Grid connection to a house is also traditional however, battery is not a typical component in a residential environment. The reason why battery is considered in the system is by the introduction of plug-in hybrid electric vehicles (PHEV), the battery will be available to house and it may be possible to use this source in a certain amount of range.

There are methods for predicting electricity demand and hot water requirements of a house according to a chosen occupation type [54, 42]. And for determining space heating loads, vast number of building simulation programs are available [3]. However, in this thesis electric and thermal demands of the typical house assumed as known with respect to time and used in simulations as demand cycles. This is also a common method in automotive industry, in which drive cycle is fed to the automotive power-train controller [23, 18].

It should be noted that, the aim of the controller is not increasing the efficiency of any device depicted in the Figure 2.1, rather the objective is finding optimal power splits between these devices to achieve a certain performance index. This is expected to increase the overall efficiency of the whole system.

2.2 Mathematical Model

In this section, a mathematical model will be developed for the system proposed in Section 2.1. Since the objective is developing a supervisory controller, a simple mathematical model that accurately predicts the device outputs will be sufficient. Otherwise, optimization techniques that will be used in the following chapters will take large amount of time with an unnecessarily detailed model.

In this thesis, a modeling strategy is developed by making analogies from a common method in automotive literature which is modeling power flow with backward facing quasi-static approach [23, 52]. In this context, quasi-static means, power and heat demand in a certain time interval (stage) are constant. Backward-facing means power outputs of the devices are inputs for the model and output of the model blocks are required fuel for the device to create that power. An example model of this approach for a parallel HEV is given in Figure 2.2 based on [52];

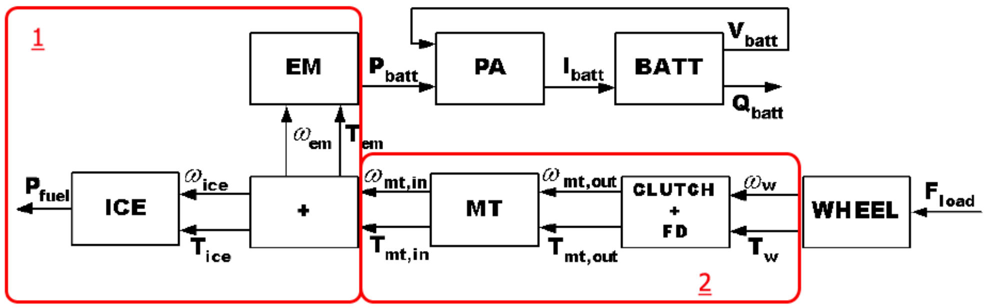

Figure 2.2: HEV Backward Facing Model

The model in Figure 2.2 consists from two parts, which are selected with red triangles. First part represents different energy sources available to provide requested torque and second part is accounted for transmission losses. By using this model, the required power from energy sources can be calculated for a given load demand from the driver.

Fore residential system, second part of the model is omitted because transmission losses are considered negligible in distributed generation. The proposed model for the residential system proposed in Figure 2.1 is given in below Figure 2.3.

As it can be seen from Figures 2.2 and 2.3, there are some fundamental differences between models but the analogy is same which is calculating required power levels for the given demand. First significant difference is, in HEV case there is only one power flow which is required power to rotate shaft at a demanded level. In contrast, there are two different power flows, namely electric and heat in residential environment. Although these two demands from occupants are not depended, due to the devices like mCHP, production of these demands are coupled and solved together. Another difference is number of power sources. For instance, in home energy system there are three energy sources to provide electricity demand which are national grid, mCHP and battery. On the other hand, in HEVs there is only two sources to provide requested torque which are internal

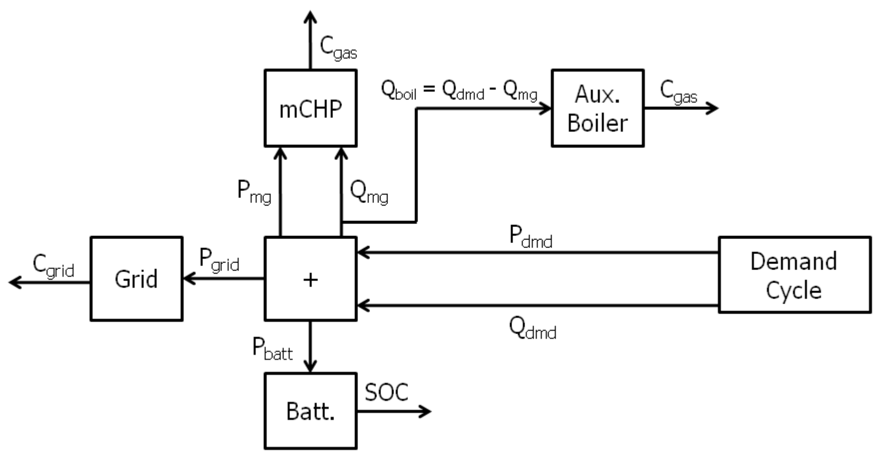

Figure 2.3: Backward Facing Model of the Proposed System

combustion engine (ICE) and electric motor with battery. Thus finding optimal power split becomes more complicated in residential problem.

In the remainder of this section, mathematical models for the devices seen in Figure 2.1 will be introduced. Also energy demand cycles for a certain occupation type will be generated to be used in optimization and simulations.

2.2.1 Converter Devices Used in the Residential System

2.2.1.1 Micro-Combined Heat and Power (mCHP)

Micro combined heat and power devices are developed in last the decade and intended to replace conventional boilers used in residential environment. The output of these devices are the same as combined heat and power (CHP) plants which is obtaining electricity and thermal energy from a single energy source (like coal or natural gas). Only power levels are much smaller compared to conventional CHP plants.

The prime-mover technologies that are used in mCHP system can be based on fuel cells, Stirling engine (SE) or internal-combustion engine (ICE). In this thesis, ICE based devices are chosen as micro-generator for the dwelling due to their availability in the market, efficiency values (only fuel cells are more efficient then ICE but they are not commercialized yet) and ability to modulate their output power [40]. Although the created formulation is generic enough to adopt other sources.

By using the notation in [22], a micro-CHP device can be treated as single input, multiple output device. Natural gas, which is a standard connection to a dwelling, is the input for the mCHP and outputs are electricity and heat. But since the modelling approach is backward facing, these are vice-versa in the model. Graphical representation of the model is given in 2.4.

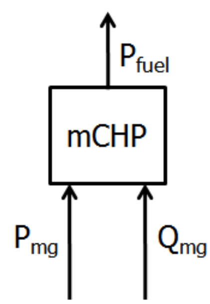

Figure 2.4: Backward facing, quasi-static representation of mCHP device

Mathematical model of the ICE based mCHP device used in this thesis is based on [41]. It consists from a simple parametric model of 6 kW Cummins gas engine and it is developed according to performance data from manufacturer. This model incorporates dynamic efficiency values of the device thus permitting variable power output. The mCHP models used in the literature such as [25, 44], have only full-power and one part-load operation mode which limits controllability of the device.

In the following, mCHP model used in this thesis is investigated. First, a fraction load is defined;

$$X = P_{mg}/(P_{mg})_{max} \tag{2.1}$$

Then Heat-to-Power Ratio (HPR), which is the ratio of electricity produced over heat produced from the device, is determined by the Equation (2.2) below, which is found from a series of tests.

$$HPR = 18.347X^3 + 45.76X^2 - 39.933X + 15.7 \tag{2.2}$$

After finding HPR, heat output of the device can be found for the required electricity output which is depicted in Equation (2.3).

$$Q_{mg} = HPR.P_{mg} \tag{2.3}$$

By using an empirical formula, specific fuel consumption of the deivce can be found as shown in Equation (2.4) which is again found from a series of tests.

$$SFC = 965.6X^2 - 1767X + 1164.2 \tag{2.4}$$

Finally the model output, mass flow rate of the fuel used, can be calculated with using the Equation (2.5).

$$\dot{m}_f = SFC.P_{mg} \tag{2.5}$$

Important parameters that are used in the model are plotted in the following pages according to fraction electric load to give insight about working characteristics of the device.

In Figure 2.5, Heat-to-Power Ratio (HPR) versus fraction electrical load is plotted. It can be seen that the ratio of the heat produced from the device decreases with respect to increase in electricity production. Therefore a calculation must be done according to the cost function at every step whether a high thermal production with lower electricity or a high electric and thermal production is needed in case of a peak consumption situation.

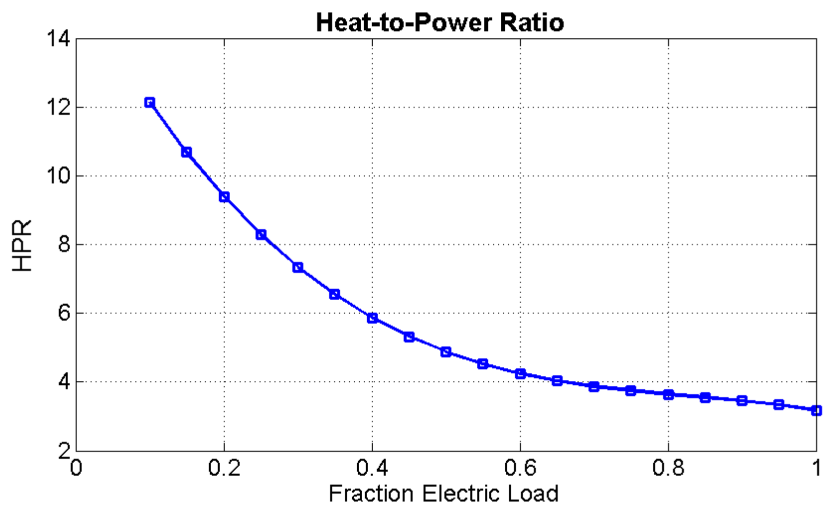

Figure 2.5: HPR vs. Fraction Electrical Load (X)

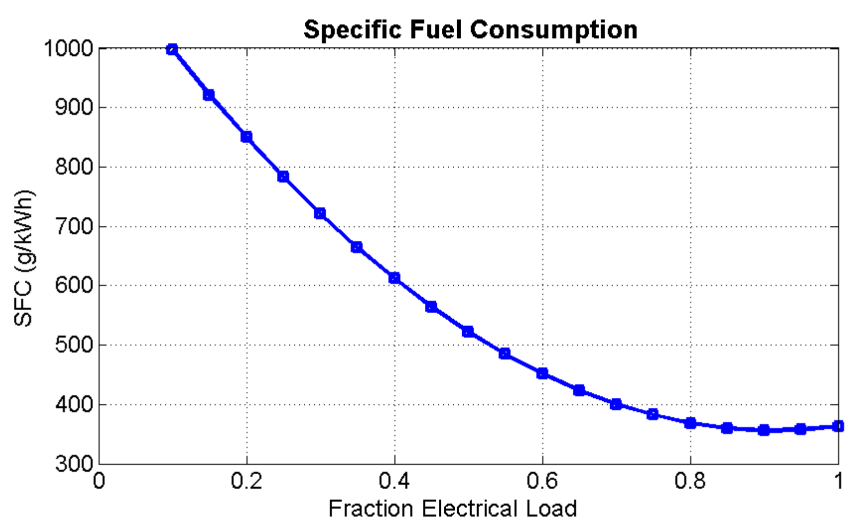

Figure 2.6: SFC vs. Fraction Electrical Load (X)

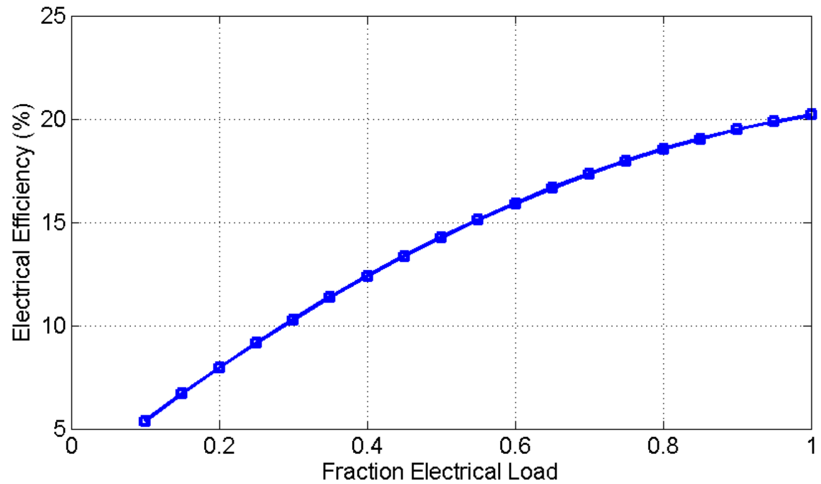

Figure 2.7: Electrical Efficiency vs. Fraction Electrical Load (X)

From Figure 2.6 and 2.7, it can be concluded that using the device in low energy zones makes it inefficient. This was an expected result, which can be concluded as characteristics of an ICE. Thus, size of the device must be selected according to the occupation type. For instance, a mCHP device with a high output , like 6 kW electricity and 15 kW thermal used in this thesis, will be too big for single-occupation type. When the device size is not selected accordingly, it will always work on inefficient zones and the cost will likely to be worse than the current infrastructure used in residential sites.

The model described here can be further improved by considering transient operation modes of the device. This type of operation characteristic occurs when the mCHP device started from cold or when it is turned off. In the former one, it takes certain amount of time to reach requested power output from the device and in the latter operation, mCHP device continues to generate power some time interval and then turns off.

Variables and parameters used in the model equations through (2.1) to (2.5) is given in Table 2.2.

Table 2.2: Parameters for mCHP

Name	Description	Value	Unit
P_{mg}	Electric power generated from mCHP	[0,6]	kW
Q_{mg}	Thermal power generated from mCHP	[0,15]	kW
$\dot{m}_f$	Mass flow rate of natural gas to mCHP	[0,2]	kg/s
LHV	Lower heating value of natural gas	47.1e6 from [15]	J/kg
ν_e	Electric efficiency of mCHP	[0,0.2]	-

2.2.1.2 Electro-Chemical Battery

As mentioned in the beginning of this chapter, battery is not a typical household gadget. However with the introduction of plug-in HEVs, the use of battery may be available for residential energy management in the future applications. Therefore a model of the battery used in parallel HEV simulations also employed in this theses.

An electrical storage battery is known to be difficult to model due to ongoing chemical reactions inside the battery which changes the terminal voltage. The approach here is based on [51], in which certain voltage values are measured corresponding to the SOC values.

From [51], change of the battery current is given in (2.6) and change of the battery state-of-the-charge is given in (2.7).

$$I_{batt} = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_{int}P_{batt}}}{2R_{int}} \tag{2.6}$$

$$SOC = SOC_{old} - \frac{I_{batt}\nu_{batt}t}{Q_{batt}} \tag{2.7}$$

where V_{oc} represents open circuit voltage across the battery, R_{int} is the internal resistance of the battery and P_{batt} is either charge or recharge power of drawn/to battery. As mentioned in the beginning, V_{oc} and R_{int} values in Equations (2.6) and (2.7) are found from current SOC value according to a pre-calculated look-up table, which can be found various sources such as [2] or could be created through measurements. For instance, the relation between SOC change and internal resistance of the battery used in thesis is given in Figure 2.8.

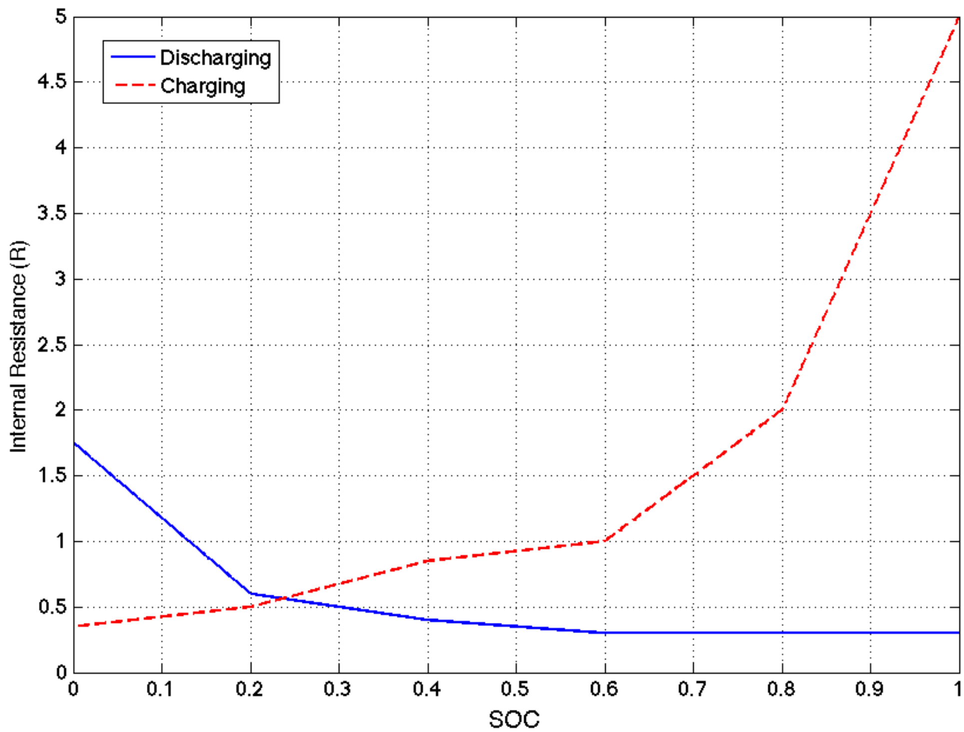

Figure 2.8: SOC vs. Battery Internal Resistance

From Figure 2.8, it can be seen that internal resistance of the battery increases while trying to charge a loaded battery. Battery resistance also increases when trying to discharge an empty battery though resistance is not high as charging case.

Besides the relations given in (2.6) and (2.7), there are also upper and lower bounds for battery state of the charge (SOC) in order to avoid degradation of the battery. In addition losses occur when charging the battery, so a constant charging efficiency of 0.9 is also included into the model.

Parameters and variables that are used in the model equations are tabulated in Table 2.3.

Table 2.3: Parameters for battery

Name	Description	Value	Unit
V_{oc}	Open circuit voltage of battery	[230,260]	V
R_{int}	Internal resistance of battery	[0.3,5]	Ω
$(I_{batt})_{max}$	Battery max. discharge current	100	A
$(I_{batt})_{max}$	Battery max. charging current	125	A
P_{batt}	Charge / Discharge power of battery	$f(I_{batt}, V_{oc})$	kW
Q_{batt}	Capacity of the battery	6	Ah
SOC	State of the charge of battery	[0.4,0.7]	-
η_{batt}	Battery charging efficiency	0.9	-

2.2.1.3 Natural Gas Fired Boiler

By using the notation defined in [22], a boiler can be considered as a single input, which is natural gas, and a single output, which is heat, system. Using the backward facing approach, graphical representation of the natural gas fired boiler can be showed as in Fig. 2.9.

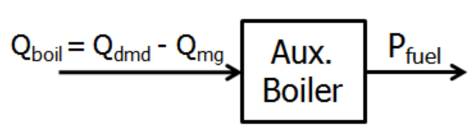

Figure 2.9: Backward facing, quasi-static representation of boiler

Traditionally, Higher Heating Value (HHV) of the combustion source, in this case natural gas, is used for calculating the efficiency of a boiler [8, 10]. HHV quantity assumes that water, which is the by-product of the combustion process, is in liquid state that can also be used in heating duty.

Another important property of the boilers that influences the mathematical model is their transient operation. Boilers reach steady-state much faster than mCHP devices [53]. So warm-up and shut-down periods of the boiler can be neglected and a steady-state efficiency is used in the formulation. Efficiency value is selected based on the available commercial devices.

The mass flow rate of the fuel used by the boiler is calculated via the Equation 2.8 which is in the line with [29].

$$\dot{m}_f = \frac{Q_{boil}}{\eta_b.HHV} \tag{2.8}$$

where Q_{boil} to be determined from optimization algorithm.

Parameters used in the model are given in Table 2.9.

Table 2.4: Parameters for battery

Name	Description	Value	Unit
$(Q_b)_{max}$	Max. output power of boiler	20	kW
HHV	Higher heating value of natural gas	60e6	J/kg
η_b	Steady-state boiler efficiency	0.89	-

2.2.1.4 National Grid

It is assumed that, when supervisory controller requires a certain amount from grid, it is obtained in exact amount with no delays. Because grid dynamics are much faster according to our simulation time, thus neglected.

2.2.2 Energy Demand Cycles

As mentioned in the beginning of this chapter, demands of the dwelling will not be calculated directly or simulated via a building simulation program. Instead, a set of representative demand cycles for certain occupation types will be used which are found from previous measurements conducted by International Energy Agency (IEA) Annex 42 program [11].

One of the dominant parameters affecting the performance of the proposed system is total amount of demand from the dwelling. According to occupancy type, appropriate capacities for the multiple sources should be selected, otherwise controller developed will not give better outcomes from conventional system due to sizing problem. However, the sizing problem is beyond the scope of this thesis. Therefore appropriate capacities for the devices are chosen for the selected occupation type which is given in detail in the following paragraphs.

The electricity and Domestic Hot Water (DHW) demand cycles of a typical EU dwelling in January are given in Figures 2.10 and 2.11.

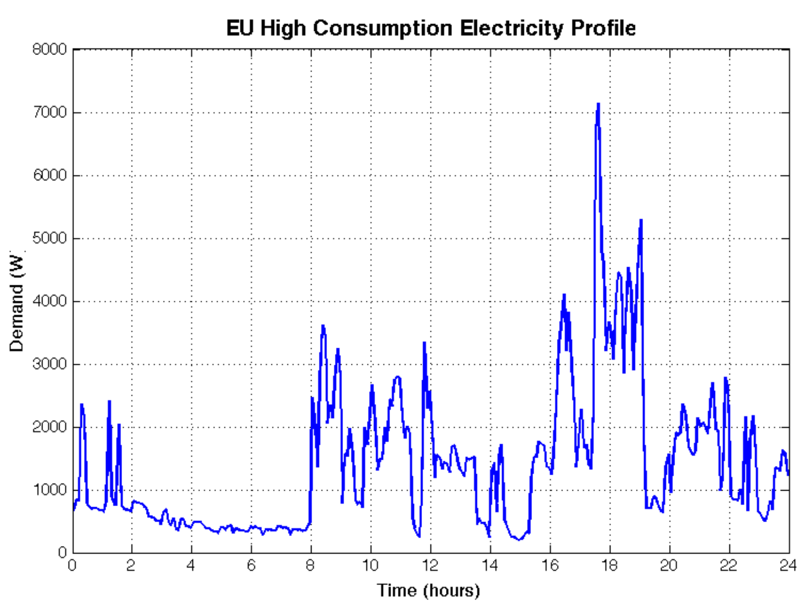

Figure 2.10: Electricity demand profile throughout a day [31]

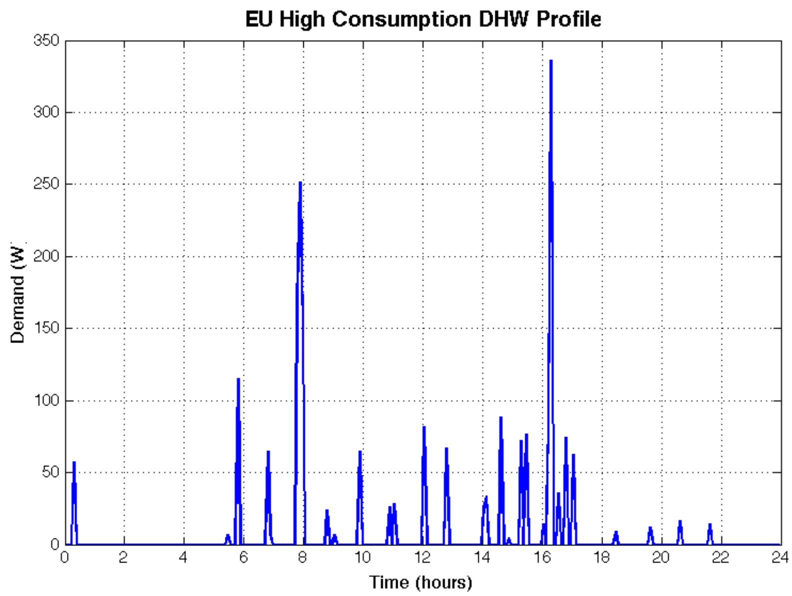

Figure 2.11: DHW demand profile throughout a day [31]

The graphics in Figures 2.10 and 2.11 are generated based on the data from [31]. Both consumption data are measured in 5 minute intervals and it shows *high* consumption demand according to Annex standards. The high consumption demand cycle represents a family with 5 children [31]. Although it looks like an extreme case, it is selected since the model used for mCHP has relatively higher output than other commercially available mCHP products, thus requiring a larger family for an efficient operation.

Last demand cycle for residential system is for SPace Heating (SPH) demand, which is plotted in Figure 2.12.

The Figure 2.12 shows space heating demands of a typical EU dwelling in a bright winter day. Data measured in Germany between 15 minute intervals. For consistency with other demand data's, these 15 minutes data points are assumed as constant for three 5 minute intervals. As mentioned in the beginning, one can use building simulation programs to derive similar SPH demand cycles. However, for the scope of this work a typical SPH data like in Fig. 2.12 is sufficient.

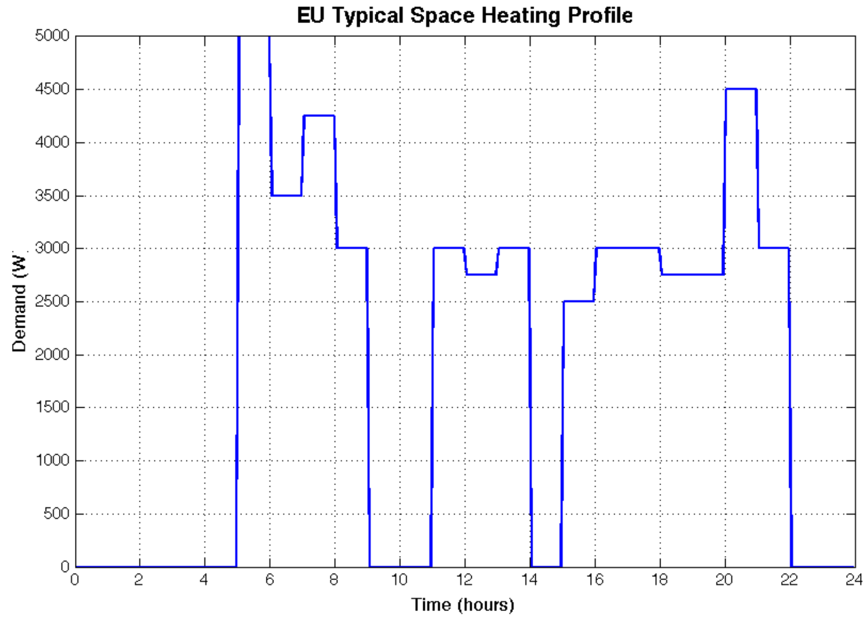

Figure 2.12: SPH demand profile throughout a day [9]

2.3 Optimal Trajectory Generation

As mentioned in Chapter 1, dynamic optimization techniques will be used to solve residential EMP. Main advantage of dynamic optimization methods is possibility to consider the dynamic nature of the system components.

A dynamic optimization problem can be solved by a technique called Dynamic Programming (DP) [14]. This method allows non-linearity in dynamic models and also constraints within the mathematical formulation of the problem. One of the main advantage of the DP method is, it guarantees global optimum solution for the system since optimization is made for entire time horizon, not for an instant time or a small predicted time interval. The method relies on Bellman's theory, Principle of Optimality. According to principle of optimality, if a trajectory is optimal, then every sub-trajectory must also be optimal [14].

Main disadvantage of the DP is if the system order increases, computational time increases exponentially. Thus it is not possible to use very detailed models in DP. This is known as the *curse of dimensionality* [14, 35].

By using DP method, optimal trajectories for the states and control inputs will be obtained. However, real-time implementation of DP is not possible since it requires future demands in advance for computation. So the optimal trajectories found from DP will be used for extracting implementable causal control rules.

Block diagram for the DP procedure is adopted from [14] and given in Figure 2.13.

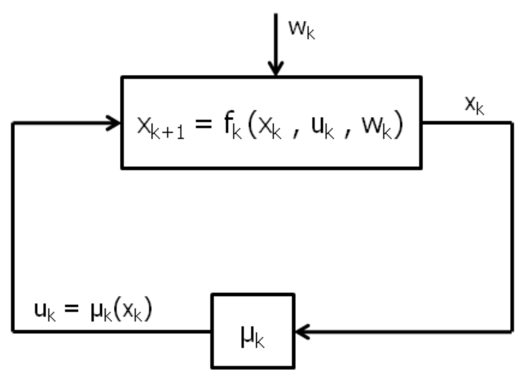

Figure 2.13: DP Procedure

In Figure 2.13, "x" represents state of the system, "u" represents control inputs, "w" is random parameters and μ is the control policy. By applying closed-loop optimization, controller can make appropriate reaction to the unexpected states that are developed since current information of the system, i.e. state of the system, is fed to the DP algorithm. Also energy demand requirements of the occupants are assumed as known, which are given in subsection 2.2.2. This means random parameters of the residential system, w, is known which results a deterministic problem.

Due to the *curse of dimensionality*, battery state-of-the-charge (SOC) chosen as only state variable. This is in the same line with the backward facing model developed in Section 2.2, with battery being the only dynamic block and other sources modelled as quasi-static. On the other hand, two control inputs are defined for the power-split approach. The two level representation of the power split algorithm used in this work is given in Figure 2.14.

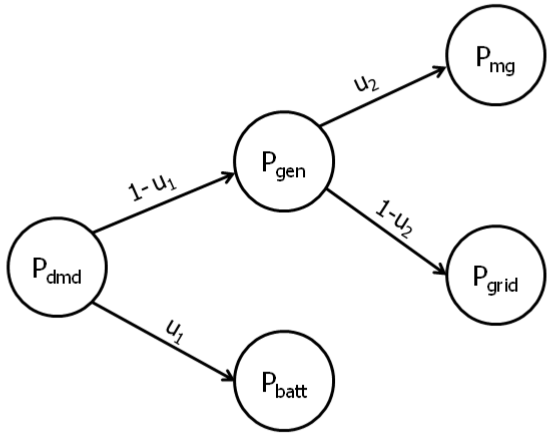

Figure 2.14: Power Split Method

The "power-split" approach used in this thesis is a common method in automotive industry [35, 52, 23]. With this approach, instead of separately determining the operation modes and associated power levels of electric motor and engine, a power split ratio is defined. Power split ratio couples this two sources by dividing power level of a one source to the total power requested by the driver. By this way DP only calculates this ratio and power level of these two sources extracted from it.

For residential problem, this power-split algorithm is extended into two layers. In the first split, the aim of the DP algorithm is determining battery operation mode for the current demand from the occupants. According to this decision, battery can be turned-off for the corresponding time interval or some portion of the requested power can be supplied by battery. If DP algorithm decides that battery needs a recharge, then more power must be generated from power demands of the occupants. Amount of the power requested is updated according to battery contribution, which is shown with P_{gen}. In the second split, DP algorithm decides that how much of the required power generation, P_{gen}, is taken from grid, P_{grid}, and mCHP, P_{mg}. By using this power split-method, instead of calculating three control inputs, for battery, mCHP and grid, only two control variables are calculated.

It should be noted that, the decisions are not made isolated. All possible power levels for the devices are generated from this power-split algorithm, then the combination that minimizes the constructed cost function is selected.

Finally, to solve problem numerically, mathematical model of the system is discretized on a state and time grid. DP procedure starts with solving the sub-problem which includes only last stage, then it extends to last two stages, last three stages and until the beginning.

A mathematical formulation developed is written according to formal standard representation which can be found in [14].

Cost function:

$$J(\vec{x}(k), \vec{u}(k)) = \min_{\vec{u}} [G_N(\vec{x}_N) + \sum_{k=1}^{N-1} L(\vec{x}(k), \vec{u}(k))] \tag{2.9}$$

$$x_{k+1} = f(x_k, u_k) + x_k \tag{2.10}$$

$$x = [0.4, 0.7] \tag{2.11}$$

$$x_0 = 0.55 \tag{2.12}$$

$$x_N \geq 0.55 \tag{2.13}$$

$$u_1 = [-1, 1] \tag{2.14}$$

$$u_2 = [0, 1] \tag{2.15}$$

$$T_s = 5 \quad min \tag{2.16}$$

$$N = (24 * 60)/Ts \tag{2.17}$$

As mentioned earlier, only one state variable, $\vec{x}$, is defined for the system which is battery SOC. It is assumed that battery starts to the day with a half full of charge (i.e 0.55), Eq. (2.12). Upper (i.e 0.7) and lower (i.e 0.4) bounds for the battery SOC is defined in Eq. (2.11) to prevent battery from depletion and overcharging, since they decrease battery life. These operational bounds are consistent with the literature [51], and increasing the operation zone of the battery will shorten its life-span besides it will have a small contribution to the overall efficiency of the system since the battery size is relatively small. As mentioned in the beginning of this chapter, a plug-in HEV battery used in this residential system for future references which has a capacity of 6 Ah that is small compared to traditional batteries used in residential systems which generally have a capacity around 25 Ah [28]. Finally, for the numerical solution, the area formed from upper and lower bounds is discretized with 1001 steps. This number is found from convergence analysis which is given in Appendix A.

Function G represents the final cost, which is not required in this system since the final state of the battery is already constrained with Eq (2.13) thus depletion of the battery in the end of the simulation is not an option. Cost function L and state equation f, which represents change of the state according to time, is given in equations (2.19) and (2.20).

Power splits in Figure 2.14 are represented with $\vec{u}$. First power split requires negative values for the battery recharge mode. Since they are ratio, they have an upper bound of 1. Control input domains are divided into 101 equal spaces in grid map. This number, again, obtained through a convergence analysis which is given in Appendix A. The power split algorithm is given in equations from (2.21) to (2.25).

The demand cycles generated in subsection 2.2.2 was obtained 5 minute interval measurements, thus simulation time T_s is selected as 5 minutes. Dynamic optimization will be performed over a full day which is in total 1440 minutes. Dividing this value to simulation time will give optimization horizon, N, which results 288 stages.

$$G_N(x_N) = 0 \tag{2.18}$$

$$L(\vec{x}(k), \vec{u}(k)) = \dot{m}_{fuel}C_{fuel} + P_{grid}C_{grid} \tag{2.19}$$

$$f(x_k, u_k) = -\frac{I_{batt}\eta_{batt}t}{Q_{batt}} \tag{2.20}$$

$$\dot{m}_{fuel} = f(P_{mg}, P_{boiler}) \tag{2.21}$$

$$P_{batt} = u_1 P_{dmd} \tag{2.22}$$

$$P_{gen} = (1 - u_1)P_{dmd} \tag{2.23}$$

$$P_{mg} = u_2 P_{gen} \tag{2.24}$$

$$P_{grid} = (1 - u_2)P_{gen} \tag{2.25}$$

This DP formulation is solved by using a toolbox software developed by the Swiss Federal Institute of Technology, Institute of Dynamic Systems and Control [50]. This software provides a MATLAB function that can solve deterministic DP problems. The developed formulation is generic, function requires only model equations and the objective function. Then it solves the discrete-time optimal control problem automatically by using Bellman's Principle of Optimality. It is a well coded program which results a fast computational time and can be downloaded for free from the Institute website. However the software requires solid knowledge of DP algorithm, System Theory and MATLAB programming, thus it is not easy to handle for novice users. Obtained optimal trajectories from the formulation given in Eq. (2.9) thru. (2.17) by using this software is given in Figure 2.15.

Jenkins et. al. [28] states that a battery can be used to cover peak demands from the occupants. From Figure 2.15, it can be seen that DP algorithm follows this statement and tries to discharge the battery in the evening zone when demand of the dwelling is high. Also battery charging sequences coincide with mCHP operation. For instance, between 6-8 a.m. battery is in charging mode since mCHP device is open while battery is off at 10 a.m. since mCHP is not working. This was an expected result since electricity provided from this device is an additional free power alongside its thermal power generation, which can be used to charge the battery.

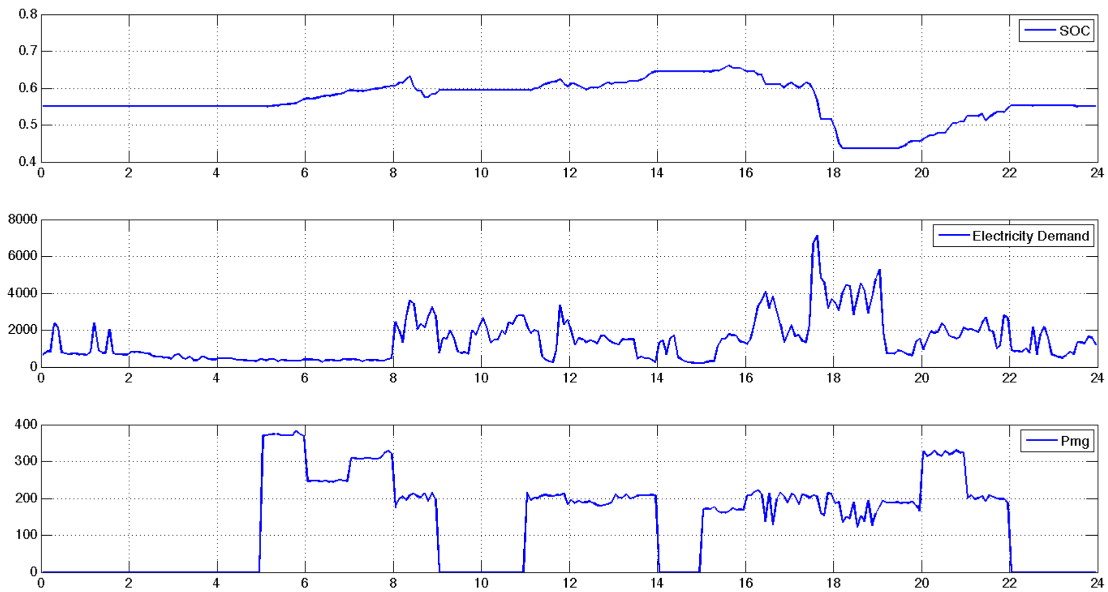

Figure 2.15: Optimal State Trajectory

By using optimal control inputs, in other words power splits, the trajectories obtained for the energy sources is given in Figure 2.16.

From Figure 2.16, it is clearly seen that mCHP is a thermal device. While it supplies large amount of the thermal demand of the house, it contributes a small amount to the electricity generation. DP algorithm turns the device off when there is no thermal demand in other words heat to power ratio of the house is zero or small. This makes sense since production of electricity from mCHP device is expensive according to grid electricity, if the generated heat will not be used. From this figure it can also be concluded that besides optimal part load values, mCHP device will work three times during the day while it works only two times with a time-led controllers. This implies better utilization since extra electric power can be generated with mCHP which can decrease operational cost at the end of the day.

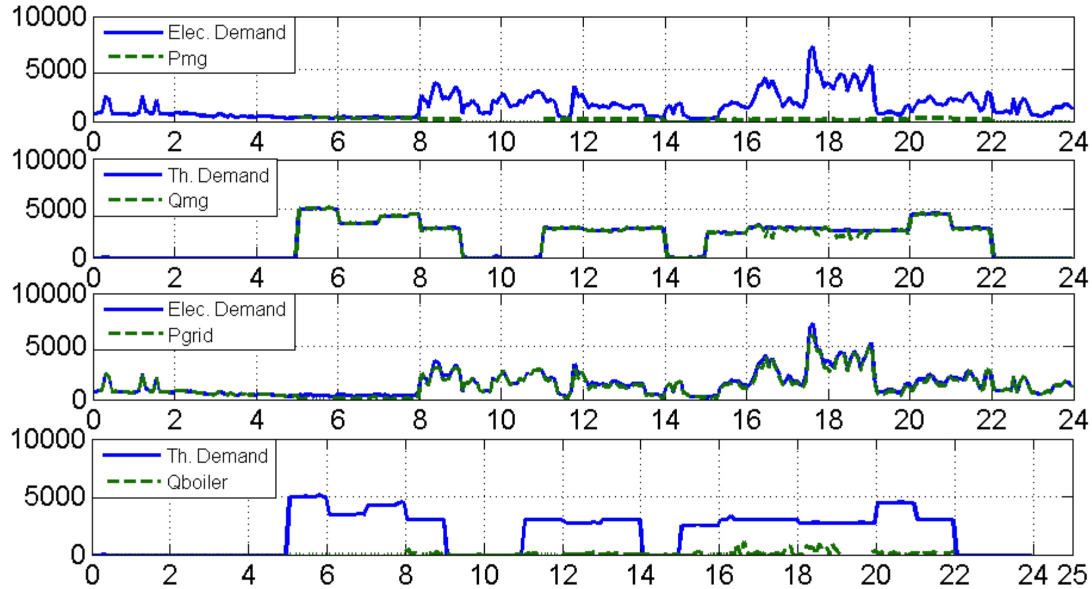

Figure 2.16: Optimal Usage of Devices Throughout the Day

2.4 Real-Time Supervisory Control

The aim of the controller is to enhance the system performance. The proposed system shown at the beginning of Section 2, Figure 2.1 can perform without an external, supervisory controller, by manual operation of each component by the residents of the house. But by adopting a supervisory controller, which coordinates the operation of the devices, system performance can be increased. This is the motivation for controller development.

Current commercial control strategies involving a mCHP device generally adopts heuristic control methods, in particular an approach called ”time-led” [53, 43]. In time-led strategy, mCHP system works with an internal controller which opens the device automatically before the occupation time. The occupation time is set manually by the end user. In this manner, the mCHP device reaches steady-state and works in full power when demand is increased in other words when the occupation begins. This type of a strategy uses the mCHP device only two times in a day, morning and evening intervals. So the advantages of the machine cannot be fully exploited. For instance, when the thermal demand exceeds the electric demand, which can happen at any time during the day, it is very beneficial to use this device. In conclusion, a supervisory controller with a new rule set can increase the system efficiency significantly.

In order to determine optimal power split between sources, a dynamic optimization procedure is done in the previous section. Dynamic optimization gives, for a specific demand, optimal power split values for the devices. However, since DP makes decisions not isolated with one stage but considering the future, globally optimum results found from DP cannot be used in real-time because algorithm requires whole demand information for the selected period, in advance. So a new control algorithm that can work on real-time must be developed.

In real-life applications, controller will only fed with current demand information and battery SOC level. By considering only these parameters, controller should make power splits between multiple energy sources.

A new control algorithm will be developed based on DP results. DP optimal trajectory maps will be analysed to create implementable rules. The aim here is to find effective decisions in real life when similar demands occur. DP algorithm considers and calculates many parameters to make decisions but sub-optimal decisions can be obtained by considering available parameters to the controller in real life.

2.4.1 Creating Rules

First step for creating implementable rules is determining all possible operation modes of the residential system. In Figure 2.17, a possible set of operation modes for a residential system is generated.

From Figure 2.17, which respects the power split algorithm shown in Figure 2.14, the controller must determine the battery operation mode firstly. Than according to this mode, states of mCHP device and grid electricity is decided.

In order to make decisions for the battery operation mode, DP decisions is studied. Thus, battery operation modes plotted against electricity demand from

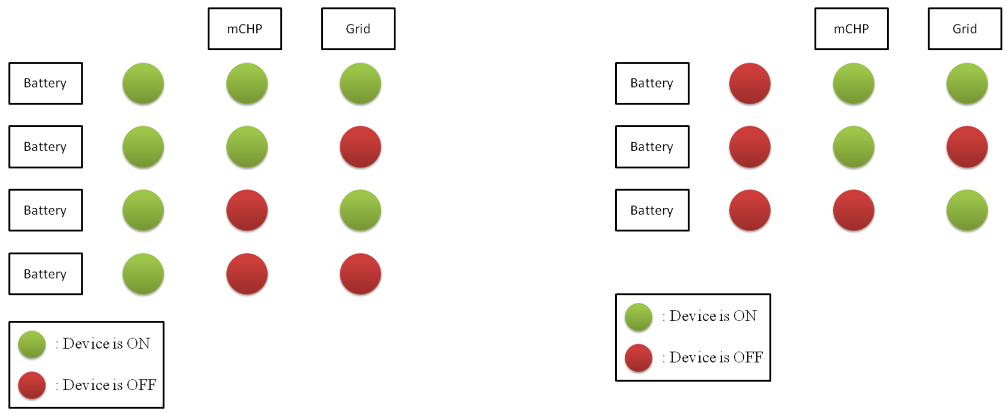

Figure 2.17: Operation modes for residential system

the dwelling in Figure 2.18.

From Figure 2.18, operation of the battery cannot be distinguished especially when demanded power level is below 2000 W. It can be concluded that the electric power demand level is not only the dominant parameter when making this decision.

Here, engineering intuition suggests that when battery SOC low, it should be charged and when battery SOC is high, it should be discharged. This can be seen from the simulations as well. So current SOC level of the battery also plays an important role in making decisions apart from electricity demand of the dwelling. Therefore, a surface is created for determining first power split of the system which is between battery and remaining energy sources which is plotted in Figure 2.19.

In real-time operation, controller benefits from the surface shown in Figure 2.19. This surface is created in MATLAB surface fitting tool with $R^2 = 0.97$. According to current electricity demand from the house and battery feedback data SOC, amount of power that will be generated with multiple sources is determined from this surface which is denoted as P_{gen}. The difference between the electricity demand and Pgen gives the battery operation.

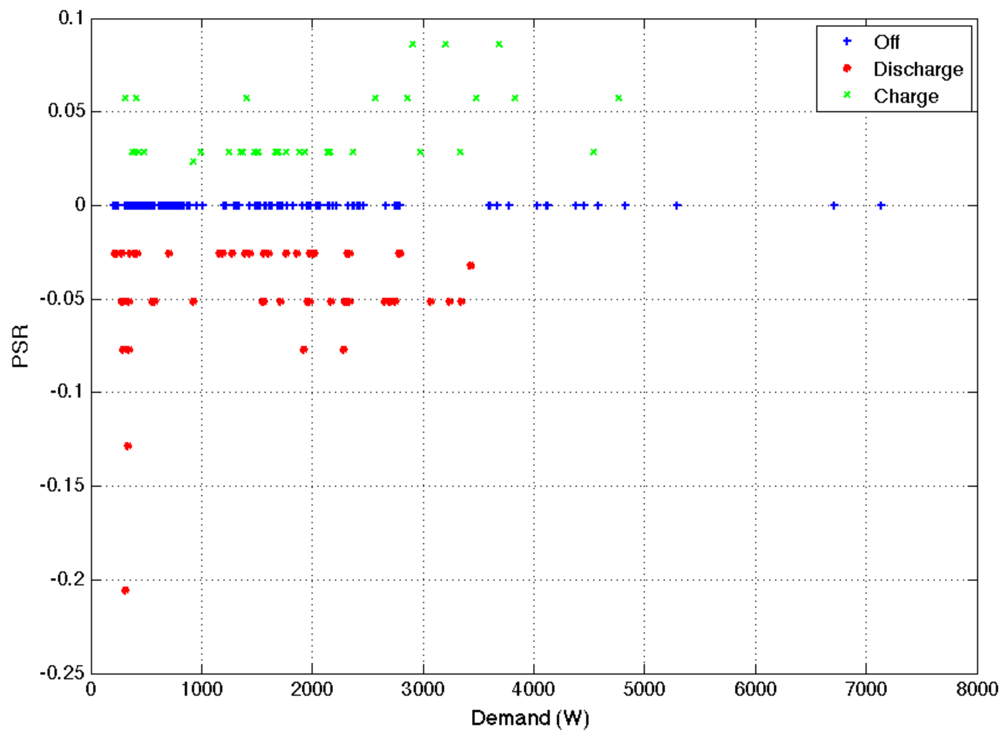

Figure 2.18: Battery Operation with respect to Electricity Demand

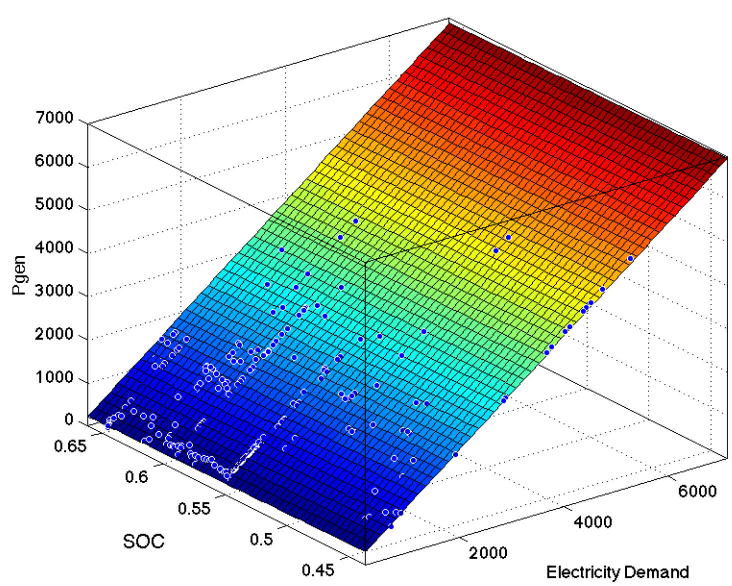

Figure 2.19: Power Split for Battery Operation

$$P_{gen} = 238.7 + 0.9587P_{dmd} - 0.313.9SOC \tag{2.26}$$

$$P_{batt} = P_{dmd} - P_{gen} \tag{2.27}$$

Similar approach is taken for second split in Figure 2.14 to find proper power split values between national grid and mCHP device. The surface fitted is given in Figure 2.20.

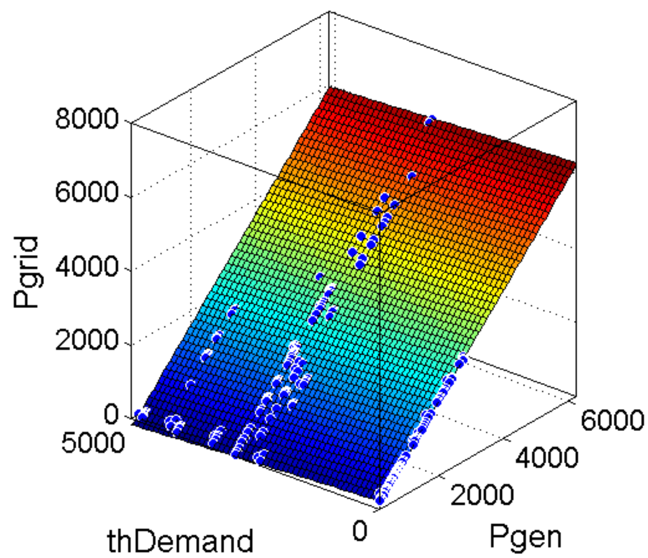

Figure 2.20: Power Split between Electricity Grid and mCHP

The supervisory controller uses this surface shown in Figure 2.20 to find power to be taken from electricity grid. This surface is created in MATLAB surface fitting tool with $R^2 = 0.98$. According to the total amount of power to be generated, P_{gen}, and thermal power required from users, P_{th}, electricity that will be taken from national grid, P_{grid}, can be found from Equation (2.29). As it can be seen from this figure, a 2-D curve fit can also be obtained for Pgrid however as seen from Figure 2.16, mCHP operation strongly correlated with thermal demand. It is seen that including this parameter to the rule generation increases the tracking capability of the controller.

$$P_{grid} = -5.813 + 1.008P_{gen} - 0.071P_{th} \tag{2.28}$$

$$P_{mg} = P_{gen} - P_{grid} \tag{2.29}$$

At the specific stage and corresponding SOC of battery, demand values from occupants, supervisory controller can found sub-optimal operation points for the battery, mCHP and the amount of electricity to be taken from national grid by using Equations (2.26) to (2.29).

2.4.2 Charge-Sustaining Strategy

The implementable rules developed above does not consider battery constraints. Because of this, battery can be depleted or overcharged depending on the real world applications. This problem can also be seen in references [35, 52]. So, an additional rule set is required to keep battery between desired SOC levels.

The battery prevented from depleting or overcharging by a simple rule set. If the battery SOC comes near to lower bound, the first power split replaced by a rule that charges battery a certain amount. Similarly, if the battery SOC approximates to upper bound, first power split overrode by a rule that discharges battery a certain amount according to current SOC level.

This algorithm is given in equations (2.30) to (2.34).

$$if(SOC > SOC_{max}) \tag{2.30}$$

$$P_{batt} = \mid 0.7 - SOC \mid 100 \times 175 \tag{2.31}$$

$$if(SOC < SOC_{min}) \tag{2.32}$$

$$P_{batt} = - \mid SOC - 0.4 \mid 100 \times 200 \tag{2.33}$$

$$P_{gen} = P_{gen} - P_{batt} \tag{2.34}$$

The battery used in the system approximately drops 1% of SOC when discharges 175 Watt between the selected upper and lower operation bounds of 0.7 and 0.4 respectively. The amount of total discharge required when the battery reaches upper bound is determined by the amount of SOC difference. If the difference big, more extreme cautions are taken which means more power is discharged. Since SOC is a fraction, it is multiplied with 100 to obtain a coefficient. The value 175 Watt increases to 200 Watt when battery reaches lower bound. This is because battery needs charging when it reaches to lower bound and due to charging efficiency more power is needed. After the new value determined for the battery power, remaining power to be generated is updated which is shown in Equation (2.29).

This subsection concludes the development of supervisory controller for residential EMP. The control flow for this case is given in Figure 2.21.

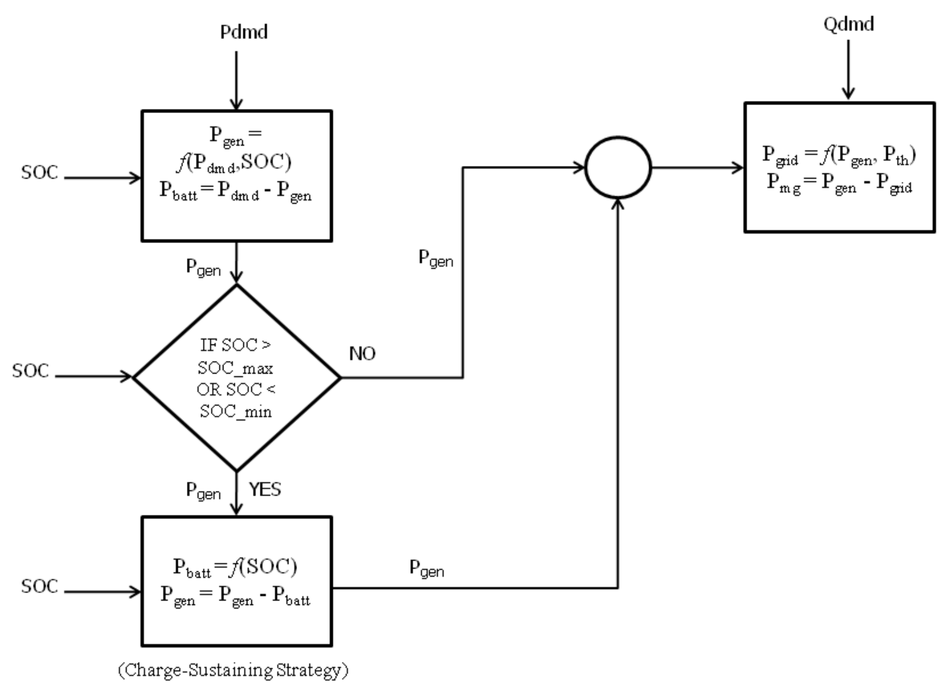

Figure 2.21: Control Strategy

In this strategy, supervisory controller is fed with current states of the dominant parameters and demand of the users. According to these values and generated surface fit maps in Figures 2.18 and 2.19, set-points for the sources are determined. An example of this control strategy shown in 2.21 is given in Appendix C as a Simulink diagram.

2.4.3 Rule Sensitivity

In the previous subsection, the sub-optimal rules for the supervisory controller created by using optimal DP results. As it can be recalled from Section 2.3, DP algorithm uses demand profiles of a typical day to find optimal trajectories for the state and control inputs. So it can be inferred that the rules generated are valid only for the selected day used in DP solution. Thus requiring the procedure for rule generation to be re-made for every day of the year.

However, it is found that demands from the dwelling is similar for seasons. For instance electricity and domestic hot water (DHW) demands for the winter season is given in Figures 2.22 and 2.23.

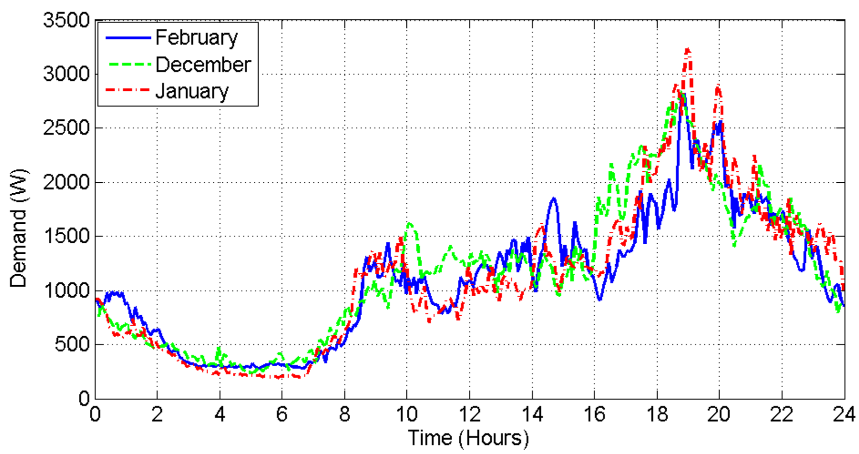

Figure 2.22: Average Daily Electricity Consumption in Winter

These figures are created by summing daily consumption data for the particular month and then dividing it into total number of data. From the figures it can be seen that consumption data are similar in winter months, following the

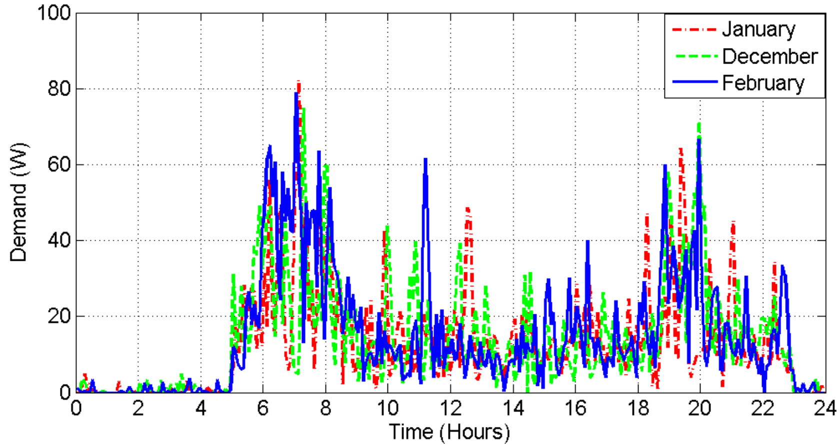

Figure 2.23: Average Daily DHW Consumption in Winter

same trend during the day.

For DP solution, a particular consumption data for a day in winter and an initial point for SOC was given. It can be concluded that since the demands are in good correlation for winter months, and the SOC initial point is always the same (0.55), the rules to be generated will be very similar for for winter months. In other words to rules that are generated in the previous subsection will work during the winter smoothly.

2.4.4 Comparison with Optimal Trajectories

In this section, performance of developed real-time rule based controller will be compared to optimal solutions found from DP solution. The expectation here is that real time controller will follow the optimal trajectories with an acceptable ratio.

In Fig. 2.24, a one-day simulation is made, according to demand cycles used in DP algorithm, to demonstrate capabilities of real-time rule based controller.

From the first plot in Fig. 2.24, it can be concluded that the electricity demand of the house satisfied perfectly by the developed controller. No deviations occur from the demand. This was an expected results since occupant demand

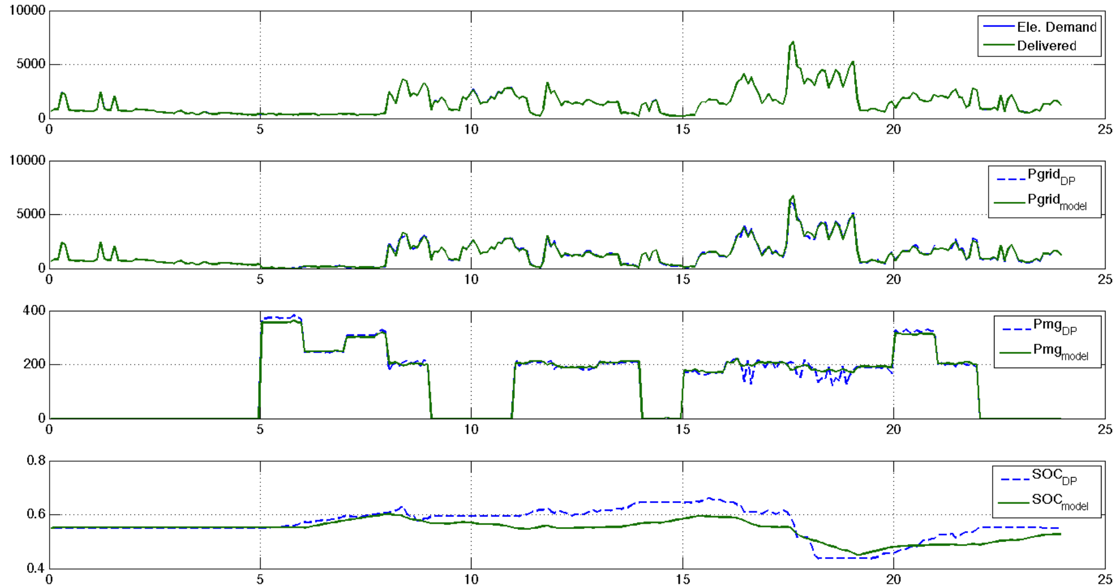

Figure 2.24: DP Results Compared to Real-Time Controller

satisfaction was one of the constraints in DP formulation. And the subsequent rules generated from this formulation uses demand data to do power split.

Second and third plots in Fig. 2.24 shows power split capability of the rule-based controller along multiple sources. In the selected residential system, there was a mCHP device and a national grid connection. The controller splits necessary power required, after the battery contribution extracted or included, between these sources. Blue dashed line represents global optimum solution from DP results and the solid green line is real-time decisions made by the developed controller. From the second and third plot, it can be seen that rule-based controller follows the optimal results successfully, there is only minor differences between them. These differences caused by the polynomial surface fit found on Equation 2.29. Since it is not a perfect fit, $R^2 = 0.98$, minor differences such as between 15 p.m. and 20 p.m. occurs.

Fourth and the last plot in Fig. 2.24 displays SOC change of the battery. Again, dashed blue line is the optimal result obtained from DP and solid green line is gathered from real-time simulation with rule-based controller. Although rule-based controller follows the DP results in majority, there are also some small differences differences between them, especially in between 10 a.m. to 15 p.m. This happens because surface fit found on Equation 2.26 is not perfect, $R^2 = 0.97$, which results deviations from optimal value. The deviations are bigger according to P_{mg} and P_{grid} since battery SOC much more sensitive which means a small difference in P_{batt} can cause a big change in SOC. However, these differences have no critical impact to the system efficiency since constrained battery capacity is small compared to whole system. From this plot, it can be also seen that the developed charge-sustaining strategy works smoothly. Between 5 to 6 a.m. battery SOC comes near to upper constraint, which is 0.7, and charge-sustaining strategy starts to automatic discharges to make sure that SOC does not exceed selected level.

2.5 Simulations

In this section, two different simulations will be held for three types of control strategies and the conventional case. First simulation will be based on the demand cycles used in DP formulation and second simulation is made with different set of demand cycles. The first simulation will show performance of the controller while the idea behind second simulation is to show that developed supervisory controller that is tuned on DP results can work even with different demand cycles, thus provides a robust performance.

First control strategy is theoretical optimal controller obtained from DP solution, which gives globally optimum results for the selected scenario and will be used as benchmark. The other control strategy is the supervisory controller extracted from DP results. These two systems are explained in detail, which can be found in the previous sections.

In order to show effectiveness of the developed controller, a heuristic controller available in the literature is also created which can be found in [53, 43]. This controller consists of hybridization of time-led and heat-led strategies which means mCHP device opens automatically two times in a day, in morning and evening periods and follows thermal load of the dwelling. The starting hour is selected according to a predicted occupation period, generally one hour prior to occupation, so that mCHP device reaches steady-state when the occupation begins. Since the mathematical model used in simulations does not include transient operation of the device, in simulations mCHP opens when the occupation begins in morning and evenings. And battery used only for catching sudden peaks in demand [28].

Finally, a conventional case is created to represent general residential infrastructure of today's world. Electricity demand is supplied by national grid and required heat for the house is obtained by a condensing boiler through a natural gas connection.

2.5.1 Performance Assessment Parameters

Three indicators will be used to compare performances of the control strategies developed. These are selected based on the works in literature and their meaningful definitions.

First indicator is the operational costs. Four different system investigated here will be compared based on operational costs to the end user. It is an important parameter since the proposed system is not compatible by price than it will simply cannot enter the commercial market. Most of the works in literature considers operational costs as a performance parameter [7, 43, 25, 17, 37].

Second performance indicator is primary energy consumption (PEC). By calculating this term, amount of primary energy consumed in a household including losses, which occurs due to generation and distribution of the primary energy source consumed, is considered [6, 20, 7]. Therefore it is an important indicator for energy efficiency. Lower PEC shows that the system uses energy sources more efficiently. The computation of PEC value is given in 2.35 which can be found in [45, 19].

$$PEC = P_{ngas}PEF_{ngas} + P_{grid}PEF_{grid} \tag{2.35}$$

$$PEF_{ngas} = 1.14 \quad [kWh_{eq}/kWh_{used}] \tag{2.36}$$

$$PEF_{grid} = 2.35 \quad [kWh_{eq}/kWh_{used}] \tag{2.37}$$

In equation (2.35), P_{ngas} represents total amount of natural gas used by mCHP device and auxiliary boiler. Primary energy factor (PEF) values in equations (2.36) and (2.37) are average values for European EU-17 standard and taken from [45]. Since grid and natural gas usage values changes according to system configuration and control strategy adopted, PEC will be different in the four systems investigated here.

Third and final parameter for performance assessment is selected as amount of CO_2 emissions created by the system. Reductions in CO_2 emissions is crucial for environmental performance. This parameter is computed according to [45].

$$CO_2 = P_{ngas}(CO_2eq)_{ngas} + P_{grid}(CO_2eq)_{grid} \tag{2.38}$$

$$(CO_2eq)_{ngas} = 247 \quad [g/kWh_{used}] \tag{2.39}$$

$$(CO_2eq)_{grid} = 430 \quad [g/kWh_{used}] \tag{2.40}$$

Carbon-dioxide equivalent values (CO_2eq) values in equations (2.39) and (2.40) are average values for European EU-17 standard and taken from [45]. It should be noted that this constants considers all greenhouse gases into account, not only CO_2.

2.5.2 Simulation I: Validation of the developed supervisory controller

In this simulation, control strategies explained in the beginning of this chapter will be tested with the demand cycles used in DP formulation and creation of the supervisory controller. First table shows the usage frequency of the devices according to control type.

Table 2.5: Usage Frequency of Multi-Sources in a day (24h)

	Tot. Elec. Demand	Tot. Ther. Demand	Grid Usage	mCHP Usage	Battery Usage	Boiler Usage
Conv. Case	33.7580 kWh	46.1736 kWh	100%	-	-	46.1736 kWh
Heuristic Contr.	33.7580 kWh	46.1736 kWh	93.4%	2.081 (Elec.) 29.074 (Th.) kWh	0.7479 kWh	17.0996 kWh
Superv. Contr.	33.7580 kWh	46.1736 kWh	91.3%	3.1894 (Elec.) 45.087 (Th.) kWh	1.2866 kWh	1.1963 kWh
DP	33.7580 kWh	46.1736 kWh	91%	3.0659 (Elec.) 43.4577 (Th.) kWh	0.6251 kWh	2.8535 kWh

The Table 2.5 shows change of usage pattern of the multiple energy sources subject to control algorithms. Conventional case in the first row included for comparison purposes. As expected, with the built-in rule-based controllers inside the mCHP devices, potential of this device is not fully exploited. By adopting current commercial rule based approach for mCHP device and using battery only peaks produces substantially lower energy according to optimal DP and developed sub-optimal rule based controller. This results higher costs and higher dependency to national grid.

Second table shows cost and PEC reductions for the selected day.

Table 2.6: Cost and Primary Energy Reduction (24h)

	Tot. Elec. Demand	Tot. Ther. Demand	Cost (Euro)	PEC	CO_2 Reduction
Conv. Case	33.7580 kWh	46.1736 kWh	4.9575	100%	100%
Heuristic Cont.	33.7580 kWh	46.1736 kWh	4.7370	−3.8%	−3.5%
Superv. Contr.	33.7580 kWh	46.1736 kWh	4.6489	−5.3%	−5.00%
DP	33.7580 kWh	46.1736 kWh	4.6348	−5.6%	−5.2%

As seen in Table 2.6, daily cost is lowest for optimal but non-causal DP approach. This was an expected results since DP results gives global optimum for the system. The developed sub-optimal controller gives second best daily cost but still higher from DP. Then the heuristic control strategy and as expected conventional approach for homes produces the highest cost. It should be noted that, although decrease in cost is small but the results are daily. When it is expanded to monthly and yearly periods the cost gain will be highly competitive.

Second result from Table 2.6 is achieved reduction in primary energy consumption with new residential infrastructure. A 5.2% of daily PEC reduction can be achieved with the developed controller. This value drops to 3.8% since energy sources in the infrastructure are not operated optimally.

2.5.3 Simulation II: Verification of the developed supervisory controller

The purpose of second simulation is show robustness of the developed improved rule based controller. To do this, another set of demand cycles are created, again based on same references but for a different day.

The difference in electricity demand is given in Figure 2.25.

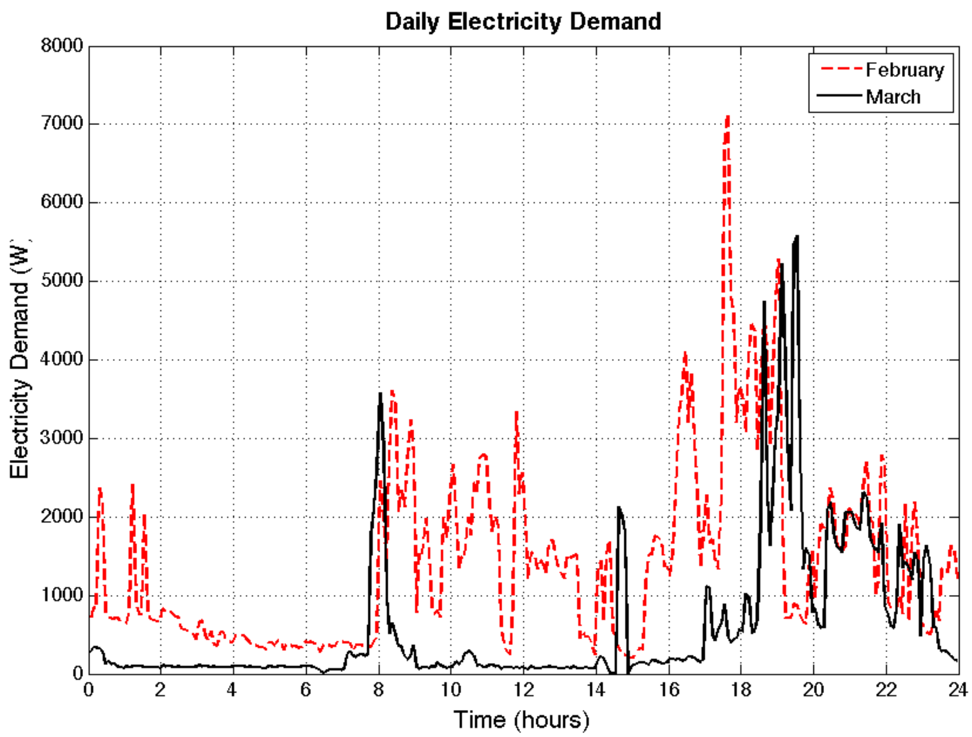

Figure 2.25: Daily electricity demand of a typical house

As seen from Figure 2.25, the new demand cycle is distinctly different than the demand cycle, which is demonstrated with dash lines, that was the base for creating implementable rules. There are certain shifts from original demands and also brand new demand values to test the controller's robustness. Similar updates, according to selected new day, conducted to domestic hot water and space heating demands as well but not shown here.

The response of the developed supervisory controller and optimal DP solution for new demand cycles is given in Figure 2.26.

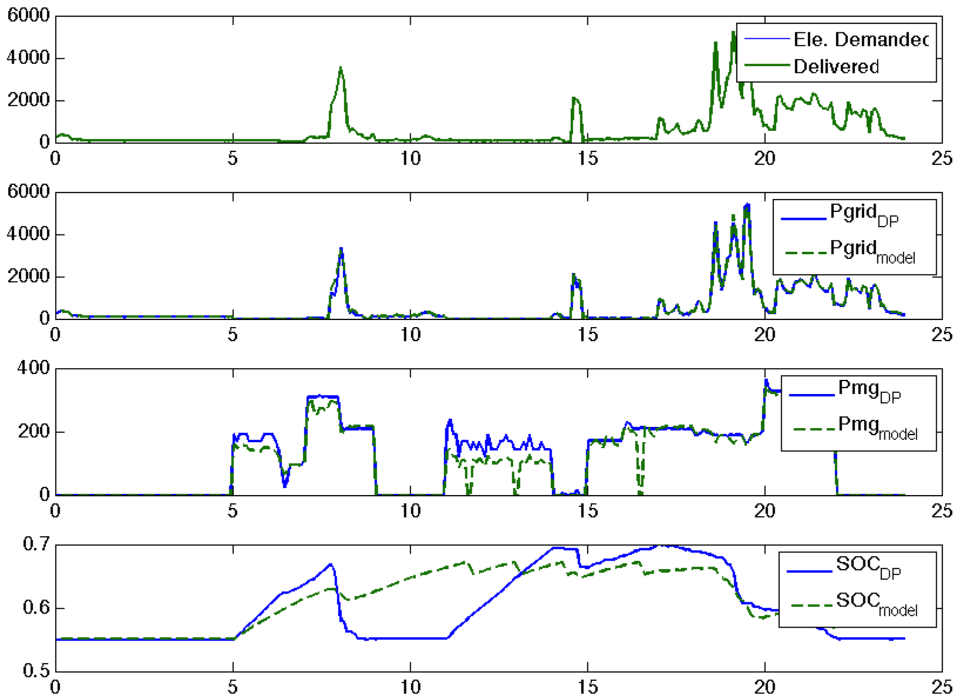

Figure 2.26: Comparison of Optimal Trajectory with new demand cycles

From Figure 2.26, it can be seen that demand of the house is fully satisfied even if the demand cycle changed. Also optimal grid trajectory found from DP solution is followed well with the developed controller. On the other hand, although some portions are followed well, there is substantial differences between optimal operations of the mCHP device and battery with the real-time solution. This problem occurred due to a small error in grid operation. Around 10 a.m. supervisory controller decides to import more electricity from the grid compared to demand. This extra electricity used to charge the battery and since it is small battery, the capacity reached to upper bound quickly. This caused to charge sustaining strategy to step-in to prevent battery from over-charging. So battery started to discharge power which results subsequent on and off operation of mCHP device, seen in around noon time. However since the size of the battery is small, it is effect effect on the system not expected to be high. In addition, subsequent on and off operations can be prevented if the transient operation mode of the mCHP device is included to the mathematical model.

Table 2.7: Cost and Primary Energy Reduction (24h)

	Tot. Elec. Demand	Tot. Ther. Demand	Cost (Euro)	PEC	CO_2 Reduction
Conv. Case	14.04 kWh	46.5296 kWh	2.9979	100%	100%
Heuristic Contr.	14.04 kWh	46.5296 kWh	2.7887	−5.2%	−4.5%
Superv. Contr.	14.04 kWh	46.5296 kWh	2.757	−6.2%	−5.5%
DP	14.04 kWh	46.5296 kWh	2.7159	−7.5%	−6.8%

From Table 2.7, it can be seen that operational costs are reduced since total electricity consumption of the house decreased. As expected theoretical DP solution gives the best results while conventional infrastructure is the worst performer in all three parameters. Comparing to results in 2.6, supervisory controllers performance declined according to DP. In the first simulation, the developed supervisory controller performed well with only 0.2-0.3% deviations from globally optimum results. However, in this simulation, this difference increases to 1.3% levels since the rules in supervisory controller was not tuned according to this demand cycles. However, supervisory controller still performs better than the heuristic controller with an amount of 1%.

In summary from these simulations it is seen that, a residential environment with multiple energy sources operating under the developed supervisory controller can reduce the operational costs up to 8% daily, compared to traditional houses. However, to achieve this performance, a certain capital investment must be made to the conventional house environment. According to [7], a payback period of 10 years is required to a capital cost of 5000 Euro if the natural gas and grid import prices stays within a 5% interest rate. However, it is also seen that the developed supervisory controller performs better than available heuristic techniques which may reduce this payback period.

Chapter 3

Generic Formulation for EMP

In this chapter, the procedure used in the residential EMP to create a causal sub-optimal controller will be generalized; so that it can be applied to all kinds of energy management problems.

The first section of this chapter provides baseline definitions to be used in the generic formulation. Section 2 is devoted to generalization of the dynamic programming formulation which will provide a non-causal optimal controller to be used as base. In the section following, techniques for creating causal sub-optimal controller from this base is discussed.

Final two sections of this chapter provides examples of using the developed generic formulation. The first example generates problem formulation for energy management in HEVs and the second example discusses mobile EMP.

3.1 Definitions and framework

In order to make a systematic approach, energy concept is divided into two main categories;

1. Raw energy sources

2. Useful energy products.

Raw energy sources are the input to create useful energy products and they are supplied by nature. This group can also be divided into two subcategories: fossil fuels and renewable sources. Coal and natural gas are examples of fossil fuels while sun and wind are examples of renewable energies. These examples can be augmented. Extracting fossil fuels also requires specific technology, thus they have a unit price. On the other hand renewable energies are free of charge.

Useful energy can be defined as, type of energies that we use in daily life. For example electricity, hot water and torque. In order to obtain useful energy products, raw energy sources must be converted by appropriate technologies. In these type of processes certain amount of losses from raw energy sources occurs due to conversion efficiencies and other technological or physical constraints.

In today's world, there is a lot of different energy converter technologies for different purposes and also for same purposes. Every different technology has it's own advantages and disadvantages. Some of them have high conversion efficiency while some of them emit low amount of harmful gases. Thus, a diverse set of technologies can be used together to achieve certain environmental and performance targets. However, this type of usage creates a new problem which is optimal supply of the requested power.

Optimal supply structure can be determined according to a performance index or objective function. However, parameters like maximum device output, minimum inlet flow rate or desire of keeping storage devices between a certain limits make this problem a constrained optimization problem. When the problem is properly formulated in a widely accepted standard form, there are lots of tools and techniques for solving a constrained optimization problem. The solution of the constrained optimization problem will give optimal trajectories for the devices employed in the energy structure.

Nowadays, using more than one energy converter device is common in many systems. An example is Hybrid Electric Vehicles (HEV). In HEV's there is an Internal Combustion Engine (ICE) and an electric motor which is connected to an electrical storage device, battery. Other examples can be given for a residential environment or even in portable devices. Types of components in terms of energy management for various different systems are given in Table 3.1. It should be noted, although obtaining grid electricity involves conversion devices, for simplicity it can be assumed as raw energy source since it has a unit price.

Table 3.1: Case Specific Examples

Application Area	Demand (Useful Energy)	Converter Devices	Storage Devices	Raw Energy Sources
Automotive (HEV)	Torque from Driver	ICE EM	Battery	Oil
Residential	Electricity Hot water	mCHP Sun Collector Boiler	Battery Hot water tank	Natural Gas Grid Electricity Sun
Portable Devices	User-Specific Applications	CPU, Monitor Solar Panel	Battery	Grid Electricity Sun

As it can be seen from Table 3.1, for every system there is different kind of demands, converters and raw energy sources. However the problem is same: determining optimal supply structure by using the degree of freedom composed from multiple sources and converters. This is the motivation for developing a generic formulation.

Components of a multi source - multi sink energy system can be distinguished and following vectors can be generated;

- ($\vec{d}$) : Demand of the users, i.e. demand vector or useful energy. (examples are electricity, hot water, torque, etc.)
- ($\vec{r}$) : Raw energy sources in order to fuel converter devices (examples are oil, natural gas, sun, wind, etc.)
- ($\vec{c}$) : Converter devices to obtain useful energy. (examples are turbine, internal combustion engine, PV module, boiler, etc.)
- ($\vec{s}$) : Storage devices to obtain extra degree of freedom. (examples are battery, hot water tank, etc.)

3.2 System optimization

In an energy management problem, generally there is no single objective. Minimum cost to end user is desirable to compete in the market while minimizing the greenhouse gas emissions from the devices is also desirable. In some cases, due to carbon footprint restrictions, minimizing harmful emissions can be top priority since a fine may result much higher operating costs. So a composite multi objective function is constructed using weights and given in below Eq. (3.1);

$$L(\vec{x}, \vec{u}) = L_C + \mu L_E + \nu L_{CS} \tag{3.1}$$

The function L in (3.1) consists from three functions. The functions inside the parentheses are essential objectives to consider in any energy infrastructure and second part includes Case Specific (CS) objectives.

First term in the objective function, L_C, represents operational costs. It is directly related to demand from the users and efficiency of the converter devices. In general, it is multiplication of unit price and the amount of usage of raw energy sources. It could be amount of fuel usage or grid electricity used or combination of them.

Second term L_E, corresponds to emissions from the converter devices. Thus, by using a device that has an high emission rate increases the cost function. A weight factor, μ, is associated with this objective to arrange this parameter's dominance on the system.

L_{CS} objectives are, by definition, special to the systems that are worked on. For example Primary Energy Reduction (PER) for residential areas is an important factor to consider [7, 20]. By minimizing PER, residential areas can be more grid-independent which is a good thing in case of blackouts. Another example can be given for vehicle sector, which is minimizing gear shift changes in order to obtain stabilized driving conditions for user. Also just as L_E, a weight factor, υ, is associated for specific arrangements.

The constrained optimization problem will be solved by dynamic optimization methods instead of static optimization methods. In this manner problem can be solved with respect to a time horizon rather than an instant time. This approach will provide better results since it considers future possibilities when making decisions, and it is already proved by automotive industry [18].

The method of solving is selected as Dynamic Programming (DP). It is a powerful algorithm that can handle non-linearities and always converge to a global optimum. In order to make solution with DP, system has to be discretized. A sample formulation is given below;

Cost function:

$$J(\vec{x}(k), \vec{u}(k)) = G_N(\vec{x}_N) + \sum_{k=1}^{N-1} L(\vec{x}(k), \vec{u}(k)) \tag{3.2}$$

s.t.

System Dynamics:

$$\vec{x}(k+1) = F(\vec{x}(k), \vec{u}(k)) + \vec{x}(k) \tag{3.3}$$

$$\vec{x}(0) = x_{init} \tag{3.4}$$

$$\vec{x}(N) = x_f \tag{3.5}$$

$$\vec{x}(k) \in \mathcal{X}(k) \subset \Re^n \tag{3.6}$$

$$\vec{u}(k) \in \mathcal{U}(k) \subset \Re^m \tag{3.7}$$

$$\vec{s}(k) \in \Re^a \tag{3.8}$$

$$\vec{c}(k) \in \Re^b_+ \tag{3.9}$$

$$\vec{d}(k) \in \Re^c_+ \tag{3.10}$$

$$\vec{r}(k) \in \Re^r_+ \tag{3.11}$$

Device Capacity:

$$g_1 = \vec{c} - \vec{c}_{max} \leq 0 \tag{3.12}$$

Storage Level:

$$g_2(\vec{x}) = \vec{s}_{CAP} - (\vec{s}_{CAP})_{max} \leq 0 \tag{3.13}$$

$$g_3(\vec{x}) = -\vec{s}_{CAP} - (\vec{s}_{CAP})_{min} \leq 0 \tag{3.14}$$

Customer Comfort:

$$h_1(\vec{x}, \vec{u}) = \vec{d} - \vec{c} - \vec{s} = 0 \tag{3.15}$$

Case Specific Constraints:

$$g_4(\vec{x}, \vec{u}) = \vec{g}_{CS} < 0 \tag{3.16}$$

$$h_2(\vec{x}, \vec{u}) = \vec{h}_{CS} = 0 \tag{3.17}$$

Inequality constraint on converter devices ($\vec{c}$), which is given in Eq. (3.12), represents power capacities of the converters. By using this constraint, maximum device capacity will be not exceeded. Another set of inequality constraints is enforced, given in Eq. (3.13) and (3.14), to make sure that storage device capacities (CAP) are between a certain range, so that their durability will be longer. To ensure that demand of the users are always satisfied, an equality constraint, given in Eq. (3.15), is applied which basically subtract the total amount of generated power from the requested power. And there is also Case Specific Constraints ($\vec{h}_{CS}$, $\vec{h}_{CS}$) for zones that are not covered in original formulation. These type of constraints can arise from transmission parts between CD's such as maximum shaft rotation rate.

Due to *curse of dimensionality* of DP method, state variables ($\vec{x}$) should be kept at minimum number in order to save computational time. This can be achieved by choosing storage devices as only state variables since decisions on these devices effects all the other components in a system. If storage devices are not available in the system, similarly one must choose a component that effects all others.

In dynamic programming, solution is made in backward recursion. A cost-to-go matrix is calculated for all possible states in the discrete map for all stages and finally an optimal trajectory is generated which gives the least cost for all time horizon.

Stage N-1:

$$J^*_{N-1} = \min_{\vec{u}(N-1)} \quad [G(\vec{x}_N)) + J(\vec{x}(N-1), \vec{u}(N-1))] \tag{3.18}$$

Stage k:

$$J^*_k \quad = \min_{\vec{u}(k)} \quad [J(\vec{x}(k+1), \vec{u}(k+1)) + J(\vec{x}(k), \vec{u}(k))] \tag{3.19}$$

In equation (3.19), first term is the optimal cost from previous state (since the solution is backwards it's actually the next state), and the second term is instantaneous cost for the current state. Solving this equation backward in time for entire horizon will provide optimal trajectories for the converter devices, $(\vec{c})$, and storage $(\vec{s})$.

3.3 Developing Generic Baseline Control Strategy

Optimal trajectories obtained from dynamic programming cannot be implemented in real-time because the algorithm requires future knowledge of the demand. Also calculation time is way too much for real-time implementation. However optimal trajectory maps can be studied in order to create control strategies. Although the optimal results, hence extracted rules, specific for the corresponding demand cycles used in the DP algorithm, the control strategies developed can provide near-optimal results for any demand cycle. This possibility arouses because either the suboptimal region of the energy management problem is large [49, 52] or demand trends of the users follows a similar trend for a certain amount of time, as happened in this thesis. So a baseline control strategy that is developed from DP results can be used to achieve the objective which is determining optimal supply between energy sources.

In order to make a numerical DP solution, system dynamics were discretized and obtained results are also operation points for a specific demand. However in real-time control, one must need a continuous function. To achieve this, Li and Peng created a neural network fit from the discrete DP results [35]. Guzella on the other hand, tried to lump whole information on drive cycle to a single parameter by evaluating the Hamiltonian function of the objective [23].

In this work, first optimal trajectories found from DP solution decomposed according to operation modes of the system. Then a curve-fit obtained for every map occurred from different operation modes.

If the system cannot be decomposed into it's operation modes, as happened in residential EMP which is shown in Figure 2.18, dominant parameters that are effecting the DP decision other than user demand must be determined. For instance, in residential EMP, battery SOC was the dominant parameter effecting the first power split decision other than the user demand. After the dominant parameters effecting the power split process is found, there are two options available. Either a surface fit can be created or in between sample layers a set of curve-fits can be gathered. The latter option is time consuming, thus examples on this thesis focuses on the first option.

A surface fit can be obtained by either polynomials or through a regression analysis in MATLAB's surface fitting tool (sftool). If a polynomial equation can be found for the surface fitted, then supervisory controller just uses this equation to determine power levels of energy sources. This can be seen in Figure 2.19. Otherwise a contour plot must be generated and by carefully investigating this plot, rules and thresholds for the controller can be gathered. This type of a map is given in Figure 3.1.

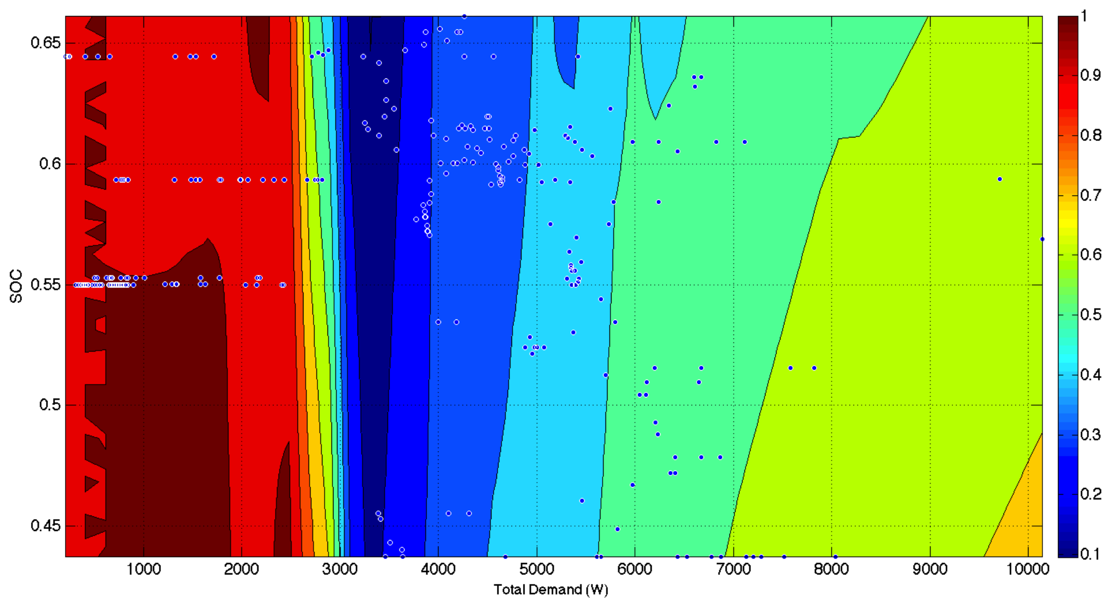

Figure 3.1: Contour Map

The contour plot in Figure 3.1 extracted from residential EMP. The aim here is finding power split between the battery and the total energy to be generated from converted devices. The color-bar represents power split ratio. From this plot, it can be seen that if the user demand is below 2 kW and SOC of battery below 0.55 than PSR equals to 1 which means battery will be switched off and all power will be generated from converter devices. Demands above 7 kW, regardless of battery SOC, the PSR value will be 0.65 which means hybrid operation mode, battery and converter devices work together to supply this peak demand. In conclusion, these types of rules can be gathered from contour plots, to be used in supervisory controller.

The solution sequence for developing supervisory controller is summarized below;

I. Add appropiate system dynamics and constraints to generic formulation.

II. DP solution of the constrained optimization problem.

III. Define operation modes of the multi-source system.

IV. Decompose optimal trajectories obtained from DP solution into operation modes (if possible).

V. Find curve fits for every operation mode (if possible).

VI. Find dominant parameters (if needed).

VII. Create a surface fit by using one of these parameters and user demand (if needed).

VIII. Determine a polynomial equation or rule-sets according to the type of surface fit (if needed).

After the rule sets are extracted from optimal DP results by following the above steps, a generic control strategy is given in Figure 3.2. In this control flow, first split determines the storage operation mode. Second split determines how much power will be generated from first converter device, c_1, after the storage contribution is extracted from the original demand. Third power split determines the power will be generated from second converter device after the first converter devices contribution is reduces from the remaining demand. This split algorithm continues in the same manner until there is only two converter devices are left. An example of this control strategy is given in Appendix B as a MATLAB file.

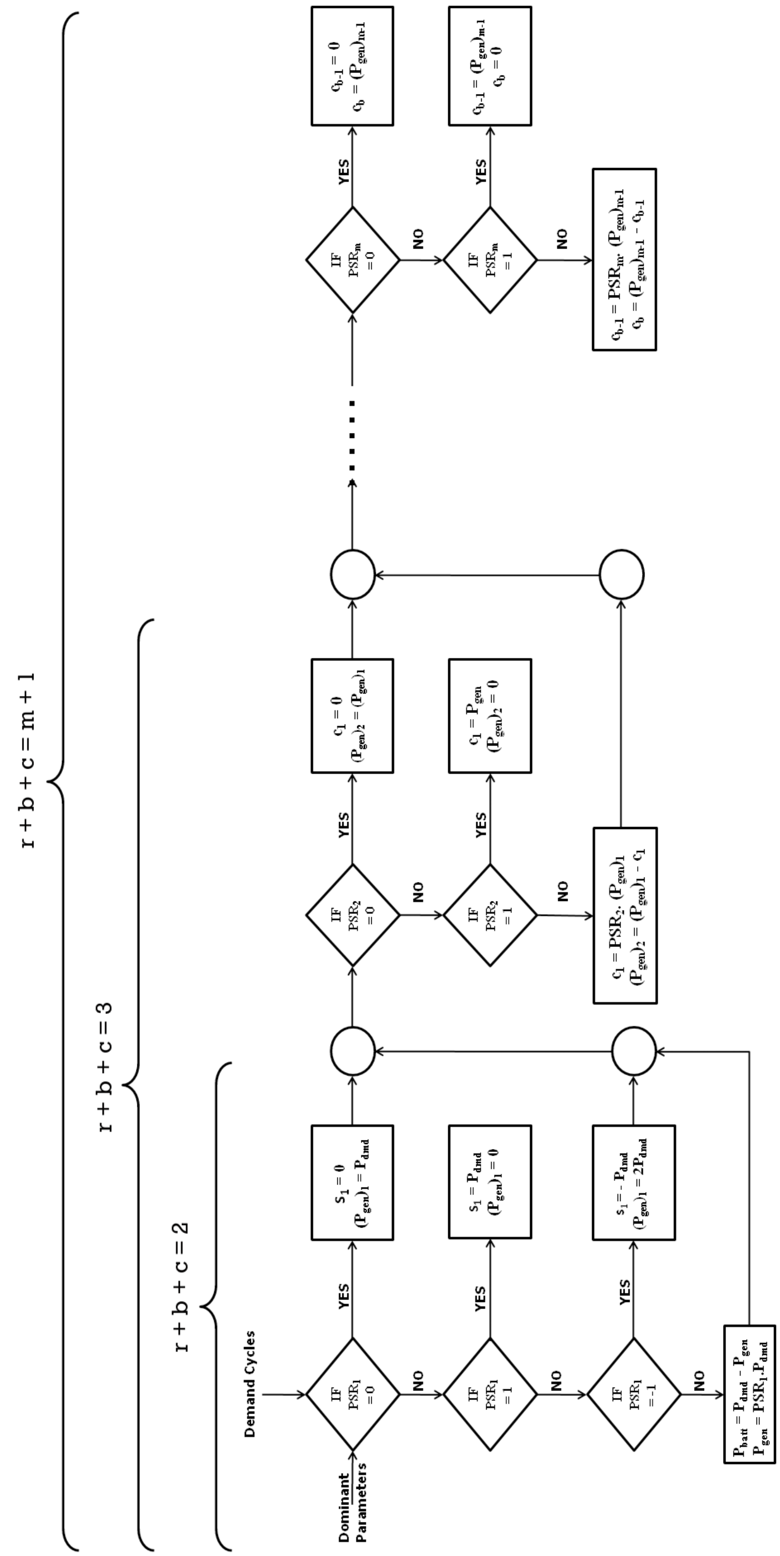

Figure 3.2: Control Strategy

3.4 Example for Generic Formulation: HEVs

In this part, the generic formulation developed, will be customized for energy management problem of hybrid electric vehicles. It should be noted that generic formulation developed can be applied to any multi source, multi sink problem however, for demonstration purposes HEV case selected since it is a much studied problem in the literature, thus making comparisons will be easy.

A survey on automotive power-train control is given in [18] with a specific chapter for energy management problem for HEVs. Comparison of current EM strategies for HEVs is given in [48]. It can be seen from these references that, there is a lot of good works published in this area so it is impossible to cover all of them. Therefore references [35], [51], are taken as representative examples, which are most comprehensive works according to us.

A typical configuration of a parallel HEV is given in Fig. 3.3 which is taken from [35];

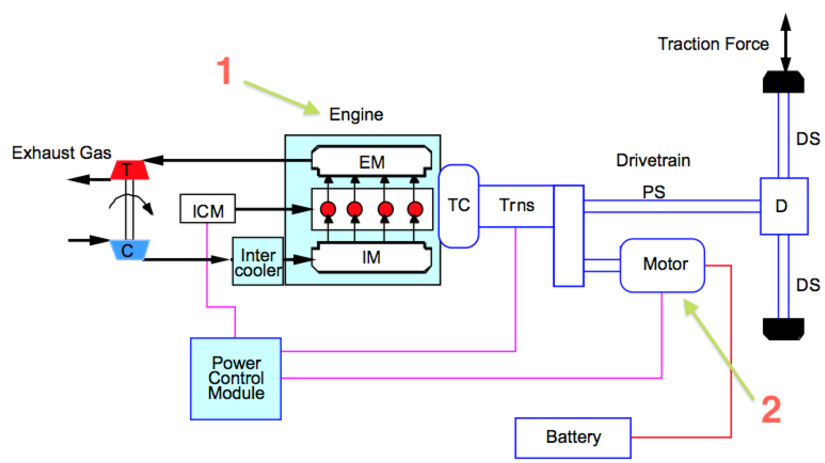

Figure 3.3: Parallel HEV Layout from [35]

From Fig. 3.3, it can be seen that driver's demand, which can be either acceleration or brake, is fulfilled with the wheels via a mechanical traction force. There are two possibilities to generate this traction force within the system, which are internal combustion engine and electrical motor. The devices are pointed with green arrows in the figure. Power produced from these devices combined on the middle with a differential gear.

By looking Fig. 3.3, system vectors defined in Section 3.1 can be obtained. They are tabulated in Table 3.2.

Table 3.2: Vectors for HEV

Vector	Components	Unit	Explanation
$\vec{d}$	T_{dmd}	Joule	Torque requested from driver
$\vec{c}$	T_{ICE}	Joule	Torque obtained from ICE
	T_{EM}	Joule	Torque obtained from EM
$\vec{r}$	$P_{fuel} = m_{fuel}.LHV_{fuel}$	Joule	Oil required to produce T_{ICE}
$\vec{s}$	P_{batt}	Watt	Power charged/discharged to/from battery

In [23], five possible operation modes for a HEV is listed. These are tabulated in 3.3;

Table 3.3: Operation Modes for HEV

Operation Mode	Description
1	EM Only
2	ICE Only
3	ICE + EM Together
4	Recharge
5	Regenerative Breaking

By adopting a parallel HEV configuration, four more possible operation modes become available comparing to conventional vehicles. By exploiting this new operation modes fuel consumption and emission targets can be achieved.

In every stage, optimal controller must determine the operation mode according to the created performance index. This will be achieved by dynamic programming algorithm. For real world applications, this must be done continuously in other words DP is not applicable. Because of this a rule based controller will developed based on DP optimal trajectory maps.

For DP solution, generic formulation developed in the previous chapter must be customized for the specific case which is HEV energy management problem.

First step is constructing the cost function, based on required expectations from the system. In HEVs, it is important to minimize fuel usage. Besides, due to the environmental concerns, exhaust emissions also desired to be kept at minimum [18]. For these reasons, one can see many different cost functions derived in the literature, however cost functions from the selected representative examples will be examined in this thesis. The aim here is seeing whether the proposed cost function in (3.1) is robust enough to develop performance indexes used in literature. If these performance indexes can be derived from the proposed generic cost function, then it can be said that the proposed generic cost function can be used in energy management problems and can be customized for specific purposes. In this manner, the cost function in (3.1) constructed is rewritten on top of the Table 3.4.

Table 3.4: Cost Function Construction

$J = (C + \mu E) + \nu CS$				
	C	μ	ν	J
Lin et. al. [35]	$\dot{m}_{fuel}$	1	1	$\dot{m}_{fuel}(k)$ + μ (NOx(k)) + ν(PM(k))
Sundstrom et. al. [51]	$\dot{m}_{fuel}$	0	0	$\dot{m}_{fuel}(k)$

From Table 3.4, it can be seen that, the proposed cost function is robust enough to capture desired performance indices.

Next step will be implementing system dynamics. This part of the formulation is customizable and will be defined by the user, according to level of detail required. For instance, it is suggested in [48] that, the SOC of the battery can be chosen as the only state variable since other power-train components have faster dynamics than the SOC. This approach can be seen in [51], while [35] and [33] used more than one state variables according to level of detail they needed. Comparison of the states extracted from representative examples are tabulated in Table 3.5.

Table 3.5: State Determination

	$\vec{x}$
Lin et. al. [35]	vehicle speed trans. gear no SOC
Sundstrom et. al. [51]	SOC

Finally control inputs must be selected according to the HEV system configuration. One control input will be sufficient, different from two layer system used in residential EMP, since the HEV configuration seen in Figure 3.3 has only two power sources. So in the first control input, the decision will be made, which is how much torque will be gathered from ICE and EM according to a specific demand. The power split algorithm is given in Equations (3.14) thru. (3.17).

$$\overrightarrow{P}_{batt}(k) = \vec{u}_1.\vec{d}(k) \tag{3.20}$$

$$\overrightarrow{P}_{ICE}(k) = (1 - \vec{u}_1).\vec{d}(k) \tag{3.21}$$

$$\vec{u}_1 = [-1, 1] \subset R^m \tag{3.22}$$

After the system equations is implemented as above, constraints through (3.12) to (3.17) must be set. With respect to these equations, a constraint set is extracted from [35] and [51] and is given below;

Device Capacity:

$$T_{ICE}(w_{ICE}(k)) \leq (T_{ICE}(w_{ICE}(k)))_{max} \tag{3.23}$$

$$-T_{ICE}(w_{ICE}(k)) \leq (T_{ICE}(w_{ICE}(k)))_{min} \tag{3.24}$$

$$T_{EM}(w_{EM}(k), SOC(k)) \leq (T_{EM}(w_{EM}(k), SOC(k)))_{max} \tag{3.25}$$

$$-T_{EM}(w_{EM}(k), SOC(k)) \leq (T_{EM}(w_{EM}(k), SOC(k)))_{min} \tag{3.26}$$

Storage Level:

$$SOC(k) \leq SOC(k)_{max} \tag{3.27}$$

$$-SOC(k) \leq SOC(k)_{min} \tag{3.28}$$

Case Specific Constraints:

$$w_{ICE}(k) \leq (w_{ICE}(k))_{max} \tag{3.29}$$

$$w_{ICE}(k) \leq (w_{ICE}(k))_{min} \tag{3.30}$$

$$I_{batt} \leq (I_{batt})_{max} \tag{3.31}$$

$$T_{dmd} = T_{ICE} + T_{EM} \tag{3.32}$$

This will complete the optimization formulation scheme. As a comparison a summary between HEV and residential EM problem is tabulated in 3.6;

Table 3.6: Generic Energy Management Problem

	Automative	Residential
J	$\triangle\ \dot{m}_{fuel}$	$(P_{mg}+P_{boil}).C_{gas}\ +\ P_{grid}.C_{grid}$
x	SOC	SOC
x_0	0.55	0.55
x_N	0.55	0.55
g_{CD}	$T(w_{ICE}) \leq (T_{max})_{ICE}$ $T(w_{EM}) \leq (T_{max})_{EM}$	$P_{mg}(\dot{m}_{fuel}) \leq (P_{max})_{mg}$ $Q_{boil}(\dot{m}_{fuel}) \leq (Q_{max})_{boil}$
$g_{SD_{CAP}}$	$0.4 \leq SOC \leq 0.7$	$0.4 \leq SOC \leq 0.7$
g_{CSC}	$I_{batt} \leq (I_{batt})_{max}$	$I_{batt} \leq (I_{batt})_{max}$
h_{CSC}	$T_{prod} = T_{dmd}$	$P_{prod} = P_{dmd}$ $Q_{prod} = Q_{dmd}$

The formulation will be solved by Bellman's dynamic programming method [14]. This solution will give $\vec{x^*}$ and $\vec{u^*}$. Then by using these optimal trajectories, all of the system component's optimal trajectories can be found by making a forward simulation. An example optimal trajectory extracted from [51] is given in Figure 3.4.

Although these trajectories gives guaranteed global optimums, they are not implementable in real-time since they require future knowledge of demand. So the rule extracting procedure in Section 3.2 must be applied.

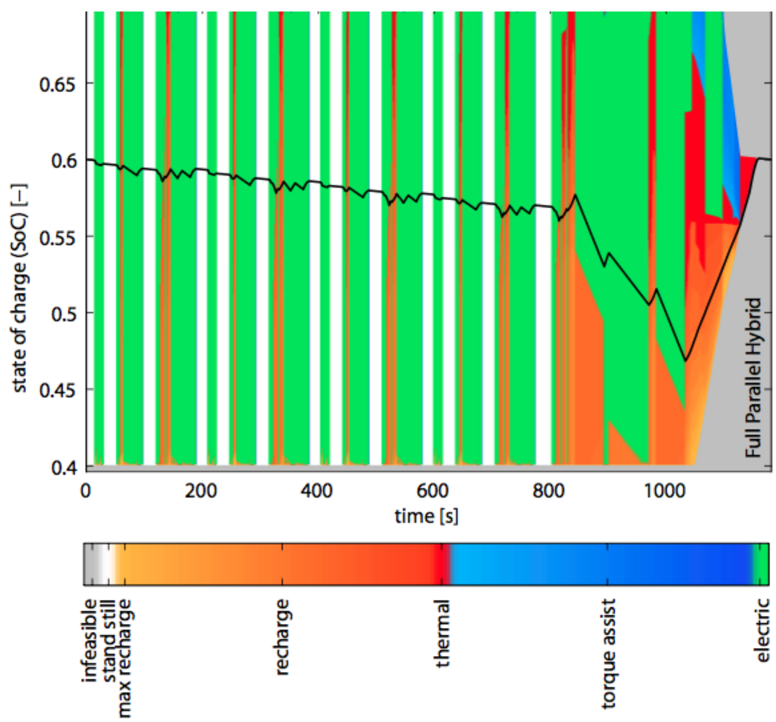

Figure 3.4: Example optimal SOC trajectory

The aim here is, to replicate DP results. These results are very important since they are found from extensive calculations and converged to a global optimum. Every point in the optimal trajectory represents global optimum for the specific demand from driver. So in real-time when this specific demand arrives, controller will know what to do, in other words, controller knows the split ratio between electric motor and internal combustion engine.

The first step will be determining operation modes according to driver demand by using optimal trajectories obtained from DP solution. However, when this is done, one can see that the resulting map is difficult to decompose, complicated and not convenient for a polynomial fit. An example plot of this problem is given in Fig. 3.5 which is taken from [35].

This situation happens because, sometimes for the same demand, decision space can be different. This arouses from the complexity and interactions of the energy system. There is a lot of parameters that changes the decisions of the algorithm. For example if battery SOC comes close to the minimum constraint,

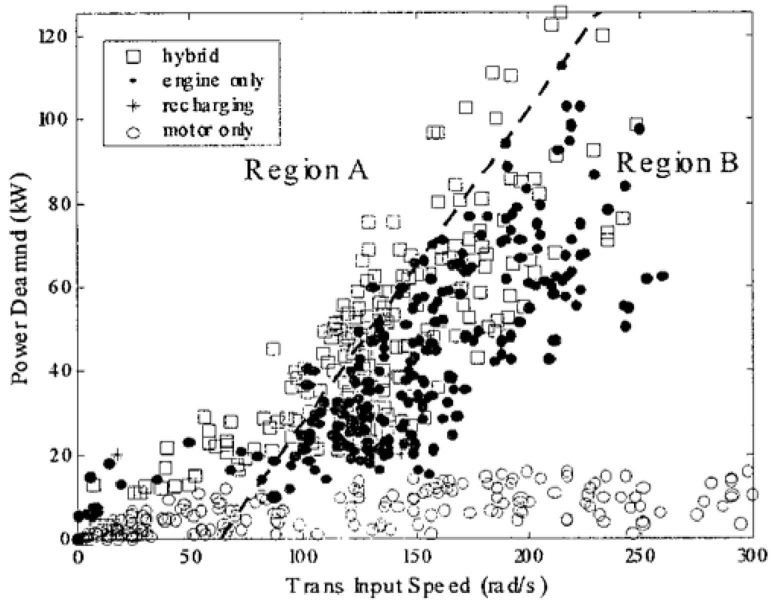

Figure 3.5: Example sparse operation points for HEV

then DP algorithm will naturally want to charge the battery regardless of the demand. However, when the battery charge is within a safe a range, then DP can make a decision to use battery and this demand can be coincide with the previous demand.

In order to obtain implementable rules, one must also find dominant parameters that effects the DP decisions other than demand from user. These parameters can be found intuitively if the system that is worked on is well known or by trial-and-error or by making a regression analysis. For example, by making a regression analysis [35] found that for HEVs, dominant factors that effects DP decisions are torque demand of the driver, engine speed and transmission input speed. By using these parameters, a 3-D surface fit can be calculated, as it is done in Residential EMP in Section 2.

Other than this approach, instead of creating layers from dominant parameters, [35] did a neural network fit which can yield to very different thresholds but the output results will be similar. For instance, for operation mode no.3 (combined usage), implementable rules are given in Fig. 3.6, taken from [35].

If $P_{req} \leq 15$ kW,	$P_m = P_{req}$ $\quad P_e = 0$	
Else If Region A,	$P_m = Nnet_1(P_{req}, \omega_{trans}, \omega_{eng})$	$P_e = P_{req} - P_m$
If Region B,	$P_m = 0$ $\quad P_e = P_{req}$,	
If $P_e > P_{e\_max}$,	$P_e = P_{e\_max}$ $\quad P_m = P_{req} - P_e$	

Figure 3.6: Example rule set for HEV operation

Continuing with the proposed approach, after the curve fits are obtained, control strategy that is given in figure 2.21, will reduce as below for the HEV energy management problem.

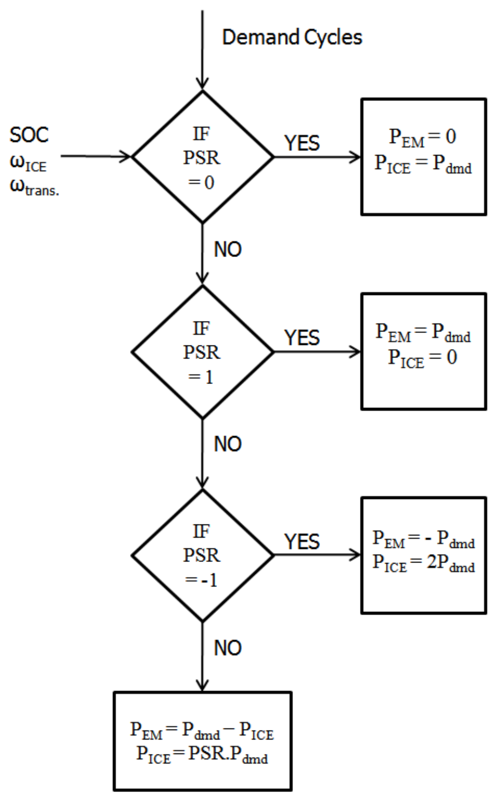

Figure 3.7: Control Strategy for HEV

3.5 Example for Generic Formulation: Mobile Devices

In recent years mobile devices like laptops, cell phones and personal digital assistants (PDAs) started to occupy a considerable portion of our lives. A typical mobile device relies on only a thermo-chemical battery for energy source and requires an electricity grid for battery charging purposes or plugged-in usage. Thus, although these technologies made life easier, growing usage of portable devices put extra load on electricity infrastructure [16, 34]. In addition, these devices become more powerful day by day due to performance requirements from the users. This causes problem in mobile usage, which is limited autonomy due to battery capacities. Therefore, it is crucial to constrain energy consumption in portable devices [27, 12, 34]. Also charging the battery unknowingly by users causes a decrease battery life-span. In conclusion, the main objectives of energy management strategy for mobile devices can be listed as below;

1. Increasing the usage time of the device in mobile usage while respecting user comfort. This can be achieved by limiting energy consumption of the components, however, actions like reducing the monitor back-light too much causes a decrease in user comfort since reading becomes harder.

2. Decreasing operational costs for the users while in plugged-in usage or charging mode . This can be achieved by an operational strategy that intercepts low cost zones in a variable price electricity market.

3. Increasing the battery life-span with a proper charging strategy.

In order to limit energy consumption, computer industry have been working on energy management or so-called Dynamic Power Management (DPM) techniques for more than a decade. It is a well researched area with an established interface standard, called ACPI, which is co-developed by leading computer manufacturers like Hewlett-Packard, Intel and Toshiba [1].

DPM policies generally try to exploit two common properties seen in mobile devices. These are listed below;

- Usage of mobile devices are event-driven.
- Mobile devices consists from components that have several operating modes.

Based on these properties, a DPM policy changes the states of components according to the system workload. For instance, by considering system workload, DPM can reduce or increase the CPU power, shut down the display and put the hard drives into sleep mode. As listed, system workload relies on external events and generally is non-existent due to lack of activity by the user.

By adopting DPM, a power reduction between 15 to 65% is achieved in various mobile devices [12, 13]. This results in increased usage time, also lower fan noise and heat dissipation due to decreased power consumption. However, as it can be inferred, DPM policy makes a certain trade-off between usage performance and energy consumption. Also complex computations must be made when developing DPM policies since state transitions require extra power consumption and certain amount of delay in which may cause worse results than neutral case [36, 27, 12].

The generic formulation developed in this thesis can be constructed to tackle second objective of energy management problem for mobile devices. Assuming that DPM gives lowered consumption values to power generation unit (PSU), operational costs can be decreased in plugged-in usage by adopting energy management strategies.

As mobile devices getting more powerful day by day, they are started to preferred against desktop devices so plugged-in usage is also increased. This situation can be seen especially in laptops against desktop computers. In plugged-in usage, the power requested from components of the mobile device can be either taken from electricity grid connection or built-in battery. Unfortunately, these are the only energy sources in mobile devices generally, no extra converter device ($\vec{c}$) for power generation available. System vectors are tabulated in Table 3.7;

Table 3.7: Vectors for Mobile Devices

Vector	Components	Unit	Explanation
$\vec{d}$	P_{dmd}	Joule	Total power requested from components
$\vec{c}$	-	-	-
$\vec{r}$	P_{grid}	Joule	National grid electricity
$\vec{s}$	P_{batt}	Watt	Power charged/discharged to/from battery

Desired objective is minimizing operational cost of the mobile device. Besides this, case specific objectives like decreasing charge/discharge sequences of the battery so that it's life-span can be increased or shifting the charging of battery in time zones where load on the grid is low can also be considered. By taking these into consideration, the cost function proposed in Equation (3.1) can be reconstructed as in Table 3.8.

Table 3.8: Cost Function Construction for Mobile Devices

$J = (C + \mu E) + \nu CS$				
	C	μ	ν	J
Suggestion 1	Pgrid.Cgrid	0	1	Pgrid(k).Cgrid + υ |Pbatt(k)|
Suggestion 2	Pgrid.Cgrid	0	0	Pgrid(k).Cgrid

The first objective function in Table 3.8 considers operational costs and battery charge/discharge sequences. The latter objective is represented with second term such that if battery is off then P_{batt} equals to zero which means no additional costs. However if the battery is used, P_{batt} will no longer be zero thus causes an additional cost. The dominance of the second objective on power split decision can be adjusted with the weight, υ. The second suggested objective function in table tries to minimize only operational costs. In all of the objective functions created, emission term is neglected since, emissions from these devices are relatively low thus they are not an important subject.

Next step will be determining power split algorithm. There will be only one power split decision which is between grid electricity and battery. Thus, two layer approach used in residential EMP is not required. The power-split approach for this problem is given in Equations between (3.33)-(3.35).

$$\vec{P}_{batt} = \vec{u}_1.P_{dmd}(k) \tag{3.33}$$

$$\vec{P}_{grid} = (1 - \vec{u}_1).P_{dmd}(k) \tag{3.34}$$

$$\vec{u}_1 = [-1, 1] \tag{3.35}$$

Again for comparison, mobile formulation will be tabulated with residential energy management problem in Table 3.9.

Table 3.9: Mobile Energy Management Problem

	Mobile Device	Residential
J	Pgrid(k).Cgrid + υ |Pbatt(k)|	$(P_{mg}+P_{boil}).C_{gas}$ + $P_{grid}.C_{grid}$
x	SOC	SOC
x_0	0.55	0.55
x_N	1	0.55
g_{CD}	-	$P_{mg}(\dot{m}_{fuel}) \leq (P_{max})_{mg}$ $Q_{boil}(\dot{m}_{fuel}) \leq (Q_{max})_{boil}$
$g_{SD_{CAP}}$	$0 \leq SOC \leq 1$	$0.4 \leq SOC \leq 0.7$
g_{CSC}	$I_{batt} \leq (I_{batt})_{max}$	$I_{batt} \leq (I_{batt})_{max}$
h_{CSC}	$P_{grid} + P_{batt} = P_{dmd}$	$P_{prod} = P_{dmd}$ $Q_{prod} = Q_{dmd}$

This will complete the formulation part. Next step will be solving the developed formulation with DP. Then optimal DP trajectories should be analysed to create implementable rules.

In order to create implementable rules, first system must be decomposed in to operation modes according to components total demand. If the operation modes are clearly distinguishable, then simple threshold values, according to demand value, can be extracted to be used in supervisory controller. If the operation modes cannot be distinguished then other dominant parameters must be found different from power demand. Finally by using these dominant parameters a 3-D surface fit can be obtained for use in controller.

After the rules are extracted from optimal trajectories the control flow is given in Figure 3.8.

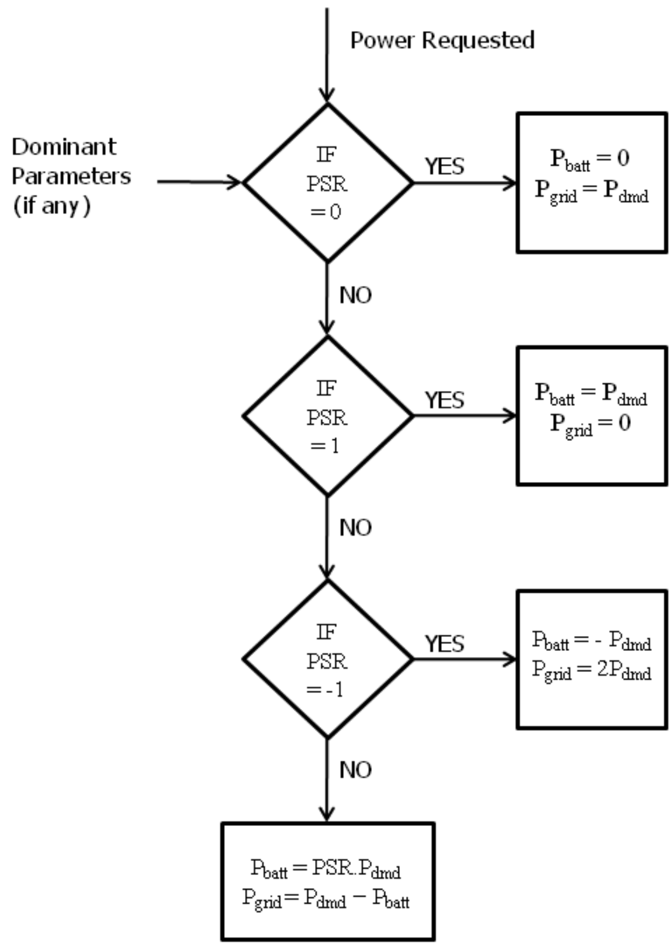

Figure 3.8: Control Strategy for Mobile Devices

In summary, increased usage of mobile devices resulted an extra burden on consumption map. Also since they are getting powerful day by day, batteries that are powering them deplete quickly. For these reasons, energy consumption of these devices must be lowered. In addition to current DPM methods, energy management techniques can also be considered since the increased number of alternative components make this possible.

Chapter 4

Conclusions and Future Work

In this thesis, a previously successful method in automotive industry is applied for residential EMP. First, by using dynamic optimization techniques an optimal controller is created. Then from this non-causal optimal controller, a causal sub-optimal controller developed by adopting rule extraction techniques.

The developed sub-optimal controller is tested on Matlab/Simulink environment by using standard EU energy consumption profiles. Daily operational costs reduced between 6-7.5% compared to conventional infrastructure which consists of a gas-fired boiler and a national electricity grid connection. It is also shown that the developed sub-optimal controller performs 1.9% better than available heuristic strategies, such as thermal load following, in terms of operational costs.

In residential systems, due to environmental concerns, CO_2 emissions are also an important aspect when quantifying system performance apart from operational costs. According to the simulations made, an approximate 5% reduction is obtained according to conventional case. Also another important parameter, primary energy consumption, is also calculated and it is seen that primary energy use decreased around 5.5% daily by taking conventional case as base scenario. The developed supervisory controller also performed better for both parameters compared to thermal-led heuristic controller, around the range of 1.5% rate.

In order to verify the developed supervisory controller, a simulation based on different demand cycles are conducted. It is seen that the developed sub-optimal controller follows optimal trajectories obtained by dynamic programming in a good agreement. However, as expected, performance of the controller reduces a bit. In the previous simulations, only a 0.3% deviations occurred between DP results and the developed controller. On the other hand, with different demand cycles, this value increased to 1.3%. Although the sub-optimal supervisory controller still outperformed the heuristic controller with an amount of 1%.

Finally the formulation generated for residential EMP is generalized so that it can be applied all types of EMPs. In order to show the capabilities of generic formulation, a mobile energy management problem is constructed, however it is not solved.

To sum up, in this thesis a generic formulation is created, based on an example from automotive industry, to develop a supervisory controller that can be used in all types of energy management problems. This controller is used in the residential energy management problem which is a novel approach in this area. It is seen that the developed supervisory controller performs better than available heuristic controllers.

4.1 Future Work

For future work, sizing problem could be carried out since, from the simulations, it is seen that choosing the right configuration and device capacities have a huge impact on system performance. Thus quantifying this impact would be of interest.

The simulation study conducted can be further extended by applying varying electricity prices, adding renewable energy sources and thermal storages then investigating their effects on system performance. By adding a thermal storage to the system, mCHP device can also be turned on in the evenings and surplus thermal energy can be stored. Variable electricity prices can cause DP algorithm to apply pre-cautionary energy stores on battery.

Also, the developed supervisory controller can be implemented to an experimental setup to verify its performance. Obtained experimental results could be used for tuning the supervisory controller. However, there are some challenges in real life applications. For instance, extra devices may be needed such as a smart meter due its bidirectional communication capability which can be used to send demand information from the house to the supervisory controller and national electricity grid. Also a communication interface, wireless or ZigBee [30], must be set up between the supervisory controller and the energy sources for an experimental testing.

Finally, for more accurate simulations and model based control design, transient effects in the devices can be included in mathematical models. For example, if the mCHP device was not operating when the signal from supervisory controller received, then it will take some time to achieve required power level since internal combustion engine needs a certain warm-up period. These type of simplifications in the mathematical models could lead to a deviation from the results found by simulation studies.

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Appendix A

Parameterization Study

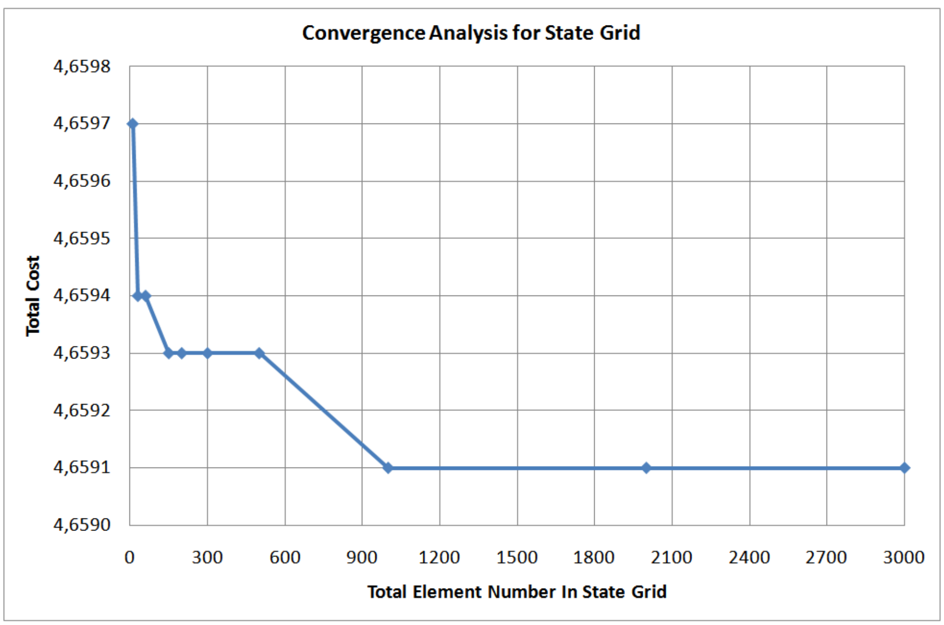

Figure A.1: Convergence Analysis Conducted on State Grid

In Figure A.1, the effects of state grid discretisization on cost function is investigated. It is seen that increasing the step size, yields to better results. This is an expected results since DP algorithm calculates *cost-to-go* from one state on time "t" to another state on time "t+1". Thus if the state grid is not dense enough, lower cost states cannot be available. From the figure the system converges to a solution after 1001 element numbers.

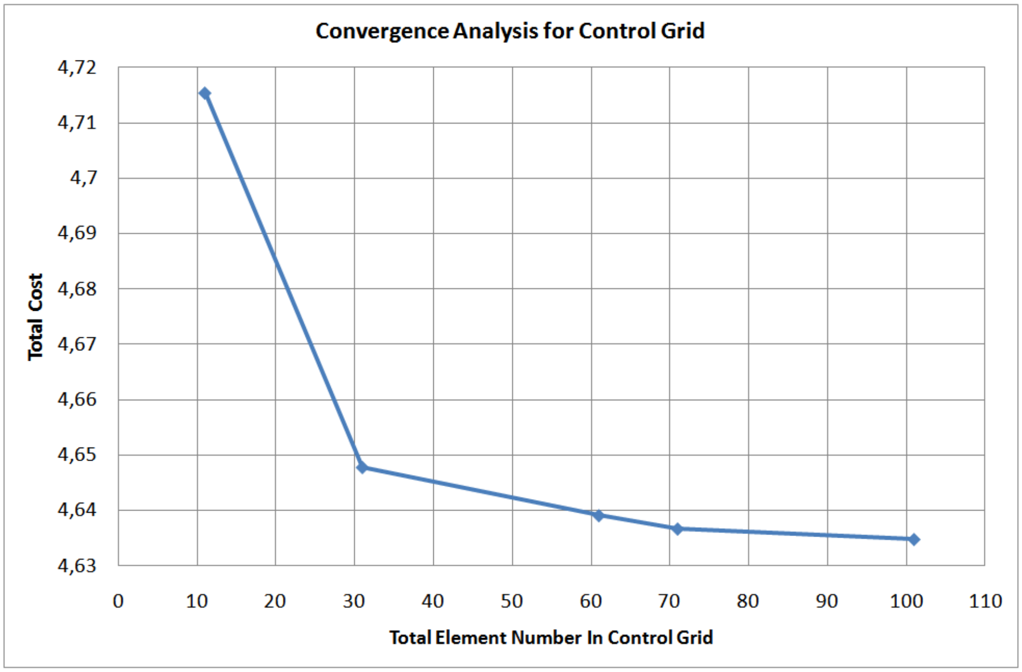

Figure A.2: Convergence Analysis Conducted on Control Inputs Grid

In Figure A.2, the effects of control grid discretisization on cost function is investigated. Again, it is seen that increasing the step size, yields to better results. This happens because increasing the step size of control inputs results more sensitive power split between energy sources which consequently effects total cost. From the figure, it can be seen that convergence occurs at 101 division steps.

Appendix B

MATLAB Code

```
function [s1,c1,r1] = fcn(d1,d2,DomPar1)
% Example Supervisory Control Strategy Function
% s1 stands for storage device #1, like battery
% c1 stands for converter device #1, like mCHP
% c2 stands for converter device #2, like boiler
% r1 stands for raw energy source #1, like electricity grid
% d1 stands for requested useful energy #1 from users, like torque
% d2 stands for requested useful energy #2 from users, like electricity
% DomPar1 stands for extra parameter #1, which dominantly effects power splitting process, like battery SOC
% # of devices can be increased according to the system worked on

ControlFlow = 1;      % use 1 if a function that relates energy sources can be found
                      % use 2 if the system can be decomposed into operation zones

```

```
if(ControlFlow == 1)

    % 1st power split
    d1Updated = 238.7 + 0.9587*d1 - 313.9*DomPar1;
    s1 = d1 - d1Updated;

    % 2nd power split
        % polynomial coefficients
        p00 = -5.631;
        p10 =  1.008;
        p01 = -0.07116;
    r1 = p00 + p10*d1Updated + p01*d2;
    c1 = d1Updated - r1;

elseif(ControlFlow == 2)

    % 1st power split
    if(d1>3200&&d1<4500)
        PSR = 0.3;
        d1Updated = PSR*d1;
        s1 = d1-d1Updated;
    elseif(d1>4500&&d1<5500)
        PSR = 0.35;
        d1Updated = PSR*d1;
        s1 = d1-d1Updated;
    elseif(d1>5500)
        PSR = 0.45;
        d1Updated = PSR*d1;
        s1 = d1-d1Updated;
    elseif(d1>2000&&d1<3200)
        PSR = 0.5;
        d1Updated = PSR*d1;
        s1 = d1-d1Updated;
```

```
    elseif(d<2000)
        if(DomPar1<0.56)
            PSR = 1;
            d1Updated = PSR*d1;
            s1 = 0;
        else
            PSR = 0.9;
            d1Updated = PSR*d1;
            s1 = d1-d1Updated;
        end
    elseif(DomPar1>0.63&&d<1000)
        PSR = 1;
        d1Updated = PSR*d1;
        s1 = 0;
    elseif(d>2000&&d<2600)
        PSR = 0.9;
        d1Updated = PSR*d1;
        s1 = d1-d1Updated;
    end

    % 2nd power split
        % polynomial coefficients
        p00 = -5.631;
        p10 =  1.008;
        p01 = -0.07116;
    r1 = p00 + p10*d1Updated + p01*d2;
    c1 = d1Updated - r1;

end

% This type of layers can be increased according to the
    sources in the structure
% Finish control flow
```

Appendix C

Simulink Diagram

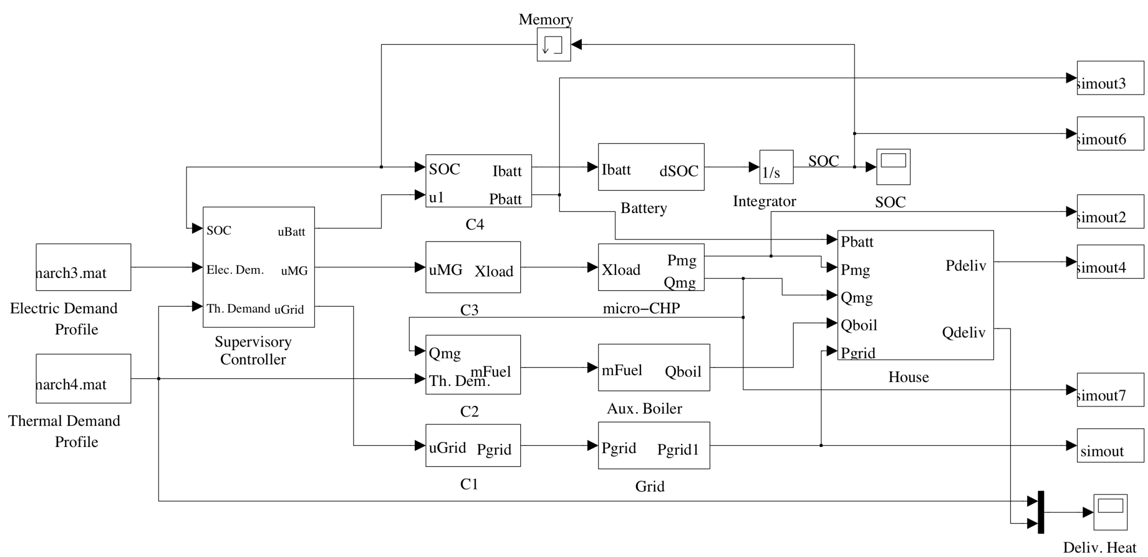

Figure C.1: Simulink Diagram of the Supervisory Controller

Real-time control of a residential system with supervisory controller.