Multi-Sector Demand Management in Smart Cities

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Environmental concerns are on an all time high and can no longer be ignored. The majority of electricity is generated using fossil fuels, this is troublesome as fossil fuels are depleting off the face of the earth. Moreover, they contribute heavily to the harmful emissions affecting our environment. This has caused a global movement towards greener, more sustainable sources of electricity generation. The main concern with renewable sources of energy is their intermittent output. This could be dealt with through large amounts of operational flexibility and storage in the system. Traditional storage technologies are foreign to the electric system and require high initial and maintenance investments to ensure proper operation. This work aims to propose innovative ways to use resources that are readily connected to the electric system instead of introducing foreign storage technologies.

Demand response is based on the presence of operational flexibility and/or energy storage ability by a specific electric load. There are several energy systems that are partially or fully fueled by electricity who could poses DR abilities through their own energy vectors. This would be directly reflected on their electricity consumption. Through controlling this process, these resources can be added to the existing electric DR resources in the system. This comes at approximately no additional costs. The idea is to allow different energy systems to join the DR fleet of the electric system through operational integration.

This work presents a systematic approach to identifying additional DR resources that can be used to benefit the electric system. Four resources (wastewater treatment system, drinking water treatment system, building heating systems and public electric transportation system) are then chosen to highlight the potential of the proposed idea. Numerical models focusing on DR capacity were developed or chosen (based on availability) to be used in this work. The work shows results of independent operation of each resource as well as, an integrative operation of resources to benefit the system as a whole. The results obtained show an improvement in DR performance under operational integration as opposed to independent operation.

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First and foremost, all praises to Allah Almighty for providing me with the opportunity, patience, and guidance to finalize this thesis work and my Masc. degree successfully. I would like to express my deep appreciation and gratitude to my advisors Professor Magdy Salama and Dr. Mostafa Shaaban for their invaluable guidance, limitless support, and continual encouragement. I would also like to thank Dr. Mohamed Ahmed for his assistance through the beginning of this journey.

Dedication

To anyone who has ever suffered with their mental wellness,

To my loving parents Hemmat and Adel,

To my precious sister Yasmin and my beloved brother Ayman,

To my sunshine and soon to be husband Ahmed,

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Chapter 1: Introduction

1.1 Preface

Demand side management programs are gaining more academic and industrial interest since their debut in the early 1970s. DSM programs focus on one of three main goals: energy efficiency, demand response (DR) and/or strategic load growth. DSM programs in their many shapes and forms have made their way into several energy sectors including but not limited to the electricity sector, gas sector, heating and cooling sector, transport sector and, the water treatment and supply sector in varying degrees. The motive is simple, each sector aims to tweak their operation to improve their energy efficiency and/or reduce their operating costs. The former is usually achieved thorough an intensive energy-audit of the system, followed by system retrofits and upgrades as well as, additional DR resources. Amongst the most popular DR resources are storage facilities. Storage systems introduce the highest forms of flexibility of operation to the system as they can be used to increase or decrease load on cue. This gives the operator the physical 'room' needed to take DSM actions effectively and on a scalable level. The physical 'room' needed comes in many forms depending on the nature of the system i.e. this can be larger delivery pipes, additional reservoir tanks, thermal storage units, or the more commonly known batteries, flywheels and capacitors of the electricity system. This work will focus on DR actions as the main driving-force for any load altering efforts.

Load altering efforts are carried out on two main scales, a unitary scale, and a global scale. The former is done on a facility level to improve energy efficiency and/or minimize electricity bills. While the latter is performed on a network level and can have a wide range of objectives such as: load leveling, improving social welfare, minimizing system loses, minimizing harmful emissions, improving power quality, easing congestion, providing ancillary services to the network and so on. Unitary scale programs can be found in almost every energy sector, from home energy management systems (HEMS), to monitoring and control strategies for water systems, natural gas systems, heating systems, public transport, street lighting etc. There are clear and repetitive load patterns across all these sectors. These patterns can be broken down into base loads and peaks loads, conventional DR actions focus on eliminating the peak and flattening the curve. A flatter curve indicates a higher capacity factor and better performance. The aforementioned storage or DR resources (DRR) are typically sized to facilitate DR actions when they are needed the most, during peak load hours. However, on average peak loads do not normally surpass the range of 3-5 hours a day [1-3]. Hence, DR resources are kept unused, on standby for the majority of their lifetime and are called into action approximately 15% to 25% of the time when a peak is observed. This lack of efficient resource usage can be observed in most DR-integrated energy sectors, this raises the question of whether this usage metric can be improved. These resources are not being used for a large portion of the time since there is no real need for their participation (outside of peak hours). However, they can be utilized to indirectly improve the performance of the network.

Conventionally each sector functions as an independent entity with independent objectives, controlling only the resources that fall within their facility no matter how scarce or abundant they may be. Research proves that effective conductance of load altering schemes usually takes place in facilities with abundant resources that are not utilized to the fullest [4,5]. In this work, we aim to find a way to allow sectors of different energy types, different characteristics, different modes of operation and different control mechanisms to communicate with one another to better themselves and the global system. This platform will allow us to manipulate energies in all their different types and forms away from the limited, conventional electrical perspective of DSM. In turn, we will be able to use all the resources that are naturally present in the system to enhance our DR capacities without the need to employ additional resources that are foreign to the system such as batteries and flywheels.

1.2 Motivation

The global energy crisis is a threefold, starting with the growing electricity demand, the depletion of fossil fuels and the increasing environmental concerns. The overall demand for electricity has been growing rapidly on a global scale, according to the International Energy Agency electricity demand in 2030 is going to be at least 50% higher than the demand observed in the early 2000's [6]. This is mainly due to industrialization, digitalization, and the introduction of new electrical loads such as electric vehicles. This has introduced new challenges and excessive stresses on the existing electrical grid. In attempts to alleviate the additional stress and postpone the need for infrastructural upgrades and reinforcements, utilities worldwide have implemented demand side management technologies. DSM technologies are used on several scales to improve energy efficiency and to manipulate load profiles to combat several economic, environmental, and technical challenges.

Our constant interest in maintaining and improving DSM technologies stems from their undeniable benefits and added values. The basic essence of DSM is to manipulate electricity on the demand side instead of the supply side alone, which is proven to be more economical since electricity saved is eventually worth more than electricity generated [7]. This can be explained by considering line losses across the transmission and distribution systems, where a unit of energy saved at the demand side is worth 10% more at the generation side [8]. Some of the benefits provided through DSM technologies include:

1. Increasing energy efficiency
2. Minimizing start-ups and shutdowns of thermal units and the costs associated with them
3. Delaying the need for infrastructure upgrades and retrofits
4. Improving power quality
5. Improving system reliability
6. Providing ancillary services
7. Maintaining voltage stability
8. Increasing system flexibility in operation and in preventative maintenance scheduling
9. Increasing renewable energy integration by balancing off their intermittency
10. Minimizing harmful gas emissions
11. Managing line congestion on the transmission and distribution levels;
12. Improving market performance

13. Reducing market power and price volatility and finally
14. Increasing consumer satisfaction

This has made demand side management a very attractive option for many utilities worldwide since its emergence in the early 1970s [9]. Since then, researchers have worked on growing and nurturing this technology in terms of application, market participation and control techniques to reap as much benefit as possible from DSM schemes. However, these benefits have an upper limit imposed by the size and capacity of the resources present in any given system. These resources mainly consist of flexible loads, storage systems and distributed generation units. Each of which are of limited size and capacity in an electrical system. While the presence of a limiting factor will always be true, in this work we aim to stretch these limits by looking beyond the resources present in the electrical energy system. DSM can be applied to energy in all its types and forms, whether it was thermal, potential, kinetic or electrical energy. We aim to bridge the gap between different energy sectors to allow them to work together with one another, in efforts to exploit the inherent flexibility and storage that each sector has to offer. By looking beyond the limits of the narrow scope of the electrical system, we find a lot of promising potential for increased DSM capacity. The challenge in this case is to allow systems and processes of different natures, time windows, control algorithms and characteristics to communicate with one another in a clear and efficient manner. This will be discussed in detail in the chapters to follow.

1.3 Research Objectives

The advantages and benefits of DSM programs are undeniable in magnitude and importance. As with any new technology, there is an infancy stage and a maturity stage. Currently, the DSM is a mature technology. In this work, we aim to present another layer of maturity and improvement to the commonly known strategies of demand side management by expanding the scope of participating facilities and the types of energy sectors. The need for higher levels of cooperation and integration across energy sectors is not a novel idea. It has been showcased in *Integrated Energy Systems* as well as, *Smart Energy Systems.* Both systems rely heavily on the strong integration on infrastructural and resource-based levels through converters and energy hubs. While these setups have their own benefits and drawbacks, they are quiet far from realization in our present situation, as they require massive investments in resources, infrastructure and personnel training. As well as several operational and legislative changes. Instead, we shift our focus on to the needed changes in communication and control algorithms to achieve operational integration without the need for physical integration of the participating energy sectors and facilities.

This work aims to advance demand response technologies by pushing past the limits of the electric system. The goal is to increase the capacity of demand response through operational integration of multiple energy sectors/carriers that communicate with the electrical system. All energy sectors are considered equal participants in this novel multi-sector demand side management scheme. This thesis has three main objectives:

- To identify and model sources of operational flexibility and/or storage to cast as DR resources across different energy sectors.
- To create a general benchmark to model multi-sector DR with special considerations on the electric system
- To prove the efficacy of the novel DR resources in DR events

1.4 Thesis organization

This thesis is organized in the following structure; chapter 2 presents a thorough literature review of demand side management, demand response technologies and smart cities. It also explains the limitations of DR and some of the existing solutions, including integrated energy systems and integrated demand response. Chapter 3 then explains the process of identifying possible demand response resources across different energy systems. The DRR selection criteria, selection process and findings are presented in this chapter as well. Chapter 4 presents a deeper insight into the workings of the proposed DR resources, their operational flexibilities, and limitations as well as the proposed mathematical models to be used. Chapter 5 presents the benchmark system suggested for multi-sector demand response considerations, this chapter presents the generation side as well as the demand side of the system. Simulation results are presented and explained in chapter 6. Finally, chapter 7 concludes this thesis with a summary of the completed work as well as suggestions and recommendations for future research on this topic.

Chapter 2: Background and Literature Review

2.1 Demand Side Management

DSM is considered to be an essential element in future electric systems and is thought of as one of the building blocks of a functioning smart grid. DSM has been widely recognized as a powerful and effective solution for many modern-day challenges facing the power world. Through comprehensive energy management schemes, DSM promises to improve system performance on many fronts including economical, technical, environmental and social fronts. DSM actions fall into two broad categories, energy efficiency and demand response (DR) actions. The former aims to reduce the overall energy consumption through system upgrades, resource reimbursements and operational changes. The latter works by altering the timing and/or level of instantaneous demand of an end-user customer in response to an offered incentive or a varying electricity price. DR actions usually have the single or combined effect(s) of peak clipping, valley filling or load shifting to improve grid performance. The numerous benefits of demand response also include reductions in operational cost, reductions in power loss, improvements in diversity factor, congestion management and, power quality improvement. This has driven the development of a large number of DR solutions and techniques over the years, which are outlined, in this section.

2.1.1 Demand Response Technologies

To help us better understand, model, and correctly utilize demand response schemes, researchers globally have worked on creating DR categories and classifications. The most commonly used classifications are based on common features such as, the control mechanisms used in DR programs, the motivation presented to end-user participants as well as, the control variables generated through the DR scheme. This breakdown is presented in Figure 2.1. The first category describes the type of control algorithm employed in DR signal generation. DR signals are either generated through centralized or decentralized control algorithms resulting in higher levels of controllability and predictability or increased promptness and reliability [10]. Centralized control entails a sole decision-maker in charge of generating and sending all control decisions to end-user participants. This approach can be incredibly effective however; it grows rapidly in complexity and computational time with large systems. Larger systems maybe more suited for distributed control, where users communicate with one another to create their own control decisions. The second DR category is concerned with the type of encouragement used to convince end-users to take part in DR programs. Motivations are necessary to push consumers to amend their natural consumption behaviors. These motivations can be in the form of incentives or electricity price differences. Incentives are an essential factor in the success of any DR program; they are usually offered by the utility to reduce demand in response to peak loads or system contingencies and are referred to as Incentive-based programs (IBP). Price-based programs (PBP) work using variable electricity pricing which would naturally drive consumers to change their consumption pattern to reduce their electricity bills. The third classification strategy includes task scheduling- and energy management- based demand response. This is mainly governed by the flexibility of participating loads. Certain loads such as washing machines offer time-based flexibility where only the activation time is decided by the DR program, leaving the consumption level unaffected. The latter considers loads such as heaters and air conditioners whose consumption level can be altered in response to a DR signal. Other classification strategies consider desired objectives of the DR program; objectives could be of technical nature such as, congestion management and power quality improvements. They could also be of an environmental nature such as harmful gas reduction and integration of renewable energy sources (RES). Moreover, DR objectives usually have an economical aspect with a focus on cost reduction through minimizing the need for more expensive generation units or customer bill minimization and so on. DR technologies can also be classified based on the response time of participating loads. Loads can be grouped based on the amount of time required for a change in consumption level to be noticed following a DR command. This can help decide which load groups to use in a DR scheme based on its objective and technical requirements, i.e. a power quality improvement-based DR program might require a faster acting group of loads than an emission reduction-based program and so on.

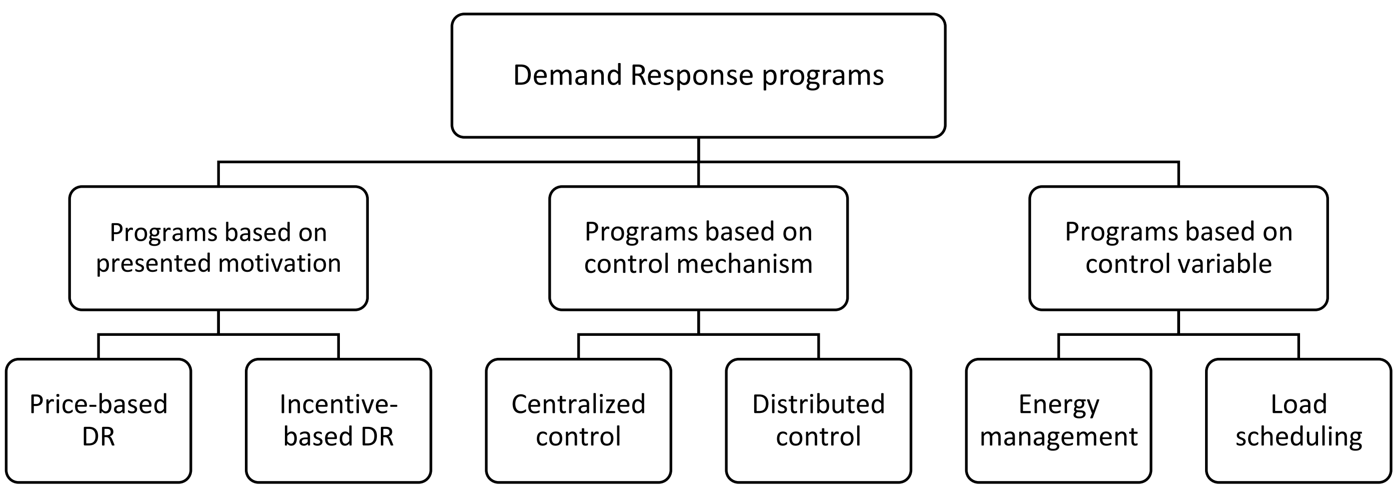

Figure 2.1: DR program classification

2.2 DR Capacity (what makes DR programs effective?)

Demand response is very powerful in terms of the services it can provide to the grid, to the utility and, to the consumer. However, the success of any DR program is governed by the resources available in the system. System resources fall generally into three categories, flexible loads that can be ramped up, ramped down or shifted in time, distributed generation (DG) units which are sometimes considered 'negative loads' or more accurately 'negative flexible loads', and energy storage systems (ESS). The first and most accessible layer in a DR program is the flexible load layer; flexible loads are naturally present in a power system and require minimal additional costs and maintenance to upkeep. However, they require special considerations to account for user preferences, comfort levels and enforced legislations and/or standards [11]. DG units are classified as dispatchable or non-dispatchable units; the former refers to units with controllable output levels and time of dispatch, which are usually run on fossil fuels or biogas. However, the majority of DG units on a distribution system level are renewable in nature such as photovoltaic (PV) panels. Renewable energy sources (RES) in general are of intermittent output due to their dependence on environmental conditions such as wind speed and solar irradiance. Therefore, they cannot be controlled by an operator and are automatically ruled out of the race of DR participants. Energy storage systems on the other hand, are ideal candidates for DR programs as they can virtually increase or decrease demand through charging and discharging in response to a control signal. However, traditional storage technologies such as battery energy storage systems (BESS), flywheels and capacitors are foreign to the power system and require additional costs to install and maintain. Moreover, large-scale electricity storage technologies (i.e. 100 MW and up) suffer from low round trip efficiencies in the ranges of 65% and 85% for compressed air energy storage and hydroelectric energy storage systems respectively. This encourages us to turn our focus to other storage options; energy storage and direct electricity storage are two different concepts that should not be confused with one another. Energy storage exists in all energy types and forms. However, converting electrical energy to another energy form for the sole purpose of reinjecting it in the electricity grid entails significant losses and should not be encouraged [12]. Instead, storage solutions focusing on the end use energy courier such as thermal or potential energy should be considered. This invites for a more open system with lower barriers between electrical energy and other energy forms.

One of the prominent uses of DR programs is to minimize the demand-supply mismatch using the aforementioned tools. Thinking outside the box, the power system has several assets that can serve as energy imbalance moderators. Aside from the three main players mentioned above, an operator could opt for transmission upgrades [13,14] curtail wind or RES production [13,15] as well as, utilize energy from a neighboring market with an existing interconnection [16,17] Another innovative option is to include different energy sectors in the equation [18]. Heating, cooling, gas and transport sectors are prime examples of energy sectors, which are treated and operated as purely independent structures, while in reality, their operation has a strong impact on the overall electricity profile. There are numerous barriers and differences between energy sectors, starting with their production technologies, transport techniques, storage systems, and ending with the final consumption ports. These walls exist in the real world as differences in the physical systems, devices and networks of each energy sector. Other barriers are intangible but equally difficult to overcome such as data sharing and information transparency between different producers and consumers in different sectors. This problem is aggravated by the inherent differences in business models, markets and, governing policies and regulations [19].

2.3 Integrating Energy Systems

The current energy crisis raises the need for innovative and sustainable energy solutions. The overall global dependence on electricity for most human activities including cooling, heating, transportation, lighting, and manufacturing has led to electricity-focused solutions. This includes smart grids, smart cities and net-zero energy structures [20-22], where the electrical system is manipulated on generation, consumption or operational levels to accommodate all other energy sectors (e.g., heat, gas, transportation). This is an electricity-based solution, it is important to note that sector-based solutions are limited by the available reserves and resources in that given sector. This gave rise to a new direction of research geared towards identifying synergies and management strategies of multi-energy sectors. This would allow us to utilize the wider range of resources and flexibilities present in a combined suite of energy vectors (electrical, thermal etc.).

Technological advances in energy coupling and conversion devices, such as heat pumps, air conditioning systems, gas and electric boilers, gas turbines, electric vehicles and combined heat and power (CHP) generators have all helped pave the way for integrated energy solutions. Several multi-sector systems have been developed over the past few years with similar motives and origins, they overlap in many aspects, but each retain their unique identity and definition. This idea was first introduced under the naming of integrated multi-energy systems which then developed to be known as smart energy systems. Despite the recent growing interest in smart energy systems, there is no strict definition of the phenomenon yet. After a thorough review of all the instances where the term was used, a broad classification of two main categories was found. The first focuses on the smart computing aspect of the phenomenon, where the term is used almost analogously with the term Smart Grid [23,24]. The work in this category is directed towards creating smart and innovative energy management systems, load forecasting engines and human-computer interaction platforms [23-31]. The essence of the aforementioned work resonates in control engineering with a sole focus on the electricity sector. Other works target control algorithms of smart grids in conjunction with heat and gas systems on a supervisory level [32-35].

The second category focuses mainly on the system under study in terms of cross-sectoral integration. Where a smart energy system is defined by several energy carriers working together in synergy to reach a greater goal. The sectors involved typically include heating, cooling, power, gas and transportation systems. The root of smart energy systems comes from the need for sustainable energy solutions, which by definition, encompasses renewable energy systems. The main challenge in large scale integration of renewable energy systems comes from the intermittent and fluctuating nature of their output. This is generally presented as a utility problem and is solved using purely electrical measures. When in reality, this is a sustainable energy dilemma that extends beyond the narrow window of the electrical system. Coordinated management of multi-energy sectors offer increased flexibility levels that can aid in the supply-demand balance problem and counteract the fluctuations introduced by RESs in the network [36,37]. In the fight to increase renewable energy generation, it is common to think of manipulating existing generation sources to work together, calling for the existence of flexible multi-generation system (FMG) [38,39]. Where an FMG system is defined as "a system of integrated facilities that provide multiple links between layers of the energy system, enabling adjustable operation in response to changes in prices and demands of the consumed and delivered services [40]. In theory, FMG would combine power, natural gas, biogas, solid and liquid fuel networks through technological retrofits, such as combined heat and power (CHP) units and biogas (biomethane) producing facilities to reduce system imbalances and increase RES integration. Other efforts consider increasing the flexibility of traditional generation units through pushing the limits of cycling time, ramp rates and technical minimums [19]. However, this approach is not preferred as operation beyond technical limits is expected to have technical and economic drawbacks including reduced efficiency levels and higher maintenance requirements.

From generation-based algorithms, we shift to comprehensive control algorithms, which consider both the supply and demand sides. Comprehensive algorithms often outperform single-sided management techniques due to the increased resources and control variables. Some of the additional resources would now include flexible thermal loads, hydro storage, and electricity-based storage systems [19,38]. Other proposed solutions focusing on the demand side make use of the noticeable improvements in district heating systems and CHP systems which have paved the way to linking smart grids with smart heating systems. This allows the demand, supply and conversion between heat and electricity to be controlled to reduce the supply-demand mismatch [16,33,34].

For a system to be considered smart and sustainable, it must be affordable, reliable, clean and of adequate resources. After a thorough review of the literature, Smart Energy Systems, were defined as, "an approach in which smart electricity, thermal and gas grids are combined with storage technologies and coordinated to identify synergies between them in order to achieve an optimal solution for each individual sector as well as for the overall energy system" [41,42]. Figure 2.2 shows an arbitrary concept of what a smart energy system would look like. Energy Internet (EI) is another smart and sustainable technology that is analogous to smart energy systems in terms of removing the existing barriers between energy sectors, creating a more open and flexible system with the goal of identifying possible points of synergy. EI systems are based on the integration of heating, cooling, gas and transportation systems with an emphasis on internet cognition and technologies. This includes big data, cloud computing, internet of things (IOT) and, block chain technology which constitute the computing layer of the system. The second layer or the physical layer encompasses different generation technologies, oil, gas and power grids, and electric and thermal storage systems. All of which are linked using energy hubs and energy routers, to meet the energy demand in all its forms [43]. An energy hub is a point of interconnection that allows the conversion and storage of different energy forms. From a system level, energy hubs contain converters, direct connections and, storage elements. The term hybrid energy hubs is often used to describe the presence of a suite of energy carriers [30, 31]. Energy hubs have been used to model several systems including power plants, specifically co-generation (CHP) and tri-generation (CCHP), industrial plants, commercial buildings, bounded geographical areas and islanded power systems such as trains and aircrafts [44].

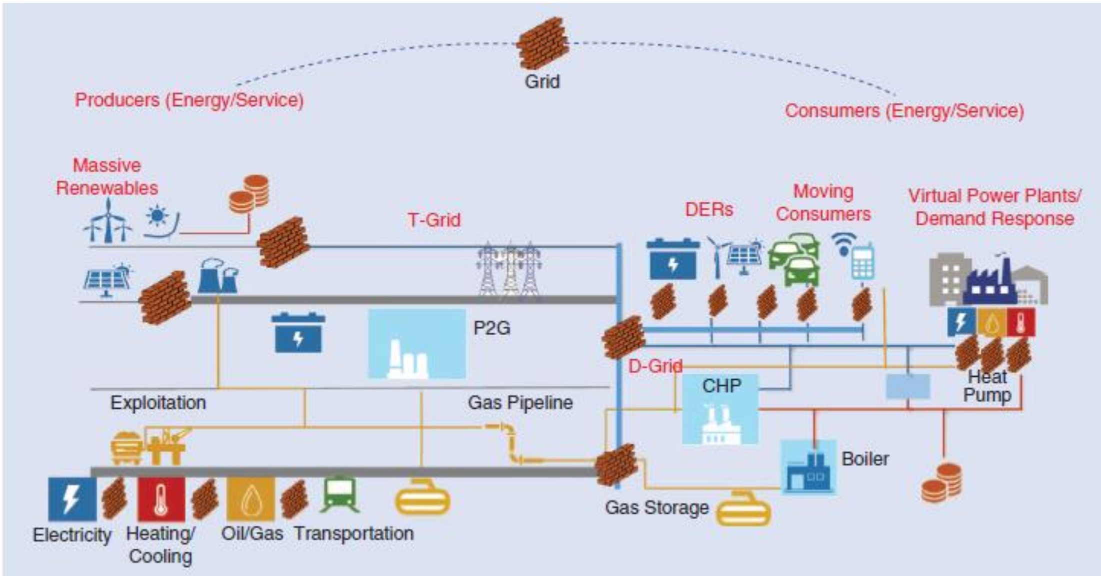

Figure 2.2: An example of a smart multi-energy system [43]

2.4 Integrated Demand Response

Multi-energy systems (MES) are seen as the future of sustainable energy systems, which help elevate many current-day power, energy, and environmental challenges. The development of several multi-energy systems as outlined in the previous section has given rise to a new line of research. A line focusing on the demand aspect of multi-energy systems, and on how to alter the demand profile in such systems. Integrated demand response (IDR) is the name given to a modified version of demand response that is specifically tailored for multi-energy systems. IDR is characterized by intentional changes in demand to change the overall consumption profile. However, it is very important to note that in MESs, profile changes can be observed due to operational changes in loads or by changing the type of energy being consumed [44]. IDR is a technology that complements the futuristic multi-energy systems, it shares several of its characteristics such as the ability to integrate more RES technologies. Higher RES participation will help further the economic benefits of the IDR scheme. The biggest benefit to IDR is increasing the capacity of DR as a system resource. This will inherently reflect as deeper improvements to all DR benefits. Moreover, by having the option to switch between energy types or energy fuels during IDR events, user comfort levels can be maintained at a higher level as there is room for changing consumption patterns without directly affecting the end-use process. Current IDR research generally focuses on one of three categories, integrated electricity and gas systems, integrated electricity and heat systems, and integrated energy systems.

The main uses of natural gas are in power generation, space heating, water heating and industrial processes. Electricity and gas systems are generally intertwined at a generation level through natural gas fueled generators. Gas generators are fast-ramping resources which play a significant role in maintaining the demand-supply balance across the system. This importance is emphasized by the increased presence of renewable energy sources due to the intermittent nature of their output. To understand this phenomenon, sufficient modeling of both natural gas and electricity networks must be utilized. It is important to note that residential users have a higher priority rank compared to gas-based generators in the eyes of the natural gas system operator [45]. This is one of many constraints that must be considered when dealing with both systems simultaneously as proposed in the co-optimization model in [46]. The work in [47] proposes another co-optimization model considering gas and electricity networks, power to gas (P2G) technologies and DR programs across both energy vectors. Electricity-based and Gas-based DR programs have been implemented in the past; electricity-based or traditional DR has the ability to reduce load profile volatility and gas network congestions [48]. While gas-based DR can relieve electricity shortages of the power system [49] however, the work in [47] considers their combined ability to improve the economic and secure operation of both networks and concludes that simultaneous optimization of both programs has better results than operating them separately. The authors in [49] study the effect of electricity and gas combined DR on market clearing and locational marginal prices of both systems. This is done through a robust scheduling model working to maximize the base-case system social welfare (i.e., revenue from price-sensitive DR loads minus energy production cost) minus the worst-case expected load shedding cost. Case studies illustrate effectiveness of the proposed model for ensuring system security against uncertainties, avoiding potential transmission congestions, and increasing financial stability of DR providers

Electricity and gas systems are also intertwined on the demand front, especially considering heating systems. This line of work falls under IDR and has gained increasing interest over the past decade [50]. CHP systems explained earlier are integrated heat and electricity systems and are usually modeled using virtual power plants in DR programs [51]. Moreover, Integrated heat and electricity systems are rather common in residential buildings. IDR in this case generally considers the heating load, thermal storage units and customer comfort levels. Thus, increasing the overall DR capacity of the system. There are several ways to manage these resources, for example, a genetic algorithm can be used to optimize electricity, cooling and heating demand curves within the comfort requirements of customers. These curves can then be used in a secondary optimization scheme to find the optimal energy production and storage schemes for both energy vectors [52]. Authors in [53] suggest multi-time scale scheduling of regional integrated energy systems (RIES). RIES is a modern energy system that integrates cooling/heating and natural gas systems with the electrical power system at its core [54]. IDR occurs across different energy subsystems with different scheduling times hence, three sub-layers of slow control, intermediate control and fast control are considered. IDR is also considered in home energy management systems (HEMS), [55] assumes the presence of a micro combined cooling, heating, and power (mCCHP) unit, which is equipped to convert energy between power and gas. A mixed integer linear programming problem uses IDR to achieve economic benefits for residential users. Residential users with HEMS, mCCHP systems and multi-energy loads were studied in [56] as well. A Stackelberg game-based bi-level programming model is proposed; where the upper-level model aims to increase the trading probability with residential users, while the lower-level model uses IDR technologies to reduce their energy costs.

The third category of IES is rather general and includes any and all integrated energy systems. Modern residential households have a full suite of energy inputs and energy requirements, which can be thought of as a MES on its own. This MES would typically include electrical loads, heating loads, a micro-

CHP unit and a plug-in electric vehicle (PHEV). All of which are fed through the electricity and gas networks. With an objective of minimizing costs, IDR can reduce consumer electricity and gas bills simultaneously [57]. A residential building complex can also be modeled as an energy hub with DR resources to perform energy management with the objective of cost reductions [58]. Energy hubs can also be used to represent, analyze and manage larger systems, consisting of wind turbine(s), energy storage systems, CHP units, boilers, thermal storage and transformer(s). The input energy carriers in this case are water, gas and electricity. The required outputs are in the forms of water, gas, heat and electricity. The objective of this energy management system considers all costs of the energy hub in terms of investment, reliability, operation, and emissions [59]. Hybrid energy storage systems can also be considered part of the MES family. The operation of hybrid energy systems consisting of photovoltaic panels, batteries and fuel cells is considered in the presence of heat storage tanks and DR programs to reduce total operational costs.

2.5 Practical implementations

This subsection provides a brief insight into existing IES projects that have been implemented over the past few years to provide a better understanding of their execution without academic assumptions. A small sample of two projects will be used for this brief. The REPLICATE (REnaissance of PLaces with Innovative Citizenship And Technology) Project was initiated in 2016 by the European Union targeting energy efficiency, mobility and ICT solutions. Participating systems include electric vehicles, district heating and cooling systems, intelligent lighting systems as well as, commercial and residential buildings. Another European-based project known as SmartEnCity's vision was implemented and tested in Spain, Estonia, and Denmark with the main objectives of improving energy savings, reducing carbon emissions, increasing renewable energy usage, and enhancing sustainable mobility. This project targets renewable generation, heating systems, smart buildings as well as, public and private transportation sectors. Both projects had similar objectives of increasing energy efficiency and sustainable mobility through retrofits and multi-sector integration. This requires massive investments in terms of energy converters and infrastructural changes needed for the execution of physical integration of different energy systems. This is reflected in their allocated budgets of € 29M and € 28M respectively. Table 2.1 provides a comparison of the aforementioned projects with the proposed scheme. In general, IES projects and academic works aim to improve energy efficiency and sustainability with a heavy focus on physical integration between systems through energy converters and energy hubs as well as infrastructural integration dictating large capital costs and enforcing a rigid operational commitment between all sectors. However, the main objective of the proposed work in this document is to expand the DR capacity of the system through operational integration instead of physical integration. Operational integration offers higher levels of flexibility and adaptability to different system as it requires minimal additional costs or set commitments between sectors. Instead, systems can choose to participate on their own terms to further improve their economic, social, or environmental objectives. Moreover, this algorithm is not limited by system structure or the availability of certain resources such as converters and energy hubs. It is built to fit into any system regardless of its physical integration and available resources.

Table 2.1: comparison of integrated energy system technologies

Project	**Objective**	**Budget**	**location**
REPLICATE [51]	• Increase Energy efficiency • Enhance sustainable mobility • Enhance integrated ICT solutions	€ 29M	Bristol (UK) Flourence (Italy) San Sebastian (Spain)
SmartEnCity's vision [52]	• Increase energy efficiency • Reduce carbon emissions • Increase RES integration	€ 28M	Vitoria-Gasteiz (Spain) Tartu (Estonia) Sonderborg (Denmark)
Proposed work	• Increase DR capacity	--	--

2.6 What is a Smart City?

The urbanization phenomenon changed human life in almost every conceivable aspect; it opened the door to countless benefits and concerns. Many of these concerns revolve around the future of our, fuels, cities and hence our lives. The vast technological advances in communication and control gave rise to the rapidly growing interest in smart cities. Smart city is a rapidly growing phenomenon that has captured the interest of researchers and professionals alike. The term smart city covers many different aspects; it has no solid limitations or single definition. One of the commonly used definitions stated that a smart city is "one that makes optimal use of all the interconnected information available today to better understand and control its operations and optimize the use of limited resources [60]." A smart city can also be defined as a "A city that monitors and integrates conditions of all of its critical infrastructures, including roads, bridges, tunnels, rails, subways, airports, seaports, communications, water, power, even major buildings, can better optimize its resources, plan its preventive maintenance activities, and monitor security aspects while maximizing services to its citizens[61]; or as "A city well performing in a forward-looking way in economy, people, governance, mobility, environment, and living, built on the smart combination of endowments and activities of self-decisive, independent and aware citizens [62]. Regardless of the exact wording used in a definition, the essence of a smart city lies in the use of information and communication technologies to develop, deploy, and promote intelligent, sustainable practices to address several concerns. The beauty of this concept lies in its openness, the list of concerns it can tackle is not close ended. On top of these concerns are urbanization challenges, environmental challenges, economic challenges, and social challenges. Intelligence in smart cities can be seen in urban planning, power generation, energy management, transportation networks, waste management, resource management, public safety and so much more [63,64].

There are several aspects of a smart city that must be explained. We will start with the managerial and organizational challenges one can expect in a smart city. A smart city is a massive project, which is bound to have several stakeholders with different or even conflicting objectives and priorities. Resistance to change, turfs and conflicts are expected to occur and give rise to difficult managerial and organizational obstacles [65]. The most obvious and irreplaceable aspect of a smart city is being 'smart' or 'intelligent', this refers to the technologies needed to give life to the Smart City concept. This is to introduce "new generation of integrated hardware, software, and network technologies that provide IT systems with real-time awareness of the real world and advanced analytics to help people make more intelligent decisions"

[66]. A smart city is built on massive amounts of data and information. This brings rise to several concerns about data management, data processing as well as the privacy and security of the sensitive data in a project of this size and importance. Another smart city aspect revolves around the governing structure in this new environment. Smart governance is the core of smart city initiatives and must answer questions regarding collaboration, leadership, participation, communication, data-exchange, accountability and, transparency [66, 62]. Smart Cities also aim at creating more informed, educated, and pro-active members of society as well as, improving the overall quality of life. Education programs, participation incentives and several other factors must be studied during the early planning stages of a smart city project [62]. Other major goals of this initiative rise from economic and environmental backgrounds. The goal is to promote sustainable practices across all fronts. This includes transportation, water treatment, waste disposal, electricity generation, electricity consumption, natural resource management and many more.

A Smart City consists of several layers, namely an infostructure (software) layer, an infrastructure (hardware) layer and a suprastructure (brainware) layer [67]. The software layer refers to all technology resources related to the management and operation of all the applications and data involved in the system. This is made possible through an intricate hardware layer, starting with sensors and actuators to data centers and servers. The brainware layer refers to all resources used in organizing, managing, and operating the former layers. This includes human resources, policies, and strategies. DSM programs belong to the software layer of a smart city and are only made possible through the other layers. This work will focus on DSM as an application. Earlier in this chapter, we established the benefits of DSM programs. DSM has been proven to have positive effects on economic, environmental, and social fronts. Due to the interconnectivity of smart city resources, DR or IDR programs will likely have rippling effects across the different sectors.

2.7 DR in Smart Cities

Energy management is amongst the most important considerations for a smart city. A smart city can provide access to massive amounts of data and information on energy consumption and consumer behavior that can help the end-user and the utility. An informed user can make better decisions and more sustainable practices, while electric utilities can use real-time measurement systems to infer the energy consumption behavior and optimize the operation of the system to meet their goal(s)[68]. Many works have presented possible frameworks for DR in smart cities, including [69] with a bi-objective model developed to determine the balance between the global operational cost and the total load curtailment provided by the DR programs. The work in [70] goes a step further and inputs the user consumption data into a deep learning model based on convolution neural networks and support vector regression to find patterns and predict the overall load consumption. The infrastructure and technology provided in a smart city allows many end-users to become prosumers with consumption/generation profiled scheduled in a manner that meets their chosen objective [71]. Following the same directions, [72] Investigates the possibility of building energy marketplaces at a neighborhood or district level within a smart city populated with smart prosumers.

High on the list of the world's 'Smartest' cities are Singapore, Helsinki and Zurich. Singapore has introduced smarter governments, smarter transportation systems, smarter business models, smarter health sectors and overall smarter living conditions. Electricity generation in Singapore has a long way to go, officials at the Singapore International Energy Week (SIEW) 2020 outlined a four-step approach to combat climate change and move towards more sustainable practices. Authors in [73] propose a model to increase end-user participation in the electricity market through demand response. Second on the smart city list is Helinski, a European city with intelligence integrated into five key areas: health, safety, transportation, energy, and governance. The smart city of Zurich is built on three goals providing equal opportunities and high quality of life for all, conserving resources, and developing sustainable practices as well as, presenting itself as an attractive business location [74]. Similar advances across different fields can be found in Zurich, advances in energy integration and management still have a long way to go. This will be the focus of this thesis.

2.8 Discussion

The benefits of demand response programs are of undisputed truths from technical, economic, environmental and social perspectives. DR programs are expected to play a vital role in the transition to a more green and sustainable future. Depending on the objective put forward, DR programs have been proven effective in reducing harmful emissions, reducing power loss and increasing the integration of renewable energy sources. All of which are important steps on the pathway to a sustainable future. However, the efficacy of any DR program is governed by the flexible resources available in the system. This encouraged researchers to think of combining energy systems together to make use of the available flexibilities across different energy carriers. Integrating different energy sectors calls for interconnection/conversion devices such as CHP generators, electric boilers, gas turbines and so on. Moreover, combining different systems is a rather complicated process in a physical, control, communication and business sense, as each system has a complete set of constraints, regulations, policies, priorities and objectives. The aforementioned solutions have done an outstanding job in combining multiple energy systems to find new synergies and improve system performance. However, they rely heavily on infrastructural integration between energy systems with a heavy dependence on the existence of multiple fuels for the same end-user process. This adds to the difficulty and impracticality of these solutions in our current times. However, there are several energy systems that are readily and closely tied to the power system which could be exploited to provide demand flexibility to the system through operational integration alone. Operational integration is a prominent solution as it requires zero to minimal changes to the physical system structure as opposed to the grand investment needed for retrofits and redesign to facilitate physical integration. The intent to convert many cities to smart cities works in favor of operational integration as it provides many of the needed technologies. On the other hand, physical integration is rigid and it imposes a long-term commitment from the participating energy sources. While the proposed work allows for energy sources to bid and participate whenever it is beneficial for them to do so. This approach of integration of energy sources allows for accommodating future changes in the use and the operation of these energy sources. In essence, the existing method of energy sources integration is a collaborative process while this work is a free-market trading operation that utilizes demand response and embraces energy efficiency. These differences are summarized below in table 2.2.

Table 2.2: Physical Vs. Operational integration

Physical integration	Operational Integration
High initial investment	Zero to minimal initial investment
Long-term commitment	Voluntary participation based on economic benefit
Single/shared entity	Independent entities
Shared objective	Independent objectives
Centralized control	Decentralized control

This chapter highlighted the benefits of DSM programs and their significance in future electric systems. The main focus fell on the demand response portion of DSM technologies, a brief summary of DR programs was presented with emphasis on their social, environmental, and economic benefits. DR resources are described based on type, capacity, and availability. Since DR benefits are capped by the DR capacity in a given system, solutions such as integrated energy systems in general and integrated demand response programs in specific were explained. A clear distinction between physical and operational integration was presented, this work will only discuss operational integration in the coming chapters. This was followed by a brief description of smart cities as the main breeding ground for this platform

Chapter 3: Choosing DR resources

3.1 Criteria for energy systems to be selected for investigation

It is important to recall our main objective at this point, to identify points of flexible operation and energy storage across different energy sectors that could participate in DR programs. The first step towards our goal is filtering through different energy systems to create a list of possible demand response resources (DRR) that can partake in this program. We devise a set of characteristics to guide us through this search. Our criteria is based on the attributes that make a system resource useful during a DR event. We start at the traditional DR resources, what makes them useful to the power system? What makes them useful to the end-user? What attributes or characteristics do we wish to find in a DRR?

Demand response resources include flexible loads, energy storage systems and distributed generation units. Flexible loads are loads that can be ramped up, ramped down or shifted in time without compromising performance measures. Energy storage systems are incredibly effective DR resources with the ability to increase, decrease or shift demand in time. However, storage is not naturally present in the system and would require additional installation and maintenance costs. The third traditional type DRR is distributed generation, which is usually viewed as negative loads that may be dispatchable or non-dispatchable in nature depending on their physical properties. Since this type of DRRs is concerned with generating units, it will not be considered in this work. This work aims to find resources that are readily connected to the electrical system i.e., resources that require electricity to fuel part or all of their operation. It is essential for their operation to have a reasonable degree of flexibility; as such, their electric consumption can be increased, decreased, or shifted to a different time without violating any performance measures or standards. For DR resources to be effective, they must be sizeable alone or as an aggregated group. This is important for the effect to be seen on the overall demand curve. Moreover, the DRR in question must have digital control and measurement tools in place. It must also have means of communicating with the network; to send and receive DR related data and information. Participating systems are assumed to have stakeholders with clear, specific goals and objectives. DR participation could very much collide with said objectives. In that case, it is safe to assume that an operator will only opt for participation if reasonably incentivized. Therefore, responsiveness to presented incentives must be considered. Looking at traditional demand response, energy storage systems have several advantages over their counterparts such as predictable behavior, fast ramp response, and of course the ability to store energy for later use. We have labeled these characteristics as preferable. Having them would improve our DR program but they are not essential for its operation. Both types of characteristics are summarized in table 3.1.

Table 3.1: DRR characteristics

Critical characteristics	Preferable characteristics
Operational flexibility	Storage potential
Control system	Predictable behavior
Reasonable load size	Quick ramp response
Interaction with electric system	
Possibility to incentivize	

3.2 DRR Investigation process

The first stage in this work is to identify and model potential demand response resources (DRR) that are often over-looked or not fully represented in the current field of DSM. The scale of the work considered belongs to the world of smart cities hence; it is a good idea to start the DRR hunt with the power-hungry loads expected in a smart city. This will include high consumption facilities such as water treatment plants but could also include residential appliances such as heat pumps. Thermal loads can be of significant effect when aggregated for use in a DR program. Once a facility is chosen for consideration, it is important to gain a basic understanding of its operation. This is done with the goal of identifying energy-intensive processes, operational flexibilities, and their effect on energy consumption with special notice to electric energy. It is essential to understand the physical, operational and legislation limits of each facility and their effect on energy consumption and/or ability to participate in a DR event. It is also important to understand the internal and external goals of the facility and their expected response to incentives. The steps are summarized in figure 3.1.

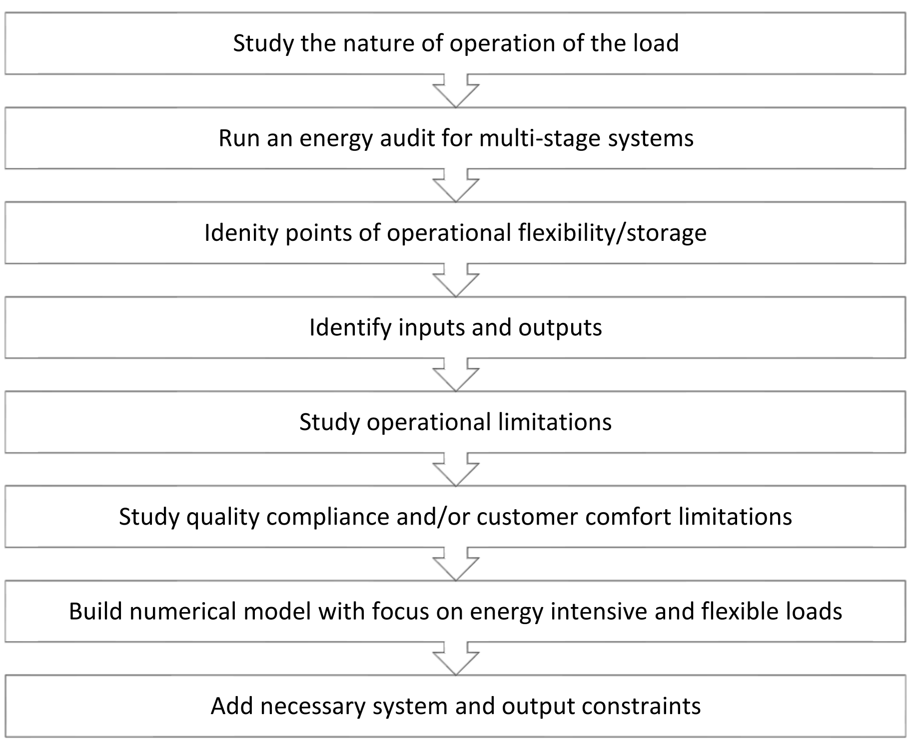

Figure 3.1: DRR identification steps

3.3 Process Findings

The outputs of the DRR investigation detailed above are explained in this section. We start with the water sector; we find that water treatment accounts for the highest energy usage for most municipal governments and over a third of municipal energy consumption in Ontario with an aggregate peak of 328 MW. The highest energy consumer in this sector for most countries with access to fresh water is wastewater treatment plants (WWTP) [75]. Moreover, consumption of WWTPs is expected to further increase by 20% in developed countries by 2025 [76]. From an environmental perspective water treatment sectors generate approximately 0.58 MTCO2 Eq greenhouse gas (GHG) emissions annually [77], 38-50% of which are a byproduct of energy consumption in WWTPs. From an economic perspective treatment plants are inclined to participate in DR programs as 60% of all their operating costs goes towards their electricity bill [77]. Shifting the focus from wastewater to drinking water treatment, there are two main options based on water availability in a specific geographic region. Countries with access to fresh surface or ground water will require simple water treatment processes while other countries will require more extensive desalination techniques in the absence of fresh water. The former has a relatively low energy consumption rate however; the load shifting potential in these systems is significant and is worth investigating. Pumping is responsible for a massive 80% of drinking water treatment plants (DWTP) energy consumption, through monitoring and control we can save around 40% of the total energy consumption and 60% of peak demand saving [75]. Energy costs currently account for up to 40% of the operating budget of a utility plant [75]. Furthermore, heat pump (HP) based thermal systems and electric vehicles (EV) will both be considered in this work. Heating and cooling requirements are amongst the highest energy consumers in residential, commercial and industrial sectors at 61% and 55% respectively. The previous study considered space heating requirements separate from water heating requirements which amount to 19% and 8% of the total energy consumption of residential and, commercial and industrial sectors [78]. Heating systems based on heat pumps are considered in this work due to their high efficiency and growing popularity. Heat pumps cover a wide range of applications including space cooling, space heating and water heating. They are cleaner, greener and of superior performance with an improved efficiency of 300-400% over traditional heating methods. While electric vehicles are sizeable loads, which can consume 10kW of electricity in one hour compared to a typical residential peak load of 3kW. EV penetration has been increasing over the past decade and is projected to continue growing rapidly in the presence of major environmental concerns and government incentives (rebates). Electric vehicles can be considered as flexible and controllable loads since they operate based on their battery size that can be recharged either when it is empty or whenever it’s convenient to the user. While electric vehicles and thermal loads have been considered in DSM programs in the past, they are included in this work as unique sources of flexibility and energy storage through batteries and thermal inertia of buildings and domestic hot water (DHW) tanks, respectively. This integration is important as part of the futuristic DR scheme which will include many features observed in today’s technologies.

Other facilities that are worth considering include gas pumping stations. Gas supply networks typically consist of gas compressors, pipelines, compression stations, pipe fittings, storage facilities, and terminal stations. Compression stations may be powered by natural gas-fired turbine or by an electric motor. In case the latter is true, compression stations become the highest electrical energy consumers in the gas network. Operational changes were found to cause an 11-16% energy reduction in [59]. Electricity dependent gas networks are sizeable loads to the power system, consuming tens of GWh per month and are hence worth considering as active players in the system. Moreover, Desalination units are vital in areas without access to fresh surface or ground water. They are highly energy intensive processes, depending on the technology being used (thermal or membrane processes). Thermal processes require 17.9 to 33 kW/m^3 of water treated, that amounts to a massive 140 PWh per year in a country with scarce freshwater resources such as the United Arab Emirates [58]. Membrane processes such as reverse osmosis (RO) and electro-dialysis are more energy efficient consuming 3.5-5.0 kWh/m^3 of treated water [58]. Most Gulf countries use RO and hybrid RO/thermal technologies. Desalination units are sizable loads and can create a significant effect on the power system through monitoring and control measures. There are many facilities with DR potential that could participate in this program, a few examples were briefly described in this section. However, due to time restrictions this thesis will not discuss them further.

This subsection provided the results of our DRR investigation, which suggested several DR participants to consider and explained in detail the reason behind their choice and why we think they would succeed as DR resources. This can be used as a guide to find other potential DR resources. It is of the utmost importance to note that this work is not limited to the six mentioned participants. The goal is to create a system that allows the exchange of information and control signals across different energy sectors that remains open to any and each energy system with DR potential. The aforementioned players were chosen for their promising DR potential and significant load size making them excellent candidates to prove the concepts detailed within this work. However, several other energy systems may be of addition to this project such as lighting and irrigation. Considering the scope of this document, one of the 6 mentioned systems will be explored in detail in the following subsection while others will be expanded on in future works. The modeling and analyses of wastewater treatment plants will be expanded on as an example of the steps to be followed in this work

Chapter 4: Modeling Chosen Resources

This chapter provides an insight into the demand response resources chosen for participation. These resources are often operated individually or over-looked by traditional DR programs. The goal is to investigate the benefits of operational integration between the multiple energy sectors. There are four main resources or players considered in this work, waste-water treatment plants, drinking-water treatment plants, heat-pump based space and water heating systems and, electric vehicles. Each of these systems has operational flexibility that has not been fully utilized. Hence, we study their operations, constraints, objectives and identify useful models to represent the DR capacity present within each of the systems.

4.1 Wastewater treatment plant

4.1.1 Brief introduction

Wastewater treatment plants are complex structures with several treatment stages. Each treatment stage has a number of technologies that can be used to satisfy the desired objective. This makes the idea of creating a universal benchmarking model unrealistic. Any benchmarking model should ideally be based on a granular, reliable, and statistically representative sample of data quantifying the treatment processes and the properties of influent and effluent flows for WWTPs. Due to the absence of comprehensive datasets for WWTP facilities; there is no single representative benchmark nor a set of benchmarks for similarly built and operated facilities [79].

In the absence of a pre-defined benchmark and in efforts to build a realistic WWTP model, the model used in this work was based on a functioning treatment plant in Toronto, Ontario. A metropolitan area was chosen for its load that is likely to match or exceed the expected load of a smart city. The city of Toronto has four WWTP facilities of different sizes, capacities and stages i.e. not all treatment plants house all treatment stages. This is referring to the optional tertiary stage and sludge processing stage. Instead, sludge collected from these facilities is transported to facilities with sludge processing capabilities. Ashbridges Bay treatment plant (ABP) shown in figure 4.1 is the largest and most comprehensive wastewater facility in Toronto, making it a great candidate for this modeling process. From an energy consumption perspective, ABP has one main pumping station to lift the incoming sewage, after which wastewater flows by gravity through the plant's structure. Another smaller pumping system belongs to the primary treatment stage and is used to pump sludge from the primary clarifying tanks to the sludge processing tanks. Sludge processing involves two energy consuming processes including dewatering centrifugation and digester heating. The former has very little operational flexibility due to its physical nature, while the latter is of relatively low consumption in comparison to other WWTP processes. However, the main reason for discarding the heating element from modeling is the absence of information and availability of heating models that could be added to the model after the platform is built and functional. It is also worth mentioning that the additional tertiary stage present relies on the addition of a liquid chlorine solution for final clarification. This process requires very little energy and is not considered in the model.

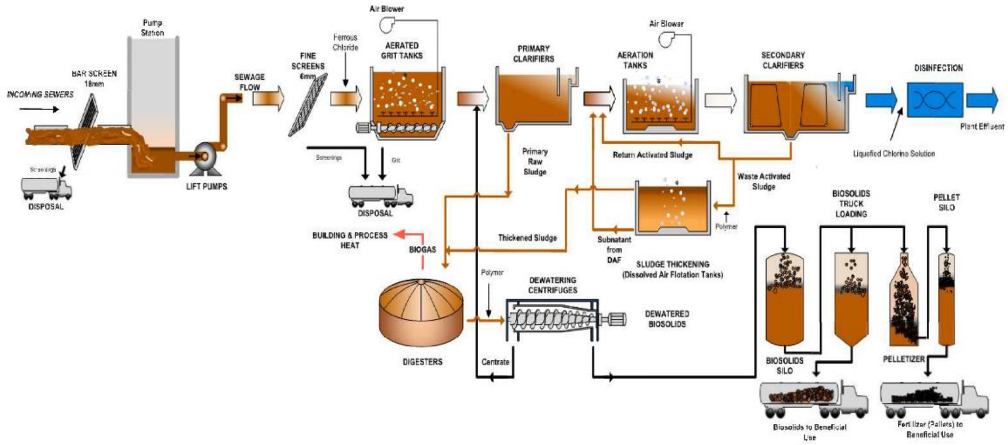

Figure 4.1::Ashbridges Bay plant schematic

4.1.2 *Operational flexibility in WWTP*

Sanitary sewage systems are of undeniable importance for human health and environmental safety. They are essential in our day-to-day lives to protect humans, animals, plants and more importantly, our clean water resources from all the toxins present in wastewater. They also play a vital role in providing a safe and easy way to get rid of excess rain and flooding in cold and wet areas. This justifies the money and effort invested in sewage infrastructure and wastewater treatment plants. Wastewater treatment constitutes several treatment stages, each of which can be carried out using different technologies. Choice of technologies used in each process will have a direct impact on energy consumption and on modeling. In order to create an accurate numerical model for WWTPs, we must analyze the physical properties of the processes involved in wastewater treatment. The treatment process usually constitutes three or more main stages: preliminary treatment, primary treatment, secondary treatment with the optional tertiary treatment and sludge processing. The preliminary treatment provides basic physical cleaning of the influent where it removes large solids and grit through the use of mechanical bar screens and grit removal systems. Grit chambers are of three types: horizontal flow, aerated and vortex chambers.

Horizontal flow chambers work by reducing the speed of the wastewater to provide sufficient time for grit particles to settle. Aerated grit chambers work by blowing air in the chamber, creating a circular flow of the liquid allowing heavier grit to settle to the bottom of the chamber while lighter organic particles remain in suspension and pass through the tank. Velocity of circular flow governs the size of particle to be removed. If velocity is too great, grit will be carried out, if velocity is too small, organic particles will be removed with grit. Vortex grit removal uses rotating paddles to create a spiraling effect in the influent causing grit to settle in the mechanically induced vortex. Removes a portion of the suspended solids and organic matter from the wastewater. Next, wastewater is sent to the primary sedimentation tank, which relies on reducing flow speed to allow sludge to settle at the bottom of the tank and scum to rise to the surface. Both fluids are pumped and scrapped off, respectively. The wastewater fluid at this point is sent for secondary treatment, where microorganisms are used to digest biodegradable matter in the liquid in the presence of oxygen. This is an essential step as it stabilizes the toxic organic matter present in wastewater. This is done through the aeration Process that constitutes several blowers, which force air through the aeration tank to supply oxygen for microorganisms to digest the organic matter and to maintain circular motion in the tank. Oxygen supply is measured through the dissolved oxygen (DO) metric, which must be monitored and maintained within a specific threshold to maintain output quality. The wastewater fluid if then passed through a secondary sedimentation tank, which slows down the flow to separate the mixed liquor suspended solids (MLSS) from the treated wastewater. A tertiary treatment step could be included to further improve the effluent quality before it is discharged to the receiving environment (sea, river, lake, ground, etc.) It usually includes a disinfection step for the removal of any harmful chemicals using agent like chlorine, UV light or Ozone (O3). Sludge processing is a separate stage that is present in many WWTP and it works on stabilizing several disease-causing microorganisms that are often found in sludge while extracting the useful organic matter that it carries. This is done through sludge dewatering via centrifugation, filtration, and/or evaporation, followed by sludge digestion to remove organic matter and harmful microorganisms. Sludge digestion can either be Anaerobic (without oxygen) where bacteria consume organic matter and turn it into water, carbon dioxide and methane. The produced methane could be combined with carbon dioxide to produce biogas to be used as an energy source. This process requires additional heat energy during digestion. Aerobic digestion (with oxygen) is where bacteria consume organic matter and turn it into water and carbon dioxide. Table 4.1 shows the main energy consumers in each stage of the treatment process.

Table 4.1: WWTP treatment stages and energy consumption

Process	**Main Energy Consumer(s)**
Preliminary Treatment	• Influent pumps • Aerated grit chambers
Primary Treatment	• Sludge pumps
Secondary Treatment	• Secondary aeration
Tertiary Treatment	• UV light • Ozone production
Sludge processing	• Sludge dewatering

Through an extensive review of WWTP energy audits, we can generalize that the largest energy consumers are the aeration processes and pumping at 65% and 23% of the total energy consumed respectively [12]. Not only are these two processes highly energy intensive, they both present high levels of operational flexibility. The modeling will focus mainly on these two components. The control variables will all fall under the pumping system and aeration process. Pumping power can be increased, reduced, or completely switched off at different times. As for aeration, blower power can be increased, decreased, or switched off at various hours of the day. This will be based mainly on the dissolved oxygen levels in the tank and facility objective. This will be expanded on in the coming section.

The aeration process can be observed once or twice in a WWTP depending on the technologies used during the primary and secondary treatment stages. Aeration is an essential part of secondary treatment but is often observed in grit removal chambers of the preliminary treatment stage as well. Aeration control in grit chambers is based on maintaining flow velocity within predetermined limits to prevent the excessive or insufficient filtration of wastewater. Aeration in secondary treatment requires a more involved control process to maintain biological activity within acceptable limits.

Organic load coming into a treatment plant are measured in biological oxygen demand (BOD), this value dictates the amount of oxygen or the level of dissolved oxygen (DO) that must be supplied to the secondary chamber at all times. The importance of DO control is measured through the BOD found in the wastewater effluent, which must be maintained within predefined values according to regulations for health and safety reasons. These values are used to find the amount of oxygen required for BOD oxidation as shown in equation 4.1. This value is then corrected for the effects of surfactants, temperature, salinity and membrane fouling to give the standard oxygen transfer rate shown in equation 4.2. A quick unit change is employed in equation 4.3 to give the standard cubic feet per minute (SCFM) of air requested. This is then used to find the mass flowrate of air through the blower as shown in equation 4.4. This is then used to calculate the total power consumption by the blower in equation 4.5. Power consumption depends mainly on the rate of flow of air being driven into the tank, as well as the intake and discharge pressure found through equations 4.6 and 4.7 respectively.

In practical situations, intake pressure should be a measured value obtained from special meters however, due to absence of data from WWTPs pressure values will be calculated. Intake pressure is corrected for the pressure drop through the intake filter in equation 4.6. The pressure of the liquid in the tank depends on the density of the liquid, which in turn depends on the amount of mixed liquor suspended solids (MLSS) in the fluid as in equations 4.7 and 4.8. In order to calculate discharge pressure we must first find both the static and the dynamic head that the blower must overcome.

The static head is based on the calculated surface pressure, density and discharge depth, which depends on tanks depth and diffuser mounting height. Static head is calculated as shown in equation 4.9. The dynamic head the blower must overcome is found using the airflow rate per diffuser and a set of diffuser pressure drop constants shown in equation 4.10. In order to find airflow rate per diffuser, we must first find the intake airflow rate, which is based on our gas theory and mass airflow rate as in equation 4.11 this is then corrected for the conditions at the diffusers output in the bioreactor to give the airflow rate per diffuser in equation 4.12. Discharge pressure is then the simple addition of static head, dynamic head and pressure drop due to the distribution system (pipes/valves) as in equation 4.13. Equation 4.14 is used to calculate blower efficiency using blower intake airflow. The following equations were modified to better the needs of our model from the following sources [61], [62].

$$OTR_{(t)} = (BOD_{in(t)} - BOD_{eff(t)}) \times 8.34 \times Con \times Q_{(t)} \qquad \text{Equation (4.1)}$$

$$SOTR_{(t)} = \frac{OTR_{(t)}}{\left(\frac{\beta \times C_{s,T} - C_{W(t)}}{C_{s,20}}\right) \times \alpha F \times \theta^{(T(t)-20)}} \qquad \text{Equation (4.2)}$$

$$SCFM_{(t)} = \frac{SOTR_{(t)}}{60 \times \rho_{air(t)} \times SOTE \times 0.23} \qquad \text{Equation (4.3)}$$

$$W_{air(t)} = \frac{SCFM_{(t)} \times \rho_{air(t)}}{60} \qquad \text{Equation (4.4)}$$

$$P_{blower(t)} = \frac{W_{air(t)} \times R \times T_{inlet(t)}}{3600 \times \eta_{blower(t)}} \cdot \frac{\gamma}{\gamma - 1} \times \left[\left(\frac{P_{Discharge(t)}}{P_{Intake(t)}} \right)^{\frac{\gamma-1}{\gamma}} - 1 \right] \qquad \text{Equation (4.5)}$$

$$P_{intake(t)} = P_{surface(t)} - P_{drop,intake} \qquad \text{Equation (4.6)}$$

$$P_{surface(t)} = P_{atm} + \rho g h_{(t)} \qquad \text{Equation (4.7)}$$

$$\rho = \rho_{h20} + A.MLSS \qquad \text{Equation (4.8)}$$

$$H_{static} = P_{surface} + \frac{\rho_{H2O} \times D_{discharge} \times g}{1000} \qquad \text{Equation (4.9)}$$

$$H_{dynamic(t)} = A_d + B_d \times Q_{a,diff(t)} + C_d \times Q_{a,diff(t)}{}^2 \qquad \text{Equation (4.10)}$$

$$Q_{a,intake(t)} = \frac{W_{air(t)} \times R \times T_{inlet(t)}}{P_{intake} \times k} \qquad \text{Equation (4.11)}$$

$$Q_{a,diff(t)} = \frac{Q_{a,intake(t)}}{no\ of\ diffusers} \times \left(\frac{P_{std}}{P_{surface(t)}} \right) \left(\frac{T_{a,inlet(t)}}{T_{a,standard}} \right) \qquad \text{Equation (4.12)}$$

$$P_{discharge(t)} = H_{static} + H_{dynamic(t)} + P_{drop,system} \qquad \text{Equation (4.13)}$$

$$\eta_{blower(t)} = A_\eta + B_\eta \times Q_{a,intake(t)} + C_\eta \times Q_{a,intake(t)}{}^2 \qquad \text{Equation (4.14)}$$

Where,

α: Ratio of oxygen transfer efficiency (OTE) in wastewater to OTE in tap water. This parameter accounts for the effects of aeration type, basin geometry, degree of mixing, and the wastewater characteristics such as the presence of surfactants;

β : Cs(wastewater)/Cs(tap water). This term corrects for constituents in the wastewater which impact the solubility of oxygen;

θ : Arrhenius constant- used to correct for the effects of temperature;

η_{blower}: Blower efficiency;

ρ_{h20}: Density of water at the specified temperature of the stream [kg/m^3];

ρ: Density of wastewater fluid corrected to MLSS present [kg/m^3];

ρ_{air}: Density of air must be calculated using pV = nRT with the pressure being corrected for the elevation

γ: Adiabatic/polytropic compression exponent (1.4 for adiabatic) ;

A: Density conversion constant [m3/g];
A_η: Blower efficiency constant [-];
B_η: Blower efficiency constant [hr/m^3];
C_η: Blower efficiency constant [(hr/m^3)^2];
A_d : Diffuser pressure drop constant [kPa] ;
B_d : Diffuser pressure drop constant [kPa/m^3/hr] ;
C_d : Diffuser pressure drop constant [(kPa/m^3/hr)^2]BOD_{in}: Biochemical oxygen demand of influent wastewater[mg/L];
BOD_{ef}: Biochemical oxygen demand of effluent;
Con: Pounds of oxygen required per pound of BOD removed;
$C_{s,20}$: Oxygen saturation concentration for tap water at 20C ;
$C_{s,T}$: Oxygen saturation concentration corrected for altitude and temperature ;
C_W : Operating dissolved oxygen concentration [mg/L];
$D_{Discharge}$: Discharge depth found by subtracting the tank depth from the diffuser mounting height [m];
F: Membrane fouling factor;
g: Gravitational acceleration [m^3 /kgs^2];
h: Height of fluid in tank [m];
$H_{static}, H_{dynamic}$: static head and dynamic head converted to kPa, respectively;
k: unit conversion constant;
$MLSS$: Mixed liquor suspended solids concentration [g/m^3];
P_{atm} : Atmospheric pressure [kPa];
$P_{Standard}$: Standard atmospheric pressure [kPa];
$P_{Surface}$: Surface pressure [kPa] ;
$P_{discharge}$: Blower discharge pressure [kPa];
P_{Intake} : Blower intake pressure [kPa];
$P_{drop,intake}$: Pressure drop through the intake filter [kPa];
P_{blower}: Power requirement of each blower [kW];
OTR : Oxygen transfer rate under process conditions [lb/hr];
$Q_{a,intake}$: Intake airflow into the blower [m^3/hr];
$Q_{a,diff}$: Air flow per diffuser [m^3/hr]
$Q_{a,intake}$: Blower intake airflow [m^3/hr]
Q : Municipal wastewater flow in millions of gallons per day. [MGD]
R: Gas constant
$SOTR$: Standard oxygen transfer rate [lbO_2/hr]
$SOTE$: Standard oxygen transfer efficiency in clean water.
$SCFM$: Standarc cubic feet per minute of air required
T : Outside temperature value in degrees C.
T_{inlet}: Inlet air temperature [K]
$T_{a,standard}$: Standard air temperature [K]
$Q_{a,intake}$: Blower intake airflow [m^3/hr]
W_{air}: Mass flowrate of air [lb/s]

The above model represents the power consumption of the diffused aeration blowers utilized in secondary treatment in most wastewater treatment plants. There are several constraints that must be imposed to guarantee safe operation and high-quality output including:

1. Physical limitations of the equipment: this includes tank capacity, blower capacity and maximum flow rates through the system.
2. Biological oxygen demand of the final WWTP effluent.
   This is mainly controlled through manipulation of DO levels in secondary treatment basins. This introduces a constraint on C_W as follows: $1 \leq C_W \leq 2$
3. Adequate mixing requirement must be maintained in the aeration tank at all time to facilitate the ongoing biological process.

Aeration loading is often measured in BOD of the incoming wastewater fluid. In many cases, BOD values are high and act as the dominating factor in aeration control. However, when BOD loads drop during late evening hours, satisfying DO requirements is no longer a dominating control strategy Instead the adequate mixing in the tank may be the controlling energy requirement. It is important to note that access to data and information for WWTP modeling is of great difficulty. Most of this information is not available online and many assumptions had to be taken to make up for the absence of information. Moreover, historic data of WWTP loading is not available to the public but was obtained with the help of local WWTP operators who have agreed to share a certain amount of data as per their guidelines.

Many wastewater treatment plants are designed in a manner that facilitates gravitational flow of fluids throughout different stages of the treatment plant. This is usually done with intake lift pumps to raise the fluid head upon entry to the treatment plant. This is second largest energy consumer in WWTP and is modeled below. Pump power depends on the flow, static head and dynamic head as shown in equation 4.15 where the dynamic head is based on the generated friction within the system as expressed in equation 4.17. Equation 4.18 shows the components of the loss coefficient in the system. While equation 4.19 relates linear and volumetric flow rate to be used in equation 4.20 showcasing the change of fluid volume in the inlet column with respect to time as a function of incoming sewage and pumping efforts. These equations were adapted from [80] [81].

$$P_{pump(t)} = \frac{Q_{pump(t)} \times H_{total(t)} \times g \times \rho}{pump\ effciency} \qquad \text{Equation (4.15)}$$

$$H_{total(t)} = H_{static} + H_{Dynamic(t)} \qquad \text{Equation (4.16)}$$

$$H_{Dynamic\ (t)} = \frac{K_{loss} {v_{(t)}}^2}{2g} \qquad \text{Equation (4.17)}$$

$$Q_{pump\ (t)} = A \times v_{(t)} \qquad \text{Equation (4.18)}$$

$$K_{loss} = K_{fittings} + K_{pipe} \qquad \text{Equation (4.19)}$$

$$V_{(t)} = V_{(t-1)} + Q_{inlet} - Q_{pump\ (t)} \qquad \text{Equation (4.20)}$$

Where,
$H_{static}, H_{Dynamic}$: static and dynamic head respectively [m];
H_{total}: the total head [m];
$K_{loss}, K_{fittings}, K_{pipe}$: Total loss coefficient, loss coefficient through the fittings and pipe respectively;
P_{pump}: Power consumption by inlet pump[W];
Q_{inlet}: is the total flow through the pipe [m^3/sec];
Q_{pump} : flow through the pump [m^3/sec];
v: Linear flow velocity in the pipe [m/s];
V: Volume of fluid in inlet column [m3];

4.2 Drinking water treatment plant

4.2.1 Brief introduction

Moving from wastewater treatment to drinking water treatment, we look at the operation of a typical DWTP. The drinking water treatment process is relatively simple when compared to sewage treatment however; it still requires a significant amount of electric power to operate. This process consists of a number of stages, usually 8. Stages can be amended, changed, or eliminated based on water quality, geographical region, and governing standards. It is therefore difficult to find an acceptable benchmark that can describe this process realistically hence, the same approach taken for wastewater treatment plants is called upon. The DWTP model used in this work will be based on the R.C Harris Water Treatment Plant, an existing treatment plant in Toronto, Ontario. Approximately 90% of Ontario' water comes from surface water sources [82] and so, this section will provide a brief introduction to surface water treatment.

The water treatment process starts with a group of pumps carrying water from the source to the treatment plant; this is followed by physical filtering to remove any solid objects that may be present in the water. Chemical compound known as coagulants are then added and rapidly mixed into the water to group any fine physical particles that were not removed by the initial screening. The water is then held in a settling tank to allow the grouped solid particles to sink to the bottom of the tank. Pumps are then needed to push the water through a series of filters to ensure the absence of any solid particles in the water. Another set of pumps is used at this stage to push clean water back through the filters to prevent blockages. This is followed by two stages of disinfection and pH correction. Depending on local regulations, fluoride may be added to the clean water at this point. The water quality is then tested and pumped to reservoirs and/or distribution water mains [79]. Figure 4.2 presents a visual representation of the treatment process.

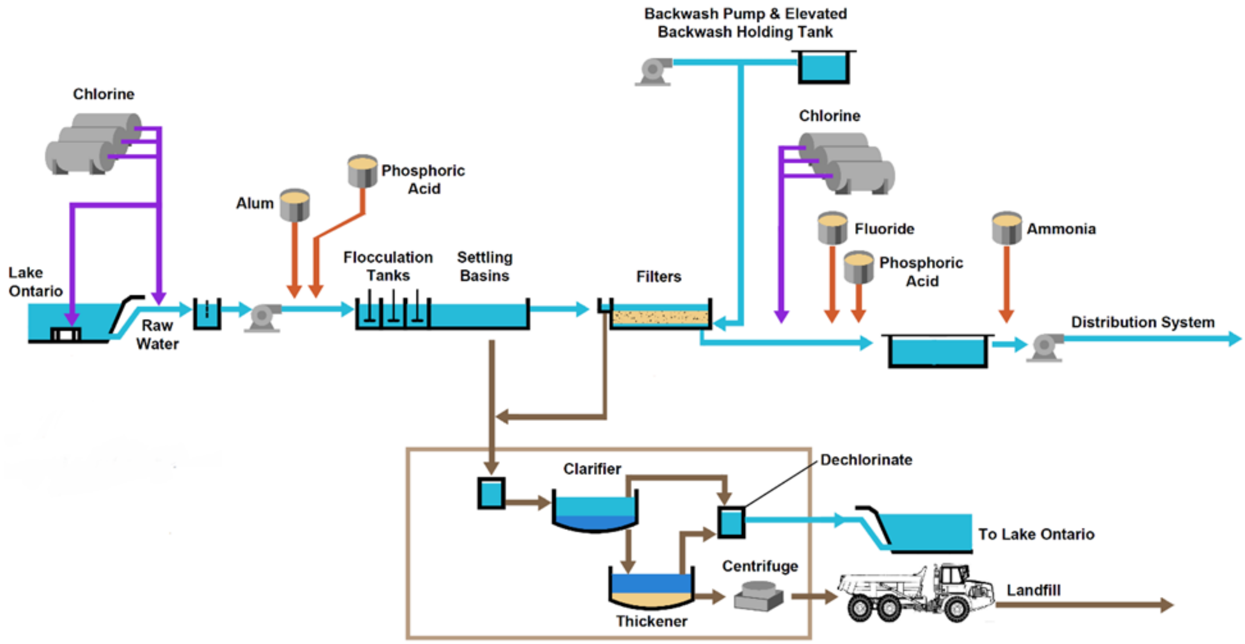

Figure 4.2: R.C Harris Plant Schematic

4.2.2 Operational flexibility in DWTP

Drinking Water Treatment Plants (DWTP) in regions with access to fresh water involve a number of electricity-dependent processes. The goal is to identify operational flexibilities in the treatment process that have an impact on the electrical cycle. Pumping is responsible for the majority of electricity consumption in a typical DWTP, this includes high-lift pumping, low-lift pumping and back-wash pumping [79]. Pumping can account for up to 90% of electricity consumption, this heavily depends on the disinfection agents and technologies used for example. Use of UV rays for disinfection requires more energy than chlorine mixing [79]. The remaining consumption goes to mixing, space heating and lighting purposes. Pumping systems offer plenty of room for DR actions through pump scheduling and off-peak pumping. Tank capacity, water head, flow rate and filtration requirements must all be considered in the modeling process.

The mathematical model used in this work focuses on the electricity consumption and energy storage potential. The model consists of the following parameters:

- Drinking water demand as a function of time
- Volume of drinking water required for storage
- Quality of surface water (Mixed Liquor Suspended Solids concentration of influent)
- Electricity price signal + DR participation incentives
- System information including number of pumps, pump ratings and capacities, number and size of storage tanks, pipe length and diameter etc.

The majority of operational flexibility in drinking water treatment plants come from their pumping systems. This includes high-lift pumping, low-lift pumping and backwash pumping. The latter is the least flexible pumping system, as it is heavily dependent on water quality, flow rate and screen condition. Moreover, even the slightest changes in backwash pumping can have an effect on output quality of the treatment plant. Low-lift pumping and high-lift pumping systems are based on the same equations used in WWTP pumping systems – equation 2.5 to equation 3.0. The model is constrained by volume of water demanded, system limits and tank size. The model works through one main control variable – pump power. This in turn controls the speed of the pump and is bounded by physical capacities or the system, and rating of the pumping system.

4.3 Thermal loads

Heating and cooling services are critical for human survival as well as manufacturing and production. Thermal loads are found almost everywhere in modern societies, heating and cooling requirements are amongst the highest energy consumers in residential, commercial, and industrial sectors at 61% and 55% respectively [83]. A whopping 40% of total city-wide emissions is attributed to heating and cooling systems [84]. This includes space heating, space cooling and domestic water heating. In Canada alone, 28% of total greenhouse gas emissions originate from thermal loads. This makes thermal loads of extreme importance from economic and environmental perspectives. Both of which align strongly with sustainable efforts and smart city movements.

Heat pumps are quickly gaining popularity worldwide due to their higher efficiency and improved performance in comparison with other technologies such as electric heaters, boilers and, furnaces. Heat pumps have the ability to provide space heating solutions in colder months and space cooling solutions during warmer periods of the year as well as, water heating for domestic use. Conventional heating and cooling systems can produce at most one unit of heat for one unit of electricity. Heat pumps introduce an improved performance and a new metric of efficiency known as the coefficient of performance (COP). COP is the ratio of heat output by the electrical energy needed to operate the heat pump under specific circumstances. The average range for COP lies between 3.5 and 4 i.e., heat pumps can produce 4 units of heat for each unit of electricity they consume [85]. Moreover, heat pumps are environmentally friendly saving on carbon emissions. Unlike burning oil, or gas, a heat pump produces no carbon emissions on site. Hence, heat pumps can helps reduce emissions, reduce consumption costs, and improve efficiency. A heat pump works by transferring heat from one place to another. A compressor is used to pump a substance, known as the refrigerant, between two heat-exchanged coils. In one coil, the refrigerant is evaporated at low pressure and absorbs heat from its surroundings. On its path towards the second coil, the refrigerant is then compressed where it condenses at high pressure. At this point, it releases the heat it absorbed earlier in the cycle [85]. The heat pump cycle is fully reversible. To act as an air conditioner, the heat pump transfers heat from inside the house to the outside. Unlike conventional heaters that turns electricity to heat, heat pumps use the provided electricity to move heat.

Thermal loads are not strangers to the DSM framework; they are included in this work as sources of flexibility and energy storage through the thermal inertia of the buildings and domestic hot water (DHW) tanks. This integration is important as part of the futuristic DR scheme, which will include many features observed in today's technologies. Heat pumps are often used in water heating, space heating and cooling of houses and high-rise structures. The mathematical model used focuses on electricity consumption and energy storage. The first step in the modeling process is creating a heat model for the structures considered. This must include the interior, surface, and exterior of the house or building in question. Equations 4.21 to 4.28 are used to represent the thermal model of the house through heat capacity and thermal resistance values. This can then be used to calculate the temperature state inside the house using differential equations numbered 4.29 and 4.30, which relate external, surface, and internal temperatures to the output of the heat pump [86]. The output of the heat pump can be chosen by the operator, based on their specific objective(s); as long as no system constraints or user comfort constraints are violated. Equation 4.31 represents an inequality constraint accounting for technical limits of the heat pump to ensure its safe and efficient operation and equation 4.32 presents another inequality constraints accounting for temperature comfort levels of the occupants.

As mentioned earlier heat pumps enjoy the ability to provide space heating, space cooling and water heating. Water heating is an essential load to any residential structure; it is the second highest energy consumer for high-rise building and accounts for roughly 20% of total consumption [87]. Domestic water systems are often fitted with large storage tanks to ensure supply of hot water is available at all times. These tanks provide the operational flexibility that is being sought after in this work. The hot water storage tank is assumed to be a perfectly stirred water tank, i.e., all the water in the tank is at the same temperature. Moreover, we assume that the water in the storage tank can only be heated by the heat pump. Accounting for the density, heat capacity of the water, volume of the storage tank, surrounding temperature and heat energy produced by the heat pump, we calculate water temperature as shown in equation 4.33. Equation 4.34 relates uses the concepts of conservation of energy and mass to find the volumetric flow rate from the hot water tank. Lastly, equations 4.35, 4.36 and 4.37 find the coefficient of performance for the heat pump based on surrounding temperatures and gives the relationship between electricity consumption and heat output for space and water heating services.

$$S = 2A + 4H\sqrt{A} \qquad \text{Equation (4.21)}$$

$$E = H\sqrt{A} \qquad \text{Equation (4.22)}$$

$$W = 0.2E \qquad \text{Equation (4.23)}$$

$$C_i = 1.3 \times 10^4 \times A \left(\frac{J}{K}\right) \qquad \text{Equation (4.24)}$$

$$C_s = 3.6 \times 10^5 \times A \left(\frac{J}{K}\right) \qquad \text{Equation (4.25)}$$

$$R_{is} = 7.69 \times S \left(\frac{W}{K}\right) \qquad \text{Equation (4.26)}$$

$$R_{ie} = 0.34 \times V \times A \times H \left(\frac{W}{K}\right) \qquad \text{Equation (4.27)}$$

$$R_{se} = 7.69 \times S \times \frac{69.05 + 1.07 \times A}{7.69 * S - (69.05 + 1.07 \times A)} \left(\frac{W}{K}\right) \qquad \text{Equation (4.28)}$$

$$\frac{dT_i}{dt} = \frac{1}{C_i} \left(Q_{HP} + R_{is}(T_s - T_i) + R_{ie}(T_e - T_i)\right) \qquad \text{Equation(4.29)}$$

$$\frac{dT_s}{dt} = \frac{1}{C_s}\left(R_{is}(T_i - T_s) + R_{se}(T_e - T_s)\right) \qquad \text{Equation (4.30)}$$

$$0 \le Q_{HP}(h,t) \le Q_{HP,max}(h,t) \qquad \text{Equation (4.31)}$$

$$T_{i,\min}(h) \le T_i(h,t) \le T_{i,\max}(h,t) \qquad \text{Equation (4.32)}$$

$$\rho \times V_{tank} \times C_p \times \frac{T_{t+1}^{tank} - T_t^{tank}}{\Delta t} = Q_t^{HP,DHW} - Q_t^{DEM,DHW} - G \times \left(T_t^{tank} - T^{sur}\right) \qquad \text{Equation (4.33)}$$

$$\dot{V}_t^{tank} = \dot{V}_t^{dem} \times \frac{\left(T^{dem} - T^{cold}\right)}{\left(T_t^{tank} - T^{cold}\right)} \qquad \text{Equation (4.34)}$$

$$COP = C_0 + C_1 T_e + C_2 T_{ws} + C_3 {T_e}^2 + C_4 {T_{ws}}^2 + C_5 T_e T_{ws} \qquad \text{Equation (4.35)}$$

$$P_{HP} \times COP = {Q_{HP}}/{3600} \qquad \text{Equation (4.36)}$$

$$P^{HP,DHW} \times COP = {Q^{HP,DHW}}/{3600} \qquad \text{Equation(4.37)}$$

Where,

$A, H\ and\ S$: area, height, and surface area of the house/building;
$W, E\ and\ V$: window area, exterior area, and air ventilation rate of the structure;
C_i, C_s : the heat capacity of the house interior, heat capacity of the house surface;
ρ: $density\ of\ water$ (kg/m^3) ;
C_p: heat capacity of water (J/kgK);
COP: coefficient of performance;
C_iCOP coefficients based on catalogue data at full load;
P_{HP}: electric power required by heat pump for space heating;
$P^{HP,DHW}$: electric power required by heat pump for domestic water heating;
R_{is}: thermal resistance between the interior and surface;
R_{ie} : thermal resistance between interior and external;
R_{se}: thermal resistance between surface and exterior;
T_i, T_e : internal and external temperatures respectively ;
T_s : surface temperature;
T_{ws} : supply water temperature;
Q_{HP}: heat output of the heat pump used in space heating;
ρ and cp: the density and heat capacity of water;
T_t^{tank} : Water temperature in the tank at time t;
T^{sur}: Surrounding temperature;
G: thermal conductance between the hot water and the surroundings (W/K) ;
Q_{HP}: thermal energy provided by heat pump;
$Q_{HP,max}$: maximum thermal energy that can be generated by heat pump;
$Q_t^{HP,DHW}$: Thermal energy provided by HP to heat water;
$Q_t^{DEM,DHW}$: thermal energy corresponding to hot water demand. ;
T^{cold}: temperature of the cold tap water;

T^{dem}: desired demand temperature;
$T_{i,\min}$: lower limit for internal temperature based on user comfort ;
T_i : internal temperature;
$T_{i,\max}$: upper limit for internal temperature based on user comfort ;
$\dot{V}_t^{dem}$: Volumetric flow rate of water demanded;
V_{tank} : Volume of water in tank;
$\dot{V}_t^{tank}$: volumetric flow rate of water stored in tank.

4.4 Electric Vehicles

Electric vehicles (EV) have gained incredible popularity amongst researchers and users alike. Their integration into the transportation fleet has been on the rise with several government incentives and rebates. Electric vehicles offer environmental and economic benefits that cannot be matched by any other transportation alternative. EVs offer reduced running costs, reduced emissions, and a possible revenue stream through discharging energy back to the grid during peak hours. From a demand response point of view, electric vehicles can be seen as flexible loads with flexible charging schedules. Electric vehicle owners can charge their cars from the electric grid or through distributed renewable resources; EVs can also play a role in mitigating intermittency introduced by renewable energy sources. They can also be treated as energy storage systems supporting bidirectional power flow through charging and discharging known as Grid to Vehicle (G2V) and Vehicle to Grid (V2G) technologies respectively. Vehicle to Grid technology allows EV owners to participate in numerous DR activities to provide economic or technical support to the grid. V2G systems come with a number of economic and technical challenges including installation and maintenance costs of grid infrastructure and V2G equipment. It also has a negative effect on the battery in terms of life cycle and degradation rates. This work will consider electric vehicles as flexible loads for DR participation only. We will focus on scheduling EV charging based on a pre-defined user objective, to do so we assume the presence of level 1, 2 and 3 charging stations at different locations to the user.

The first step in EV modeling is identifying our EV fleet, EV demand and hence DR capacity is proportional to the number of vehicles in the system. There is about 1.86 vehicles per household in North America, according to the National House Survey (NHTS) [88]. To correctly size EV demand, we use the daily travel distance data from NHTS with the assumption that each 100 km driven required 17 kWh [89]. State of charge (SOC) is a representation of the existing energy stored in the battery as a percentage of total capacity. This is used in equations 4.38 and 4.39 to calculate the total energy in an EV battery based on the last known SOC and current charging (if any) based on the level of the charging station being used. This system is constrained by safety operating limits of EV battery, user driving times and preferences. Equation (4.40) assume the user would like their EV to fully charged before the day ends. Equation (4.41) ensures the required state of charge is achieved while equation (4.42) enforces safe operating levels for each charger. This system can be used as part of an optimization problem to find the most optimal charging schedule for EVs, the main control variables in that case would be the time and amount of power to be charged.

$$E_{EV}(v,t) = chtime(v,t) \times Pch(v,t) + \ E_{EV}(v,t-1)\ for\ t > 1 \qquad Equation(4.38)$$

$$E_{EV}(v,t) = chtime(v,t) \times Pch(v,t)\ +\ SOC_0(v) \times E_{batt}(v,t) \quad for\ t = 1 \qquad Equation(4.39)$$

$$SOC_0(v) + SOC_{req}(v) = 1 \qquad Equation(4.40)$$

$$\sum_{t \in T} Pch(v,t) = SOC_{req}(v) \times E_{batt}(v,t) \qquad Equation(4.41)$$

$$Pch(v,t) \leq P_{max} \qquad Equation(4.42)$$

Where,
$E_{EV}(v,t)$: is the total energy in the Electric Vehicle's battery;
EV_{batt}: is the size of the EV battery;
$chtime(v,t)$: a binary parameter representing the parking time of EV v; one means that EV v is plugged in and can be charged;
$Pch(v,t)$: power consumed in charging EV v at time t;
P_{max}: charger power capacity;
$SOC_0(v)$: the initial state of charge of the EV;
$SOC_{req}(v)$: the required state of charge of the EV's battery.

Chapter 5: Results & findings

This chapter presents the results and findings of this work and is broken down in two main sections. The first describes the individual performance of each of the four facilities – wastewater treatment, drinking water treatment, electric vehicles and thermal loads for houses and buildings. Each facility is presented as an independent entity managing its own operation to minimize total costs in response to a changing daily price signal. The second section presents the results of the collaborative operation of the aforementioned facilities. The new objective function is the total sum of costs for the participating facilities.

5.1 Individual performance of each demand model

This section describes the building blocks of the proposed multi-sector demand side management framework. This is a more accurate representation of the current reality, where each unit or facility functions independently with its own goals and objectives. This work assumes all units have economic goals with the objective of reducing individual electricity consumption costs. Each optimization problem is formulated as a non-linear programming problem in a GAMS environment [90]. This generates the optimal operation schedule for each facility in day-ahead processing.

In general terms, the objective function can be defined as shown in equation (5.1)

$$\min_{W} \frac{\Delta t}{60} \times S_{base} \times \left(\sum_{t \in \mathcal{T}} P(x,t) \times Price_{(t)} \right) \qquad \text{Equation (5.1)}$$

Where,
$\mathcal{T}$: set of time intervals;
Δt: the time step in minutes;
t: index representing time steps;
$P(x,t)$: active power consumption function in terms of time t and facility-specific variable(s) x;
$Price_{(t)}$: cost in \$/kWh of purchasing energy from the grid at time t;
S_{base}: base power in kVA.
W, which is the independent decision variable vector in (5.1), is responsible for all the operation decisions of the facility and its loads, respectively. Decision variables, input parameters, and constraints for each facility will be described in table 5.1.

Table 5.1: Facility variables and Parameters

	INPUTS	OUTPUTS	CONTROL VARIABLES	PARAMETERS
WWTP	- Influent Biological Oxygen Demand - Influent flow rate - Ambient temperature - Electricity price signal	- Operational effluent BOD - Electrical energy consumption - Electricity demand profile - Cost of electricity consumption	- Inlet pumping - Blower operation	- Device capacity, this includes pumps, tanks, blowers etc. - Device rating, this includes pumps, blowers etc.
DWTP	- Drinking water demand as a function of time - Mixed Liquor Suspended Solids (MLSS) concentration of influent - Electricity price signal	- Electrical demand profile - Energy consumption - Cost of electricity consumption	- Pump operating schedule	- Pump rating and capacity - Tank size
THERMAL LOADS	- Outside temperature as a function of time - Customer temperature preference - Domestic hot water demand as a function of time - Electricity price function	- Electrical energy consumption - Electricity demand profile - Cost of electricity consumption - Internal temperature throughout the day	- Heat pump operation schedule	- House size and parameters - DHW tank size - Thermal model of house/building
EV	- Number of EVs - Connection place of EVs, connection time and energy required from the grid - Electricity price signal	- Electrical demand profile - Energy consumption - Cost of electricity consumption	- EV charging schedule	- EV charging stations and technologies (level 1, 2, or 3) - Connection time – based on probability of being plugged at home or charging station

5.1.1 Wastewater treatment plant (WWTP)

The behavior of wastewater treatment plants is constrained mainly by physical aspects and, quality assurance aspects. The physical capacities of tanks, reservoirs, pipes, and pumps must be respected for safe and continuous operation of the treatment plant as shown in equation (5.2). Operation is also constrained by the biological oxygen demand (BOD) of the effluent *(sewage leaving the treatment plant).* This is an environmental limitation for safe disposal of outgoing effluents to the surrounding environment(s). This constraint is often regionally specified by local governing entities and is modeled as shown in equation (5.3). The third constraint is concerned with the operating level of dissolved oxygen (DO) of the fluid in the aeration tank; these values are universally agreed upon and are important to provide suitable conditions for bacteria to digest any harmful organic content in the sewage. This can be seen in equation (5.4).

$$V_{c(t)} \leq V_{c-max} \qquad \text{Equation (5.2)}$$

$$BOD_{eff(t)} \leq BOD_{cl} \qquad \text{Equation (5.3)}$$

$$C_{min} \leq C_{W(t)} \leq C_{max} \qquad \text{Equation (5.4)}$$

Where,
$V_{c(t)}$: Variable vector containing tank/reservoir volume(s) and pump ratings;
V_{c-max}: Parameter vector with maximum tanks and pumps capacities;
BOD_{cl}: Maximum allowed biological oxygen demand as per environmental requirements valued at 25 (mg/l);
C_{max} , $C_{min:}$ Maximum and minimum allowed values for dissolved oxygen level valued at 4.0 and 2.0 respectively;

WWTP operational modeling is not common in the electrical field; this section provides the necessary details for building a realistic WWTP model. WWTP performance heavily depends on the quality of the sewage coming into the treatment plant. Many countries use combined sewage systems, in these systems rainwater is absorbed off the streets, mixed with sewage and sent to the treatment plant. Depending on weather conditions, the amount of water and hence quality of the incoming sewage can vary greatly. This will change the incoming biological oxygen demand; this work uses BOD-in based on the average of measured values from the Ashbridges Bay treatment plant located in Toronto, CA [91]. The amount of incoming sewage and rate of incoming sewage must also be specified and are calculated in this work based on data taken directly from treatment plants based in Ontario, CA. Other inputs include air temperature around the treatment plant, this will affect pump function during the aeration process as it pushes air into the tank for biological digestion.

Electricity consumption of the treatment plant can be optimized as explained above, with the goal of minimizing utility bills. The price signal used in this work is as shown in figure 5.1. The main control variables are pumping stations and aeration blowers, as these are the biggest sources of flexibility that can be used without compromising output quality. The resulting demand profile for one day is as shown in figure 5.2. Figure 5.3 shows the biological oxygen demand of the incoming sewage with values between

280 and 360 mg/L which must be reduced to a maximum of 25 mg/L for safe disposal. Figure 5.3b traces the dissolved oxygen levels in the aeration tank during the day. This value is of extreme importance since it directly affects the quality of the output, and has a a direct influence on blower power consumption – which is amongst the largest energy consumers in WWTPs. The demand is seen to be affected by both incoming BOD levels and price signal. As the price peaks between 10:00 and 14:00, demand is reduced significantly and increases from 12:00 onwards to account for the peak in BOD levels. Demand remains relatively low until the end of the peak at 14:00 where it peaks to compensate for the earlier reduction. This increase is sustained until the next price peak hits at 18:00, this reduction is seen till 20:00 when the price peak has ended. Demand then picks up until the end of the day at 24:00 due to an increase in BOD levels and to compensate for previous reductions to ensure consistent quality of output effluent.

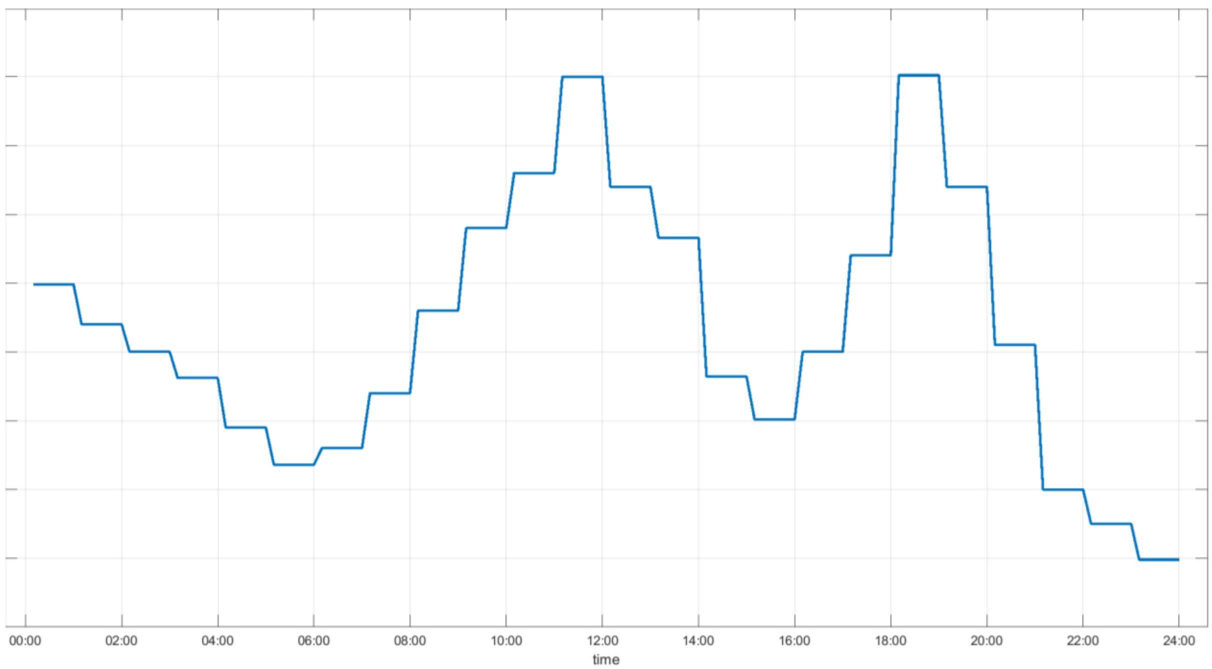

Figure 5.1: Price signal

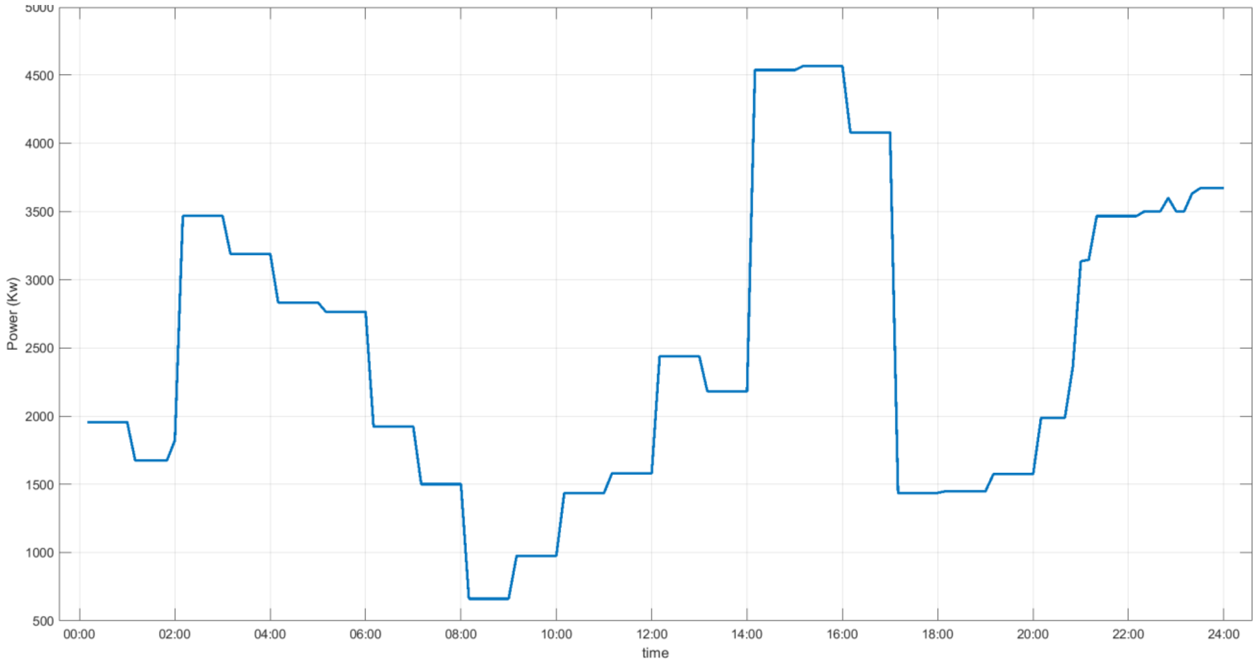

Figure 5.2: WWTP demand profile (individual performance)

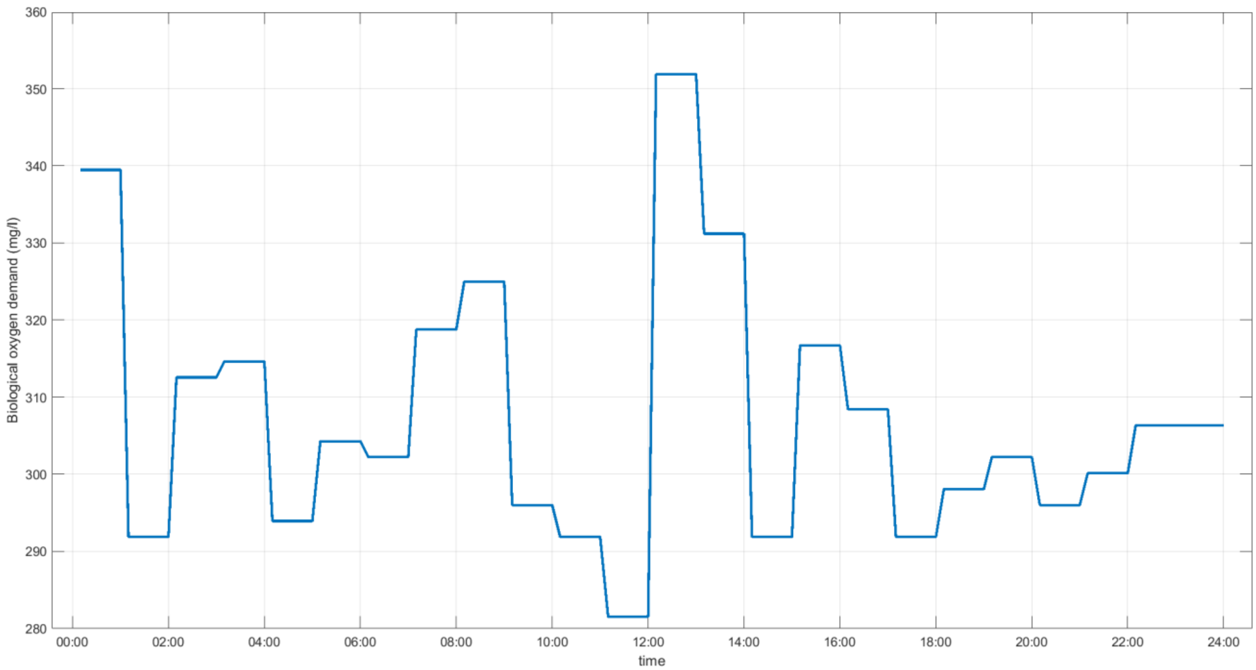

Figure 5.3: BOD of incoming sewage into WWTP

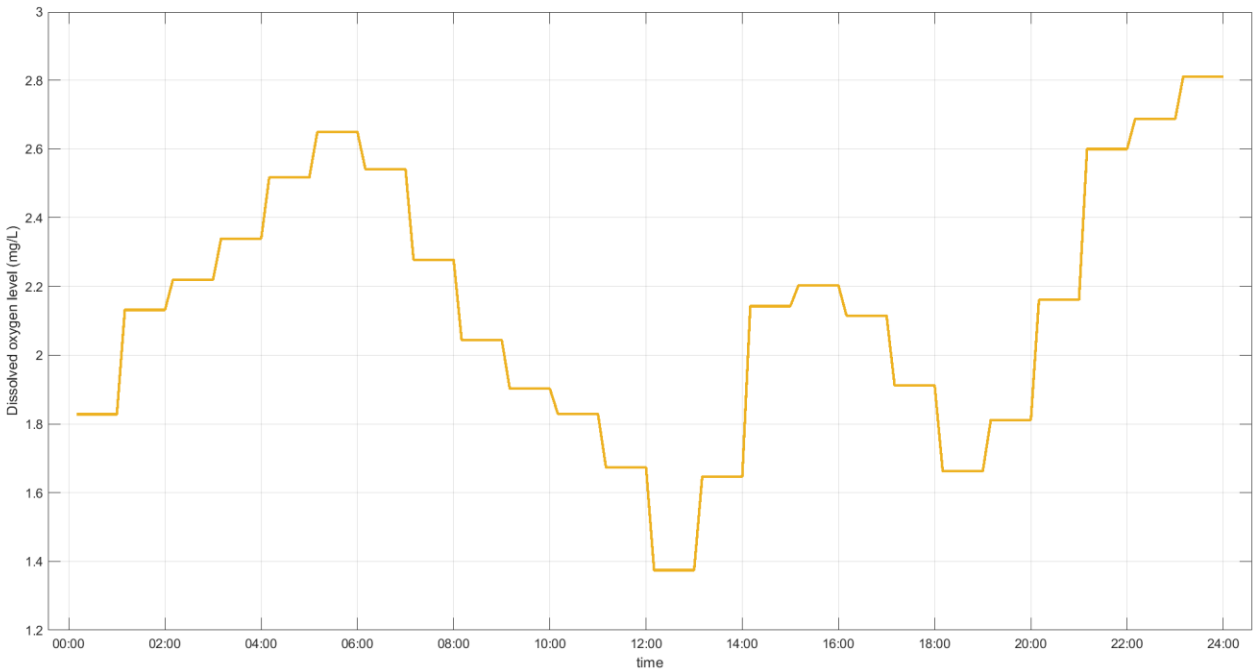

Figure 5.3b: Dissolved Oxygen Level (aeration tank) WWTP

5.1.2 Drinking water treatment plant (DWTP)

The first step in sizing a DWTP is finding the clean water requirement in an area based on the expected population to be serviced. The Safe Drinking Water Foundation's opinion is that 235 liters per person per day is a perfectly adequate amount of water to use [3] As per the Bureau of Indian Standards, IS:1172-1993, a minimum water supply of 200 liters per capita per day should be provided [4]. This is used to approximate clean water demand for the smart city. The amount of water needed greatly affects energy consumption of a treatment plant. The most important aspect in a DWTP is the quality of the output; this is not an aspect that can be compromised on to ensure the safety of the public. This constraint will not be included in this work as the treatment processes directly concerned with water quality will not be modeled or considered for DR participation. Instead, physical constraints including pump, tank and pipe sizes will be modeled as shown in equation (5.2). These values are either approximates as stated above or taken from [82].

The total electric consumption of the treatment plant for one day is as shown in figure 5.4. The model must satisfy sufficient drinking water levels at all times during the day. This is done by maintaining a minimum volume of water stored in reservoirs regardless of the changing water demand during the day. Therefore, electricity consumption is directly affected by the price signal. Demand peaks can be seen at off-peak price hours such as 2:00-8:00, 14:00-17:00 and 21:00-24:00, demand drops heavily during peak price hours of 8:00 – 14:00 and 17:00- 21:00.

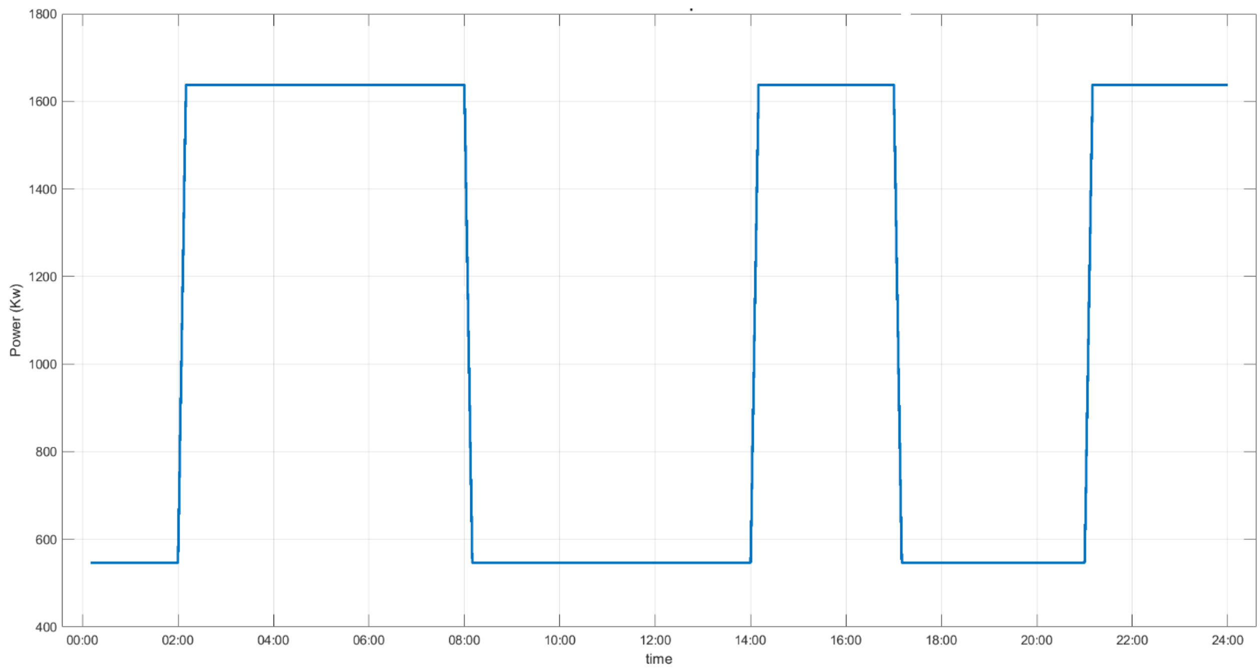

Figure 5.4: DWTP electric consumption

5.1.3 Thermal loads

Heat pumps are popular DR resources, well established in literature and practice. They are used in houses and high-rise structures. Heat pumps are sized based on the area of the house under study and the number of occupants in the household. Houses in this work are assumed to be between 1500 sq. ft to 2000 sq. ft. Parameters describing high-rise buildings and structures are assumed as given in table 5.1. The general recommendation for heat pump sizing is 1ton BTU/hr per 500 sq. ft. Heat pumps should be assigned one size bigger to account for the harsh winter conditions of North American regions [6]. This model is constrained by user comfort temperatures assumed at 293°k and 302°k, as well as, heat pump operating capacity shown in equations (4.31) and equation (4.32).

Table 5.2: High-Rise Structure Parameters

Average Number of Storys	30 – 50
Height (m)	90- 150
Length (m)	Max 40
Width (m)	Max 40

The total electric demand over one day with the economic objective of cost minimization is as shown in figure 5.5. Consumption depends on electricity price signal shown in figure 5.1 and external temperatures shown in figure 5.6. Temperatures during the entire day fall below the average comfort level for humans and hence, the heat pump is operating in space heating and water heating modes throughout the day. Consumption starts at average values and peaks during the colder hours of the day from 2:00 to 4:00. Consumption then starts to drop at the peak price hours from 8:00 to 14:00 and 18:00 to 20:00.

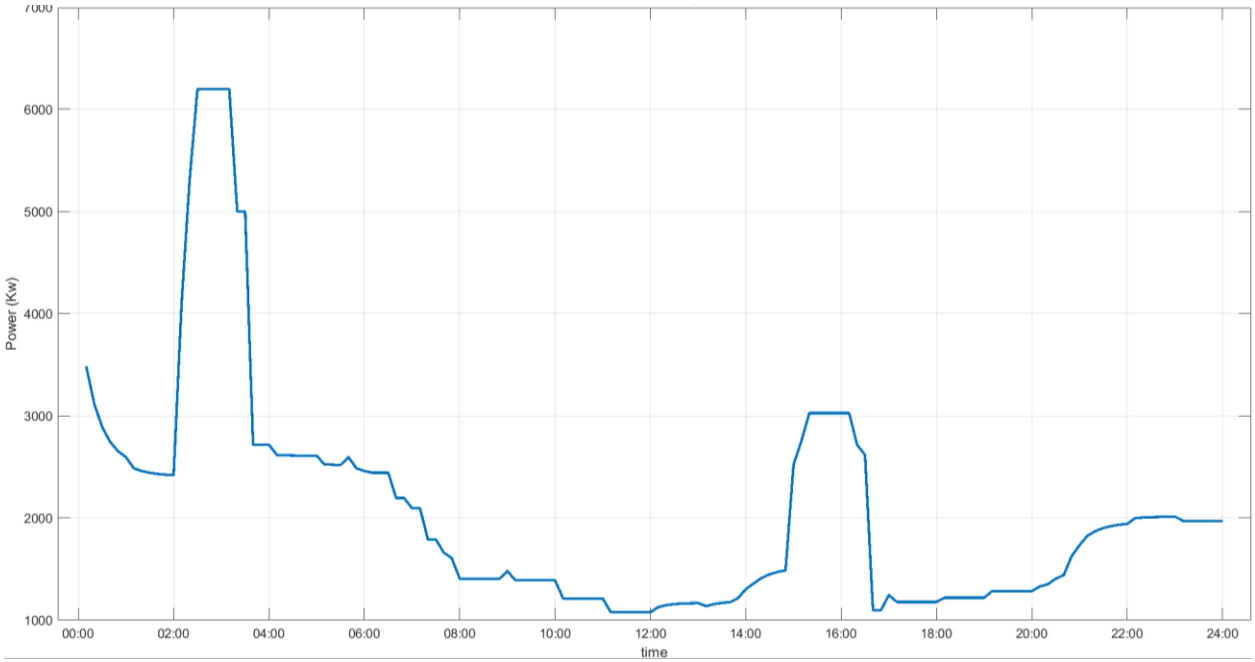

Figure 5.5: Thermal demand electricity profile

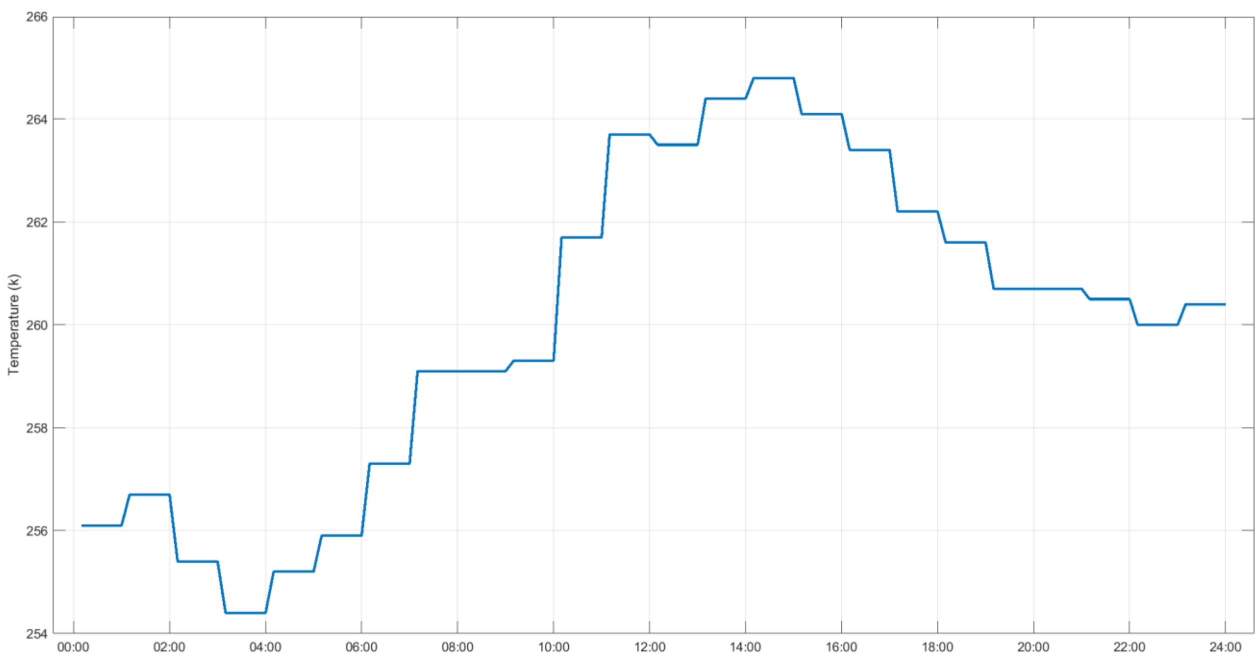

Figure 5.6: External temperature profile during the day

5.1.4 Electric Vehicles

Plugin electric vehicles (PEV) models have been well established in the literature. The total PEV demand is proportional to the number of vehicles in the system. There are about 1.86 vehicles per household in North America, according to the National Household Travel Survey (NHTS) [7]. The following assumptions have been made in this model:

- Connection time is based on probability of being plugged at home or charging station
- Arrival at a charging station can be estimated using the daily travel distance data from [8]
- It is assumed that each 100 km driven consumes 17 kWh [8].
- Each EV has a battery size of 36 kWh
- EVs are randomly assigned an initial state of charge between 0.2 and 0.3
- It is assumed that owners would want the car to be charged to at least 80% before departing

This model is constrained by charger operating limits, user availability and SOC. User availability is based on the probability of EVs being connected to charging stations at home or to commercial charging stations as shown in figure 5.7 [92]. The overall demand curve can be seen in figure 5.8, consumption is seen to closely follow the connection time of electric vehicles in the city with noticeable reductions during peak price hours between 8:00 – 14:00 and 18:00 – 20:00.

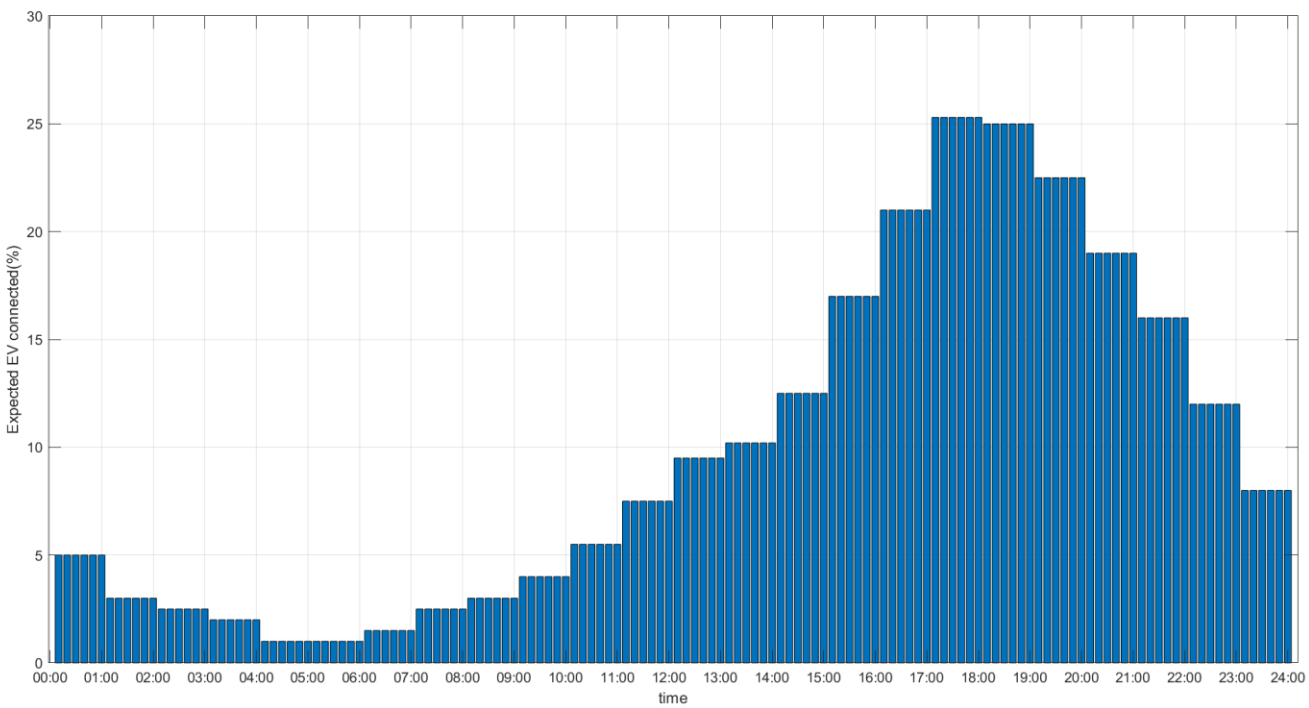

Figure 5.7: EV connection time

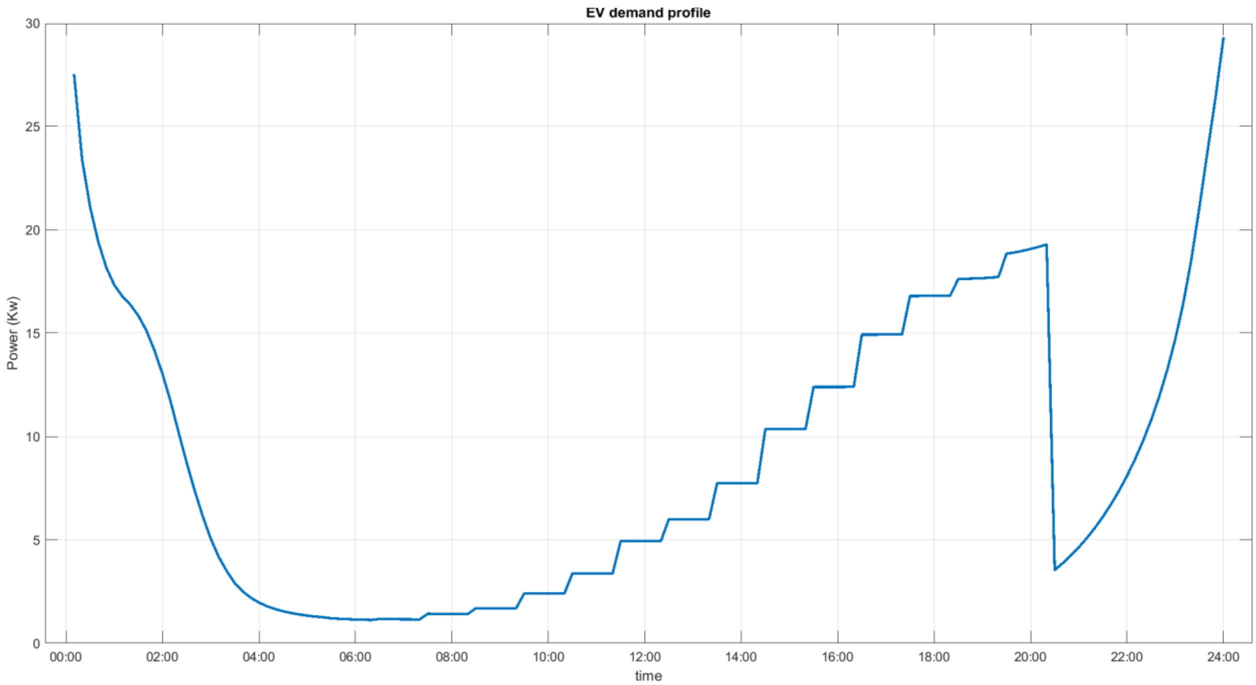

Figure 5.8: EV electricity demand during the day

Table 5.2 shows the total electricity costs and total energy consumption for each facility when operating indivdualy with the objective of minimizing costs. This will be used in the next section as a reference to compare individual and integrative operation of the facilities.

Table 5.3: Cost and Energy Values for Individual players

	Cost	Energy (kWh)
EV	$5,816	12,811
WWTP	$139,046	341,659
DWTP	$56,822	157,197
THERMAL	$2,213	3,047

5.2 Integrated/cooperative performance of demand models

Integrative operation of independent facilities with a shared economic goal is described in this section. Four participants: wastewater treatment plants, drinking water treatment plants, thermal loads and electric vehicles were combined to minimize the overall costs in the system. The cooperative optimization problem requires large amounts of memory, time and computational power which could not be provided using a standard laptop hence, only three facilities will be combined and optimized at a time. All possible combinations will be created and described hereinafter to prove the benefits of the collaborative approach on a generalized level. Objective function shown in equation (5.1) will be modified to include the sum of active power consumption for all participating facilities as shown in equation (5.5). This objective function is subject to all physical, operational, and regulatory constraints for participating facilities. Additionally, an upper limit is placed on total power consumption by participating facilities at anytime t. This is essential to ensure no system limitations are violated such as, thermal capacity of cables etc. This is calculated from the results obtained in section 5.1.

$$\min_{W} \frac{\Delta t}{60} \times S_{base} \times \left(\sum_{f \in F} \sum_{t \in \mathcal{T}} P_f(x,t) \times Price_{(t)} \right) \quad \text{Equation (5.5)}$$

Where,

$\mathrm{P}f(x,t)$: active power consumption function in terms of time t and facility-specific variable(s) x i.e blower speed and pump speed for WWTP, pump speed for DWTP, Heat pump operation level for thermal loads and lastly, charging power and time for electric vehicles. Table 5.4 presents the respective objective functions for each of the four cases.

Table 5.4: List of objective functions

Case one - minimizing the total electricity costs for the three facilities: wastewater treatment, drinking water treatment and thermal loads in houses and buildings:

$$\min \frac{\Delta t}{60} \times S_{base} \times \sum_{t \in \mathcal{T}} \left(\sum_{\hbar \in \mathcal{H}} \left(P_{\hbar}^{HP} + P_{\hbar}^{HP,DHW} \right) + \sum_{w \in W} \left(P_{blower_w} + P_{pump_w} \right) + \sum_{d \in D} P_{pump_d} \right) \times Price_{(t)} \quad \text{Equation (5.5a)}$$

This formulation is constrained by: (1) operational and physical limitations imposed by the facilities and given in equations (4.1) to (4.37), (2) maximum power consumption allowed at time *t*

Case two - minimizing the total electricity costs for the three facilities: wastewater treatment, drinking water treatment and electric vehicles:

$$\min \frac{\Delta t}{60} \times S_{base} \times \sum_{t \in \mathcal{T}} \left(\sum_{v \in V} Pch_{v} + \sum_{w \in W} \left(P_{blower_w} + P_{pump_w} \right) + \sum_{d \in D} P_{pump_d} \right) \times Price_{(t)} \quad \text{Equation (5.5b)}$$

This formulation is constrained by: (1) operational and physical limitations imposed by the facilities and given in equations (4.1) to (4.20) and equations (4.38) to (4.42) , (2) maximum power consumption allowed at time *t*.

Case three - minimizing the total electricity costs for the three facilities: wastewater treatment, electric vehicles and thermal loads in houses and buildings:

$$\min \frac{\Delta t}{60} \times S_{base} \times \sum_{t \in \mathcal{T}} \left(\sum_{\hbar \in \mathcal{H}} \left(P_{\hbar}^{HP} + P_{\hbar}^{HP,DHW} \right) + \sum_{w \in W} \left(P_{blower_w} + P_{pump_w} \right) + \sum_{v \in V} Pch_{v} \right) \times Price_{(t)} \quad \text{Equation (5.5c)}$$

This formulation is constrained by: (1) operational and physical limitations imposed by the facilities and given in equations (4.2) to (4.42) , (2) maximum power consumption allowed at time *t*.

Case four - minimizing the total electricity costs for the three facilities: drinking water treatment, electric vehicles and thermal loads in houses and buildings:

$$\min \frac{\Delta t}{60} \times S_{base} \times \sum_{t \in \mathcal{T}} \left(\sum_{\hbar \in \mathcal{H}} \left(P_{\hbar}^{HP} + P_{\hbar}^{HP,DHW} \right) + \sum_{d \in D} P_{pump_d} + \sum_{v \in V} Pch_{v} \right) \times Price_{(t)} \quad \text{Equation (5.5d)}$$

This formulation is constrained by: (1) operational and physical limitations imposed by the facilities and given in equations (4.15) to (4.42) , (2) maximum power consumption allowed at time *t.*

Where,
$\hbar$, $\mathcal{H}$: heat pump index and set respectively;
w, W: wastewater treatment plants index and set respectively;
d, D: drinking water treatment plants index and set respectively;
v, V : electric vehicle index and set respectively;

5.2.1 Case one: combining wastewater treatment, drinking water treatment and thermal loads in houses and buildings

Case one works on minimizing the total electricity costs for three facility – wastewater treatment, drinking water treatment and thermal loads in houses and buildings. The optimization model is built as a non-linear programming problem on GAMS with an objective function as shown in equation (5.5a). This formulation is constrained by: (1) operational and physical limitations imposed by the facilities and given in equations (4.1) to (4.37) as well as, (2) maximum power consumption allowed at time *t.* The goal is to investigate how much improvement can be seen when DR capacity is increased due to integrated operation as opposed to independent operation discussed in the previous sections of this chapter. Figures 5.9, 5.10 and 5.11 show the daily demand profile for WWTP, DWTP and thermal loads respectively. The day starts on a reduced performance for WWTP until 02:00 where demand starts to pick up, it is important to note that the price starts to drop at hour 2:00 as well. On the other hand, DWTP starts the day on high consumption, which drops dramatically at 1:00 and rises slowly from 4:00 to 8:00 with peak consumption from 6:00 to 8:00. It is very important to note that 4:00 to 8:00 represent the lowest energy cost in the beginning of the day hence, consumption reduction here will have significant economic benefits. These reductions were made possible by the slight increase seen in the beginning of the day (while WWTP was on low consumption) this capacity trade is the essence of operational integration. Thermal loads start the day off on average consumption and reach their highest peak between 6:00 and 8:00, this coincides with colder temperatures and off-peak prices. Moreover, WWTP performance starts reducing slowly from 6:00 to 14:00 as prices start to increase again. Prices peak from 8:00 to 14:00, during which consumption of all facilities is reduced to avoid higher charges. Consumption for all three facilities increases again from 14:00 to 17:00 as electricity prices drop. This cycle is seen to be repeated from 18:00 to 24:00 as all facilities reduce consumption with different degrees during peak prices and increase consumption during off-peak hours.

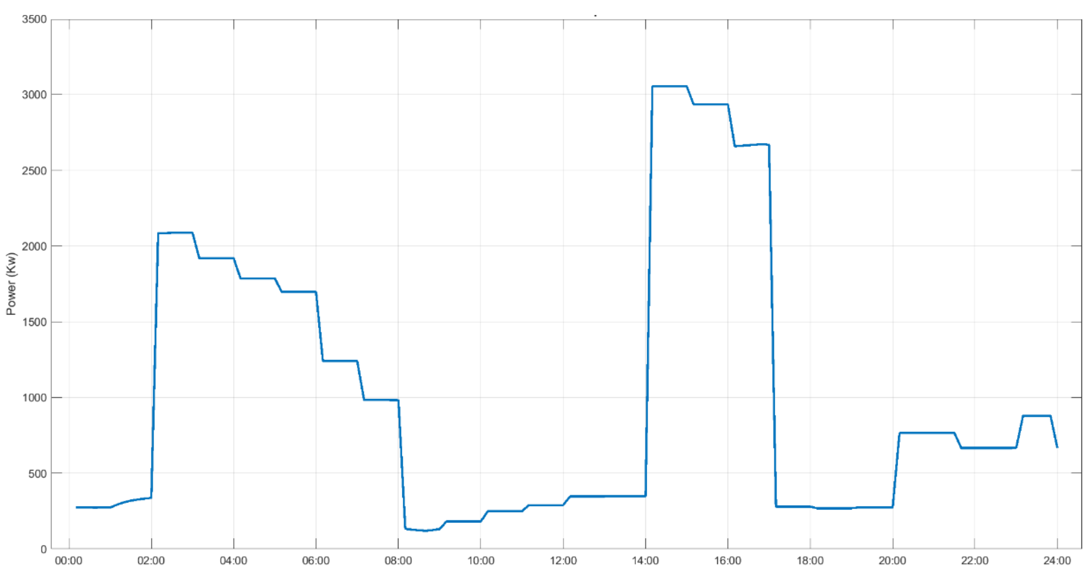

Figure 5.9: WWTP daily demand (case 1)

Table 5.5 shows the total energy consumed by the integrated system, the total cost of electricity consumed by the integrated system, the expected values for this system using independent values shown in table 5.3; as well as the percentage differences introduced by the integrative framework. We observe a 22% improvement in cost due to identified synergies and a 5% reduction in energy consumption; mainly caused by pushing operation of each facility to its permittable limit. Zooming in on the performance of each facility, we notice a slight reduction in WWTP energy consumption and an increase in thermal energy consumption. The biggest change is observed in cost reduction in WWTP. The main incentive for facilities to participate would be presented by the utility, which would be able to postpone retrofits, incorporate RESs and minimize generation costs due to the increased demand flexibility in the system.

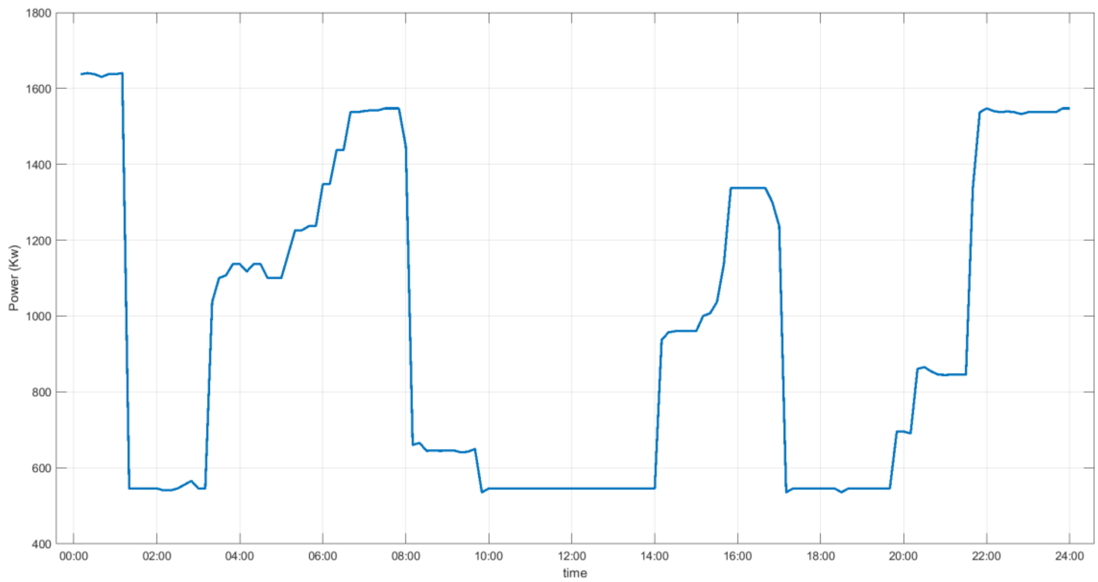

Figure 5.10: DWTP demand profile (case 1)

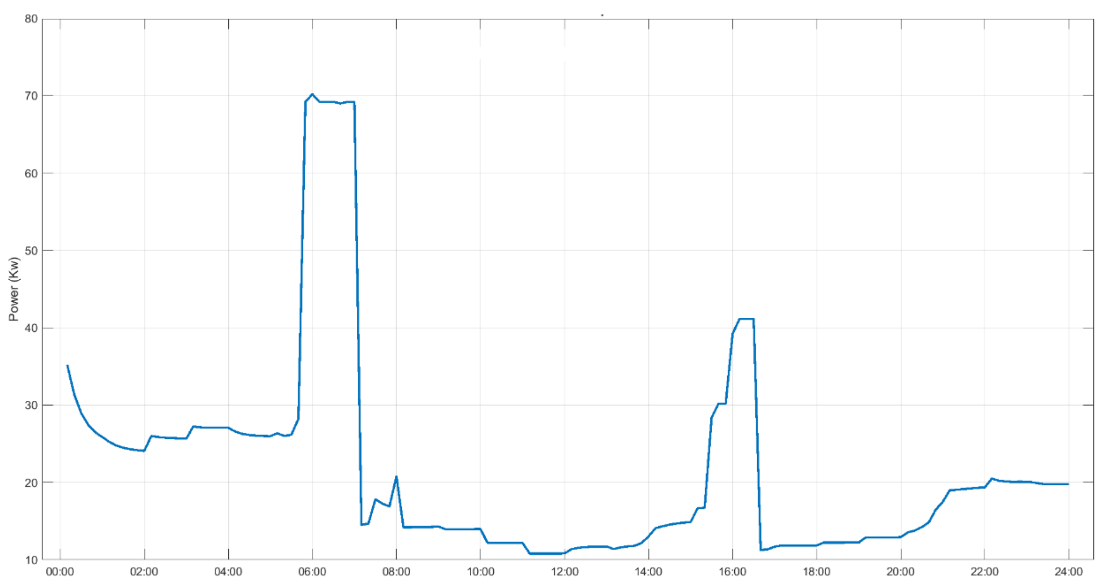

Figure 5.11: Thermal demand profile (case 1)

Table 5.5: Case one (wastewater treatment, drinking water treatment and thermal loads) Output Values

	Electricity cost ($)	**Energy consumed (kWh)**
Case one values	152,019	476,932
Expected values	196,237	501,903
Observed change	22 %	5 %

5.2.2 Case two: combining wastewater treatment, drinking water treatment and electric vehicles:

Case two combines wastewater treatment plants, drinking water treatment plants and electric vehicles under the same economic objective of minimizing the total cost of electricity consumed. The optimization model is built as a non-linear programming problem on GAMS with an objective function as shown in equation (5.5b). This formulation is constrained by: (1) operational and physical limitations imposed by the facilities and given in equations (4.1) to (4.20) and equations (4.38) to (4.42) as well as, (2) maximum power consumption allowed at time t. Output profiles are shown below in figures 5.12, 5.13 and 5.14. Case two has two components in common with case one which are the wastewater treatment and the drinking water treatment plant , the treatment plants are significantly large loads which heavily outweigh the third participant (thermal loads in case one and electric vehicles in case two). We notice approximately the same performance for both treatment plants in this scenario as that seen in case one. This is explained by the massive size of both loads. Both loads are seen to drop during peak-price periods – 10:00 to 14:00 and 17:00 to 20:00. Their consumption rises during off-peak hours – 2:00 to 8:00 and 14:00 to 17:00. Electric vehicle demand can be seen in figure 5.14 , connection time is still the largest determinant in EV consumption, the graph is seen to somewhat follow the probability of EV connections shown in figure 5.7, with slight differences seen notably at hours 4:00 to 8:00 during which consumption decreases further due to increase in price signal. Consumption is seen to increase during the day as more EVs are connected, there is a slight dip between 18:00 to 20:00 as electricity prices peak. This reduction is rather small as number of connected EVs increases.

Table 5.6 presents a comparison of total cost and total energy consumed by the integrated system verses the expected total value i.e. sum of previous total cost and energy consumption found through independent operation. Case two yields a 26% improvement in total costs through identifying synergies between the facilities. We also note a 3% reduction in energy consumption.

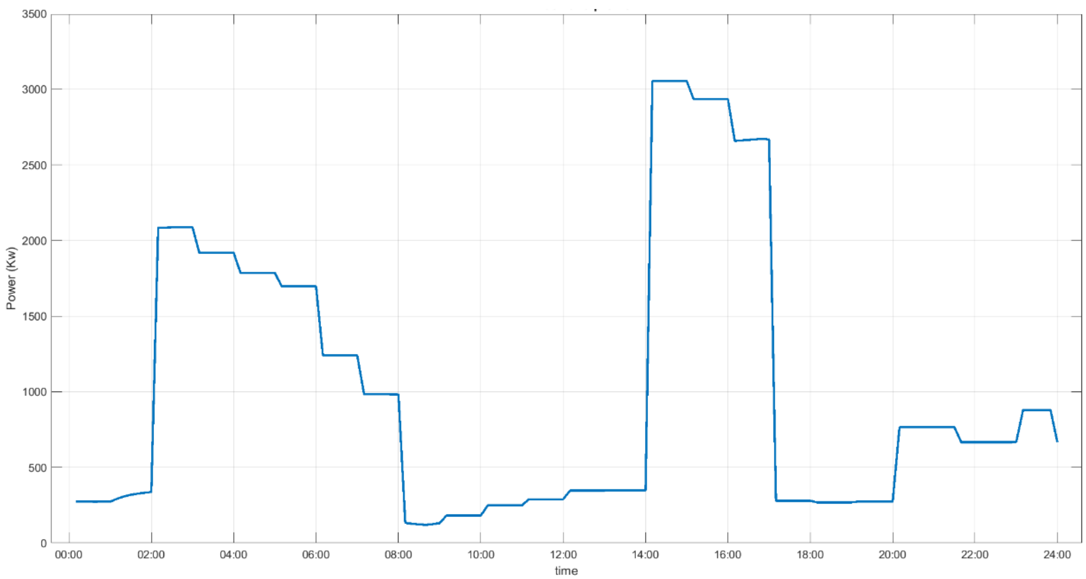

Figure 5.12: WWTP demand profile (case 2)

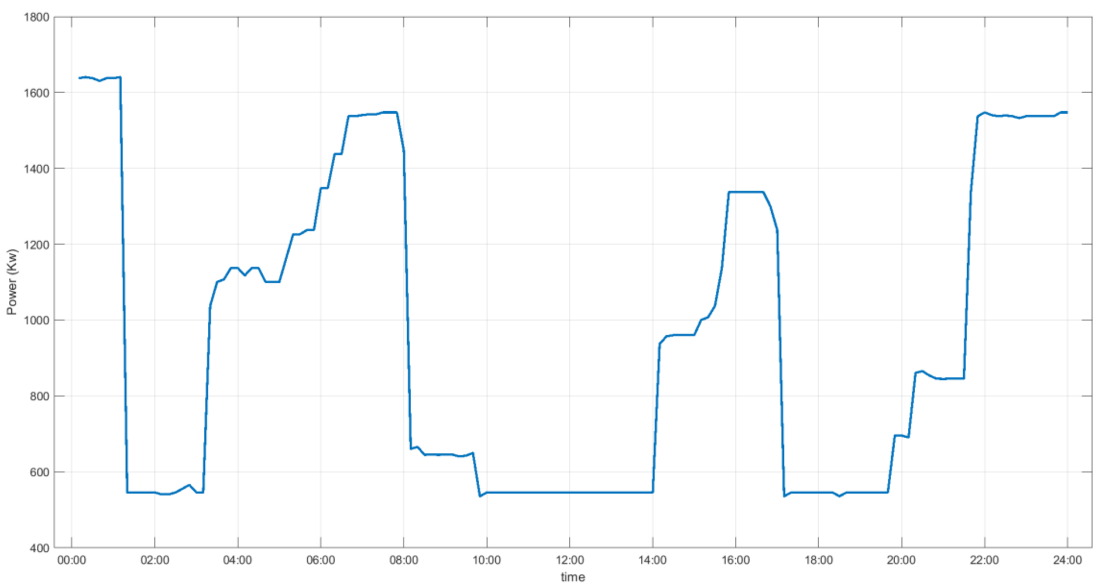

Figure 5.13: DWTP demand profile (case 2)

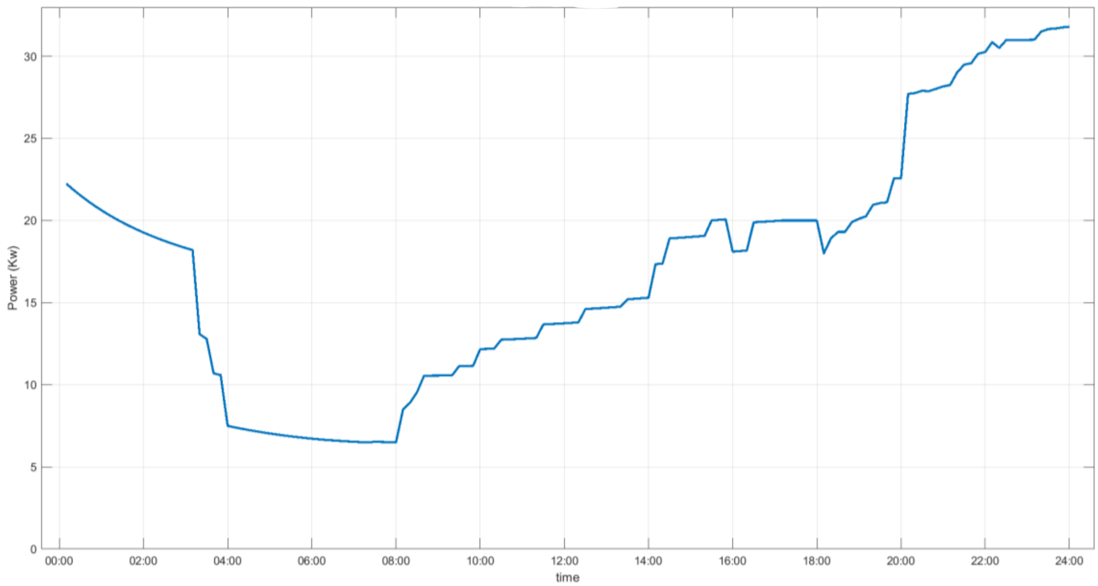

Figure 5.14: EV demand profile (case 2)

Table 5.6: Case two (wastewater treatment + drinking water treatment + electric vehicle) Output Value

	Electricity cost ($)	**Energy consumed (kWh)**
Case two values	147,927	496,811
Expected values	201,684	511,667
Observed change	26 %	3 %

5.2.3 Case three: combining wastewater treatment, electric vehicles and thermal loads in houses and buildings

Case three combines wastewater treatment with electric vehicles and thermal loads to find an optimal operational schedule for all facilities that improves the economic front for all facilities. The optimization model is built as a non-linear programming problem on GAMS with an objective function as shown in equation (5.5c). This formulation is constrained by: (1) operational and physical limitations imposed by the facilities and given in equations (4.2) to (4.42) as well as, (2) maximum power consumption allowed at time *t*. Demand profiles are presented in figures 5.15, 5.16 and 5.17. WWTP performance is seen to be much "flatter" than that of its independent operation with a noticeable increase during the first off-peak price period occurring from 5:00 to 9:00 and starts to drop with the beginning of the peak-price period between 10:00 and 14:00.

Consumption is then seen to increase slowly until the end of the day, even during the second peak price period to compensate for the prior reduction without compromising output quality. EV demand is presented in figure 5.16 and is seen to follow the basic shape of EV connection probability shown in figure 5.7 with noticeable dip during peak price periods. Figure 5.17 presents the thermal demand profile during the day, consumption is seen to peak significantly at 6:00 during off-peak price periods, with a smaller peak at 15:00 during the second off-peak price periods. Avoiding peak pricing is a proven and effective way to reduce costs. This is summarized in table 5.7, case three resulted in a 23% reduction in total costs and a 2% reduction in total energy consumption.

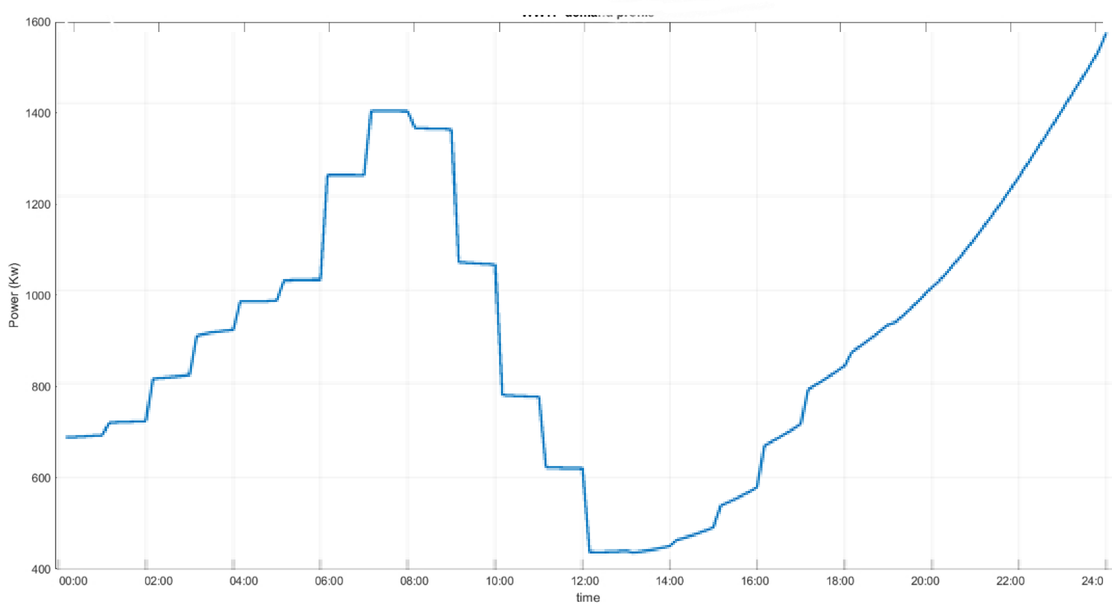

Figure 5.15: WWTP demand profile (case 3)

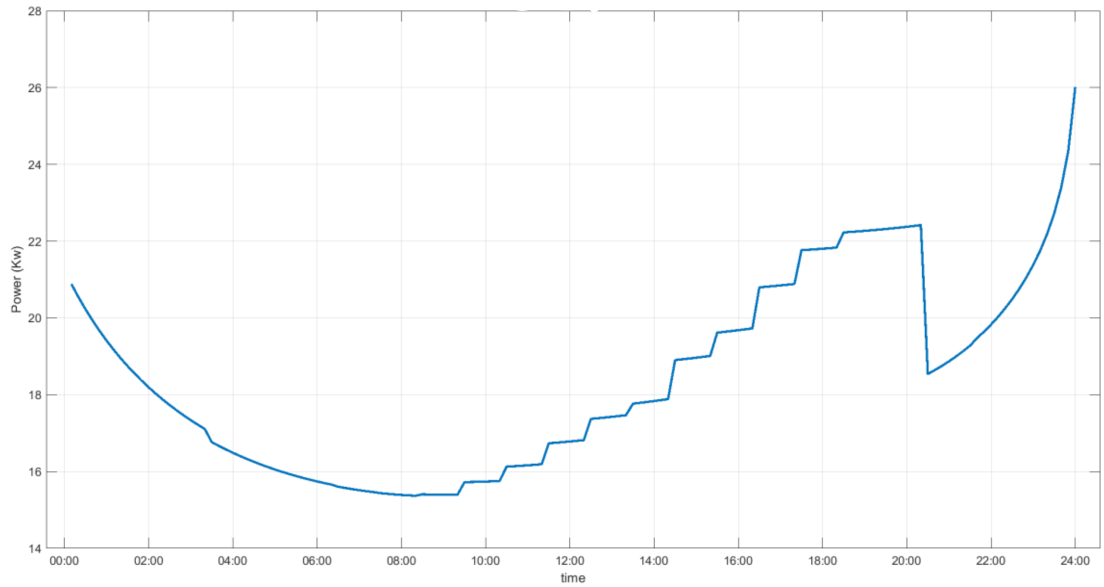

Figure 5.16: EV demand profile (case 3)

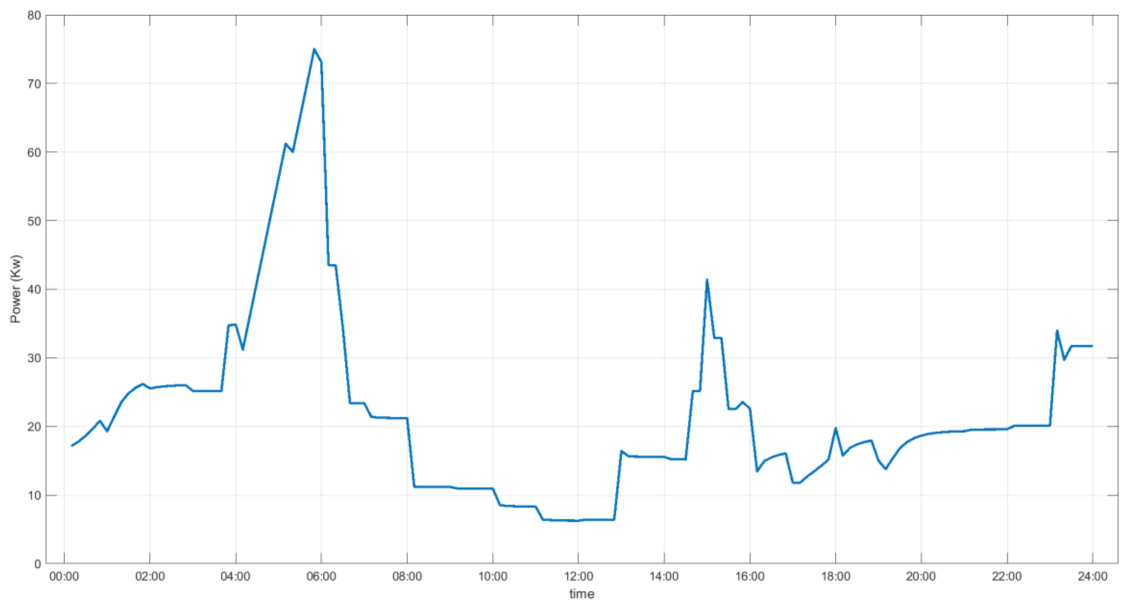

Figure 5.17: Thermal demand profile (case 3)

Table 5.7: Case three (wastewater treatment + thermal loads + electric vehicles) Output Values

	Electricity cost ($)	**Energy consumed (kWh)**
Case three values	108,815	349,179
Expected values	145,231	357,715
Observed change	25 %	2 %

5.2.4 Case four: combining drinking water treatment, electric vehicles and thermal loads in houses and buildings

The last scenario combines drinking water treatment, electric vehicles and thermal loads with the objective of minimizing their total costs. The optimization model is built as a non-linear programming problem on GAMS with an objective function as shown in equation (5.5d). This formulation is constrained by: (1) operational and physical limitations imposed by the facilities and given in equations (4.15) to (4.42) as well as, (2) maximum power consumption allowed at time *t.* Thermal demand profile, EV demand profile and DWTP demand profiles are show in figures 5.18, 5.19 and 5.20 respectively. Thermal demand starts with average consumption and peaks around 4:00 to 8:00 during the first off-peak price period, consumption is significantly reduced during peak price period of 10:00 to 14:00. Another peak is observed between 14:00 and 16:00 making use of the second off-peak price period. DWTP demand profile is shown in figure 5.19, performance seems to be 'noisy' however, the general shape of consumption peaks during price off-peak periods witnessed between 2:00 and 8:00, as well as 14:00 to 17:00. Demand is significantly reduced during price peak periods occurring from 8:00 to 14:00 and, 17:00 and 21:00. EV demand is shown in figure 5.20 and is still seen to follow the basic shape of EV connection probability presented in figure 5.7 with a noticeable increase towards the end of the day during the last off-peak price period. Table 5.8 presents a numerical comparison of system costs and energy consumption verses the expected consumption i.e. summation of individual performance values of the participating facilities. With absence of the biggest DR participant – WWTP, economic improvement is noted at 9% through identifying point of synergy between the resources. Moreover, a small reduction of 3.9% is observed in total energy consumption.

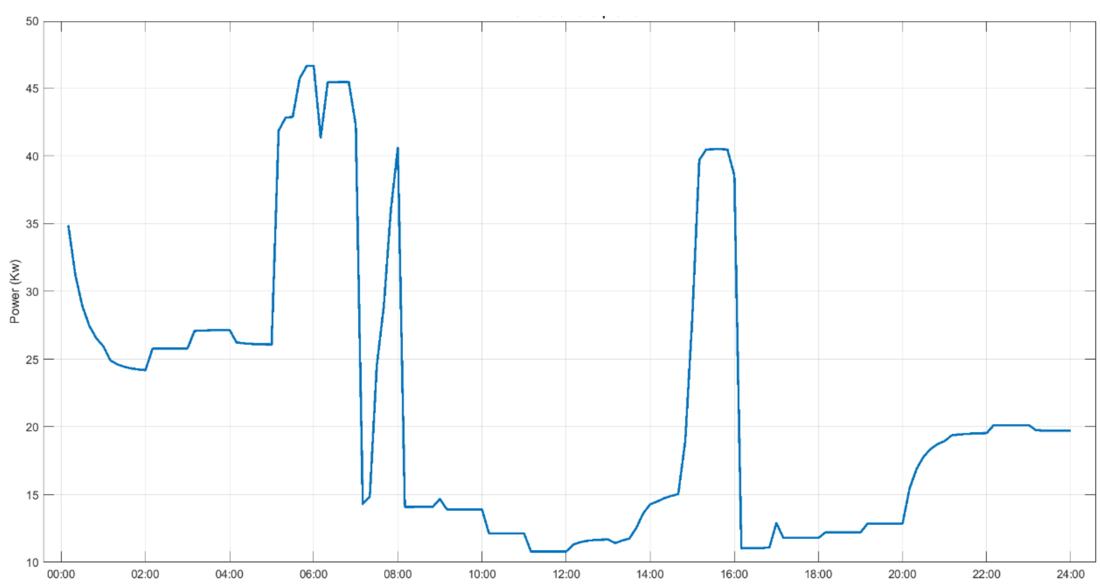

Figure 5.18: Thermal demand profile (case 4)

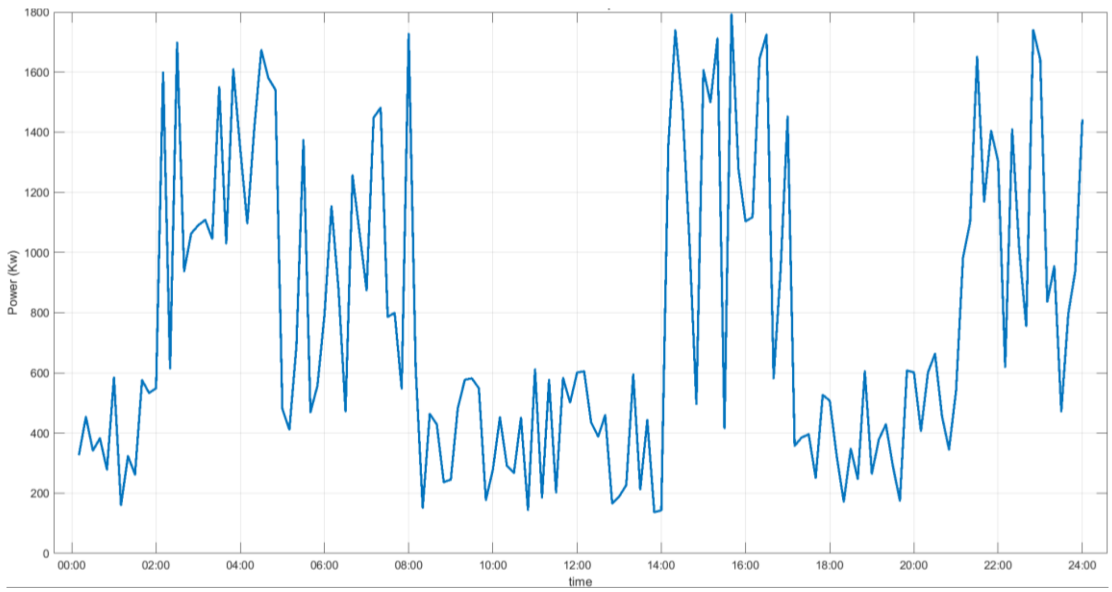

Figure 5.19:DWTP demand profile (case 4)

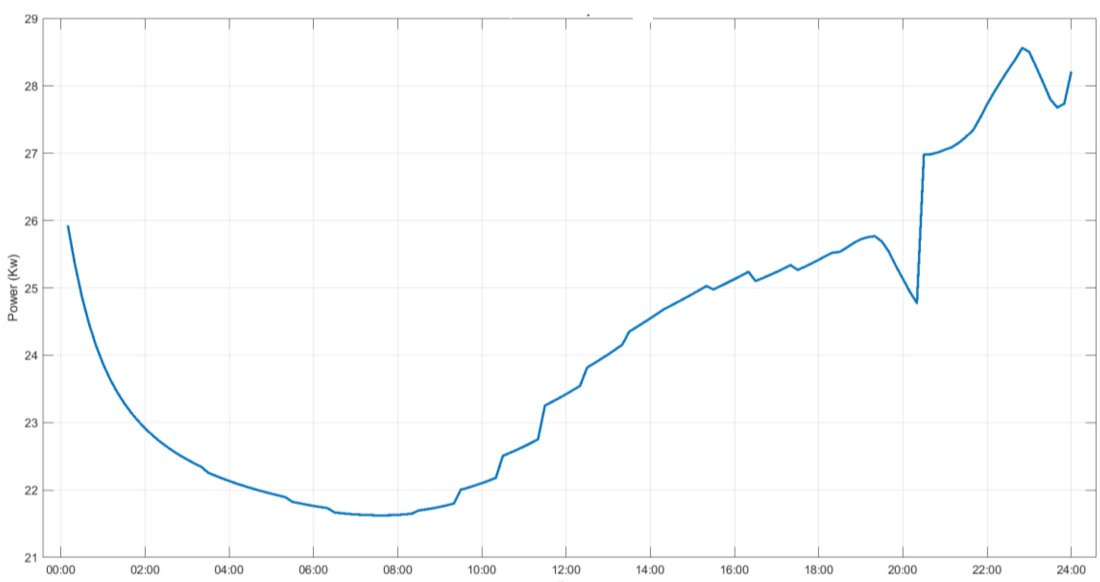

Figure 5.20:EV demand profile (case 4)

Table 5.8: Case four (Drinking water treatment + electric vehicles + thermal loads) Output Values

	Electricity cost ($)	**Energy consumed (kWh)**
Case four values	57,274	166,294
Expected values	63,007	173,055
Observed change	9 %	3.9 %

5.3 Discussion

This chapter presented the problem formulation for the optimization problems used in this work. It also provided four DR facilities operating independently from one another and operating collaboratively to minimize overall system costs. Results were presented visually as daily demand graphs for all scenarios as well as through numerical comparisons to better quantify the differences seen with collaborative verses independent operation modes.

Chapter 6: Conclusion

This work proposed an integrative multi-sector demand side management framework, where different energy vectors could take part in the DR process. Demand response is of massive benefits to the electrical system, it exists heavily in the future of electric networks as it provides the flexibility needed to counter-act the intermittent nature of renewable energy sources. Electric system on a global scale are heading towards greener, more sustainable means of energy generation, this movement encouraged us to look for DR resources past the traditional known ones. The electric system services many energy vectors, this work aimed to prove the efficacy of other sectors in participating in electrical DR programs in a collaborative operational manner.

The work proposes an 8-step process to finding and choosing DR resources outside the tight frames of the electrical network that could take place in this program. The goal is to increase operation flexibility and DR capacity. Using the suggested process, this work chose four facilities to pose as DR resources namely, wastewater treatment plants, drinking water treatments, thermal loads and electric vehicles. The first two resources are not popular participants in traditional DR programs hence; they were studied and modeled to produce a numerical model focusing on energy consumption and operational flexibility. The latter two resources are established DR resources with validated models ready to use in the framework. This was essential to show the improvement that can introduced through operational integration of DR resources.

These models were used to find the optimum operation schedule for each of the participating resources with the objective of minimizing total costs. This was done independently, where each unit functions alone, unaware of the behavior of other participants in the system. This was also carried out in an integrated, collaborative manner where the objective function included the total cost of operation for the entire system as one unit. Results show a consistent improvement in total costs and energy consumption through integrative operation as compared to independent operation. Due to computational limitation integrative operation was divided into 4 cases covering all different combination possibilities of the 4 participating facilities. The biggest economic improvement of 26% was seen in case 2, which included WWTP, DWTP and EVs. Cases 1 and 3 had an economic improvement of 22% and 25% respectively. Case 1 included WWTP, DWTP and thermal loads while Case 3 included WWTP, EVs and thermal loads. The least economic improvement was observed in case 4 with a 9% reduction in costs. Case 4 included DWTP, EVs and thermal loads. The consistent, overall economic improvement proves the advantages presented by cooperative operations to the system. The main incentive for facilities to participate will be presented by the utility. This work proves the potential DR improvements in the system, these improvements are likely to cause significant cost reductions to the utility which in turn, would be translated into monetary incentives to the facilities. This is a recommended future step for this work.

6.1 Future work and possibilities

This work serves as a proof of concept, showing the efficacy of operational integration in improving DR capacity and hence improving DSM performance. This framework is meant to serve as a guide, explaining the process of screening, identifying, and modeling multiple DR resources belong to different energy sectors under one umbrella. Future works should attempt branching out to different possible participants that can take place in this DR program. Desalination units and gas pumping stations are recommended as good starting points on the search to new DR resources.

This work assumes collaborative operation between all facilities; the next step would be to consider a more competitive approach where each player bids for their participation in the DR program. This can be done through game-theoretic approaches. This would turn participants into players. The players must have a way to communicate with one another as well as with the electric system. A set of metrics or indices representing the DR capacity of different systems from different energy sectors must be established to create an efficient communication medium.

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