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# Data Analytics for Privacy in Smart Grids

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To the Graduate Council:

I am submitting herewith a thesis written by Albraa Bahour entitled "Data Analytics for Privacy in Smart Grids." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Electrical Engineering.

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# Data Analytics for Privacy in Smart Grids

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*To my parents and siblings, for all their constant love, support, and encouragement to keep me going further, thank you for believing in me.*

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# Abstract

The emergence of smart grids has allowed for integrating new technologies in the power grid, with information flowing across the system allowing for more efficient power delivery and event response. Demand response is a new technology enabled by smart grids, which is a program aiming to reduce or shift peak demand by varying the price of electricity or offering incentives for changing consumption habits.

Despite demand response benefits, privacy advocates have raised concerns with information leakages allowed by the type of high-resolution data collected by smart meters, as it can reveal customer usage patterns and different parties can take advantage of that data. In this thesis, a utility vs. privacy framework is developed to maximize the utility of using smart meter data while also minimizing the privacy leakages from the smart meter.

Two frameworks are developed, the first, a fault localization technique for radial distribution systems by using alarm processing through binary integer linear programming. The second, a power scheduling tool that uses renewables, a battery, and appliance scheduling to disguise the customer usage patterns by matching it to an average and the resulting collected data is not revealing of any characteristics the customer wants to hide.

Fault localization was tested on two radial distribution systems, and locates the fault every time, with the variation in time till detection depending on system size, how the system is branched, fault location, and sampling rate. Power scheduling was tested using simulated home data, different scenarios are run by varying battery, solar, appliance, and privacy parameters, and results are compared for various sampling rates. Both frameworks were successful in hiding privacy leakages based their respective privacy metric.

Future research on the fault localization could expand to find two faults simultaneously, along with implementing an emergency mode to find faults quicker in a sampling cycle.

The power scheduling framework could expand to include thermostatically controlled load scheduling, by implementing deep learning algorithms on each home and factoring in variables such as historic data of weather, time of day, and day of week to determine how thermostatically controlled loads could fit into the scheduling problem.

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# Nomenclature

| | |
|---|---|
| $\alpha$ | Privacy Index |
| $\beta$ | Battery discharge Rate [watt/$k_t$] |
| $B_c$ | Battery Capacity |
| $C_p(k)$ | Cost of power at time slot $k$ |
| $K$ | Set of Time Slots |
| $k_t$ | Time between time slots in $K$ |
| $M$ | Large Constant |
| $P^s(k)$ | Solar Generation at time slot $k$ |
| $P_a^i$ | Power of Appliance $\mu_i$ |
| $P_b(k)$ | Uncontrollable Base Load at time slot $k$ |
| $S_\eta$ | Solar Efficiency |
| $S_r(k)$ | Solar Radiance at time slot $k$) |
| $S_{kw}$ | Solar System Capacity |
| $U$ | Set of Appliances |
| $\bar{V}(k)$ | Average Load Profile at time slot $k$ |
| $\delta_i^k$ | Binary variable for appliance $\mu_i$ at time slot $k$ |

$B^+(k)$ Battery charging variable at time slot $k$

$B^-(k)$ Battery discharging variable at time slot $k$

$t_i^k$ Appliance $\mu_i$ at time slot $k$ on/off variable

# Chapter 1

# Introduction

This chapter serves as an introduction to the background of smart grids, demand response, and data collection using smart meters. Afterwards, the motivation and contribution of the thesis are discussed, and the thesis structure is presented.

## 1.1 Smart Grid

The existing U.S. power system has served the traditional needs well, but moving into the future with new challenges such as, security threats, extreme weather events, along with new market opportunities and a changing supply mix, there is a need to modernize the existing grid into the so-called smart grid. There exist many improvements promised by smart grid technologies. The main differences are shown in Table 1.1.

The most important distinction between the two grids is the extensive communication. Two-way communication in a smart grid setting will save time and money, utilities no longer have to dispatch a meter reader every month for billing purposes. New programs such as Demand Response (DR) and time of day pricing can be introduced, and utilities will be able to detect outages much quicker.

**Table 1.1:** Comparison Between Existing Grid and Smart Grid [30]

| | |
|---|---|
| Existing Grid | Smart Grid |
| Electromechanical | Digital |
| One-way communication | Two-way communication |
| Centralized generation | Distributed generation |
| Few sensors | Sensors throughout |
| Manual monitoring | Self-monitoring |
| Manual restoration | Self-healing |
| Failures and blackouts | Adaptive and islanding |
| Limited control | Pervasive control |
| Few customer choices | Many customer choices |

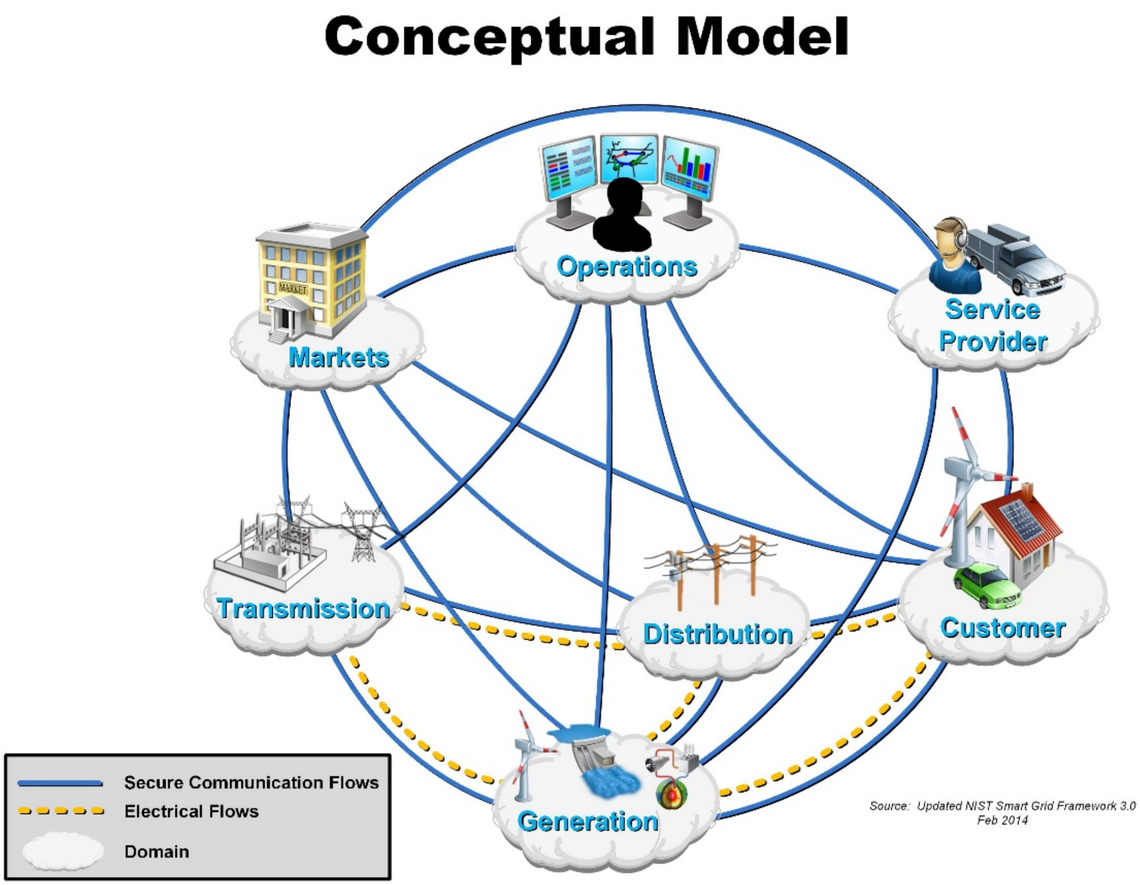


**Figure 1.1:** NIST conceptualization of Smart Grid [36]

The National Institute of Standards and Technology (NIST) developed a smart grid concenptualization shown in Figure 1.1. Two-way communication is central to achieve the anticipated benefits and requirements of a smart grid as defined by NIST, which are [36]:

1. Improving power reliability and quality;
2. Optimizing facility utilization and averting construction of back-up (peak load) power plants;
3. Enhancing capacity and efficiency of existing electric power networks;
4. Improving resilience to disruption;
5. Enabling predictive maintenance and self-healing responses to system disturbances;
6. Facilitating expanded deployment of renewable energy sources;
7. Accommodating distributed power sources;
8. Automating maintenance and operation;
9. Reducing greenhouse gas emissions by enabling electric vehicles and new power sources;
10. Reducing oil consumption by reducing the need for inefficient generation during peak usage periods;
11. Presenting opportunities to improve grid security;
12. Enabling transition to plug-in electric vehicles and new energy storage options;
13. Increasing consumer choice; and
14. Enabling new products, services, and markets.

By utilizing modern information technologies, the smart grid will be able to deliver power in more efficient ways. It will also be able to respond to different events happening across the system. It should be able to correctly match generation with load and keep transmission lines near their rating. The smart grid in theory could optimize every aspect of the electric grid to make it more efficient and lower costs overall for both consumers and utilities.

## 1.2 Demand Response

Demand Response (DR) is a "demand side management program for reducing or shifting peak demand by varying electricity prices or providing incentives to customers to change their consumption patterns" [64]. The Department of Energy (DoE) defines DR as "a tariff or program established to motivate changes in electricity use by end-use customers in response to changes in the price of electricity over time or to give incentive payments designed to induce lower electricity use at a time of high market prices or when grid reliability is jeopardized" [5]. The Federal Energy Regulatory Commission (FERC) was required to prepare a report assessing electric demand response resources across the country, along with the penetration rate of advanced smart meters, in accordance with the energy policy act of 2005 [4]. FERC was also required to perform a national assessment of DR potential along with developing a national action plan for DR, in accordance with the energy independence and security act of 2007 [6].

Since these two acts were established, DR is being slowly implemented across different markets. DR has mostly been implemented in the industrial sector successfully, as large facilities can curb their load in much larger and meaningful amounts that will be able to help system operations during peak loading times. DR can help lower costs by helping system operators to maintain a good load factor. Load factor is the average power demand divided by the peak power demand, an ideal load factor would equal 1, which means the load is steady throughout the day which would require no extra capacity to manage peak loads.

DR can have the same effect of adding a generator to the system, but DR can respond much faster with potentially high savings from functions such as peak shaving during high loads times. It also help system operators balance variable generation and load without having to call up expensive and costly generators. Residential DR has been introduced into power markets to a much less degree than in the industrial sector. Load Serving Entities (LSE) can provide services where they are able to create a DR report for each household according to their unique power usage. DR programs have generally been voluntary programs. Studies in [23, 58, 59] show demographics studies to understand who


**(a)** Elechtromechanical Meter


**(b)** Solid State Meter

**Figure 1.2:** Difference Between Meter Types

will most likely choose to enroll in a DR program, as it widely differs by demographics. For example, a liberal leaning 26 year old democratic voter is much more likely to accept and enroll in such a program than a conservative leaning 55 year old republican voter [20].

Other issues such as concern with privacy may also impact willingness to enroll in a program. A residential DR program can be as simple as offering incentives to customers who raise their thermostat setting or as involved and complex as scheduling different appliances according to prices and the overall system load at a particular time.

## 1.3 Smart Meters

There is no current consensus on what the smart refers to in smart meters, or what features should be included in these meters, but the simplest feature that all agree on is their ability to communicate timely information about power usage back to the utility [65].

Figure 1.2 depicts the difference between an old electromechanical meter and the new smart meter. The electromechanical meters require a meter worker to go out every month and record a reading for all the customers in a service area for billing purposes. The new smart meters can record that information and transmit it back to a centralized server that will calculate the bill automatically and send it to the customer. This brings costs down for both utilities and customers. There are many other benefits to smart meters and functionality that can support the grid. These benefits are listed in Table 1.2. Present meters are advanced and can record measurements frequently, up to a thousand measurements per second [38]; however, with such detailed monitoring, the issue of privacy arises.

## 1.4 Privacy in Smart Grids

Due to the nature of smart grids and the technology they employ, large amounts of data are continuously transmitted. Some of this data that can be considered highly sensitive, and would be considered lucrative to acquire for marketing firms or malicious intention third parties. The types of data that can impact peoples privacy includes: names, addresses, bank account, meter data, billing, renewable capacity installed, and energy service providers [72]. There are four different aspects of privacy considered by NIST, personal information, personal privacy, behavioral privacy, and personal communication [30]. All those privacies can be infringed upon by either utilities selling the data or the system being hacked.

Privacy advocates are wary of smart meters, going as far as to advocate against them and try to lobby local law makers to ban utilities from deploying smart meters. Utilities have faced lawsuits to prevent the use of smart meters. Other people have unfounded concerns against smart meters, such as radiation, fire hazard, and inaccuracy compared to electromechanical meters, but these issues have been widely studied and have been proven to be without basis [1]. Still, there are some legitimate concerns regarding smart meter implementation, including the security of the system from hacking by third parties with malicious intent or by data being sold to marketing firms. Because such data can reveal very telling behavioral patterns of a homeowner and would allow thieves to find out when houses are empty and will let companies start targeting advertisements even more.

Non-Intrusive Load Monitoring (NILM) algorithms have been developed which allows the intricate detection of different appliances such as the HVAC, water heater, lights, and even a phone charger, by just looking at the overall load curve of a household. With a 2 Hz sampling rate over 5 min. media content displayed over a TV can easily be identified as shown in [37]. Even if smart meter data was sampled with a granularity of 30 min over 1.5 years, different of a household can be detected [14].

**Table 1.2:** Smart Meter Benefits [62]

| Stakeholder | Benefit |
|---|---|
| Utility Customers | • Better access and data to manage energy use<br>• More accurate and timely billing Improved and increased rate options<br>• Improved outage restoration<br>• Power quality data |
| Customer Service and Field Operations | • Reduced cost of Metering reading<br>• Reduced trips for off-cycle reads<br>• Eliminates hand-held meter reading equipment<br>• Reduced call center transactions<br>• Reduced collections and connects disconnects<br>• Reduced back office re-billing<br>• Early detection of meter tampering and theft<br>• Reduced estimated billing and billing errors |
| Revenue Cycle Services - Billing, Accounting, Revenue Protection | |
| Transmission and Distribution | • Improved transformer load management Improved capacitor bank switching<br>• Data for improved efficiency, reliability of service, losses, and loading<br>• Improved data for efficient grid system design Power quality data for the service areas<br>• Reduced costs for collecting load research data |
| Marketing and Load Forecasting | |
| Utility General | • Reduced regulatory complaints<br>• Improved customer premise safety and risk profile<br>• Reduced employee safety incidents |
| External Stakeholders | • Improved environmental benefits<br>• Support for the Smart Grid initiatives |

## 1.5 Motivation

With the ongoing efforts to modernize the power grid into a more green smart grid, several different programs have been developed to help achieve that goal, one of them is DR, demand response will help bring down costs to utilities and customer alike, along with bringing down greenhouse gases used by expensive generators that get turned on during peak loading times to help get generation to match the load so the system can function reliably. DR programs coupled with smart meters requires privacy concerns to be fully addressed for gaining public acceptance. This thesis will focus on developing an approach for a mutually beneficial trade off between the privacy infringed by gathering data and the utility gains from the data. Specifically, this work proposes minimizing privacy infringement while satisfying utility data needs for grid functions. In this thesis, two different utility functions are addressed from a privacy point-of-view: outage detection in a simple radial distribution grid and a DR program using appliance scheduling.

## 1.6 Contribution

Designed a fault localization alarm processing technique which uses an iterative set covering technique in a Linear Program with incoming data to find the location of the fault on a radial distribution system in the shortest time possible while keeping privacy leakage to a minimum.

Designed a mixed integer linear program formulation to prevent privacy leakages by masking the customers power usage through scheduling appliances, renewable resources, and battery to either maximize privacy or cost savings on electric bill.

## 1.7 Thesis Structure

In chapter 2, a literature review on the current privacy hiding schemes, such as, battery and load level hiding, along with current existing appliance scheduling models is given. Chapter 3 will focus on the problem of outage detection using a binary integer linear programming model. Chapter 4 will address the problem of appliance scheduling to optimize user selection parameters so the user will be able to select between preserving privacy or lowering costs. This will be solved using a mixed integer linear programming model. Chapter 5 will analyze the results and make recommendations for future work that could be done to further optimize these models and add new models to tackle other utility problems.

# Chapter 2

# Literature Review

A literature review is conducted for material applicable to demand response in smart grids, privacy concerns, alarm processing, mixed integer linear programming, utility of smart meter data, dynamic time of day pricing, and existing solutions to the privacy vs. utility problem.

## 2.1 Demand Response in Smart Grids

Smart grids allow enhanced energy management through the deployments of smart metering infrastructure (SMI) as part of a global green initiative. From a utility perspective, smart meters should meet the following goals [63]:

1. Enable critical peak billing and support dynamic pricing
2. Support tamper and energy theft alarms
3. Support power failure and restoration notifications
4. Support residential demand response

These goals are accomplished by the smart meters ability to collect high-resolution energy data, which lets the utility forecast load demand and the ability to provide improved service to consumers in the form of variable pricing [67], an important realization of that pricing structure comes in in the form of demand response (DR), where customers change their consumption patterns in a reaction to changing prices or incentives offered by their

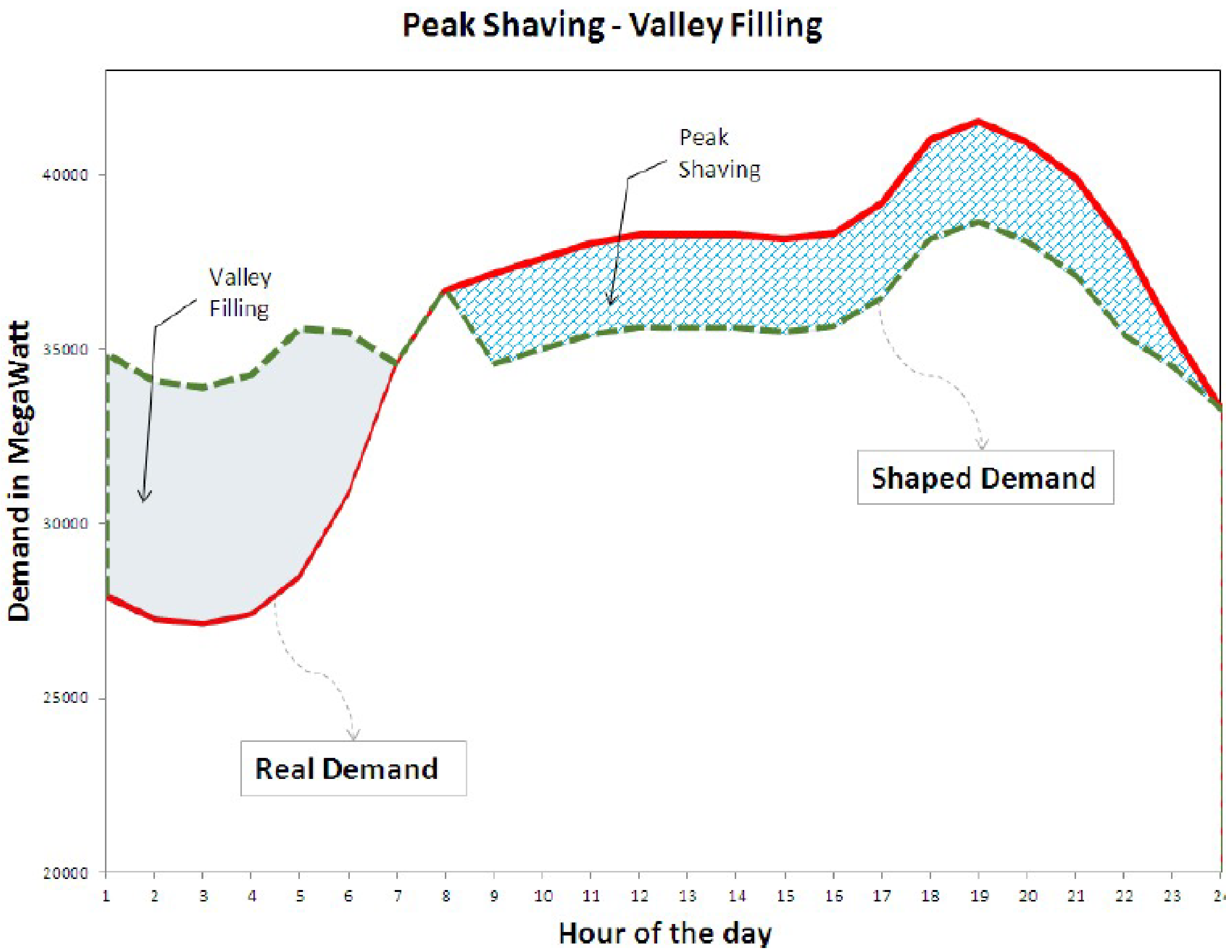


**Figure 2.1:** Peak Shaving as a result of a DR program [75]

utility provider, and in some cases the utility provider could have direct access to customers appliances to control them in the case of system instability [7]. DR also provides the ability to shave peak power consumption as shown in Figure 2.1. This can help decrease costs, even a 5% load reduction can provide up to 50% price curtailment, and that is because electricity generation costs raise exponentially when the power generation capacity is near its maximum limit and expensive generators need to come on-line to compensate for the increased peak load [8].

DR can be split into two different categories [35], price based demand response (PDR) and incentive based demand response (IDR), where PDR is based on the electric company displaying day ahead pricing and the customer can react to those prices independently to save electricity cost, and IDR where the customer directly responds to the utilities request to curb their load at a certain time. And depending on the type of IDR program, the time interval for measurements could vary from hours to seconds based on different triggering conditions [43] although this could potentially pose serious threats to customer privacy [15]. The unique challenge that IDR poses is that the metering data needs to be attributable to a certain customer for the purpose of tracking demand curtailment responses and monetary incentives to be rewarded as well as the need for that data to be fine-grained to allow the maximum benefit to the utility company.

## 2.2 Utility of Smart Meter Data

Privacy related issues to smart meter data have been addressed in the previous sections of this thesis, this section deals with the utility functions a load serving entity or a utility company can gain from using that data. The different functions utilities can accomplish relate to the granularity of the data received by the smart meter, Figure 2.2 shows that a granularity of 30 min can only reveal active\inactive periods of occupancy, but in Figure 2.3 with a granularity of 1 min, more privacy concerns start arising, as specific appliances turning on and off can be detected thereby exposing even greater privacy of the user.

However, the higher the granularity of the received data, the more utility a power company can extract value from that data. In the case where data is only read once a month, the data can only indicate the amount to be billed for a customer, and possibly

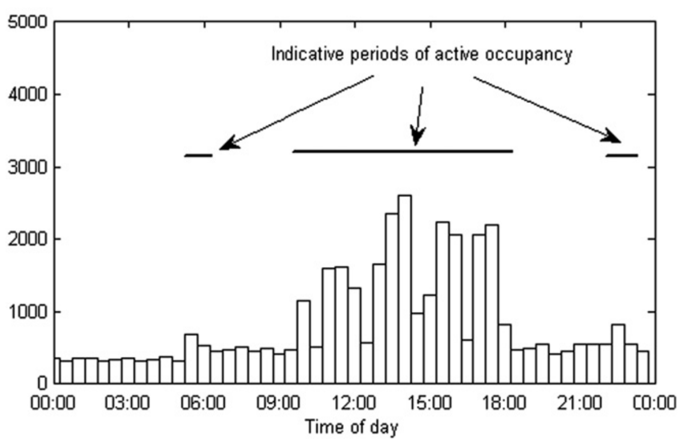


**Figure 2.2:** Demand data for a single dwelling averaged over 30 min. [41]

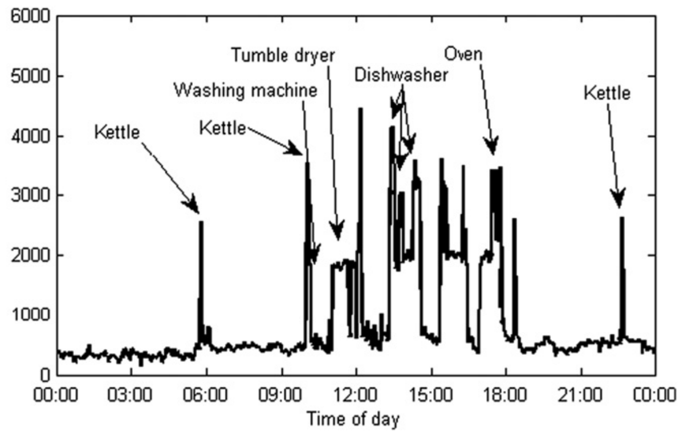


**Figure 2.3:** Demand data for a single dwelling averaged over 1 min. [41]

general occupation, in terms of this home is occupied or not, but a granularity of say, 1-min, can forecast exact demand in a specific area and help achieve DR. There are many utility functions that could be achieved by smart meter data as outlined in [60]. They include:

### 2.2.1 System Balancing and Transmission Network Power Flows

System operators constantly have to manage load and generation to maintain system frequency, and maintain secure operating regions for the system, this is usually done in bulk by looking at data coming in from substations. With the inclusion of smart meter data, and proper load modeling, the data could prove much more useful in knowing how to schedule generation across the network, historic data from several places could be an indication that a certain area will require more generation than another at some time, so system operators could be ready for that, this data will facilitate the integration of distributed generation and will allow more secure grid operation.

### 2.2.2 Demand Reduction

With the concept of dynamic time of day pricing, some consumers will want to decrease their usage during expensive peak times, and shift it to cheaper off-peak times. This will help them save costs on electricity bills, along with helping provide peak-shaving for the utility. Feedback from the smart meter to the homeowner could be useful in showing when they consume the most, and help them curtail their usage when needed.

### 2.2.3 Demand Response

The many benefits of demand response were included in an earlier section, and without fine-grained smart meter data, it would be near impossible to implement a DR system.

### 2.2.4 Retail Billing

Retail billing is a very important part of the power market, and up until recently, and in many areas, workers must be dispatched to physically look at a meters reading and record it and report back to the utility to calculate how much each household owes on their monthly bill. Smart meters need only send the usage once a month to perform the same function.

### 2.2.5 Wholesale Settlement

Wholesale settlement refers to the market operations in the electrical system, with fine-grained meter data, weather, and historical data, the utility provider could purchase exact amounts of generated power to serve to their distribution network customers.

### 2.2.6 Fast Demand Response

Fast demand response refers to the utility having direct control over different appliances, usually Thermostatically Controlled Loads (TLC)s. Where the utility can turn off these loads in the case of near system collapse, or can send out control signals to regulate the total power demand at a certain time.

### 2.2.7 Distribution System Operation and Planning

The medium and low voltage network that is operated by the local load serving entity could benefit greatly from fine-grained meter data by allowing the operators to follow trends in power usage and plan for the future. It also allows them to better operate the network in day to day operations.

### 2.2.8 Voltage and Power Quality

Smart meters can readily be fitted to test and measure voltage along with power sampling which it can relay back to the utility in case a measurement outside the limits is reported. The voltage data that can be measured could include stead-state voltages, flickers, and harmonics, all of which are of interest to the network operators who can use that data to maintain the optimal voltage level and quality.

### 2.2.9 Outage Detection and Fault Localization

With incoming smart meter data, no longer will homeowners have to call in a power outage, the occurrence and location of a fault is automatically detected and depending on the sampling rate of the data could be instantaneous.

### 2.2.10 Operation Nearer to Limits

Find-grained meter data will allow the operators to operate the system nearer to its designed limits by allowing them to distributed generation to serve the immediate surrounding area, which would not require generated power to travel far among the transmission lines and lead to network losses and lines not being fully utilized.

### 2.2.11 Planning Reinforcement

Distribution networks are designed to meet the demand of certain areas without exceeding the thermal limits of power cables and equipment, along with keeping the voltage within limits. But with the constant change in new home additions to an area, and upgrading the different appliances within a home, the amount of power used by certain areas can differ over time, and smart meter data will allow the utility to make informed decisions on where the load will increase in the future, so the process of upgrading lines and equipment to higher ratings can be done more efficiently and economically.

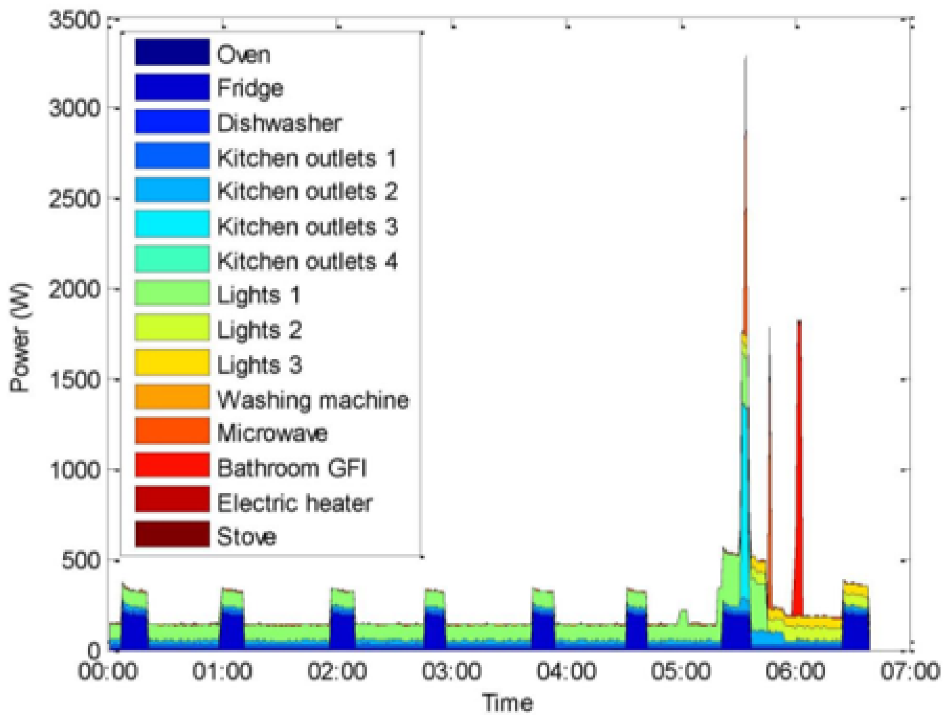


**Figure 2.4:** Example 1 of Demand Profile from Individual Household Record [40]

## 2.3 Privacy Concerns

Despite all the aforementioned benefits DR can bring, privacy leakages can limit acceptance. DR paired with SMI technologies generates high-resolution data allowing customers usage patterns to be observed and taken advantage of whether by their utility company or a malicious third party, and without proper control techniques for privacy preserving, customers participating in DR programs or even just having a smart meter installed could face unpleasant privacy infringement experiences, such as, loss of personal information and their habits disclosed through their energy usage [61, 54].

Consumers habits can be determined by looking at their overall energy usage, and that is made possible with the Non-Intrusive Load Monitoring (NILM) algorithms [48], and steady state monitoring techniques can be used to identify loads with typical on/off patterns such as coffee makers and refrigerators. This can be seen in Figure 2.4 and Figure 2.5, the different appliances can be identified by looking at the overall load profile.

Other characteristics that can be identified by looking at energy usage patterns are the number of occupants, whether the home is occupied, whether all the adults work for pay,

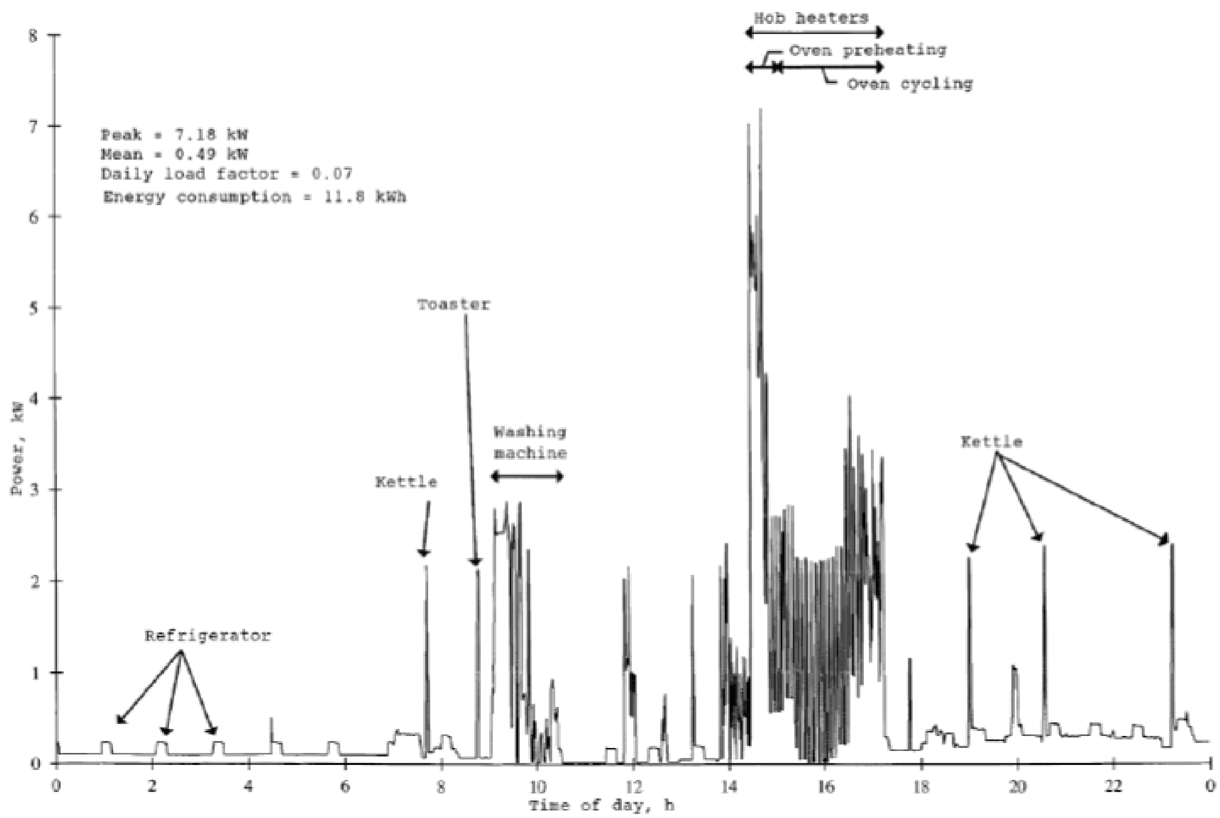


**Figure 2.5:** Example 2 of Demand Profile from Individual Household Record [40]

the duration the home is occupied, or even the retirement status of the head of household [11]. Aside form power consumption data, privacy can be disclosed in other ways as well. DR systems contain several kinds of data: power consumption, control commands, events, and alarms [54]. There are many things that can be affected by privacy leakages. For example, when electricity is expensive at peak times, if a customer choses to turn off their air conditioner, or raise their thermostat even thought the temperature outside is hot, this behavior can deduce that this particular customer prefers financial savings to comfortable temperatures. Table 2.2 shows a summary of privacy concerns related to smart meters.

Financial wellbeing can also be deduced from usage patterns, if at a certain time, the price varies, and a customer has not scheduled any appliances to shift to off peak hours, it can show the customers financial rationality. If a customer reschedules a dishwasher task to midnight, it can infer that the customer does not pay attention to the neighbors reaction to the noise it induces. [50]. Another thing that can be inferred from privacy leakages is

**Table 2.1:** Private Questions and Answers that Fine-Grained Power Consumption Data Reveals [63]

| Question | Pattern | Granularity |
|---|---|---|
| Where you home during your sick leave? | Yes: Power activities during the day<br>No: Low power usage during the day | Hour/Minute |
| Did you get a good nights sleep? | Yes: No power events overnight for at least 6 hours<br>No: Random power events overnight | Hour/Minute |
| Did you watch the game last night? | Yes: Appliance activity matching TV program<br>No: No power event in accordance with game showtime | Minute/Second |
| Did you leave late for work? | Yes: Last power event time later than Google maps estimated travel time<br>No: Last power event time leaves enough time for commute | Minute |
| Did you leave your child home alone? | Yes: Single person activity pattern<br>No: Simultaneous power events in distinct areas of the house | Minute/Second |
| Did you eat a hot or cold breakfast? | Hot: Burst of power events in the morning (microwave/coffee machine/toaster)<br>Cold: No power event matching hot breakfast appliances | Second |

appliance malfunction. In a DR program with Direct Load Control (DLC) if a utility sends a signal for an appliance to turn on at a certain time, and the energy pattern does not reflect that appliance, then it can be inferred that the appliance has malfunctioned. Then targeted advertisements can be sent to that consumer on repair services or replacement appliances. Power profiles that show very low usage during the day can infer that the customer is away at work, or away for the weekend, or whether this certain occupancy is a summer home or a full-time residence. With the right model, and the right training data and contextual clues, for scientific, curious or malicious third parties, the possibilities of what can be inferred from energy usage profiles are nearly endless. A protection scheme to protect that data is vital. [50]

**Table 2.2:** Summary of privacy concerns related to smart meters

| Application Group | Example Concerns | References |
|---|---|---|
| Illegal uses | • Burglars finding out when homes are unoccupied.<br>• Stalkers tracking the movements of their victims. | [53] [61] [67] [18] [49] |
| Commercial uses | • Targeted advertising: use of individual or aggregated household smart meter data to target advertising at a specific household or individual.<br>• Insurance adjusting e.g. do you tend to leave your appliances on when away from home? | [53] [67] [18] [10] [16] |
| Uses by law enforcement agencies | • Detection of illegal activities e.g. sweatshops, unlicensed commercial activities, and drug production.<br>• Verifying defendants claims e.g. that they were at home all evening. | [53] |
| Uses by other parties for legal purposes | • In a custody battle: do you leave your child home alone?<br>• In a landlordtenant dispute: is the property over-occupied? | [67] |
| Use by family members and other co-inhabitants | • One householder spying on another e.g. parents checking if their children are sleeping or staying up late playing video games.<br>• Partners investigating each others behavior. | [39] |

Another important, often overlooked privacy concern, is the issue of feedback and privacy within the confines of one home itself, such as different co-occupiers of a household infringing upon the privacy of others in the same household. In a household with smart meters sampling every 30 min, the only information that could be revealed from one person to another is whether the house is occupied, and that, according to [39] is information that has already been volunteered once shared occupancy was agreed upon, so no extra information is revealed in this case; however, if the sampling time was lower, such as 1-minute, the person who the utility is in their name can see the different activities their roommates, spouse, or kids are doing at certain time, which exposes those peoples privacy. This can create intra-home trust issues.

The privacy consequences of implementing smart grids are hard to anticipate for two reasons [69]:

1. The full range of technological capabilities and information extraction possibilities have not been laid out fully.

2. Our concept of privacy in this space is poorly defined and constantly shifting.

What we do know is that smart meters despite creating privacy concerns are absolutely indispensable in the context of transforming our energy system into a smart one. as a smart grid will allow many different utilities while tremendously saving costs, peak load reduction, load shaping, more efficient network management, and DR. Ref. [67] cites a list of other privacy sensitive characteristics that can be inferred from electricity load data such as if the house is occupied, personal habits, and routines. In [45], a view of privacy in smart meter information is presented where the authors identify that privacy issues relating to energy usage are an inference violation, rather than an identity violation. The authors have also proposed three different privacy metrics: a relative entropy metric, classification using clustering, and a correlation/regression metric.

**Table 2.3:** Utility vs. Privacy

| Utility Functions | | | | | | | Data Management | | Privacy Issues | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Distribution System Operating and Planning | | | | Demand Response | | | | | | | | | | |
| Planning Reinforcement | Operation Nearer to Limits | Outage Detection and Fault Location | Voltage and Power Quality | Fast Demand Response | Wholesale Settlement | Retail Billing | | | Privacy Issues Within the Home Itself | Most Appliances Detected | Major Appliances Detected | Know How Many People In Home | Know When Home is Occupied | Know Whether Home is Occupied |
| | | | | | | X | 1 Month | Sampling Time | | | | | | |
| X | | | | | | X | 1 Day | | | | | | | X |
| X | X | | | | X | X | 1 Hr. | | | | | | X | X |
| X | X | X | | | X | X | 30 min. | | X | | | X | X | X |
| X | X | X | X | X | X | X | 15 min. | | X | | X | X | X | X |
| X | X | X | X | X | X | X | 1 min. | | X | X | X | X | X | X |
| X | X | X | X | X | X | X | 1 sec | | X | X | X | X | X | X |
| | | | | X | | X | Local Feedback | Feedback Type | X | | | | | |
| X | X | X | X | X | X | X | Remote Feedback | | | X | X | X | X | X |
| X | X | X | X | | | | Voltage | Data Collected | | | | | X | X |
| X | X | | | X | X | X | Power | | X | X | X | X | X | X |

The importance of personal behavior privacy has been outlined in several studies [53, 78]. The NIST smart grid interoperability panel has outlined that the access to new energy usage data that is created and sent by smart meters, such as, unique load signatures of different electronics and appliances opens up more opportunities for general privacy invasion. Ref. [18] suggests there will always be temptation to sell private information as there will always be an interested buyer of that information, which includes: energy usage and appliance data. Therefore, the necessity to create a well balanced privacy framework that will still provide the greatest utility to the electric companies , i.e., such a framework will accommodate legitimate interests and objectives in a fair manner while preserving the privacy of consumers and not sacrificing the utility for providers of energy. Table 2.3 shows a breakdown of Utility vs. Privacy based on the data collected by the smart meter, the data sampling interval, and where the data is relayed. The Table was compiled from many sources [60, 63, 61, 67, 18, 49, 53, 67, 18, 10, 16, 39], and was assembled to support this document.

## 2.4 Mixed Integer Linear Programming

The main approach to modeling and solving linear mathematical models that seek to optimize a measure of performance is called Linear Programming (LP) or linear optimization. Traditional applications of LP have been used to solve problems such as production scheduling, finding the perfect mix or balance in a chemical solution or recipe, and in terms of power systems, solving the economic dispatch problem. More recently it is being used in the artificial intelligence and information technology fields to optimize pattern recognition problems [12]. As opposed to a normal LP problem where the optimal value of different variables or answers to a problem could be any value, a MILP has specific variables where the only solution could be an integer, this can be used, for example, in production problems, as it is not possible to build say 8.7 units, so the logical answer must be 7 or 8. A popular solver for MILP is to implement the Branch-and-Bound Algorithm. Which can be summarized as a divide-and-conquer approach, as it attempts to solve the initial problem by solving normal LP relaxations of a sequence of smaller subproblems. Some solvers also implement different advanced techniques such as pre-solving, generating cutting planes, and applying primal heuristics to improve the algorithm efficiency. The standard form for MILP problems is shown in Equation 2.1 [42].

$$
\begin{aligned}
&\max z = c^T x \\
&w.r.t. \\
&Ax = b \\
&x \geq 0 \\
&x_i \rightarrow Integer
\end{aligned}
\tag{2.1}
$$

In this formulation the $i^{th}$ value of $x$ is an integer, chosen by however the problem is setup to be solved.

## 2.5 Alarm Processing

Alarm processing in the context of power systems means that a control center needs to interpret large numbers of alarms under different conditions and to categorize the events that have happened to trigger those alarms. The alarm processing problem is an efficient way to deal with the developments in the field of information technology when it comes to SCADA systems. The solution to the alarm problem can be addressed by knowledge-based systems instead of having each alarm separately categorized to be triggered when a certain event or contingency of events happens [24]. The principal concern with alarms in a power system is the so-called multiple alarms on one event problem, which can be defined as a diagnostics problem. An attempt to solve the alarm processing problem uses the set covering [77]. This categorizes every event that could trigger a certain alarm, and then in the case of multiple alarms being triggered, it finds the least number of events that could lead to those alarms being triggered. In the context of power system, this can be described as a transmission line outage, where the operator receives the information that several areas have lost power, and after processing all the alarms for those places. It leads them to knowing which transmission line is out, and then repair crews can be dispatched to that line [9]. Alarms here can be defined as an element of a set referred to as an alarm set. Every member of an alarm set will is associated with the occurrence of a representing alarm, and an event can be described as in [24]:

$$e_i \rightarrow A_i \quad \text{where} \qquad i = 1, 2, ..., n_e$$

and,

$$e_i \in E_s$$

and,

$$A_i = \{a_k | a_k \in A_s \wedge k \in N_A\} \quad \text{where} \qquad N_A = \{1, 2, ...n_a\}$$

$e_i$ is the event $i$, $A_i$ are the alarms associated with $e$, $\rightarrow$ is the relationship between $e_i$ and $A_i$, $n_e$ is the number of events,$n_a$ is the number of alarms, $E_s$ is all possible events, and $A_s$ is all possible alarms.

**Table 2.4:** System Set of Alarms [24]

| Code | Alarm Message Description |
|---|---|
| $a_1$ | Any circuit breaker position changes |
| $a_2$ | Any pair of circuit breaker positions changes closing or opening |
| $a_3$ | Circuit breaker position changes to on |
| $a_4$ | Circuit breaker position changes to off |
| $a_5$ | Circuit breaker position leaving the off position |
| $a_6$ | Any trip commands |
| $a_7$ | Trip commands of bus-bar protection devices |
| $a_8$ | Trip commands of transformer protection devices |
| $a_9$ | Any indications of starting relays (neutral or phase) |
| $a_{10}$ | Indications of starting relays (phase only) |
| $a_{11}$ | Any indication about blocking of automatic re-closing |

Table 2.4, Table 2.5, and Table 2.6 show an example of alarm processing in the power systems domain. As seen in Table 2.6, if the operator receives alarm code $a_1$ "Any circuit breaker position changes" it could mean any one of events $e_1$, $e_2$, $e_3$, $e_4$, $e_5$, $e_6$, $e_9$, and $e_{10}$, have occurred. If alarm code $a_2$ was also received by the operator, it narrows the events down to only $e_9$ "Switching operation". This in essence explains the alarm processing problem and how it can be applied to the field of power systems.

**Table 2.5:** System set of Events [24]

| Code | Event Description |
|---|---|
| $e_1$ | Fault on bus-bar |
| $e_2$ | Tripping of transformers |
| $e_3$ | Tripping after closing |
| $e_4$ | Tripping of lines |
| $e_5$ | Unsuccessful fast re-closing |
| $e_6$ | Successful fast re-closing |
| $e_7$ | External incident |
| $e_8$ | Blocked re-closing |
| $e_9$ | Switching operation |
| $e_{10}$ | Maintenance activities |

**Table 2.6:** Relationship between Alarms and Events [24]

| Event | Alarm Group | Set of Alarms |
|---|---|---|
| $e_1$ | $A_1$ | $a_1$ $a_4$ $a_6$ $a_7$ |
| $e_2$ | $A_2$ | $a_1$ $a_4$ $a_6$ $a_8$ |
| $e_3$ | $A_3$ | $a_1$ $a_4$ $a_5$ $a_9$ $a_{10}$ |
| $e_4$ | $A_4$ | $a_1$ $a_4$ $a_9$ $a_{10}$ |
| $e_5$ | $A_5$ | $a_1$ $a_3$ $a_4$ $a_9$ $a_{10}$ |
| $e_6$ | $A_6$ | $a_1$ $a_3$ $a_9$ |
| $e_7$ | $A_7$ | $a_9$ |
| $e_8$ | $A_8$ | $a_{11}$ |
| $e_9$ | $A_9$ | $a_1$ $a_2$ |
| $e_{10}$ | $A_{10}$ | $a_1$ |

## 2.6 Dynamic Time of Day Pricing

With the introduction of smart meters, utilities can now record consumer power usage at much higher rates than under the traditional monthly meter reads. Using these readings, utilities can implement different Time of Day (TOD) pricing programs, where prices depend on the market conditions and can fluctuate from hour to hour. Customers can choose to use the more power consuming appliances such as their dishwasher or dryer at a time when electricity is cheaper. Those times will also be times when there is less strain on the power system, so a TOD program when implemented will benefit both utility and consumer by saving costs and improving system operations [3]. Most residential customers purchase electricity by having a constant rate that they get billed at the end of the month; however a significant minority of consumers have their kWh price rise marginally as more power is consumed and the prices rise for the utility to buy power that will be delivered. These prices do not depend on which time the power is consumed.

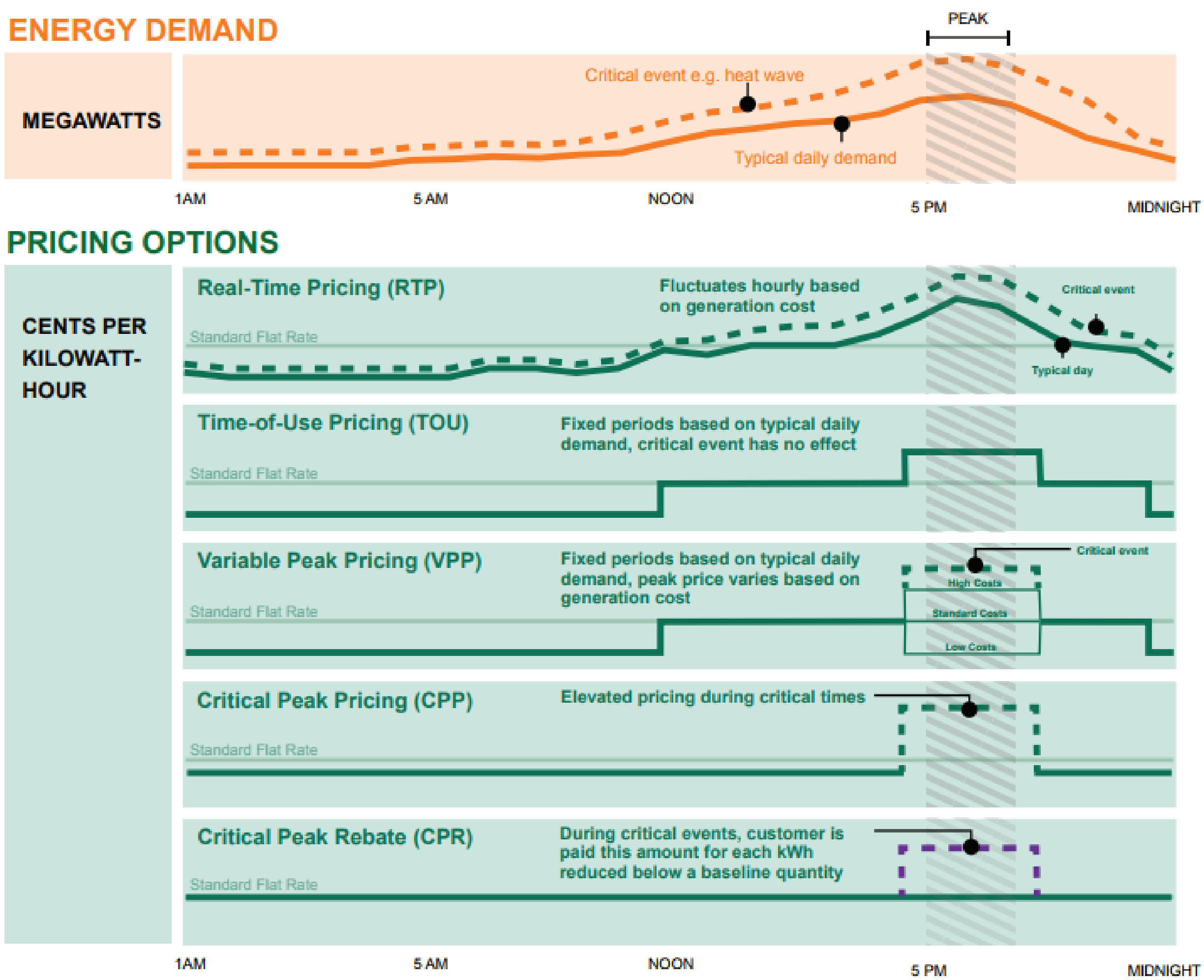


**Figure 2.6:** Time of Day Pricing [3]

There are several different pricing models that can be implemented in a TOD pricing program [2]. All programs seek to persuade people to move their load as much as possible to non peak times, whether by increasing price during peak times, or offering discounts during non peak times. The overall goal of TOD pricing is to reduce strain on the system. Several of these different pricing options are given in Figure 2.6. The most common dynamic pricing is the time-of-use (TOU) pricing in which the price of electricity varies with the time of day or week. TOU is not considered dynamic as the prices are set either the day before, or sometimes even weeks or months in advance. The consumer can then plan on when to use heavy loads based on the prices at certain times. Critical peak pricing (CPP) is also a form of dynamic pricing where the utility will increase the price of electricity at a time where they want to curb demand and decrease it at a time where they want to shift that decreased demand to. This enables a shaped demand profile closer to leveled which helps to stabilize pricing and system operations [17]. No matter which type of dynamic pricing is used, it remains one of the crucial parts in enabling a successful demand side management program. This type of pricing, while popular with economists is not so popular with regulators and consumers, e.g., [25] has shown that customers will responds positively to an opt-in type of dynamic pricing program.

## 2.7 Previous Privacy Solutions

Most smart meters currently deployed do not have any active measure to preserve privacy, and the studies that have come out have been purely theoretical with little real implementation. Different studies have involved several different ways to achieve privacy preservation those ways are shown in this section. The different papers that cover this topic will be analyzed and their different approaches discussed. It should be noted that this section only covers the power scheduling problem, and previous solutions to that problem, and not the fault localization problem, as there does not currently exist any fault localization technique that regards privacy protection in the literature and this thesis is the first to propose such a measure.

There are many works in literature that address privacy concerns using encoding, decoding, and encryption, for many different areas of study. In [35, 50, 69] are sources covering the smart grid, and how important it is to have this kind of technology on all ends of smart meters that transmit and receive data. In [35] identity-committable signatures and partially blind signatures, which are cryptographic methods, are used for an IDR program which enables the utility to compute individual DR participation and rewards while preserving consumer privacy, as well as saving that data and allowing it to be accessible later on in case of legal disputes or any other reason that would require access to the data. An investigation of a new set of privacy threats focusing on financial rationality versus inconvenience is performed in [50], along with the design of a privacy protection protocol based on attributed-based encryptions, where two privacy leakage models are formulated: a Benefit Inconvenience Evaluation where the financial benefit resulting from appliance scheduling is compared with the inconvenience that it causes, and a Rationality Inconvenience Ratio where the customers rationality for rescheduling appliances is compared with their discomfort at every time instance. Signal perturbation along with encoding and decoding to quantify a privacy utility trade off region is used in [69]. A rate distortion leakage trade off is found by proposing a general theoretical framework that brings most current treatments of the privacy utility trade off into a single model, and the spectrum of abstract privacy-utility choices is looked at and maximal points on the trade off curve are found.

A battery is a potential tool in protecting smart meter privacy as it can move energy from one time slot to another. A stochastic energy system of a house with a battery is proposed in [76]. The battery is represented by a finite state model and used for information leakage reduction. DR programs is proposed by using a battery for rate distortion and perturbation [82].

Appliance scheduling and elastic demand allows users to move their appliance start times around to hide their energy usage. An online control algorithm that determines the observed load profile by solving an optimization problem with unobservable parameters is proposed in [81], and the original load profiles cannot be recovered, therefore it is considered safe from precise load change recover attacks. A Monte-Carlo simulation based approach is proposed in [21] to jointly optimize the cost of electricity and privacy. A wallet-friendly privacy protection approach is proposed in [46] using stochastic dynamic programming.

Several different papers have attempted to use PV or renewable energy sources in general to help protect the users privacy [11, 34, 74, 45]. This is done by using solar and weather forecasts along with the expected load profile of a household to schedule the demand accordingly. In [11], PV panels are used alongside a battery demand to schedule appliances in order to minimize privacy infringements, two methods are designed, one which tries to maximize the profits of the house by exploiting day ahead prices, elastic demand, and the battery. The other method obfuscates the smart meter readings before sending them to the utility company, while maintaining the validity of those values for billing purposes. A stochastic alternative energy source is utilized in [34] instead of a battery for hiding the energy consumption profile, the alternative energy source could be a PV system or another utility provider. A combination of an alternative energy source, a battery, and an energy harvesting device is used in [74] for increasing smart meter privacy. The system is presented as a finite state model and shows a trade off between reducing information leakage and wasted energy rate. Electrical routing through a combination of rechargeable batteries and alternate power sources along with a power mixing algorithm is proposed in [45] to moderate the effects of NILM algorithms, the protection level is evaluated by measuring relative entropy and correlation.

An online control algorithm with low computational complexity that protects smart meter data privacy along with reducing the cost of electricity is proposed in [80], which is achieved by using energy storage devices along with elastic demand for appliance scheduling. A dynamic programming framework is used with realistic battery constraints to protect smart meter data privacy in a cost effective manner. There have been several works trying to increase privacy by creating doubt in the data, and giving it less meaningful values by adding noise or perturbing data between the sources [13, 69, 66, 83, 28]. Random noise sampled from a uniform distribution is added to the meter data in [13], and the impact on privacy and billing is investigated. Partial information hiding by introducing uncertainty about individual values in a time series set by using noise addition perturbation is proposed in [66], which makes averaging to attempt to recover the data useless as the uncertainty cannot be eliminated. A BLH method is proposed in [83, 28]. In [83], differential privacy is achieved by randomizing the BLH method which adaptively updates the algorithm based on the context and constraints. Ref. [28] shows that a load based load hiding (LLH) can achieve the same results as a BLH method by controlling a thermostatically controlled load, i.e., water heater to add random noise in order to perturb the data.

A third party escrow service, along with randomized time intervals for data collection is proposed in [27] to keep track of attributable and anonymous load data profiles. A neighborhood level aggregation privacy-enhancing design along with cryptographic methods is suggested in [51] for smart meter data communication. An Artificial Neural Network (ANN) using Kohonen Self Organizing Maps [26], along with cryptographic methods was proposed in [64] to hide appliance usage.

# Chapter 3

# Modeling Methodology

This chapter covers the model construction for the different problems: the fault localization problem, and the power scheduling problem. These problems were selected to find a way to solve by maximizing the utility while minimizing the privacy infringement on the customers from the collected data.

## 3.1 Fault Localization

Fault localization here refers to finding a fault on a simple radial distribution system such as in Fig. 3.1. As seen in the figure, if a fault were to occur on bus 11, it would cause a loss of power for all the homes on buses 11-15, and likewise, a fault on bus 3 would cause a loss of power for all the homes to the right of it, while keeping the power intact for the homes on buses 1 and 2. Using this kind of simple radial distribution system, this section will find a way to detect the location of a fault quickly without needing people to call in and report their power out to their utility company, and it will do that in a way that will require the least amount of data collection so it limits revealing other home energy use characteristics.

Current existing fault localization techniques for distribution systems do a good job of finding the location of faults in a timely manner [47, 71, 79, 70]. However, these techniques are not designed with privacy protection in mind, and in these systems, the utility has a constant data stream coming from users, which as shown before can leak privacy information of the users. From Table 2.3, it can be seen which privacy issue is affected by how often information

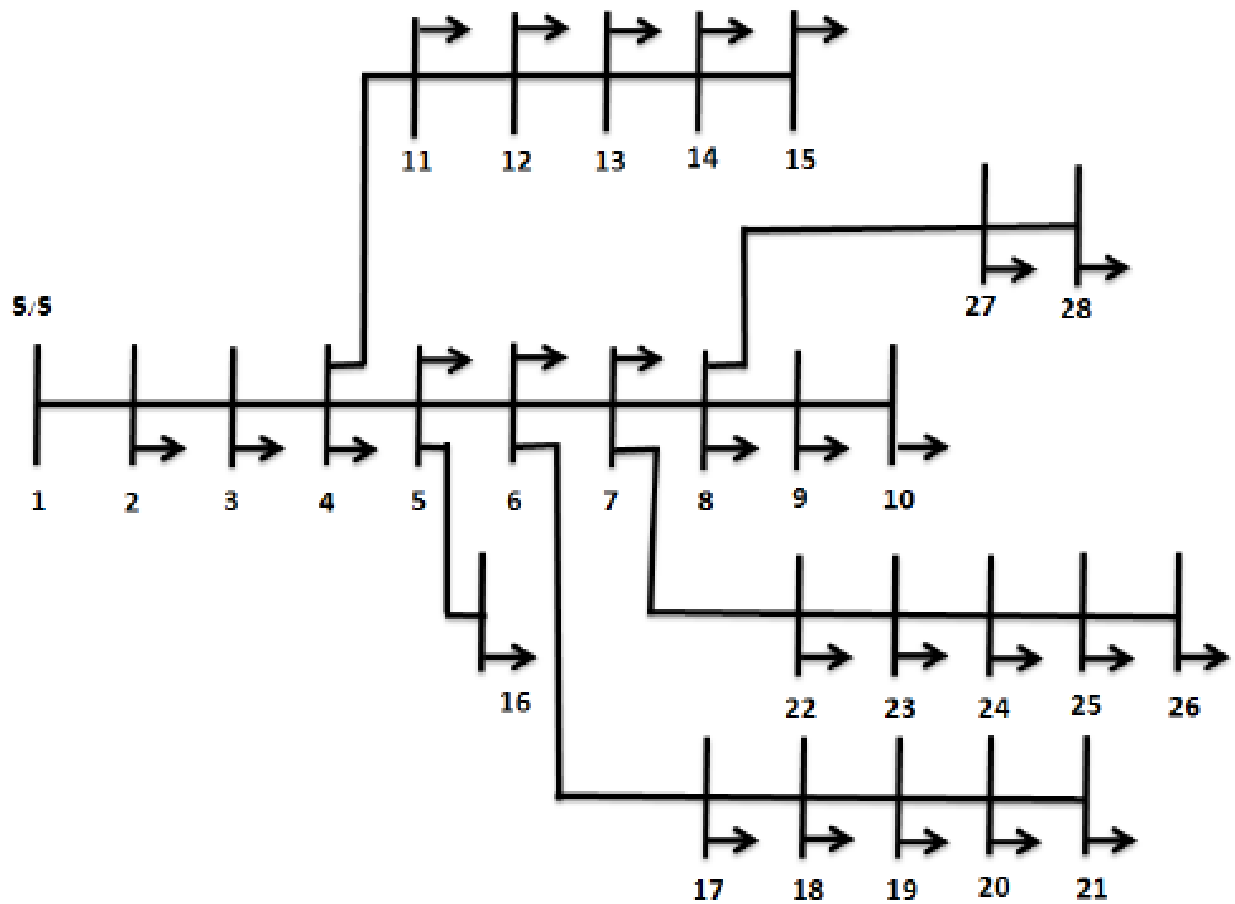


**Figure 3.1:** Simple Radial Distribution System

is sampled, and it shows that for fault localization the more frequent the information is coming in, the faster a fault can be detected. This system is designed to have a high fault detection time while keeping the infringed privacy to a minimum. We will show how that is accomplished based on the ultimate shape of the radial distribution system, along with the number of houses in the system.

A widely accepted definition of privacy in the literature is based on having access to information, where the more information is revealed, the less privacy the entity whose information is revealed has [56, 52, 55]. The proposed fault localization system looks at privacy in an implicit way, or a privacy-by-design method, where it tries to use the least amount of information possible to detect a fault in the quickest time possible. Tt tries to bridge the gap between the two different sides of Table 2.3, where it can achieve the utility of outage detection and fault location, while infringing on the least amount of privacies listed on

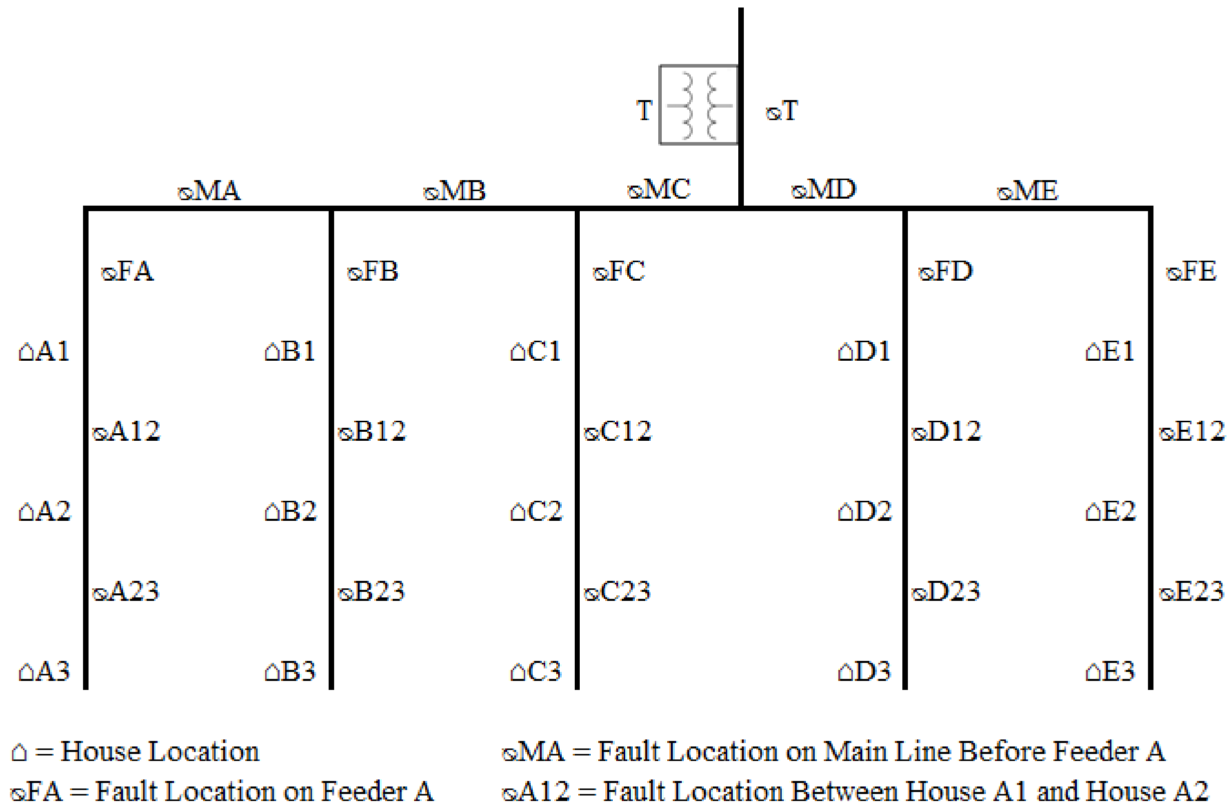


**Figure 3.2:** Radial Distribution System Chosen

the other side of the table. The idea here is to use alarm processing which uses set covering to find the location of the fault when it occurs by sampling each home every $T_s$ that will be chosen to find the fault location quickly but not reveal privacy features of any home. If a neighborhood had $H$ homes, than there will be another variable that is determined according to Equation 3.1

$$T_h = \frac{H}{T_s} \tag{3.1}$$

From Equation 3.1 $T_h$ is the frequency at which data is received into the fault localizer, and the bigger $H$ is, the higher that frequency, the faster a fault can be detected. Thus, a fault on a radial distribution system with 25 homes can be detected faster than one with 15.

**Table 3.1:** Data for Radial Distribution System shown in Fig. 3.2

| | | FAULT LOCATION | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | M | | | | | F | | | | | A | | B | | C | | D | | E | | Sum | Order |
| | | T | A | B | C | D | E | A | B | C | D | E | 12 | 23 | 12 | 23 | 12 | 23 | 12 | 23 | 12 | 23 | | |
| HOUSES | A1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 16 | 7 |
| | A2 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 15 | 12 |
| | A3 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 14 | 15 |
| | B1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 17 | 3 |
| | B2 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 16 | 8 |
| | B3 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 15 | 13 |
| | C1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 18 | 1 |
| | C2 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 17 | 4 |
| | C3 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 16 | 9 |
| | D1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 18 | 2 |
| | D2 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 17 | 5 |
| | D3 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 16 | 10 |
| | E1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 17 | 6 |
| | E2 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 16 | 11 |
| | E3 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 15 | 14 |

The radial distribution which the fault localization is designed for is shown in Figure 3.2. The accompanying data with which can be used mathematically in the alarm processing system is shown in Table 3.1. If a fault occurs at the transformer $T$ all houses lose power, and if a fault occurs at $\phi FC$ then all the houses on feeder C lose their power, and so on. The order of sampling of the houses is determined by taking the summation of all the rows shown in Table 3.1 and then starting with the highest sum until it gets to the lowest sum (if two have the same sum, any random order is taken) and then repeating the process after all houses are sampled. The order is also shown in the table here.

$$\begin{aligned} & minimize \\ & z = c^T x \\ & w.r.t. \\ & A_{eq} x = b_{eq} \\ & 0 \leq x \leq 1 \\ & x = \text{integer} \end{aligned} \tag{3.2}$$

When a new data point arrives, the first consideration is whether the reading shows that the house has power or no power. If it does have power, then the program continues running normally and waiting for the next sample. If it shows no power, then the program runs a linear program as shown in 3.2 where the $A$ and $b$ matrices from Equation 3.2 start increasing in size, with each data point. The $A$ matrix adds a new row depending on which house was just sampled. From Table 3.1, if house $A1$ was sampled, then the first row of data in the table is appended to the $A$ matrix, and the $b$ matrix gets appended by a 0 or 1 depending on if the house sampled has power or not. This process keeps getting repeated until the fault is located. The process is shown in the flowchart in Figure 3.3. The utility company will then be able to dispatch repair crews. This process could happen very quickly, especially in the more populated areas and utilities will no longer have to rely on people reporting outages by calling them in. For alarm processing, there is no real value for the objective function to minimize or maximize so it is not an important part of the linear program thus $c = 1$.

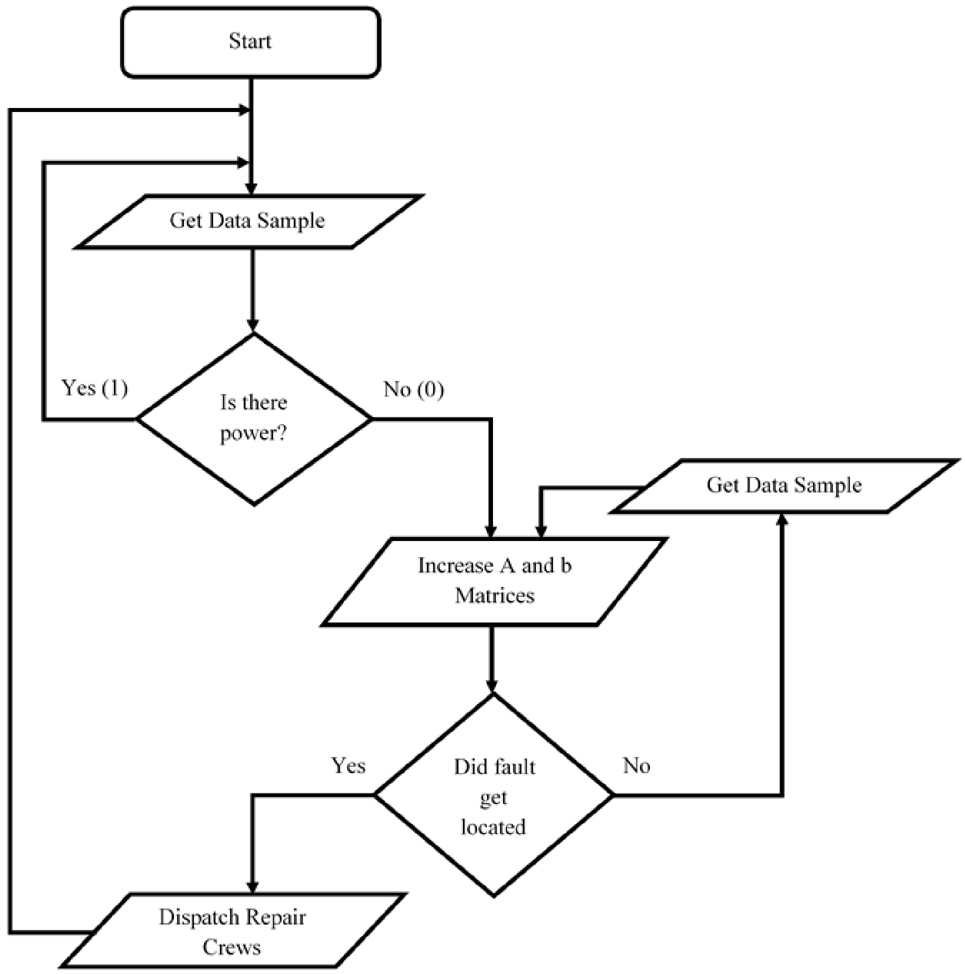


**Figure 3.3:** Flowchart with Fault Localization Process

## 3.2 Power Scheduling

Power scheduling refers to solving the mixed integer linear program problem to schedule appliances, solar power, and the battery to try and mask the power usage from the utility by modifying the expected load profile so the data seen by utility is not useful for detecting characteristics of the home while still being valid for retail billing. A widely accepted definition of privacy in a smart meter setting is yet to be agreed upon, but an accepted suggested definition when it comes to power scheduling is when it is not possible to distinguish specific appliance loads from the total power consumption [45]. Using this perspective, a very high degree of privacy can be achieved by keeping the load profile a constant flat value as seen in [73]. However, this can be difficult to and inconvenient and not practically viable

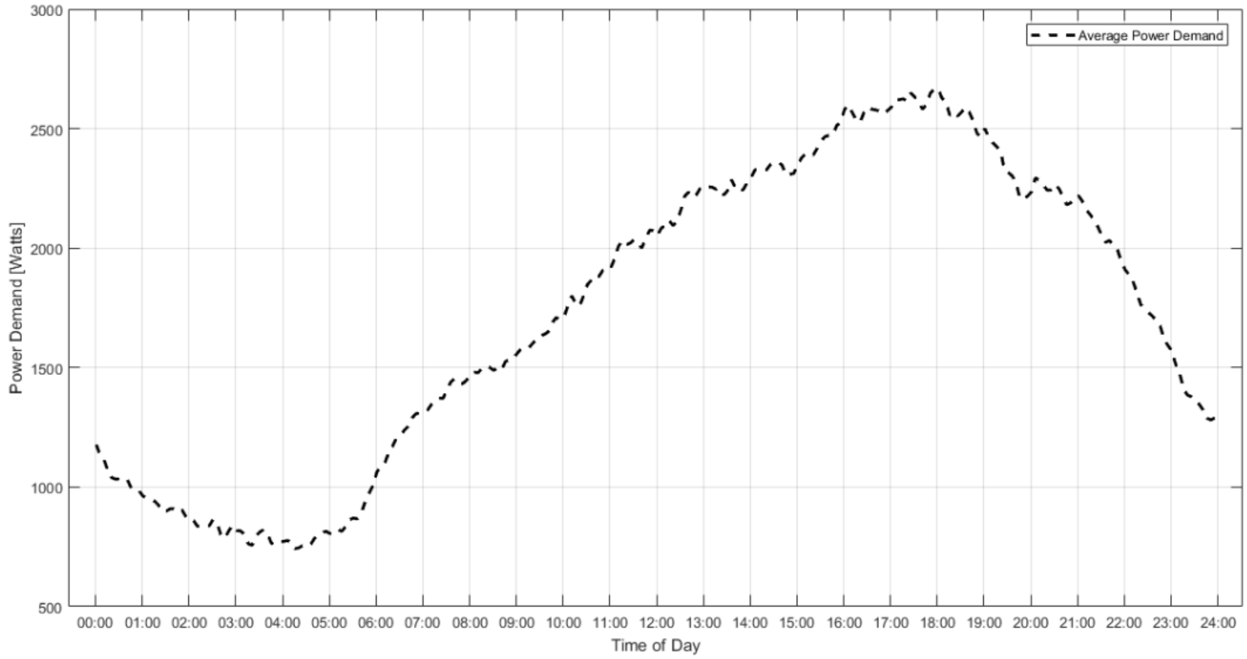


**Figure 3.4:** Average Load Profile

to keep a constant load profile due to real consumption patterns, realistic appliance, solar, and battery parameters.

It is shown in [32] and [31] that using a more general and flexible target load profile, and jointly minimizing the cost of energy along with the deviation between the smart meter reading and the targeted load profile is an acceptable measure of privacy. It can also be seen in [76, 74, 33] that a user's energy consumption profile is defined as a randomly generated time series data and the information leakage is measured by comparing that profile to the average mutual information and the deviation from that average is defined as the information leakage rate. Minimizing that mutual information leakage can be interpreted as a way of improving privacy for smart meter users. Mutual information leakage, or deviation from a defined average, has also been considered in the computational field, [57], and the computer security field [19].

This model will achieve privacy by scheduling appliances, solar power, and a battery to minimize the deviation from the average load profile shown in Figure 3.4, this notion of privacy is proven to be and adequate measure of privacy and follows from [31, 32]. The contribution of this thesis is designing the power scheduling technique which uses mixed integer linear programming to achieve this feature. The idea here is that the user will be able to select the desired privacy vs. cost savings assuming a dynamic time of day pricing model. If the user cares more about savings on their energy bill, they would schedule their appliances to run at night, when the price of electricity is the cheapest, and if they cared more about hiding their privacy, it would schedule the power in a way that would make the load profile not reveal very much to the load serving entity that receives the smart meter data.

The power scheduling problem is solved by formulating it as a mixed binary-integer linear programming problem, the binary variables for each component is the on/off state in that time period. Equation 3.3 shows how the problem will be broadly formulated. The detailed problem formulation will be shown at the end of the section in Equation 3.13 after all the components of the model are introduced.

$$
\begin{aligned}
&\min .c^T x \\
&w.r.t. \\
&A_{eq} x = b_{eq} \\
&Ax \leq b \\
&0 \leq x \leq 1 \\
&x = \text{integer}
\end{aligned}
\tag{3.3}
$$

### 3.2.1 Appliances

Appliance scheduling is a major part of the scheduling problem as they are the among the largest power consumers in the household (washer, dryer, dishwasher, etc...) and the nature of their usage allows shifting to later times. In addition, their use is generally required non time essential, e.g., a dishwasher can be programmed to run at 2:00 AM instead of 6:00 PM and help cut the cost of running it in half while helping to mask the privacy of its usage.

$$
\begin{aligned}
U &= \mu_1, \mu_2, \mu_3 ... \mu_{|U|} \\
K &= k_1, k_2, k_3 ... k_{|K|}
\end{aligned}
\tag{3.4}
$$

Equation 3.4 shows that for every time slot appliance $\mu_i$ there exists a time slot $k$. Equation 3.5 shows that variable $t_i^k$ refers to whether appliance $\mu_i$ is on or off at that time period. Equation 3.6 ensures that once an appliance remains on throughout its scheduled runtime and does not get scheduled randomly. Equation 3.7 shows that variable $\delta$ is used as a binary variable to select the appliance starting time and whether the appliance is used that day. Finally, 3.8 shows whether the appliance starts at a certain time or not as well as ensuring that the appliance runtime is concurrent.

$$t_i^k = \begin{cases} 1 & \text{if appliance } \mu_\text{i} \text{ is on at time slot } k \\ 0 & \text{otherwise} \end{cases} \tag{3.5}$$

$$\sum_{k \in K} t_i^k \leq M(1 - \delta_i^k) - d_i \quad i \in U \tag{3.6}$$

$$\sum_{k \in K} \delta_i^k = \begin{cases} 1 & \text{if appliance } \mu_i \text{ is used that day} \\ 0 & \text{otherwise} \end{cases} \quad i \in U \tag{3.7}$$

$$\delta_i^k = \begin{cases} 1 & \text{if appliance } \mu_\text{i} \text{ starts at time slot } k \\ 0 & \text{otherwise} \end{cases} \tag{3.8}$$

### 3.2.2 Battery

The battery is an essential part of the scheduling problem, as it allows additional capacity of moving energy from one time slot to another one without it being used. It can be used both for preserving privacy as well as saving on costs by charging at night when energy is cheap, or from the extra solar generation that goes unused can then being used during peak expensive times. Equation 3.9 shows that the battery's initial charge is half its capacity and that at the end of the day, the amount charged and discharged ends up the same. Equation 3.10 shows that the minimum charge and discharge rate allowed in the model is to be more than 0 and less than the charge/discharge rate $\beta$. Equation 3.11 ensures that while charging and discharging throughout the day, the battery charge never gets below 0 or above it's capacity.

$$\sum_{k\in K} B^{+}(k) - B^{-}(k) = \frac{B_c}{2} \tag{3.9}$$

$$\begin{aligned} 0 \leq B^{+}(k) \leq \beta \\ 0 \leq B^{-}(k) \leq \beta \end{aligned} \tag{3.10}$$

$$0 \leq \sum_{i=1}^{B_c/\beta} \sum B^{+}(k) - B^{-}(k) \leq B_c \tag{3.11}$$

### 3.2.3 Solar

The solar is included to show that this kind of framework can easily be integrated with renewable energy as well as energy storage. Equation 3.12 shows how the solar power for the system is calculated.

$$P^{s}(k) = s_{\eta} \times s_{kw} \times s_{r}(k) \tag{3.12}$$

### 3.2.4 Complete Scheduling Model

Equation 3.13 shows how the final model is formulated, all the variable explanations can be found in the nomenclature section of the document, this formulation will try to find the best time to turn appliances on/off as well as charge and discharge the battery, and the solar forecast based on solar radiance data to minimize the infringed upon privacy. Equation **??** shows how this function will be evaluated by taking the root mean square error and comparing it to data that has not been run through the model.

$$
\begin{aligned}
&\text{minimize} \\
&z = \sum_{k \in K} \left\{ (1-\alpha) \left( C_p^T(k) \, P(k) \right) + (\alpha) \left| P(k) - \bar{V}(k) \right| \right\} \\
&\text{where} \\
&P(k) = \sum_{k \in K} \left( \sum_{i \in U} \left( P_a^i(k) \right) + P_b(k) + B^+(k) - B^-(k) - P_s(k) \right) \\
&\text{and} \\
&\bar{V}(k) = V^+(k) - V^-(k) \\
&\text{w.r.t.} \\
&\sum_{k \in K} t_i^k \leq M(1 - \delta_i^k) - d_i \quad i \in U \\
&\sum_{k \in K} B^+(k) - B^-(k) = \tfrac{B_c}{2} \\
&0 \leq B^+(k) \leq \beta \\
&0 \leq B^-(k) \leq \beta \\
&0 \leq \sum_{i=1}^{Bc/\beta} \sum_{k \in K} B^+(k) - B^-(k) \leq B_c
\end{aligned}
\tag{3.13}
$$

# Chapter 4

# Results and Conclusions

This chapter shows the result of both frameworks with varying parameters. The results are analyzed and appropriate conclusions are drawn, and a potential direction for future work is outlined.

## 4.1 Fault Localization

The fault localization model was tested on two different radial distribution systems, system 1 and system 2 shown in Figure 4.1 and Figure 4.2 respectively, with the location of homes shown on the busses denoted by a $\triangledown$ and fault locations denoted by a red dot. The accompanying data for the systems is given in Appendix B, in Table B.1 continued in Table B.2, Table B.3 continued in Table B.4, respectively. Table 4.1 and Table 4.2 show the number of iterations it takes on both systems for each fault to be found after testing the framework for all possible fault locations.

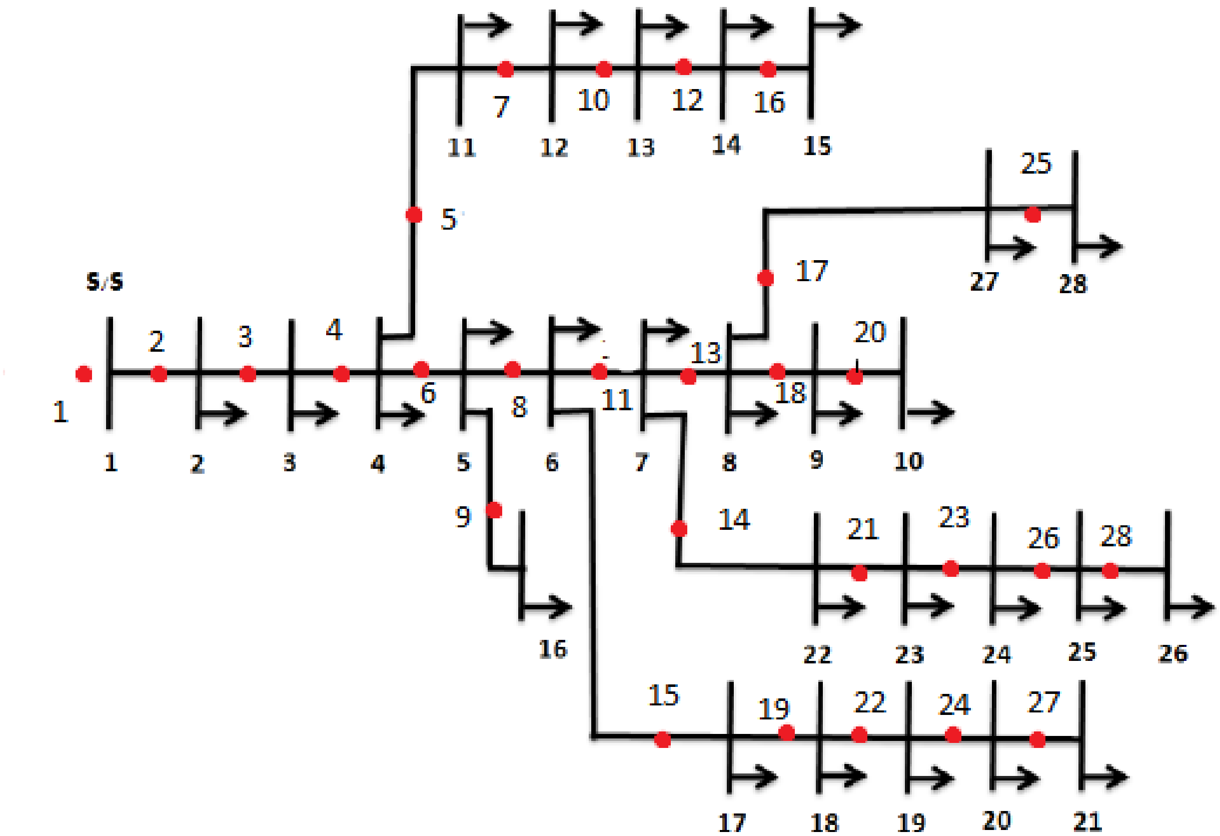


Figure 4.1: Radial System 1 [22]

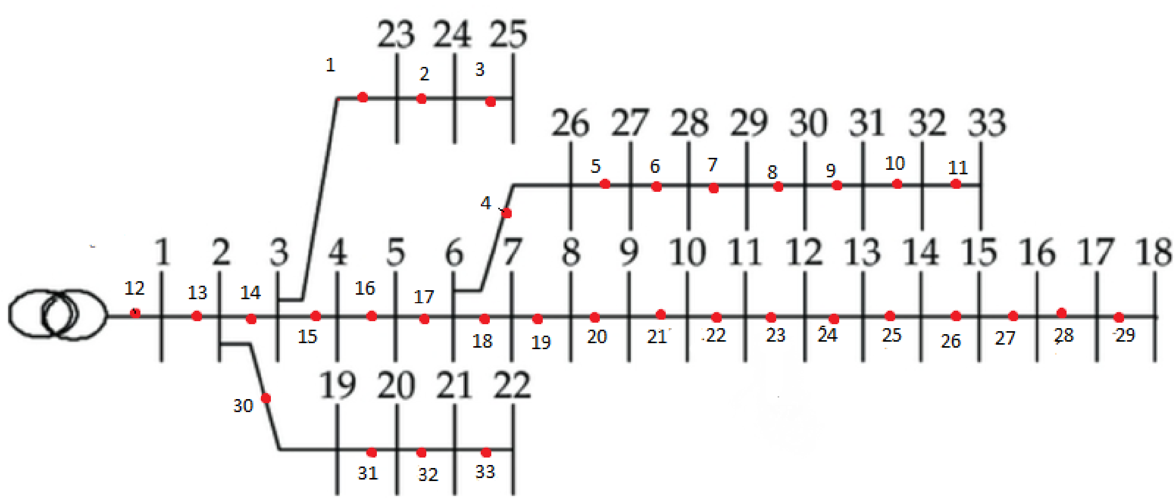


Figure 4.2: Radial System 2 [29]

**Table 4.1:** Iterations Needed to Find Fault Location on System 1

| Fault Location | Iterations | Fault Location | Iterations | Fault Location | Iterations | Fault Location | Iterations |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 8 | 7 | 15 | 12 | 22 | 19 |
| 2 | 2 | 9 | 9 | 16 | 18 | 23 | 24 |
| 3 | 3 | 10 | 11 | 17 | 21 | 24 | 23 |
| 4 | 4 | 11 | 10 | 18 | 17 | 25 | 25 |
| 5 | 6 | 12 | 14 | 19 | 15 | 26 | 27 |
| 6 | 5 | 13 | 13 | 20 | 22 | 27 | 26 |
| 7 | 8 | 14 | 16 | 21 | 20 | 28 | 28 |

**Table 4.2:** Iterations Needed to Find Fault Location on System 2

| Fault Location | Iterations | Fault Location | Iterations | Fault Location | Iterations | Fault Location | Iterations |
|---|---|---|---|---|---|---|---|
| 1 | 6 | 10 | 27 | 18 | 13 | 26 | 30 |
| 2 | 9 | 11 | 5 | 19 | 16 | 27 | 31 |
| 3 | 12 | 12 | 1 | 20 | 18 | 28 | 32 |
| 4 | 15 | 13 | 2 | 21 | 20 | 29 | 33 |
| 5 | 17 | 14 | 3 | 22 | 22 | 30 | 5 |
| 6 | 19 | 15 | 4 | 23 | 24 | 31 | 8 |
| 7 | 21 | 16 | 7 | 24 | 26 | 32 | 11 |
| 8 | 23 | 17 | 10 | 25 | 28 | 33 | 14 |
| 9 | 25 | | | | | | |

Figure 4.3 and Figure 4.4 show for both systems the number of iterations it takes to find each fault given how many possible faults affect each home.

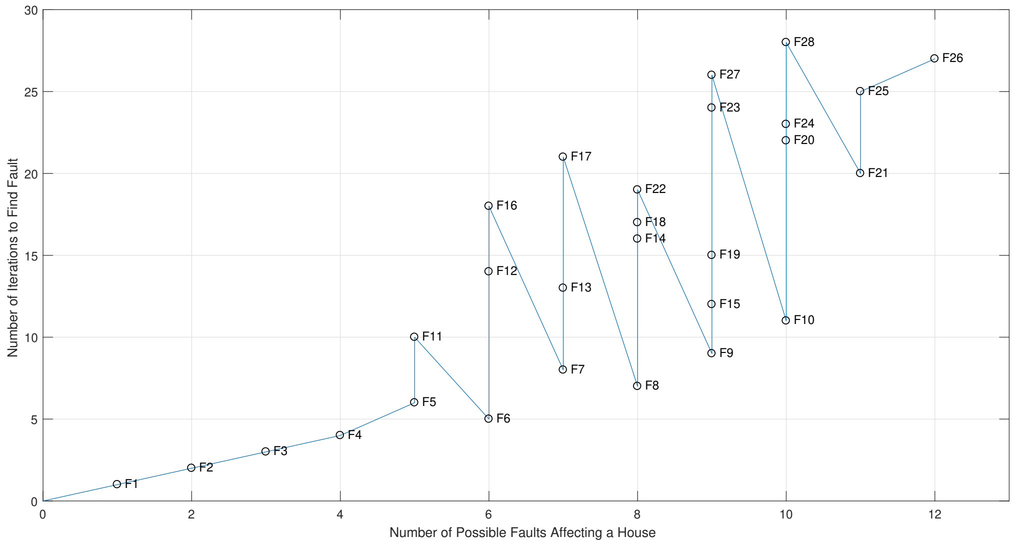


**Figure 4.3:** Number of Iterations Needed to Find Fault Based on How Many Possible Faults Affect a House for System 1

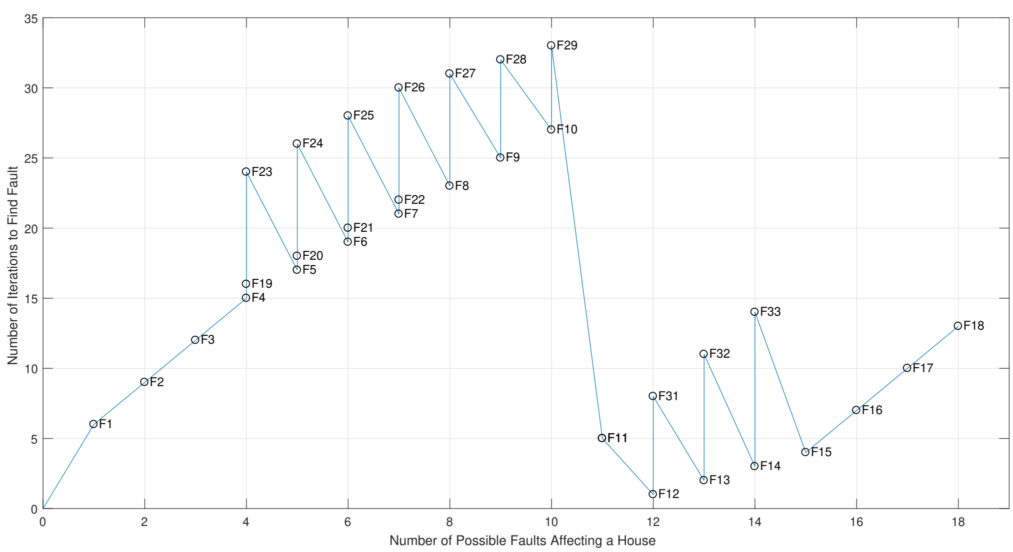


**Figure 4.4:** Number of Iterations Needed to Find Fault Based on How Many Possible Faults Affect a House for System 2

It can be seen from Figure 4.3 that the trend follows that the more possible faults affecting a house, the more iterations it would take to find the fault on that house. In Figure 4.4, it is seen that there are two increasing trends with a cutoff between them, as the overall shape of the radial distribution system along with the number of houses in the system and the number of possible faults affecting each house all have an affect on the number of iterations it will take to locate a fault.

Table 4.3 shows the mean time to find a fault on the system given different sampling rates in a home which is found using 3.1. An acceptable sampling period for both system 1 and 2 could be either 15 min or 30 min, these sampling rates provide adequate fault detection time while keeping the users privacy intact and not revealing too much information about the household. If a 15 min sampling time was chosen, the major appliances such as the washer, dryer, dishwasher, could be detected, but with a 30 min sampling time, only the HVAC and water heater would be detected, which would allow a third party observer to make some inferences about the user but not as many inferences as opposed to a 1, 5, or 15 min sampling time would allow. The in home sampling time, which is divided by the number of homes in the radial system is also a critical to how the sampling can be staggered so as to decrease the time the system gets the samples. The more homes in a system, and the lower sampling time in a home, the faster a fault can be located.

**Table 4.3:** Mean Fault Detection Time Given Different Sampling Rates

| Sampling Rate | Mean Detection Time | |
|---|---|---|
| | System 1 | System 2 |
| 1 min | 31 sec | 29 sec |
| 5 min | 2.6 min | 2.5 min |
| 15 min | 7.7 min | 7.4 min |
| 30 min | 15.5 min | 14.7 min |
| 1 hr | 31.1 min | 29.5 min |
| 2 hr | 62.1 min | 59.2 min |

## 4.2 Power Scheduling

As shown in 3 the Power Scheduling framework will use appliances, solar energy, and a battery to match the average power load, and minimize the deviation from that average in order to better preserve privacy. The selected average load profile used is shown in Figure 3.4. This data is taken from the Dynamic Simulation Tool in [44]. There will be three appliances used and their parameters are outlined in Table 4.4. The solar and battery parameters will be varied for different testing scenarios. The performance of this framework is tested by taking the root mean square of the deviation from the average load profile as shown in Equation 4.1.

$$RMS = \sqrt{\frac{1}{K}\sum_{k\in K}\left(P\left(k\right)-\bar{V}\left(k\right)\right)^{2}} \tag{4.1}$$

**Table 4.4:** Appliances Used in Testing Power Scheduling

| Number | Appliance | Power Demand [watts] | Duration [min] |
|---|---|---|---|
| 1 | Washer | 800 | 40 |
| 2 | Dryer | 3100 | 90 |
| 3 | Dishwasher | 1250 | 120 |

Table 4.5 shows 14 different scenarios where the privacy index $\alpha$, solar system size $S_{kw}$, battery capacity $B_c$, and battery charging/discharging rate $\beta$ were varied to produced different results, the RMS deviation calculated using Equation 4.1 is also shown for different sampling times and the price of electricity is also shown for the different scenarios.

The Figures for the Power Scheduling framework test are included in Appendix A, for each scenario, there are 5 figures: One that shows the smoothed power usage compared to the average load profile showing when the appliances get scheduled, and four that show the power usage compared to the average load profile with different sampling rates of (5 min, 15 min, 30 min, 60 min).

**Table 4.5:** $RMS$ Results for Different Sampling Rates Under Varying System Parameters

| Scenario | $\alpha$ | $S_{kw}$ [kW] | $B_c$ [kW] | $\beta$ [kW/hr] | Sampling Time $RMS$ | | | | | Price of Electricity [$] |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | 5 min | 15 min | 30 min | 60 min | 120 min | |
| 1 | 1 | 5 | 5 | 0.5 | 509.39 | 136.79 | 50.77 | 17.43 | 6.91 | 4.29 |
| 2 | 0 | 5 | 5 | 0.5 | 526.52 | 142.65 | 56.77 | 20.44 | 9.92 | 2.89 |
| 3 | 0.15 | 5 | 5 | 0.5 | 508.81 | 136.32 | 50.78 | 17.27 | 6.80 | 4.22 |
| 4 | 1 | 0 | 0 | 0 | 502.17 | 134.19 | 49.92 | 17.19 | 6.92 | 4.28 |
| 5 | 0 | 0 | 0 | 0 | 490.35 | 127.06 | 47.74 | 15.61 | 7.37 | 3.50 |
| 6 | 1 | 0 | 5 | 0.5 | 509.39 | 136.79 | 50.77 | 17.43 | 6.91 | 4.29 |
| 7 | 1 | 0 | 10 | 1 | 536.01 | 145.47 | 52.90 | 18.13 | 6.91 | 4.29 |
| 8 | 1 | 0 | 15 | 2.5 | 673.55 | 179.56 | 66.53 | 20.09 | 7.78 | 4.33 |
| 9 | 1 | 0 | 50 | 5 | 1109.00 | 320.91 | 94.89 | 32.89 | 6.91 | 4.33 |
| 10 | 0 | 5 | 5 | 1 | 525.05 | 137.99 | 49.26 | 17.14 | 7.09 | 3.17 |
| 11 | 0 | 10 | 5 | 1 | 549.93 | 148.50 | 56.65 | 22.07 | 9.91 | 2.53 |
| 12 | 0 | 15 | 5 | 1 | 584.43 | 162.49 | 65.76 | 27.61 | 12.89 | 1.89 |
| 13 | 1 | 25 | 100 | 10 | 2051.37 | 600.68 | 166.95 | 58.41 | 6.91 | 4.38 |
| 14 | 0 | 25 | 100 | 10 | 2096.63 | 616.12 | 175.47 | 67.46 | 19.85 | 0.24 |

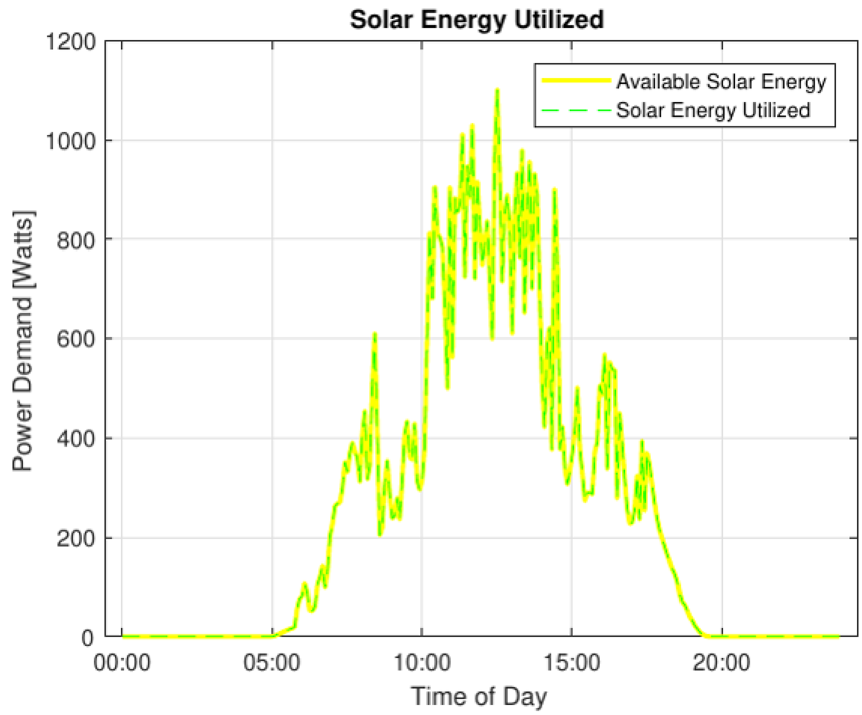


**Figure 4.5:** Solar Utilization for Scenario 1

From looking at Table 4.5, along with the relevant Figures relating to scenario 1 and 2 in Appendix A, the RMS value for the deviation from the average load profile was lower when optimizing for privacy vs. cost savings, and according to the privacy metric used for this framework as mentioned in [31, 32], it does in fact increase the privacy of the user. Figure 4.5, Figure 4.6, and Figure 4.7 show the solar utilization for scenarios 1, 2, and 3 respectively, it can be seen that when optimizing for privacy in scenario 1 Figure 4.5, the model may not even use any of the available solar energy. And when optimizing for cost in scenario 2, Figure 4.6 it will use all the available solar energy, and when choosing an in-between value of [0, 1] for the privacy index in scenario 3, Figure 4.7, the model will utilize some of the solar energy.

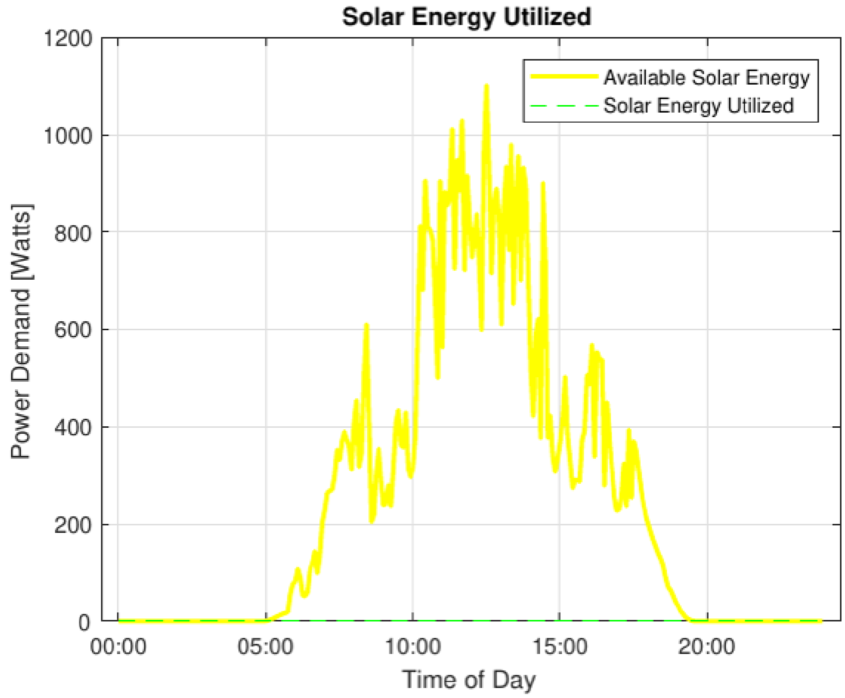


**Figure 4.6:** Solar Utilization for Scenario 2

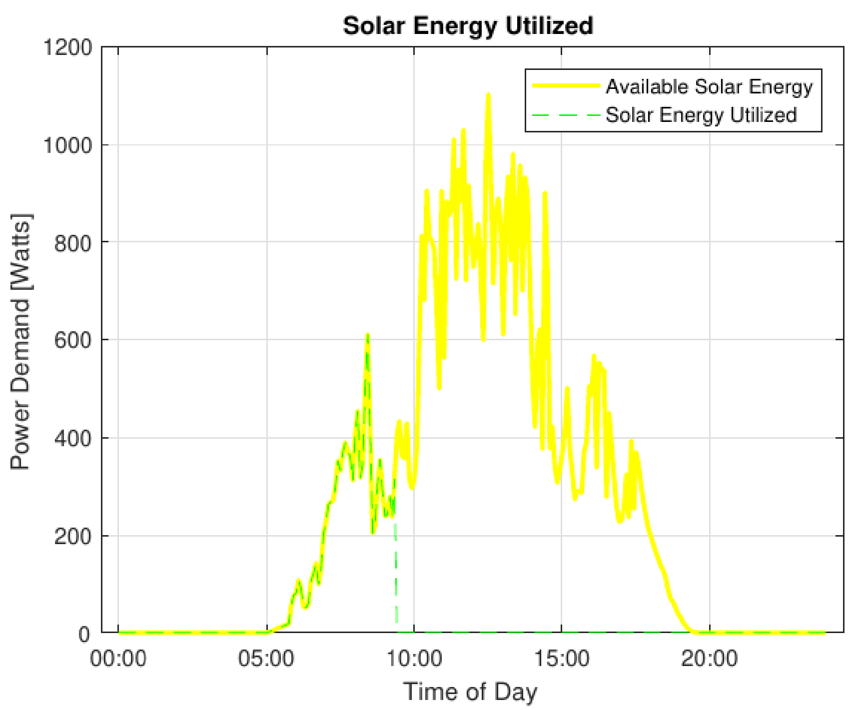


**Figure 4.7:** Solar Utilization for Scenario 3

## 4.3 Future Work

For the fault localization framework, future work could include expanding the table data for a radial system to be able to detect two faults at the same time, along with including an emergency model that would change how the samples are taken based on previous readings. The scheduling system could be expanded to include HVAC and water heater data by using deep learning techniques and using historical data for weather, time of day, day of week, etc. for each home and factoring it into the scheduling problem.

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# Appendices

# A Result Figures

## A.1 Power Scheduling Scenario 1

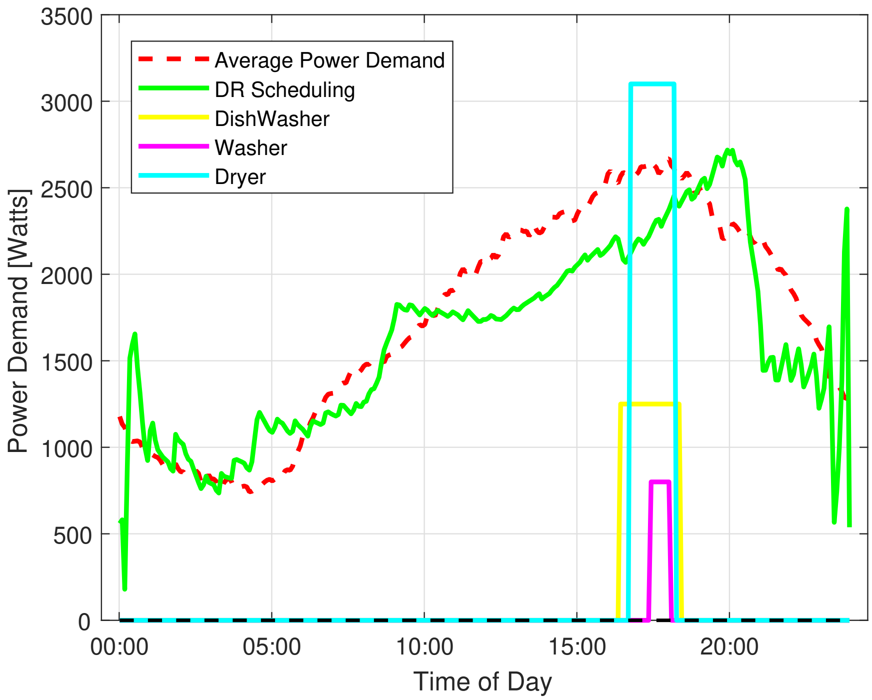



**Figure A.1:** Scenario 1 Appliance Scheduling

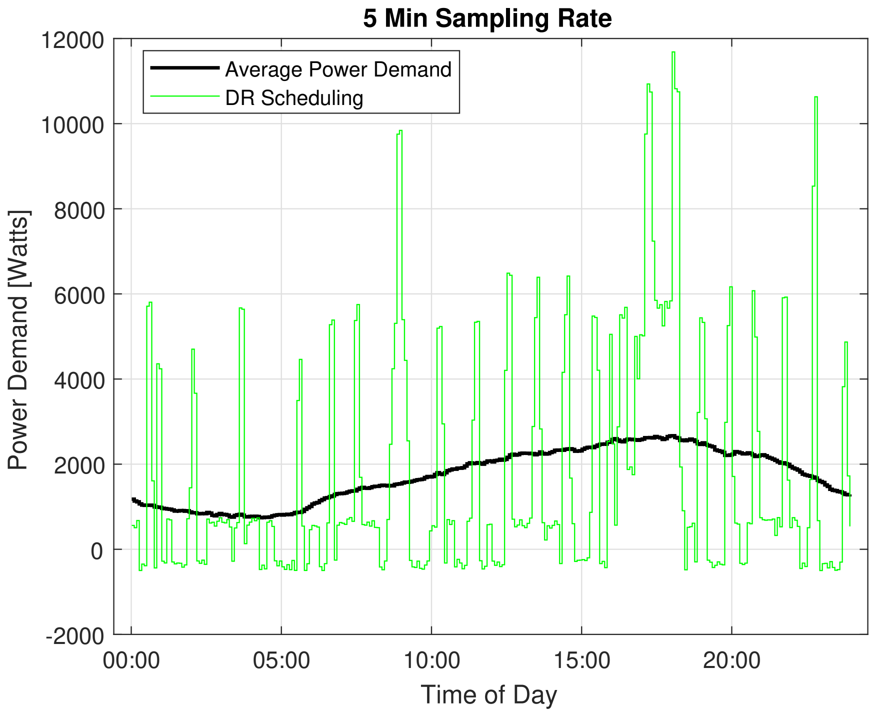



**Figure A.2:** Scenario 1 5 min. Sampling

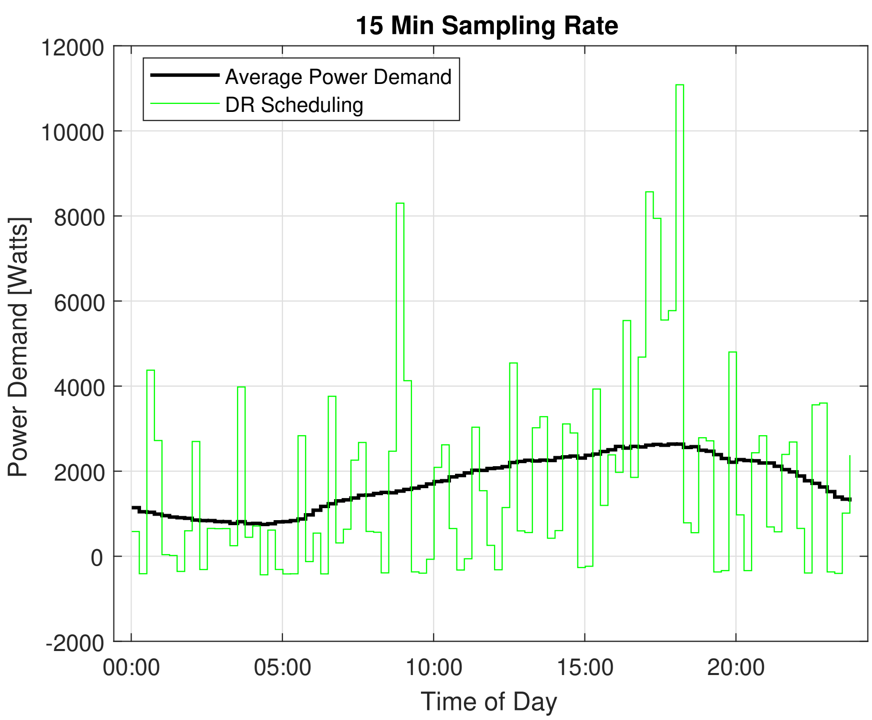



**Figure A.3:** Scenario 1 15 min. Sampling

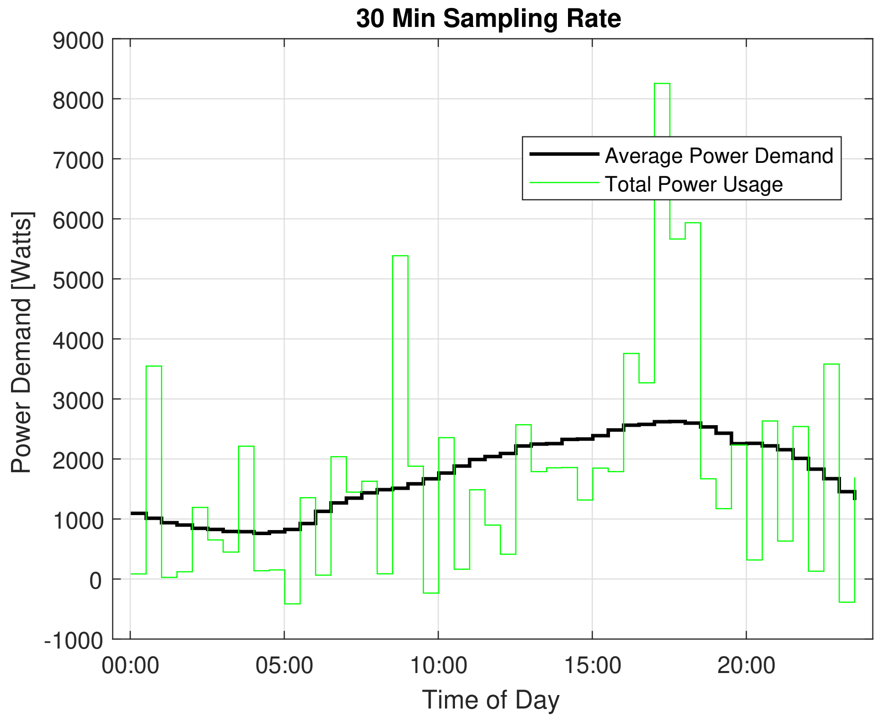



**Figure A.4:** Scenario 1 30 min. Sampling

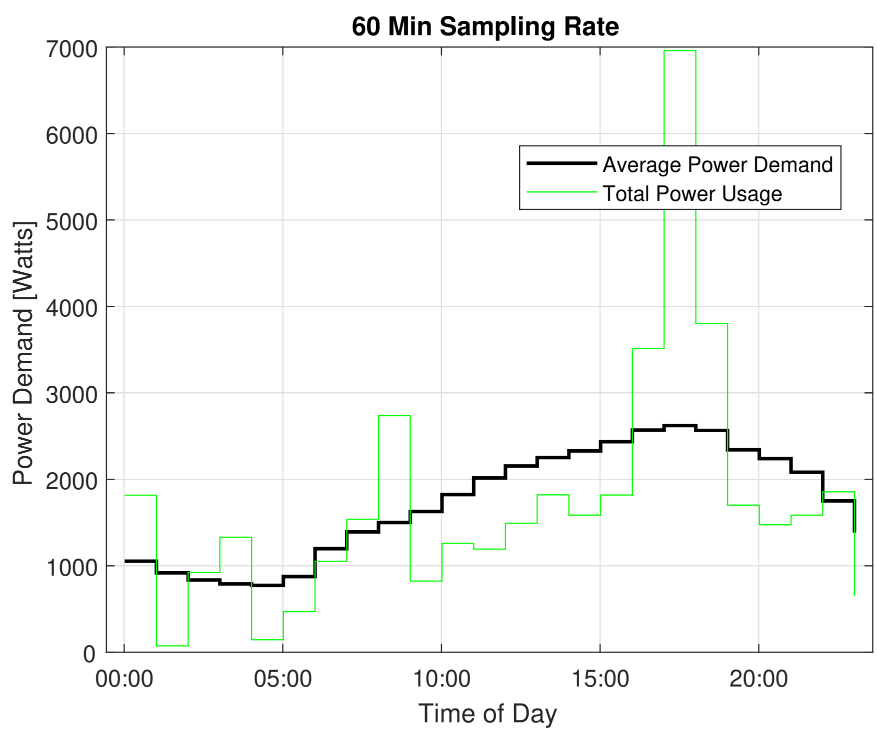



**Figure A.5:** Scenario 1 60 min. Sampling

## A.2 Power Scheduling Scenario 2

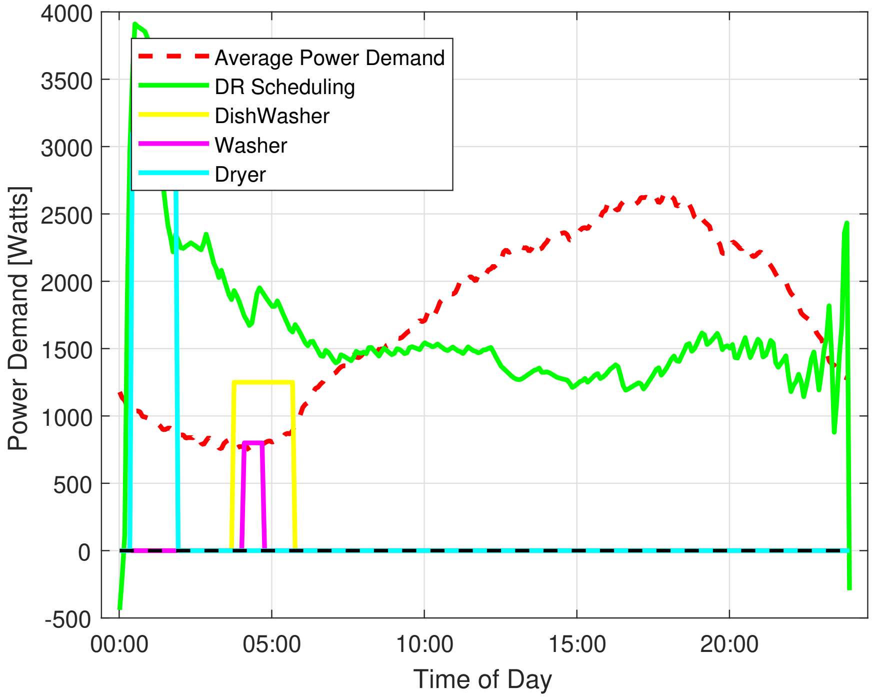



**Figure A.6:** Scenario 2 Appliance Scheduling

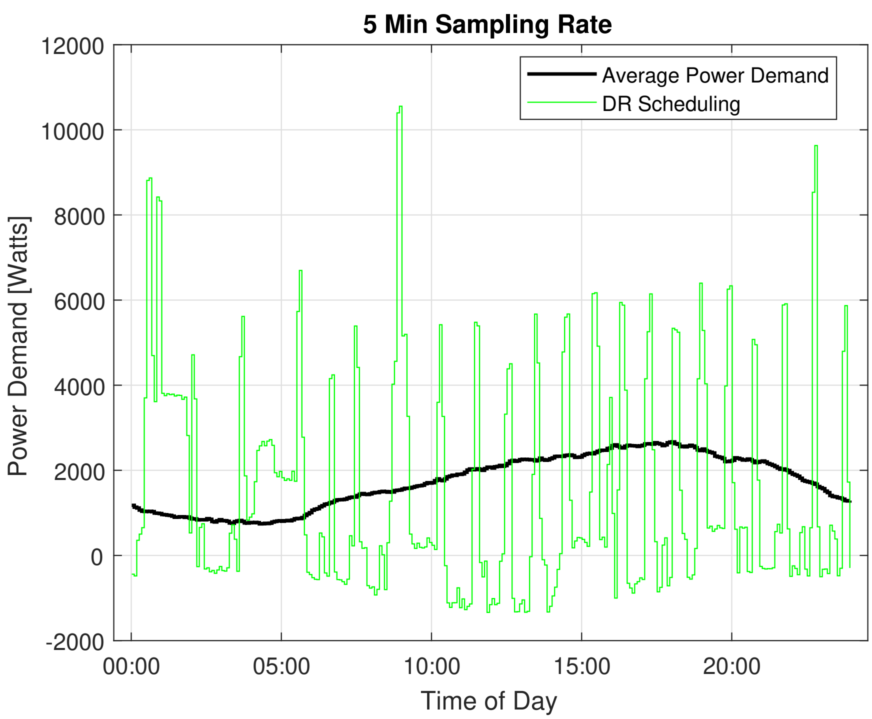



**Figure A.7:** Scenario 2 5 min. Sampling

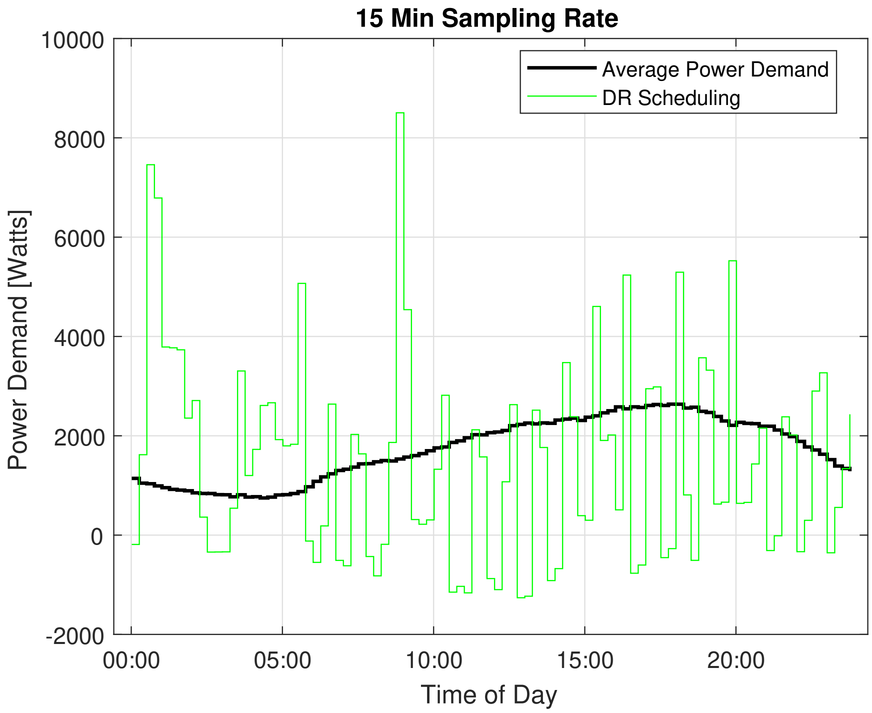



**Figure A.8:** Scenario 2 15 min. Sampling

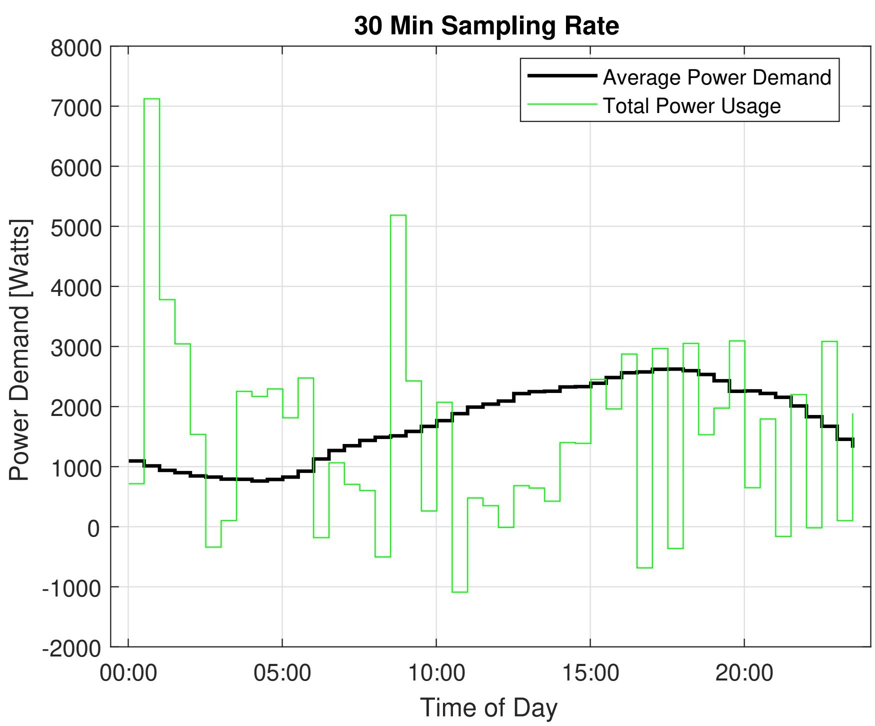



**Figure A.9:** Scenario 2 30 min. Sampling

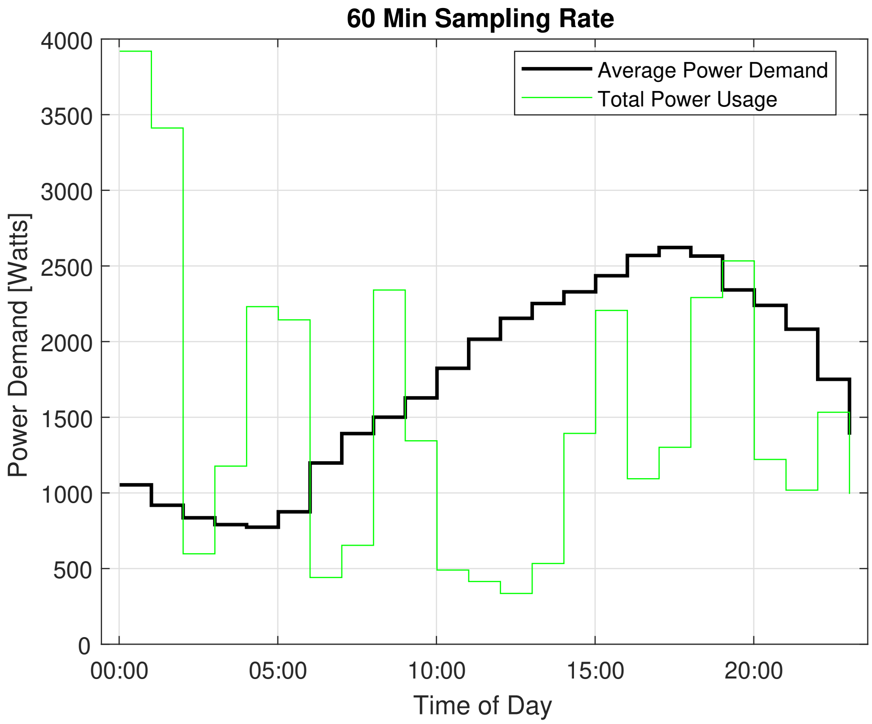



**Figure A.10:** Scenario 2 60 min. Sampling

## A.3 Power Scheduling Scenario 3

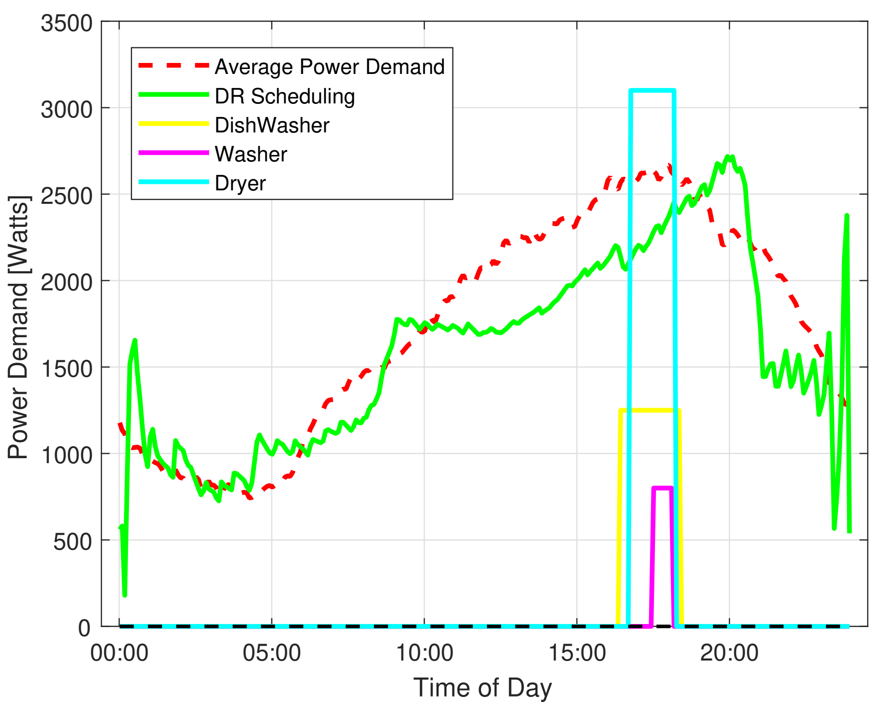



**Figure A.11:** Scenario 3 Appliance Scheduling

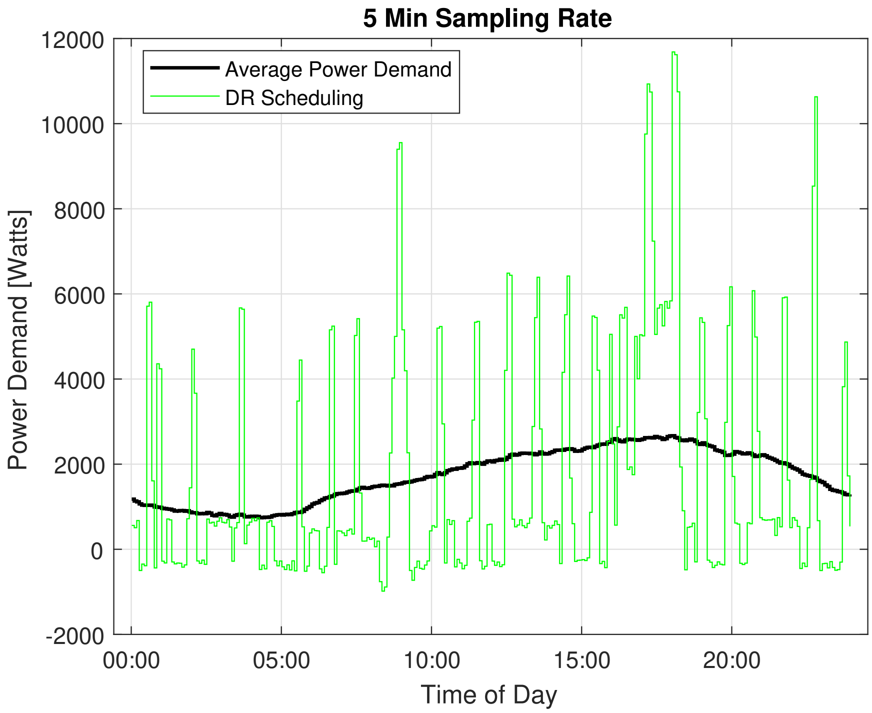



**Figure A.12:** Scenario 3 5 min. Sampling

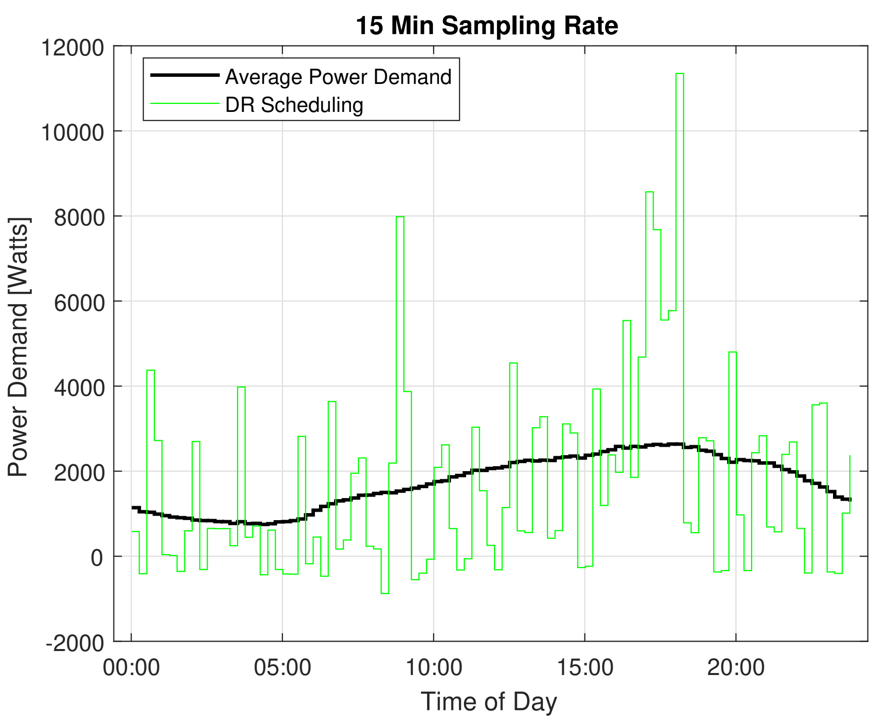



**Figure A.13:** Scenario 3 15 min. Sampling

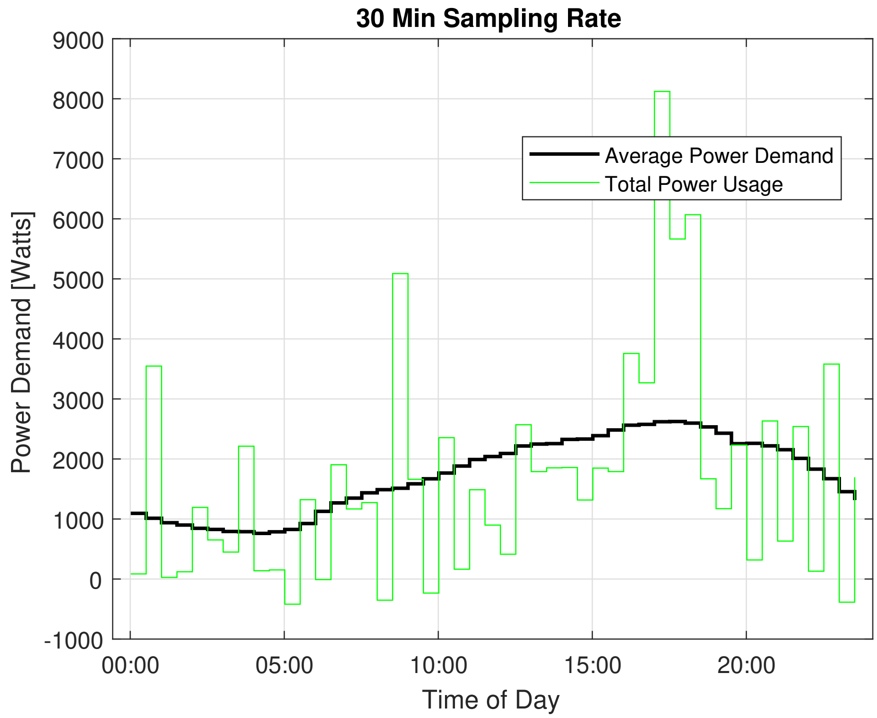



**Figure A.14:** Scenario 3 30 min. Sampling

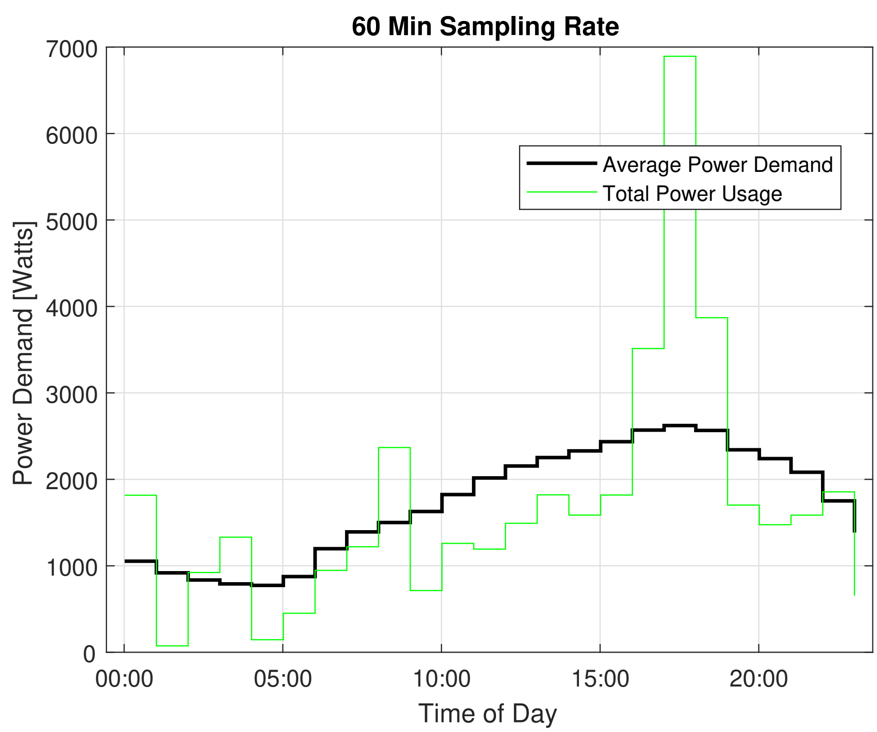



**Figure A.15:** Scenario 3 60 min. Sampling

## A.4 Power Scheduling Scenario 4

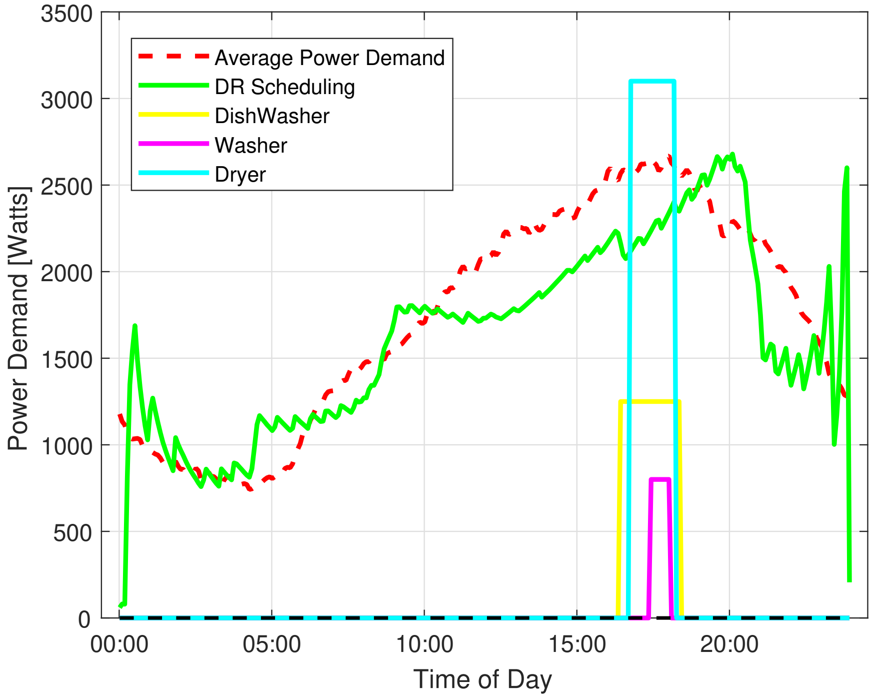



**Figure A.16:** Scenario 4 Appliance Scheduling

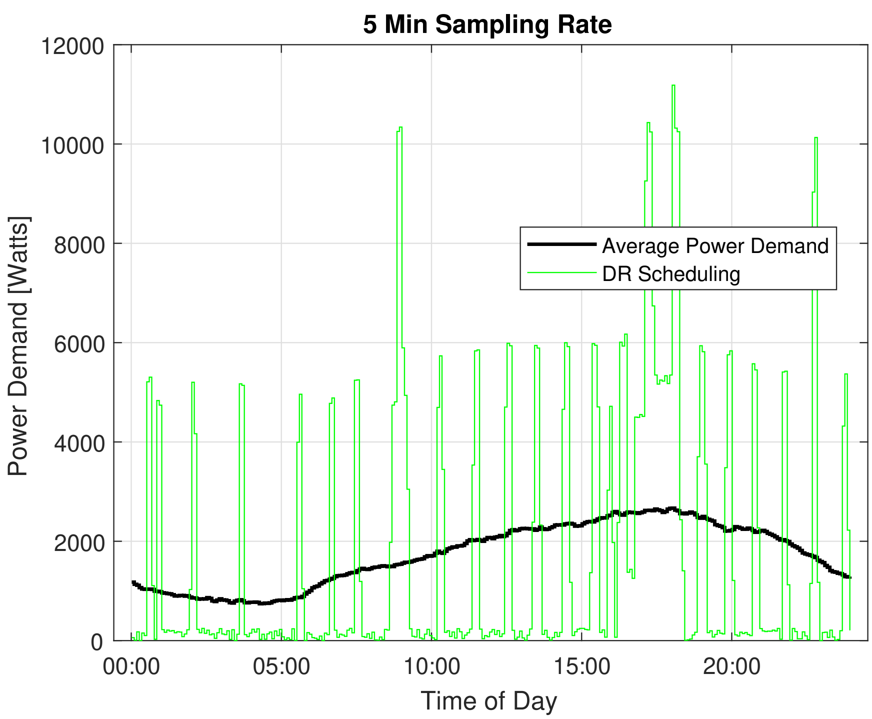



**Figure A.17:** Scenario 4 5 min. Sampling

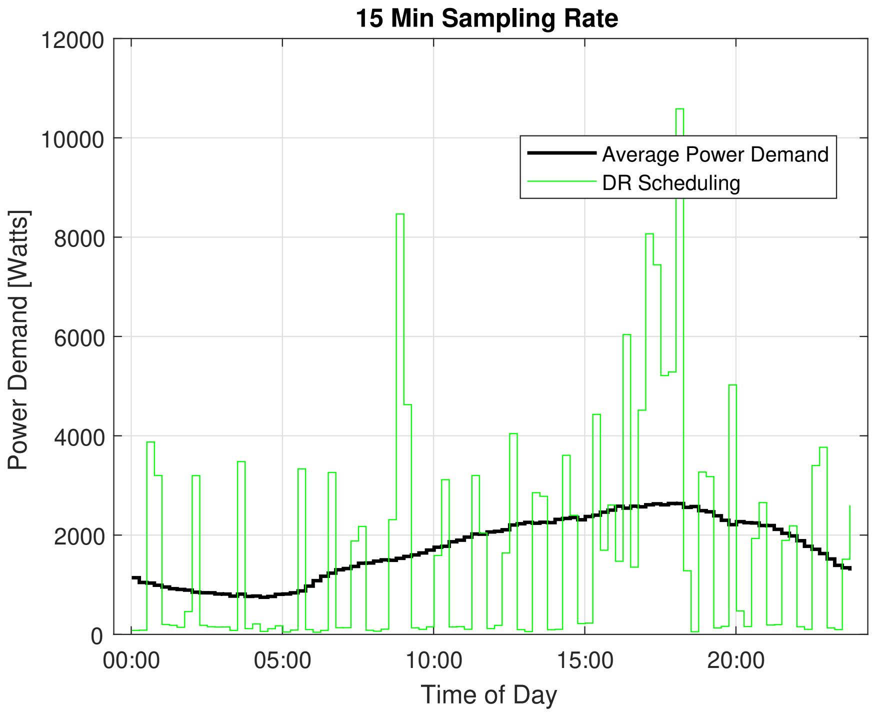



**Figure A.18:** Scenario 4 15 min. Sampling

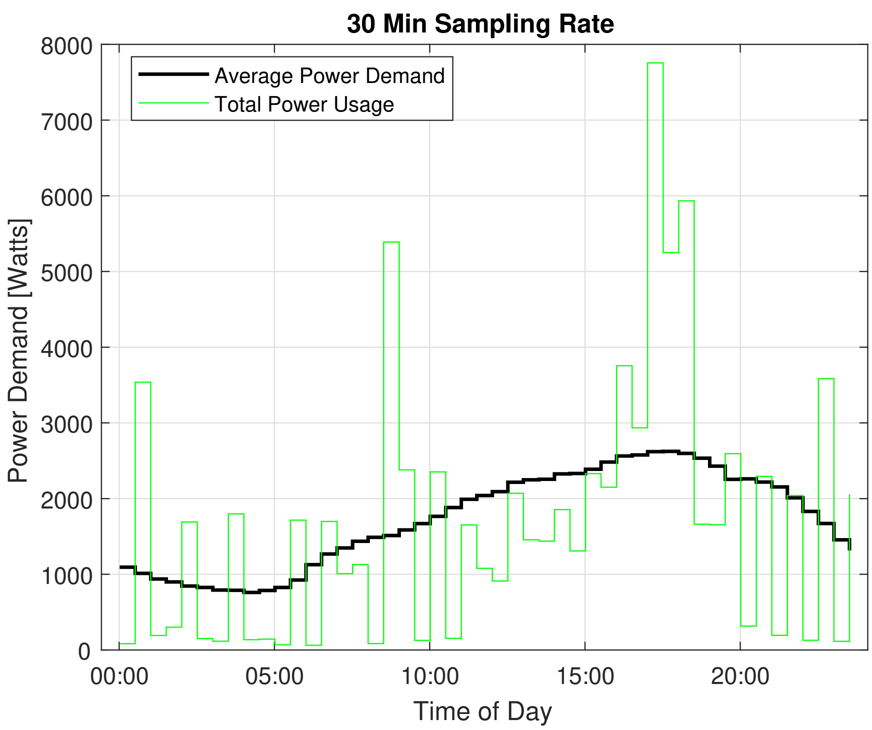



**Figure A.19:** Scenario 4 30 min. Sampling

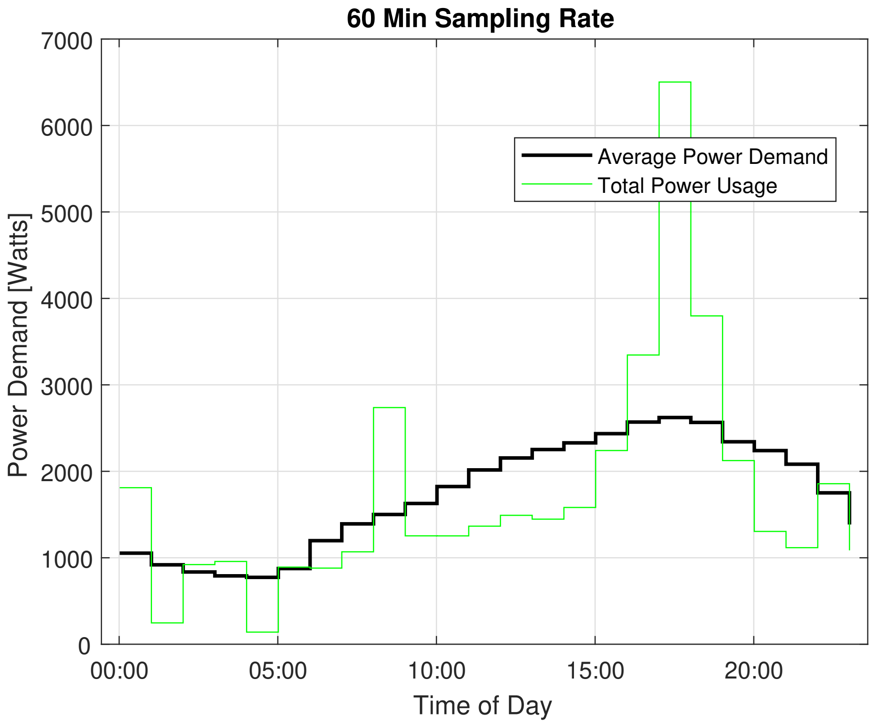



**Figure A.20:** Scenario 4 60 min. Sampling

## A.5 Power Scheduling Scenario 5

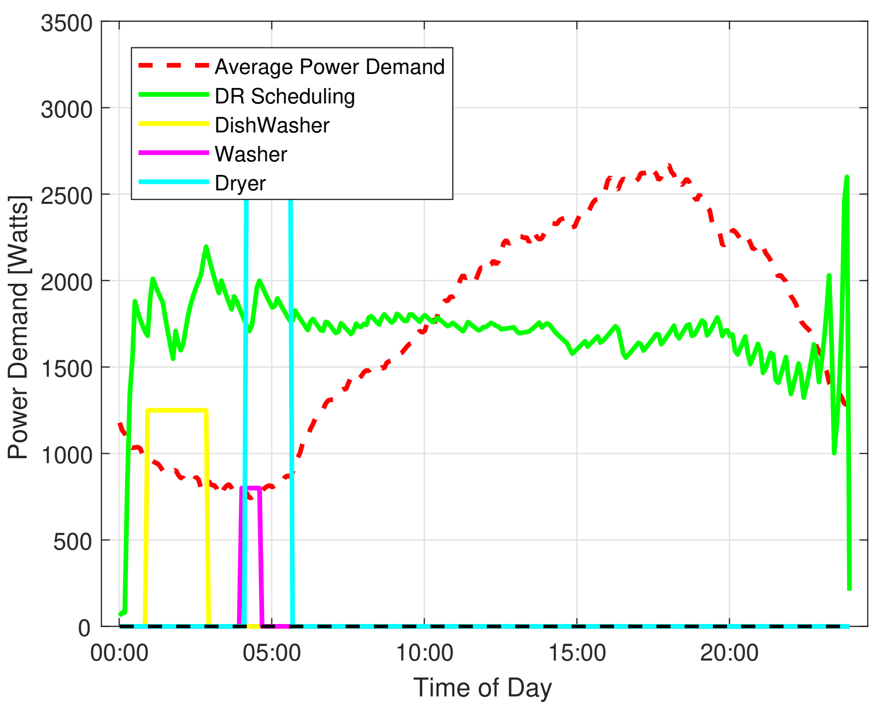



**Figure A.21:** Scenario 5 Appliance Scheduling

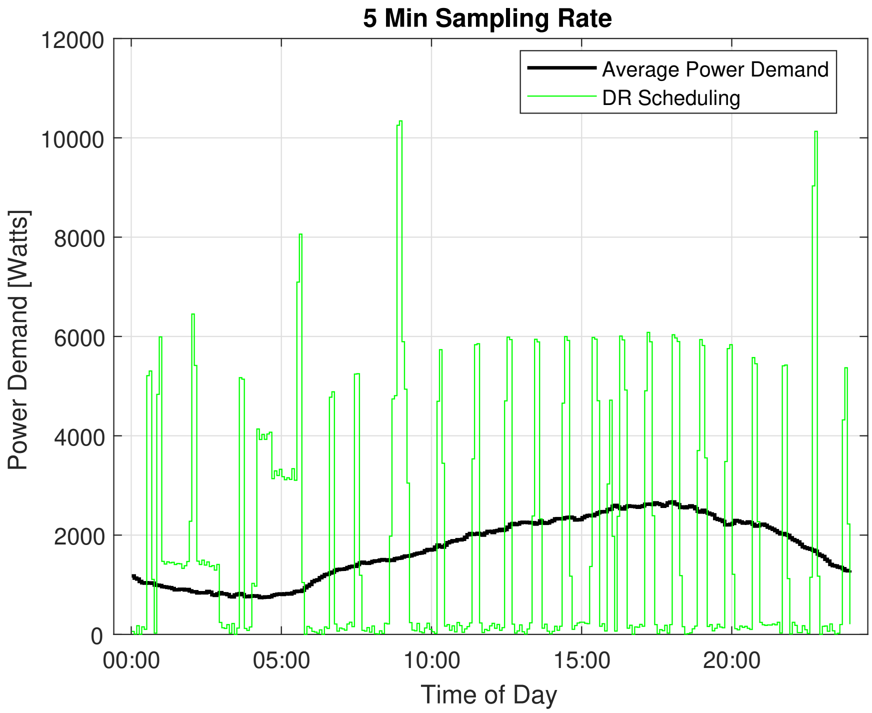



**Figure A.22:** Scenario 5 5 min. Sampling

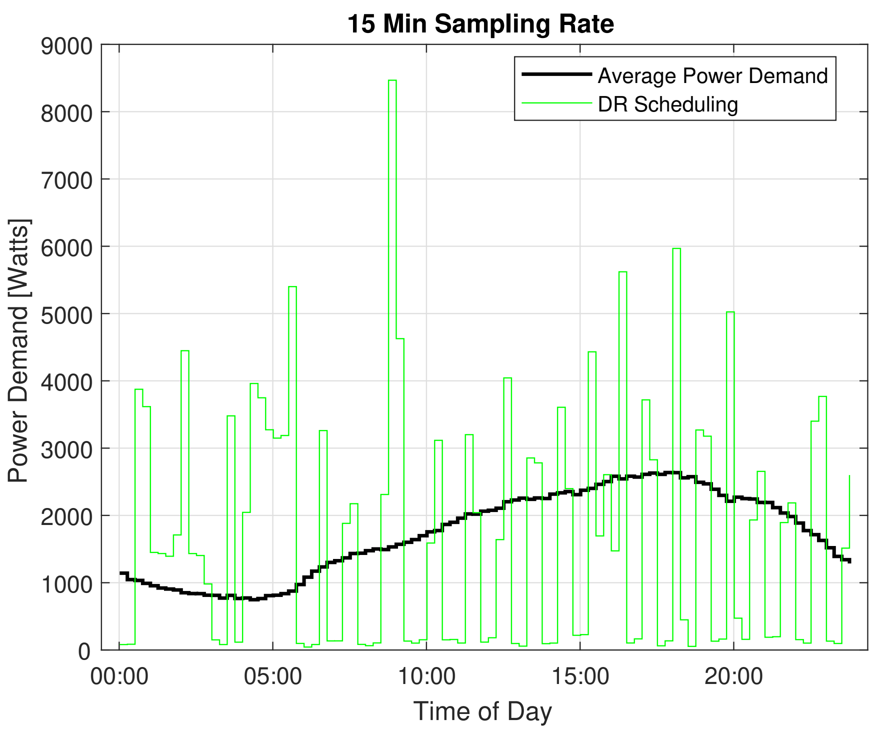



**Figure A.23:** Scenario 5 15 min. Sampling

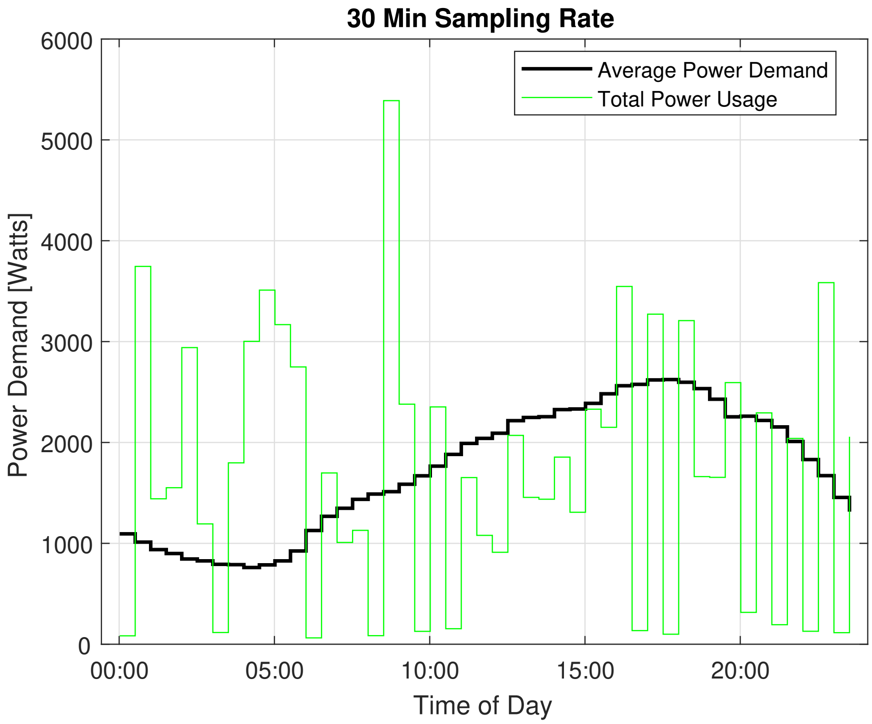



**Figure A.24:** Scenario 5 30 min. Sampling

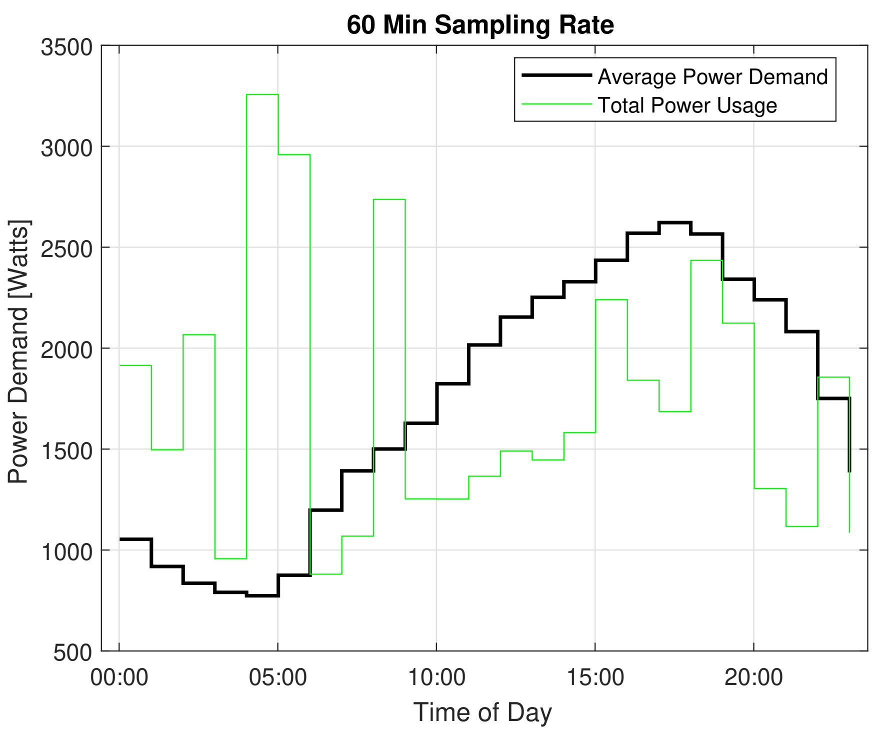



**Figure A.25:** Scenario 5 60 min. Sampling

## A.6 Power Scheduling Scenario 6

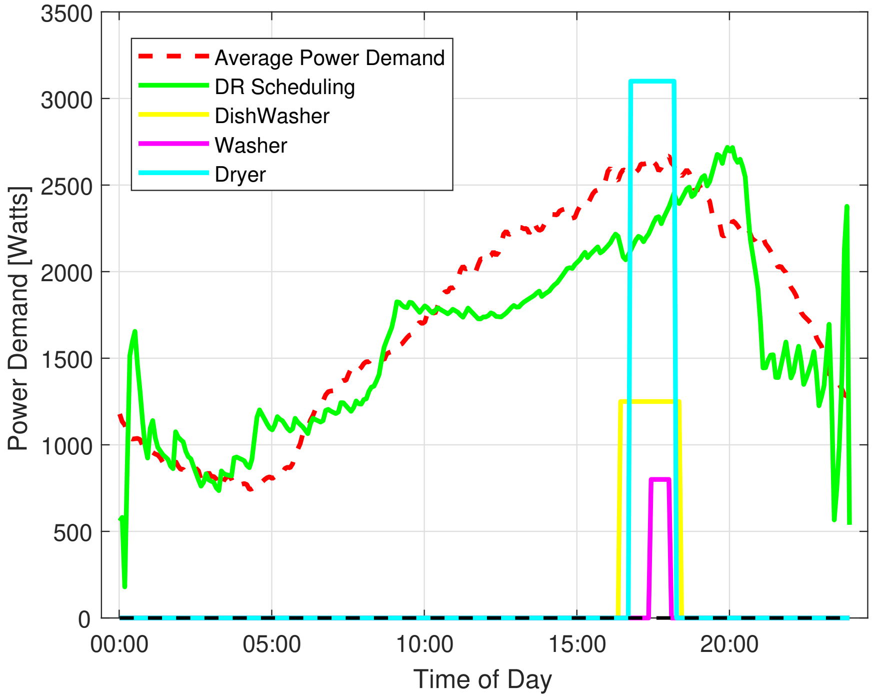



**Figure A.26:** Scenario 6 Appliance Scheduling

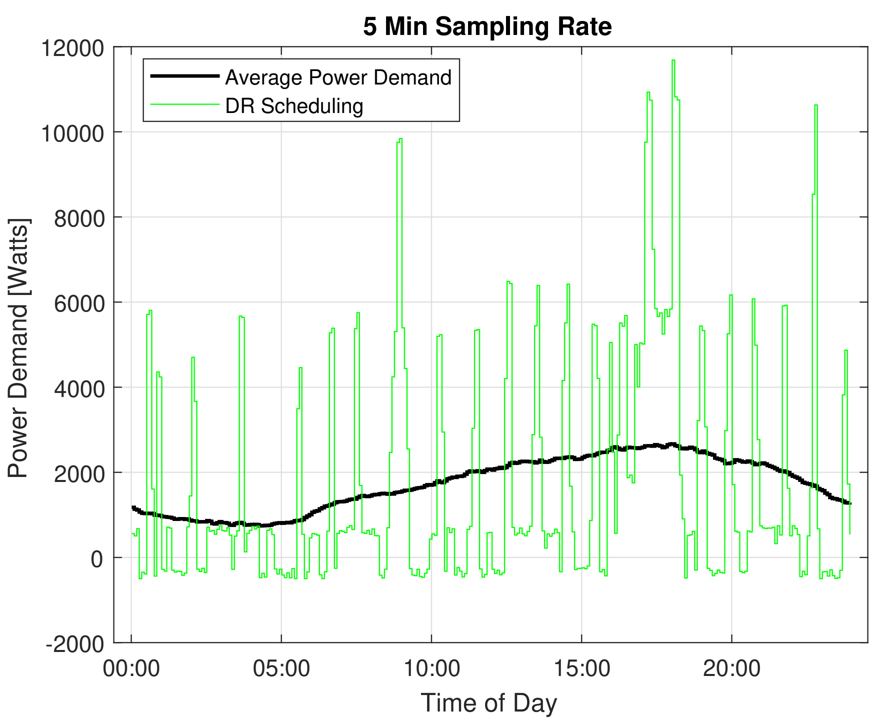



**Figure A.27:** Scenario 6 5 min. Sampling

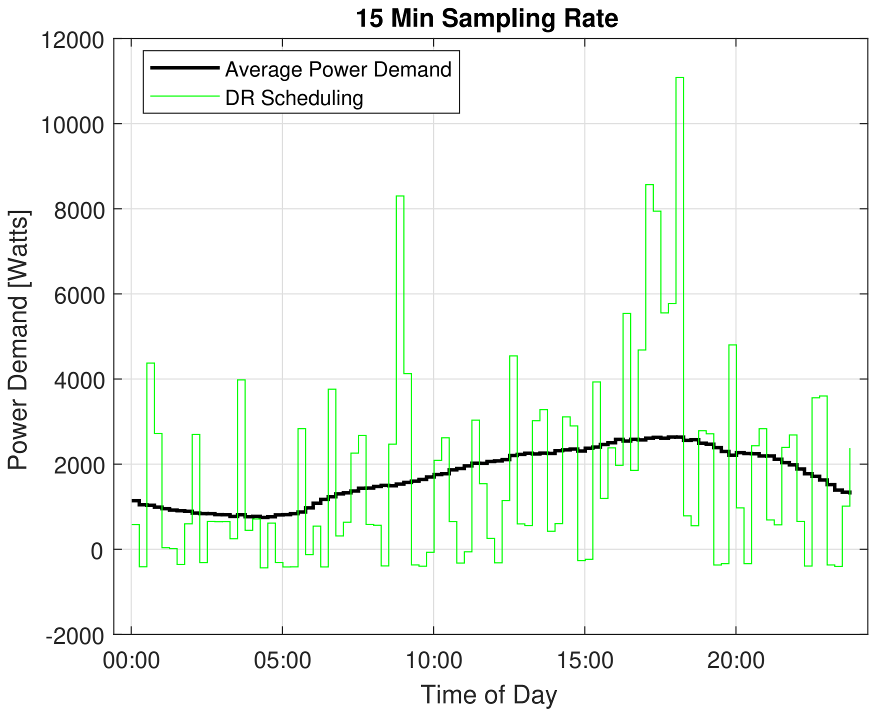



**Figure A.28:** Scenario 6 15 min. Sampling

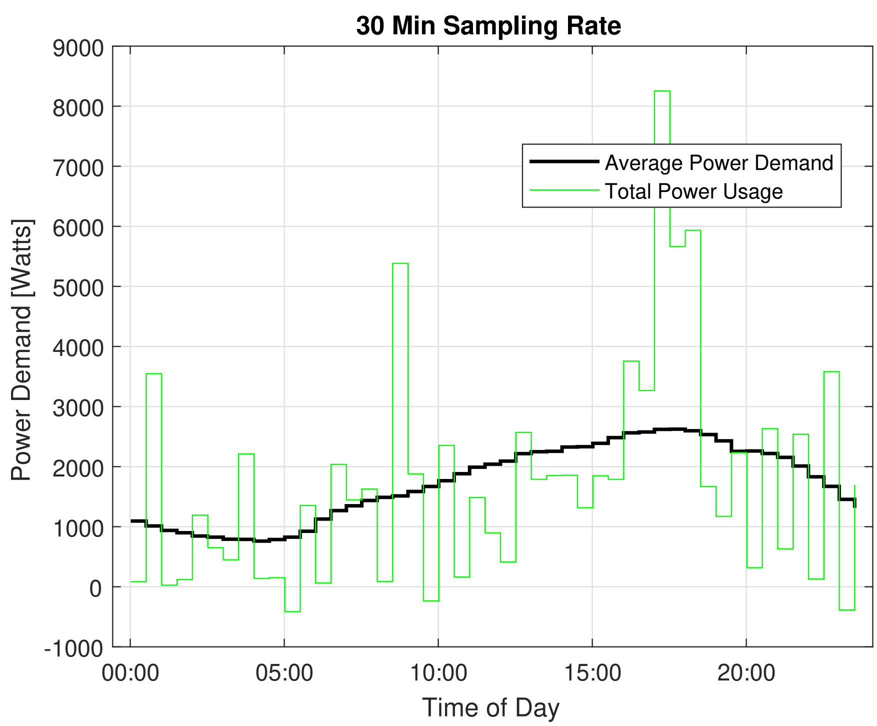



**Figure A.29:** Scenario 6 30 min. Sampling

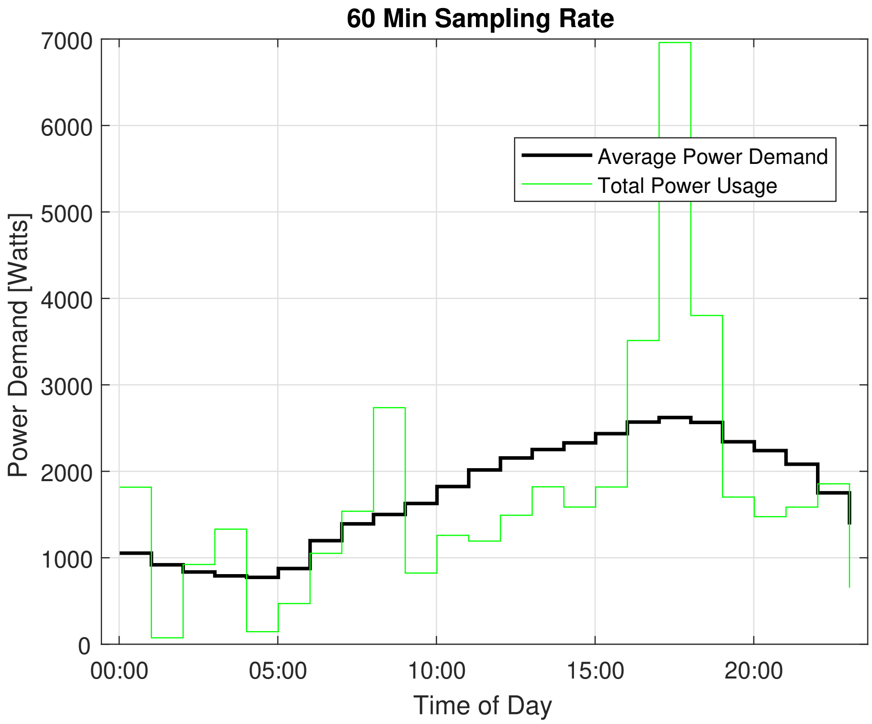



**Figure A.30:** Scenario 6 60 min. Sampling

## A.7 Power Scheduling Scenario 7

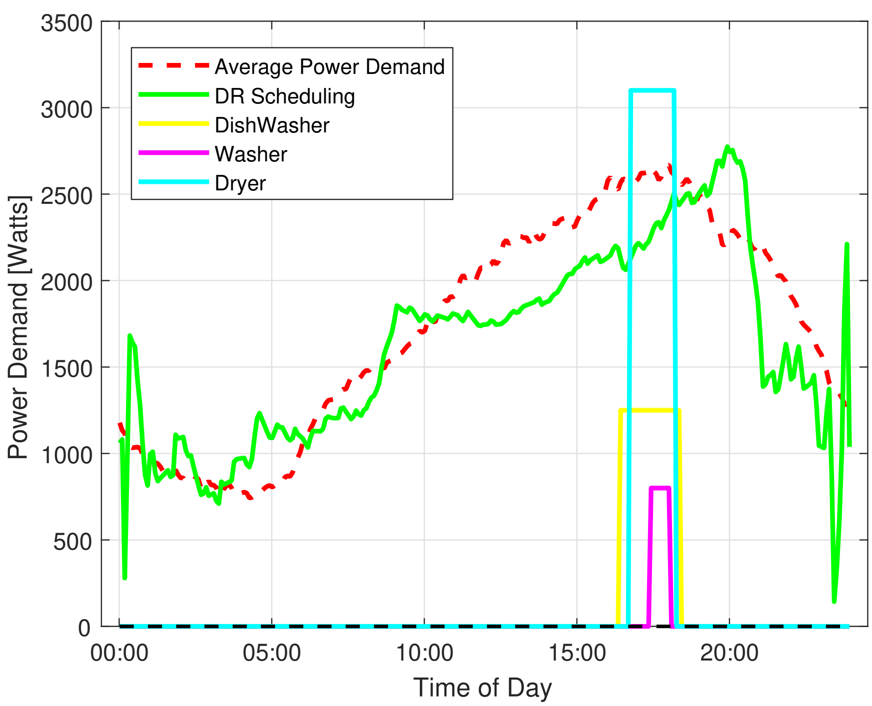
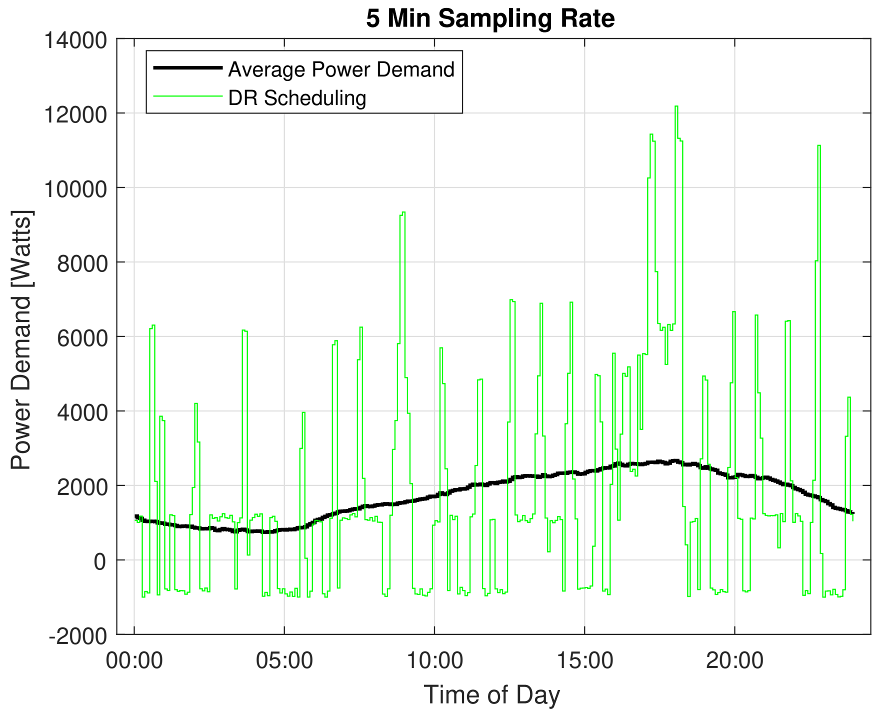



**Figure A.31:** Scenario 7 Appliance Scheduling

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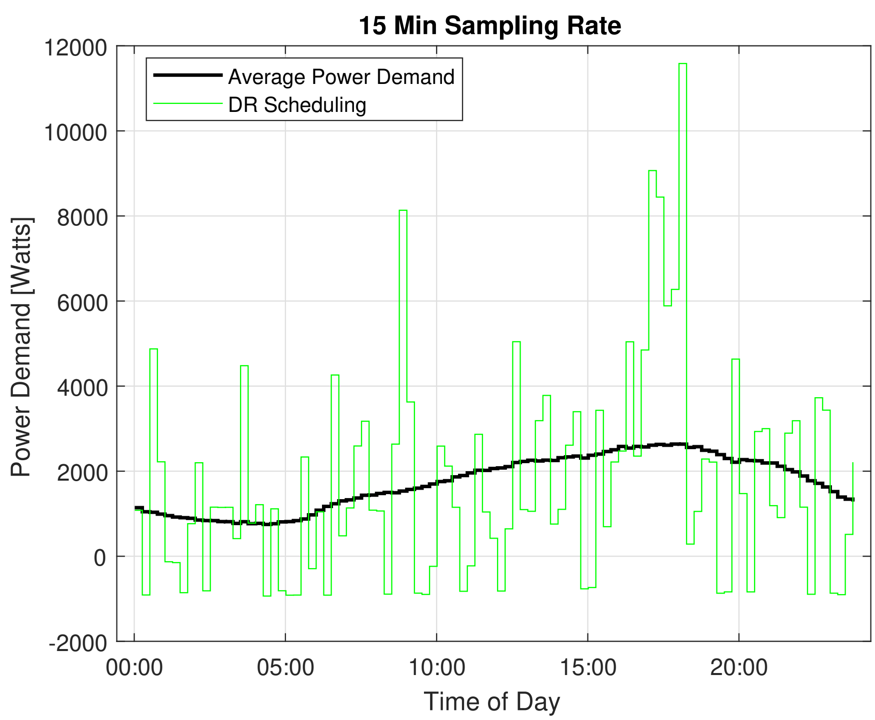


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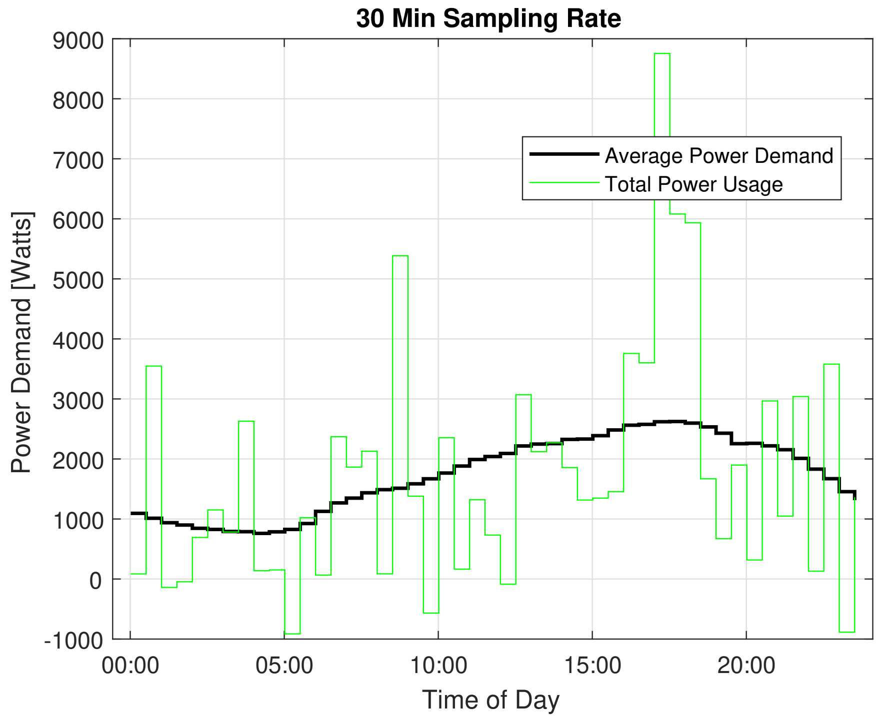


**Figure A.34:** Scenario 7 30 min. Sampling

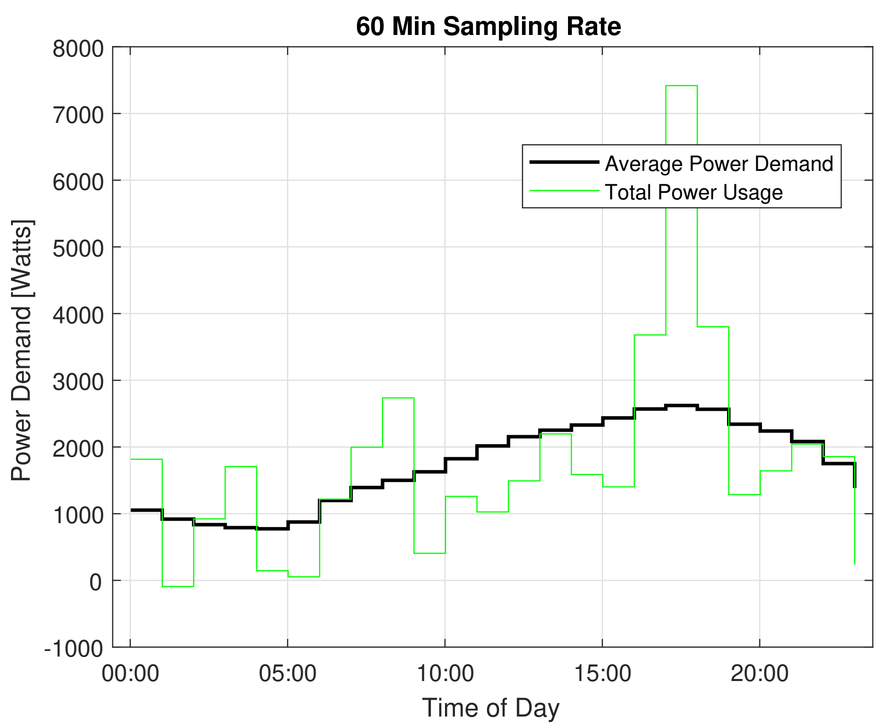


**Figure A.35:** Scenario 7 60 min. Sampling

## A.8 Power Scheduling Scenario 8

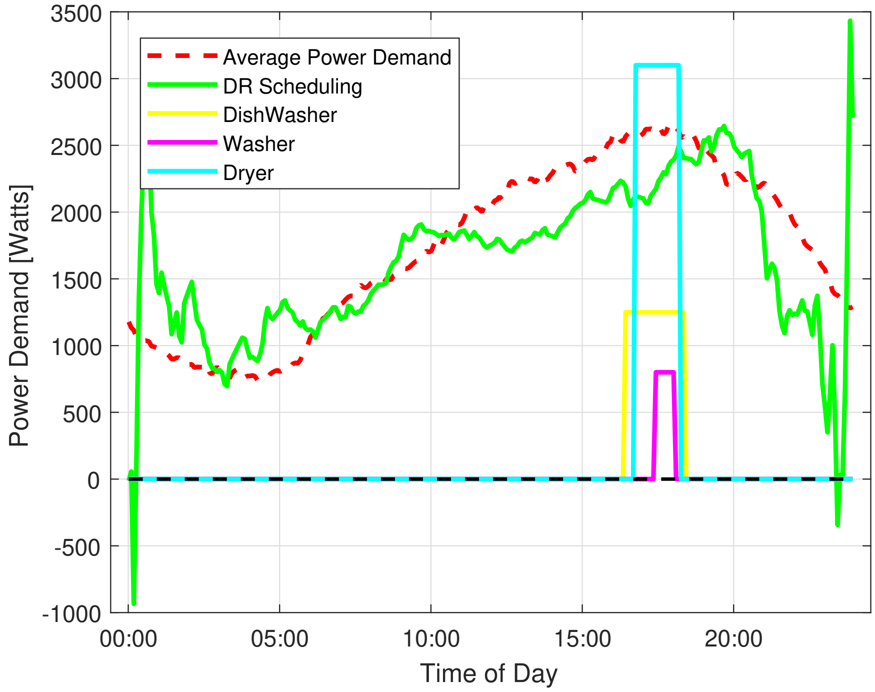


**Figure A.36:** Scenario 8 Appliance Scheduling

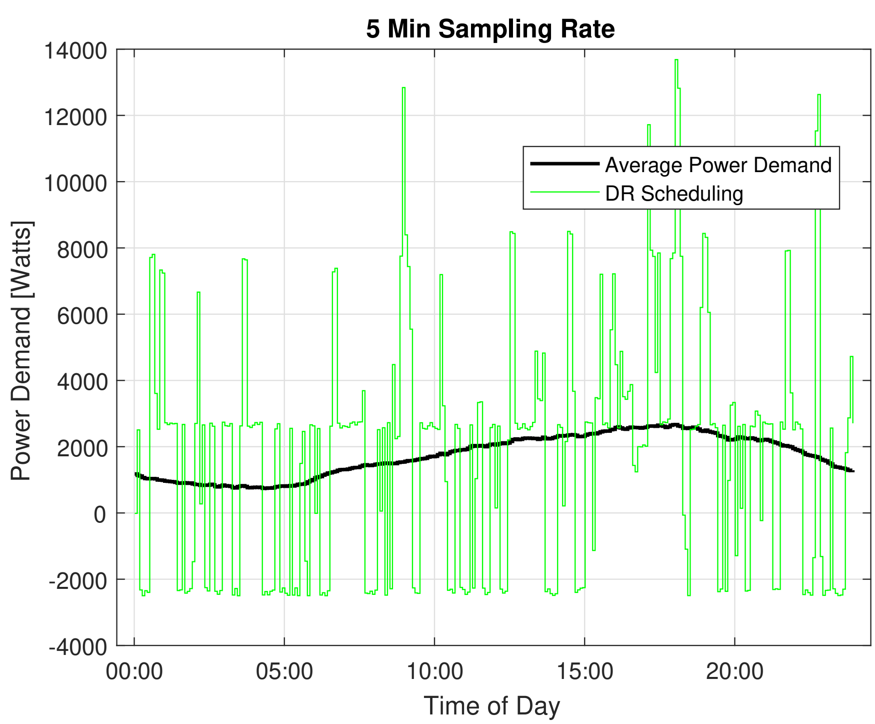


**Figure A.37:** Scenario 8 5 min. Sampling

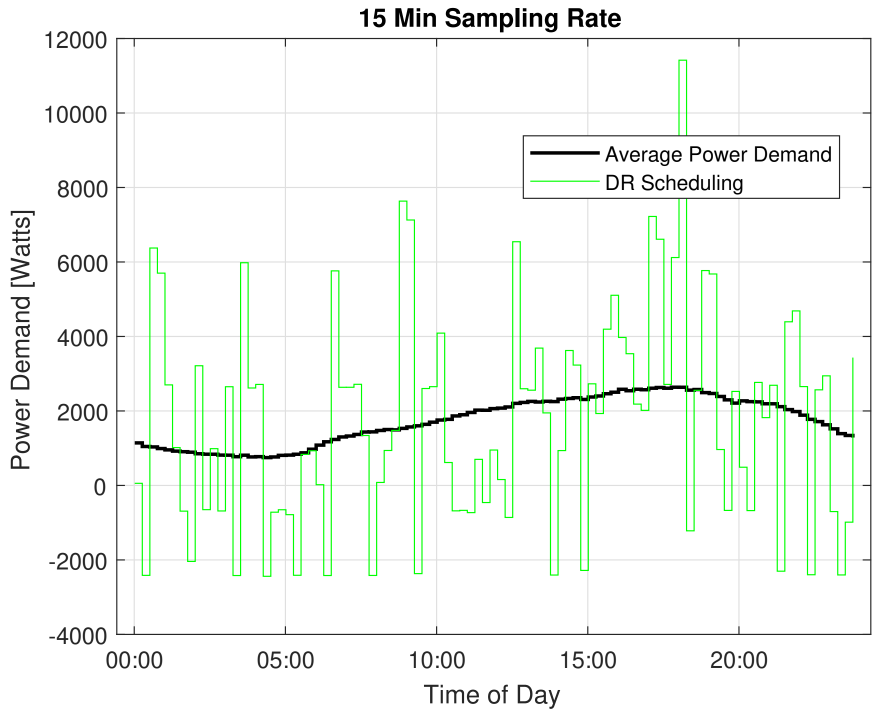


**Figure A.38:** Scenario 8 15 min. Sampling

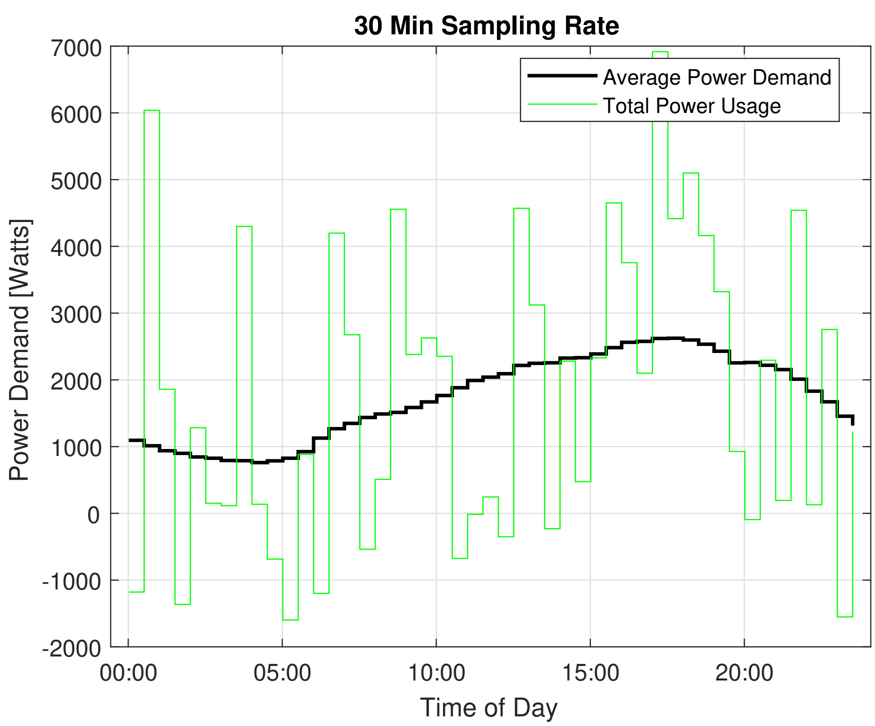


**Figure A.39:** Scenario 8 30 min. Sampling

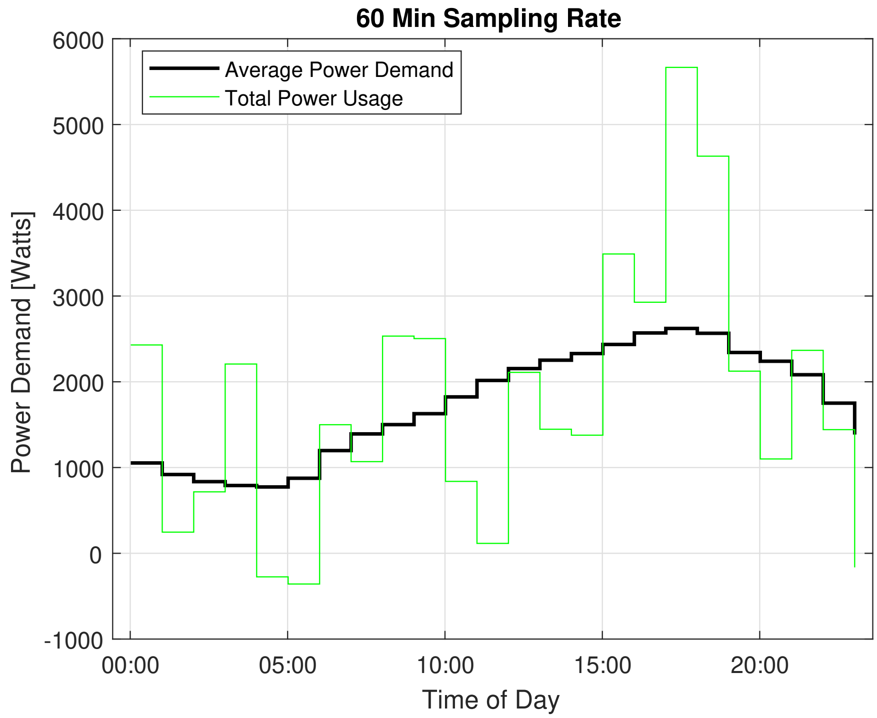


**Figure A.40:** Scenario 8 60 min. Sampling

## A.9 Power Scheduling Scenario 9

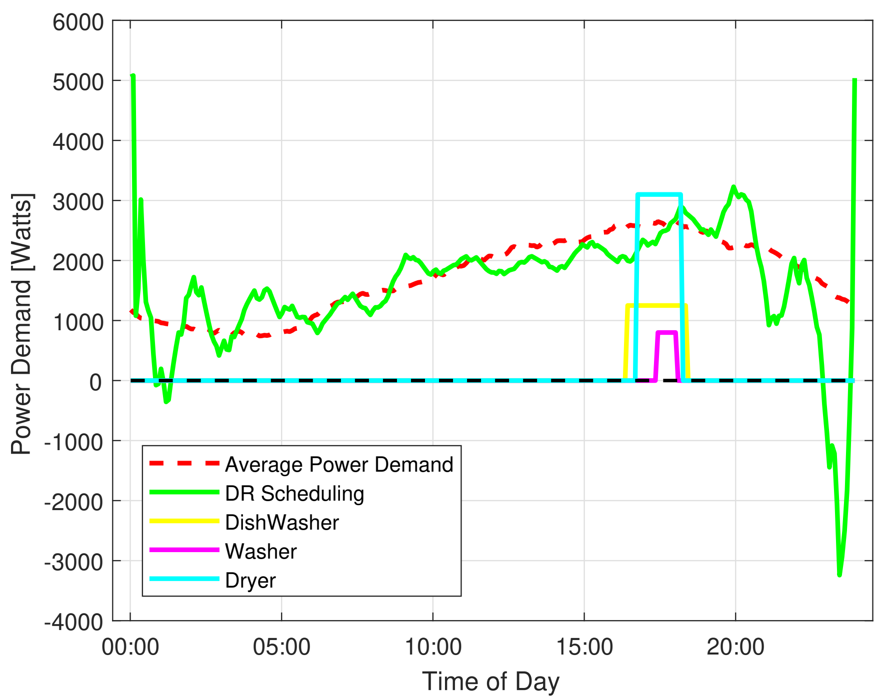


**Figure A.41:** Scenario 9 Appliance Scheduling

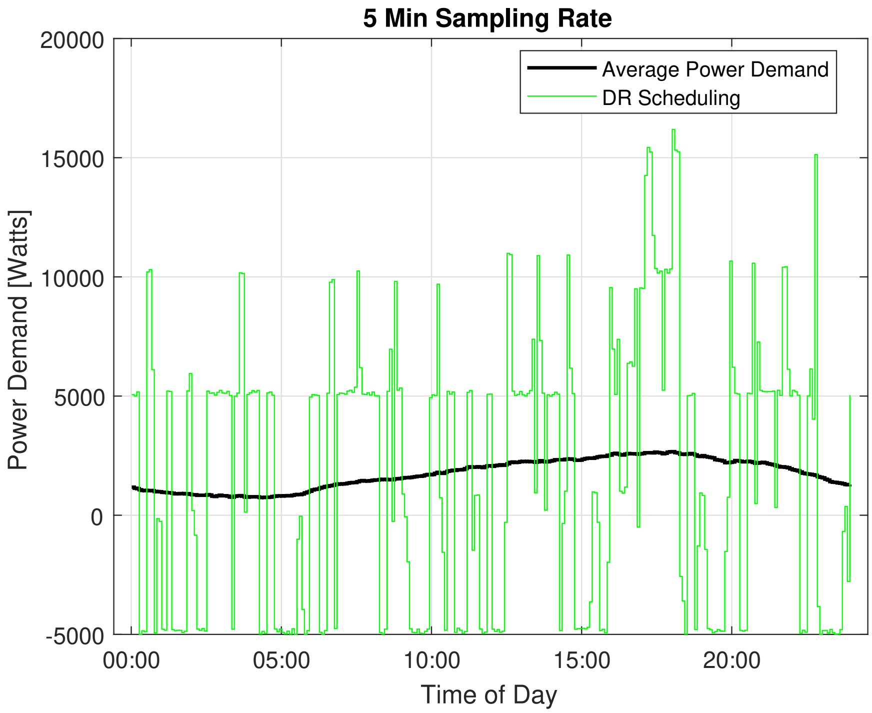


**Figure A.42:** Scenario 9 5 min. Sampling

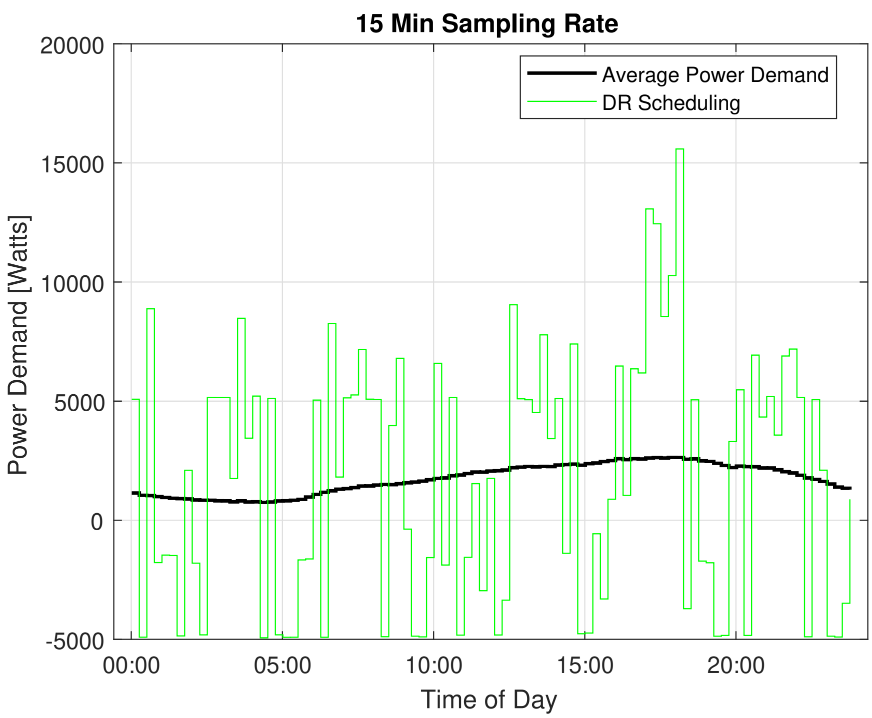


**Figure A.43:** Scenario 9 15 min. Sampling

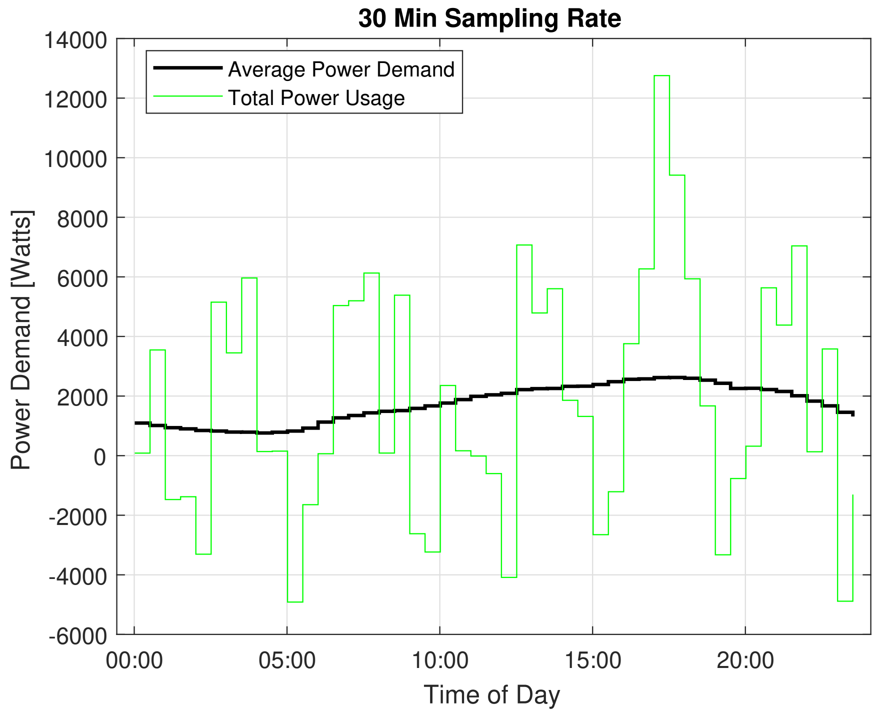


**Figure A.44:** Scenario 9 30 min. Sampling

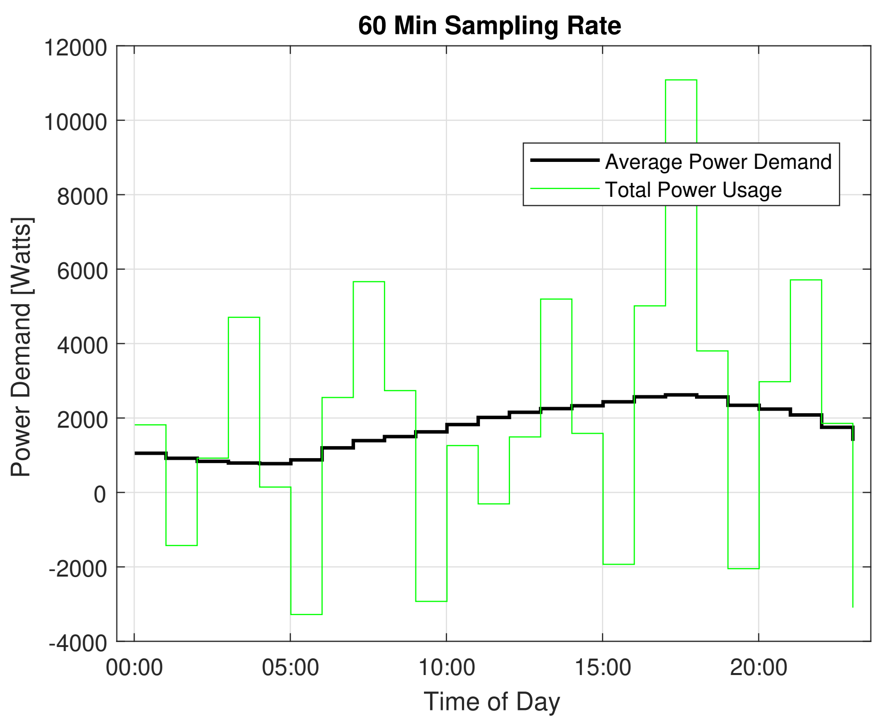


**Figure A.45:** Scenario 9 60 min. Sampling

## A.10 Power Scheduling Scenario 10

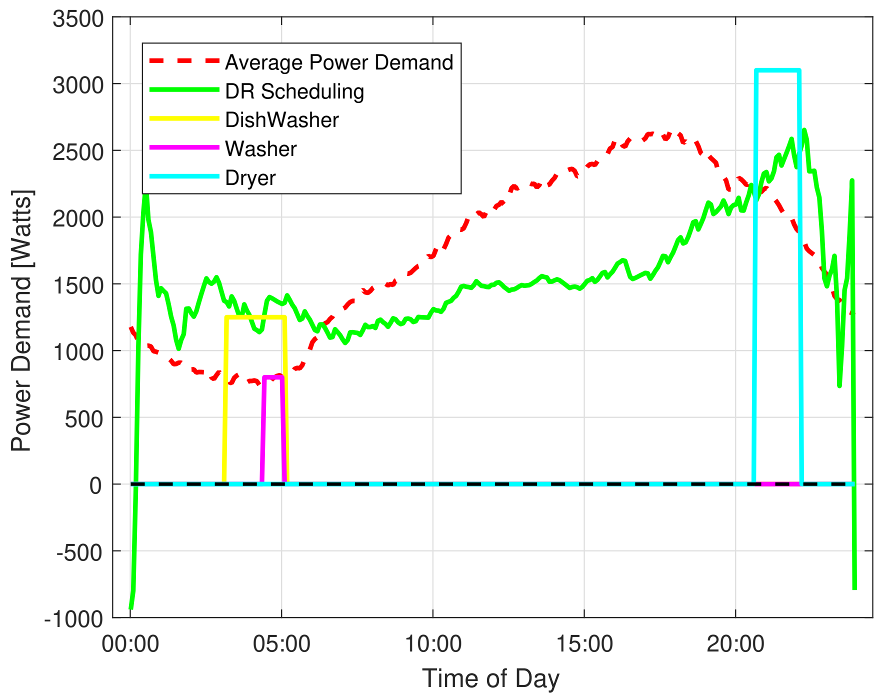


**Figure A.46:** Scenario 10 Appliance Scheduling

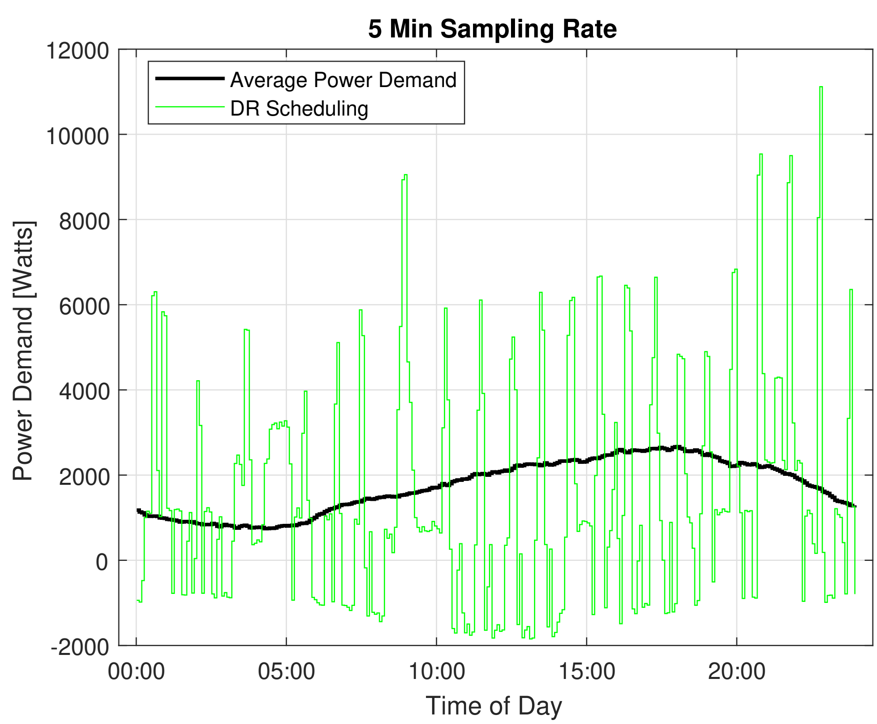


**Figure A.47:** Scenario 10 5 min. Sampling

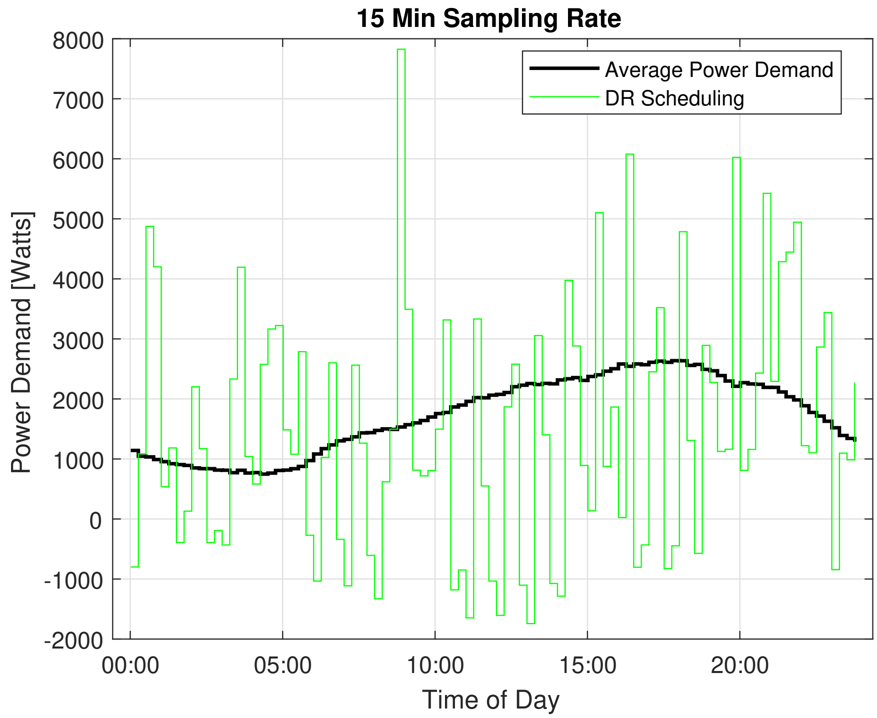


**Figure A.48:** Scenario 10 15 min. Sampling

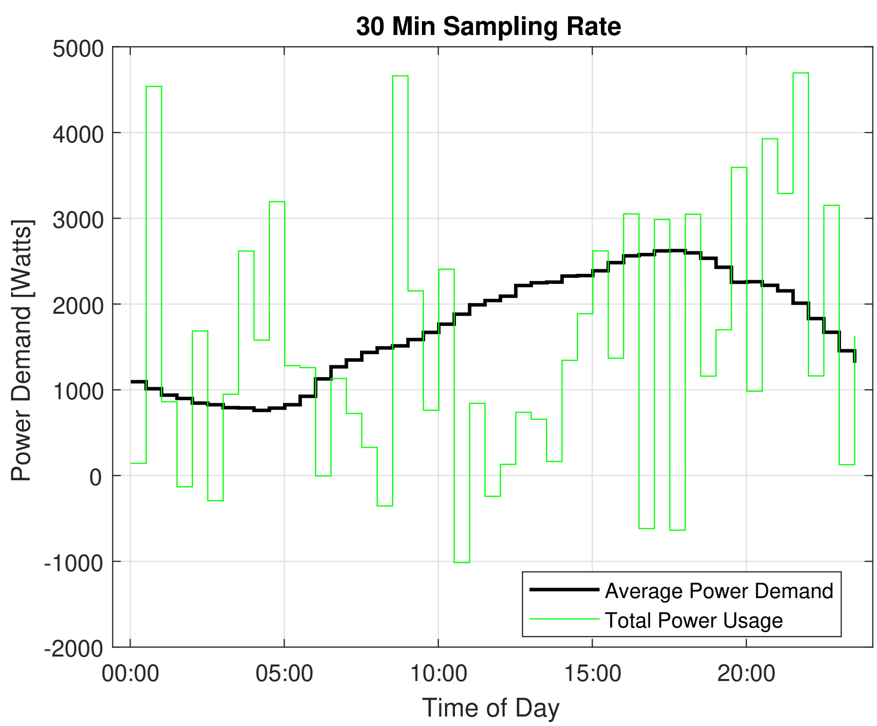


**Figure A.49:** Scenario 10 30 min. Sampling

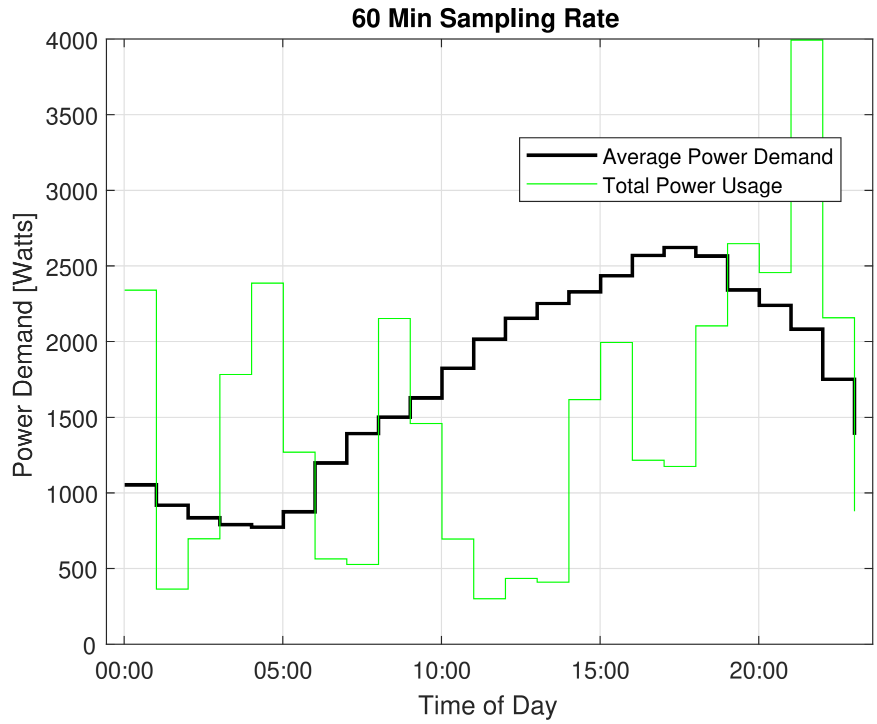


**Figure A.50:** Scenario 10 60 min. Sampling

## A.11 Power Scheduling Scenario 11

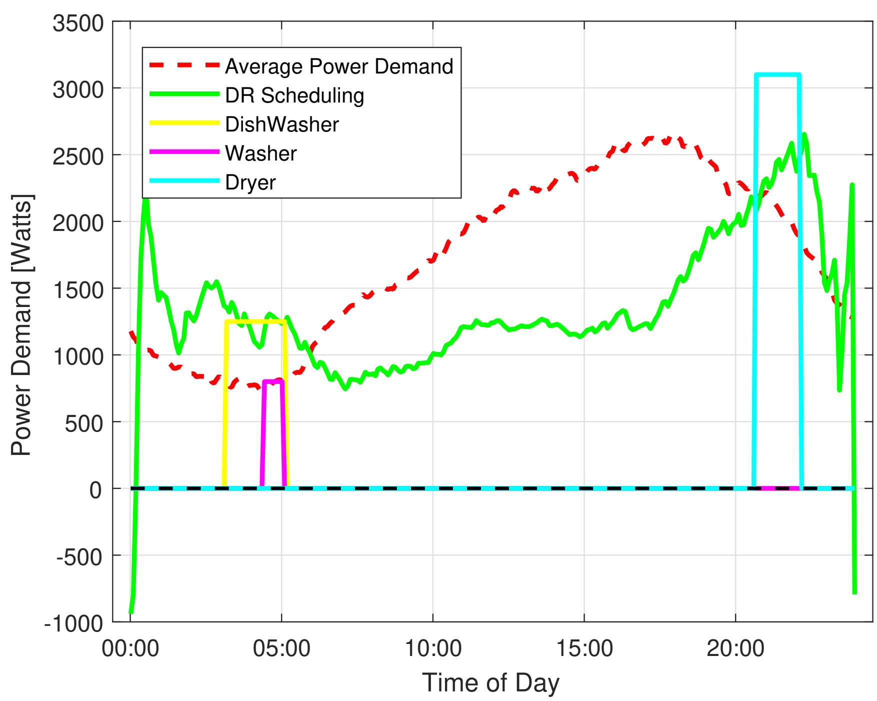


**Figure A.51:** Scenario 11 Appliance Scheduling

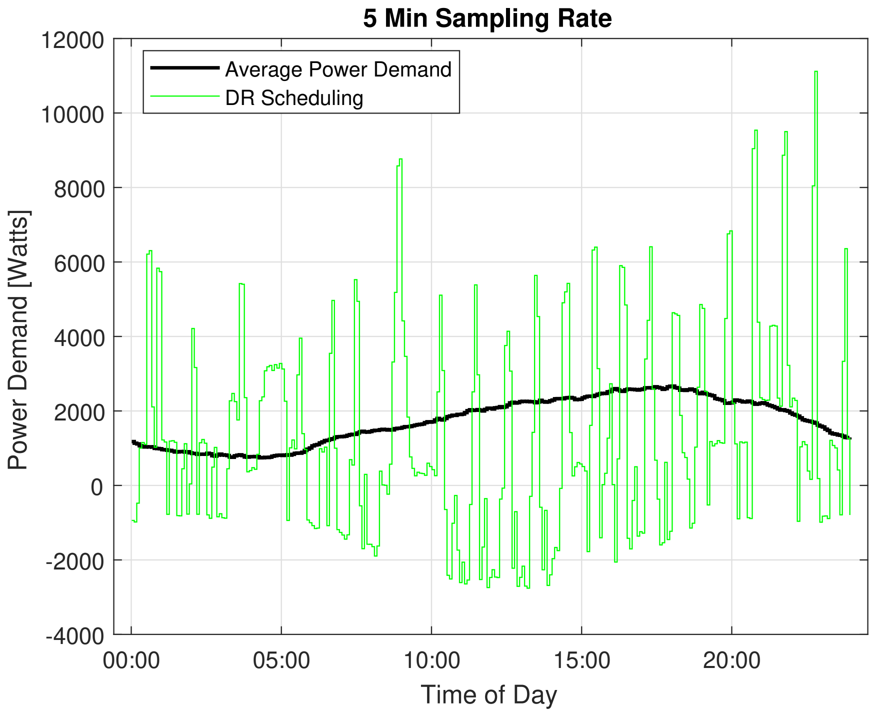


**Figure A.52:** Scenario 11 5 min. Sampling

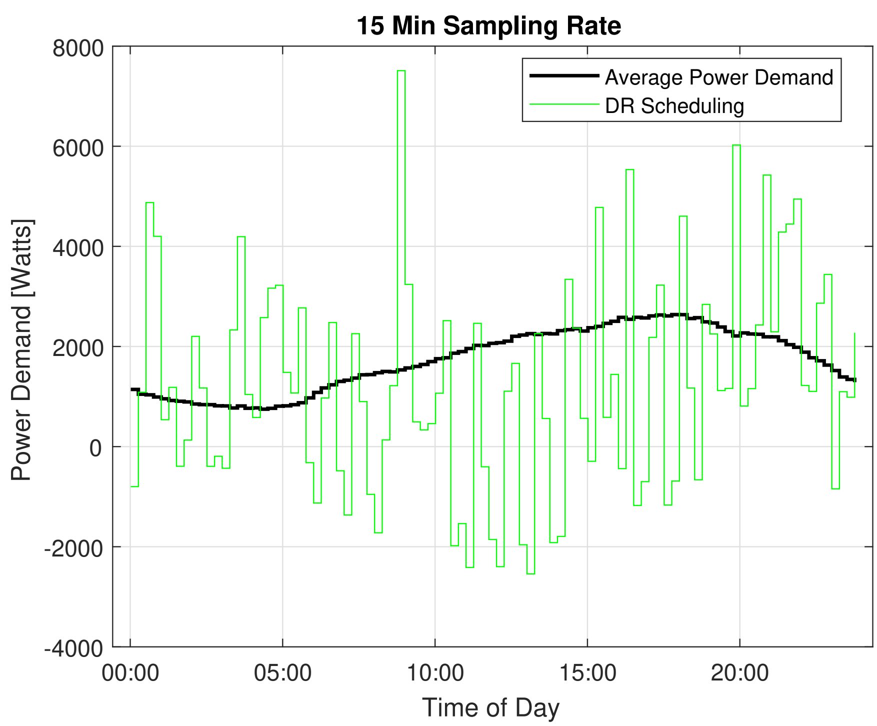


**Figure A.53:** Scenario 11 15 min. Sampling

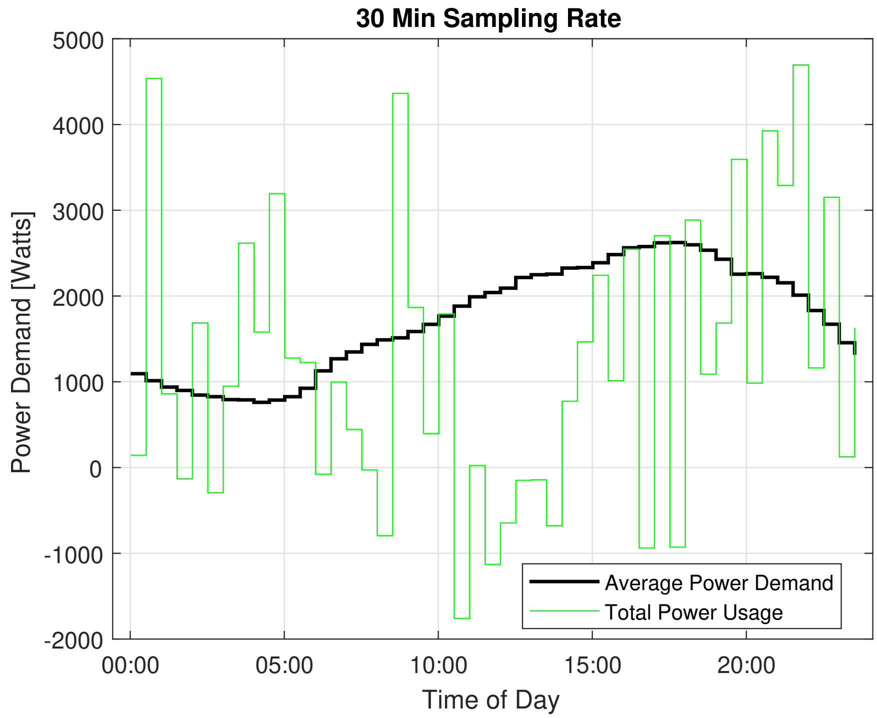


**Figure A.54:** Scenario 11 30 min. Sampling

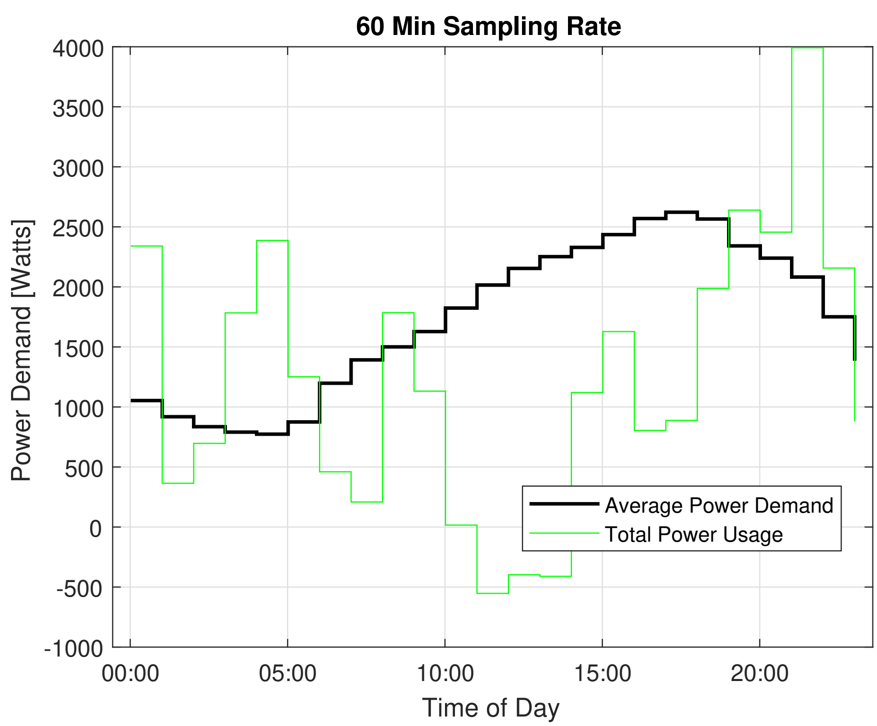


**Figure A.55:** Scenario 11 60 min. Sampling

## A.12 Power Scheduling Scenario 12

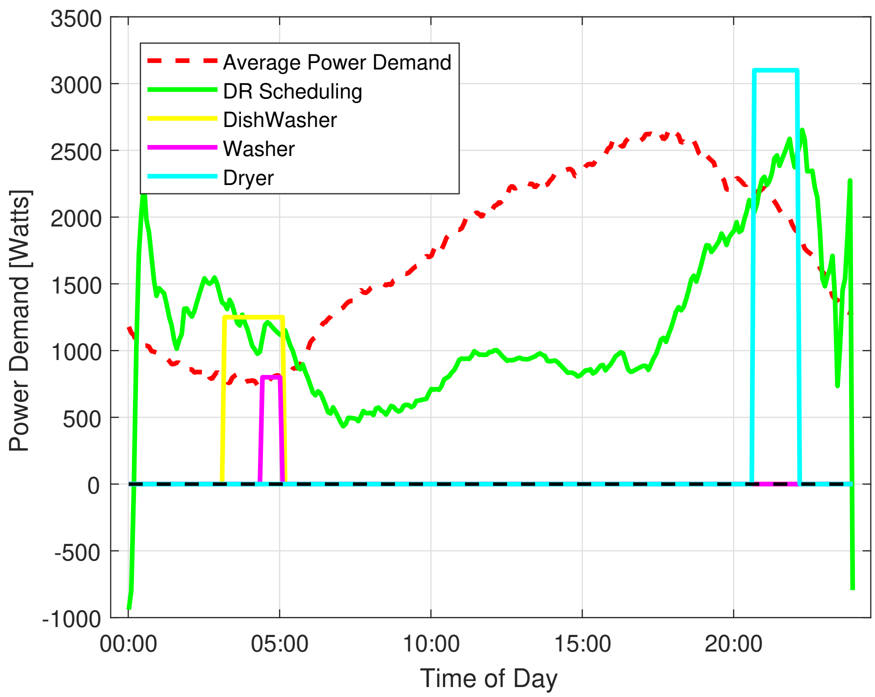


**Figure A.56:** Scenario 12 Appliance Scheduling

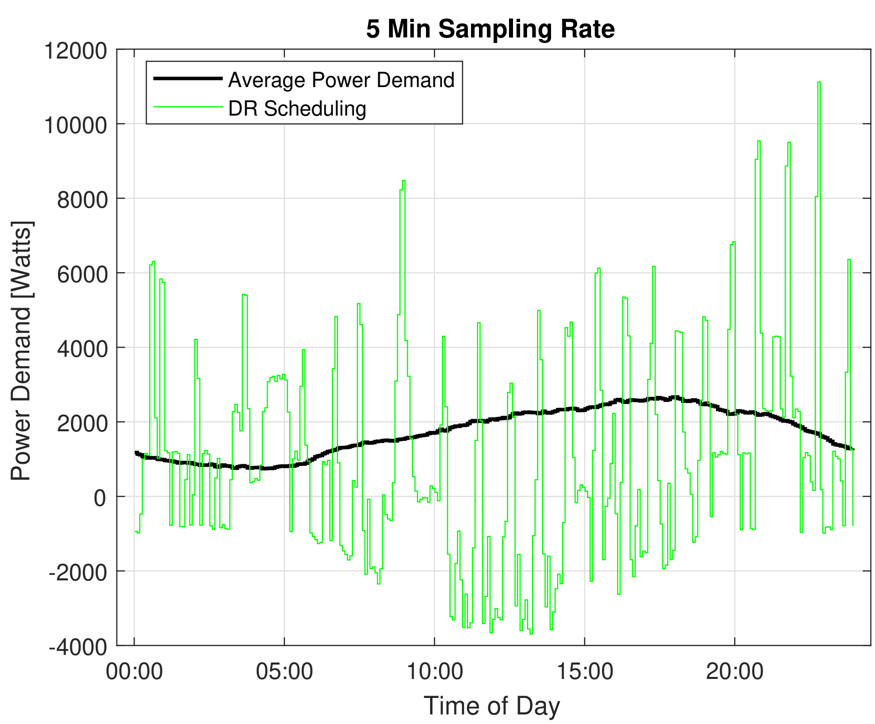


**Figure A.57:** Scenario 12 5 min. Sampling

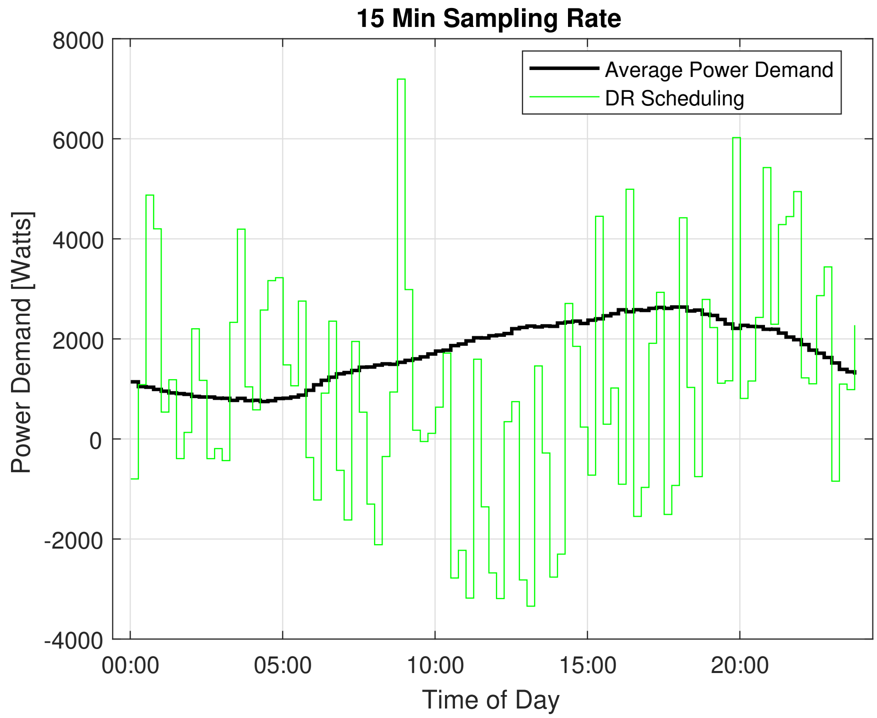


**Figure A.58:** Scenario 12 15 min. Sampling

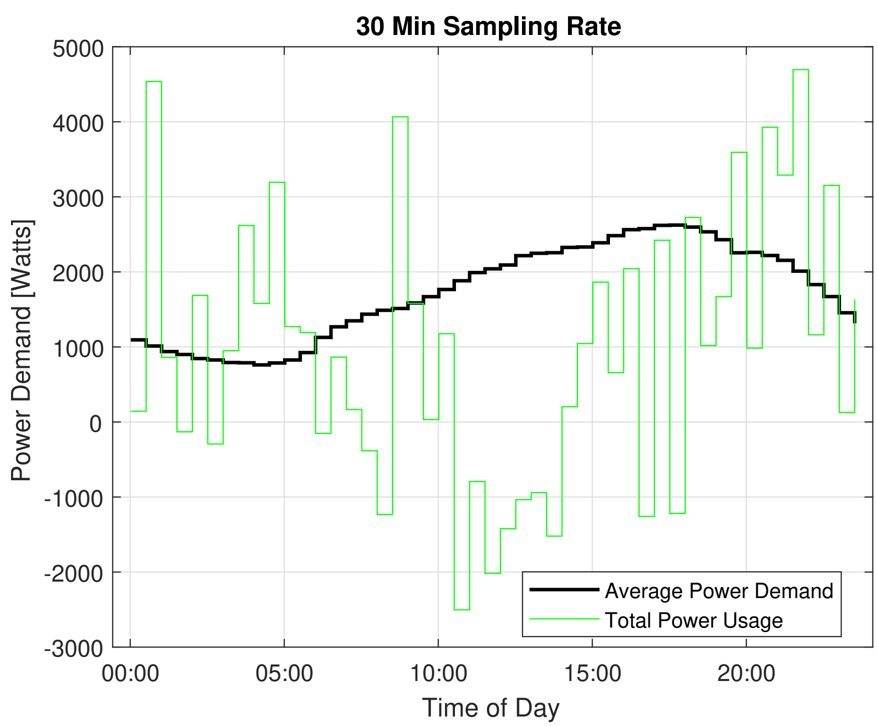


**Figure A.59:** Scenario 12 30 min. Sampling

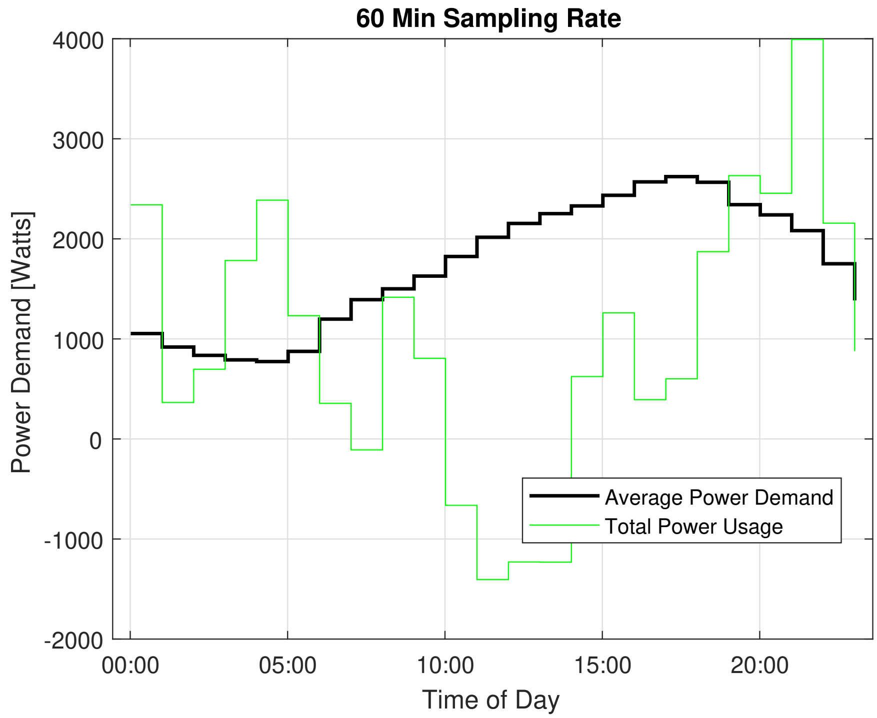


**Figure A.60:** Scenario 12 60 min. Sampling

## A.13 Power Scheduling Scenario 13

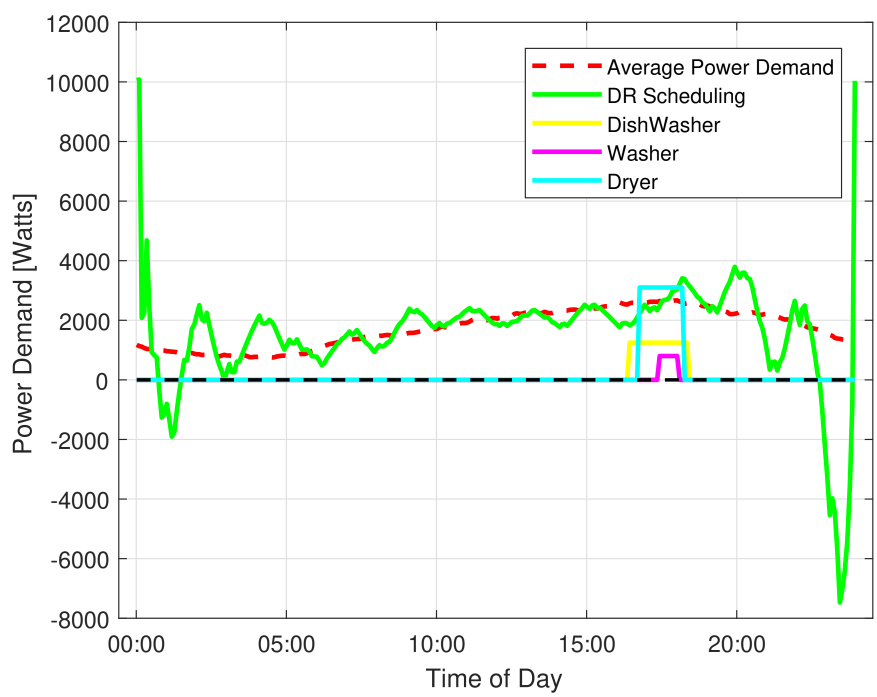


**Figure A.61:** Scenario 13 Appliance Scheduling

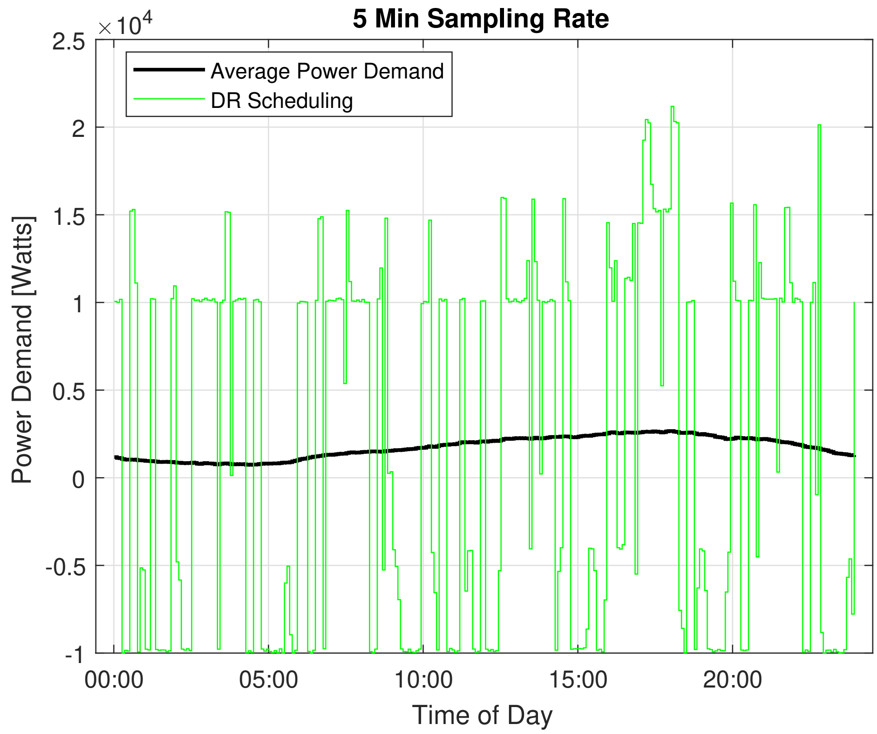


**Figure A.62:** Scenario 13 5 min. Sampling

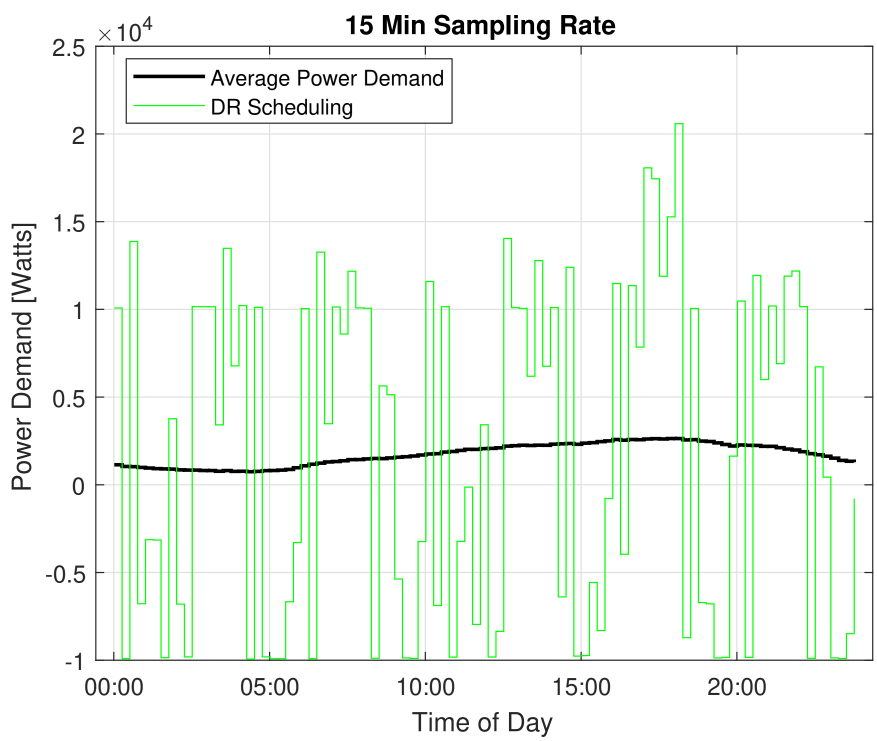


**Figure A.63:** Scenario 13 15 min. Sampling

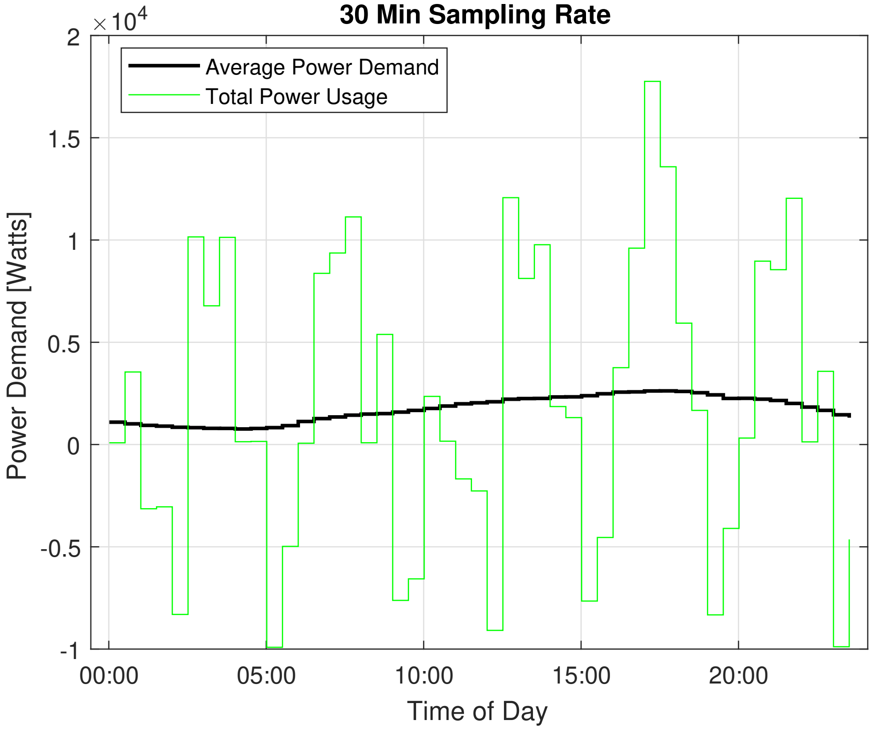


**Figure A.64:** Scenario 13 30 min. Sampling

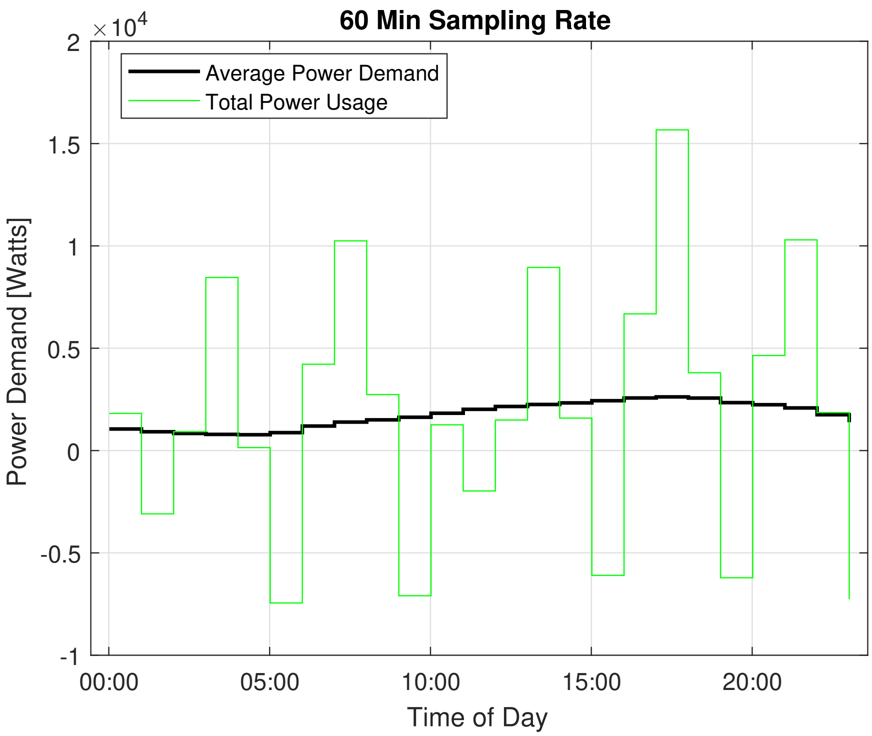


**Figure A.65:** Scenario 13 60 min. Sampling

## A.14 Power Scheduling Scenario 14

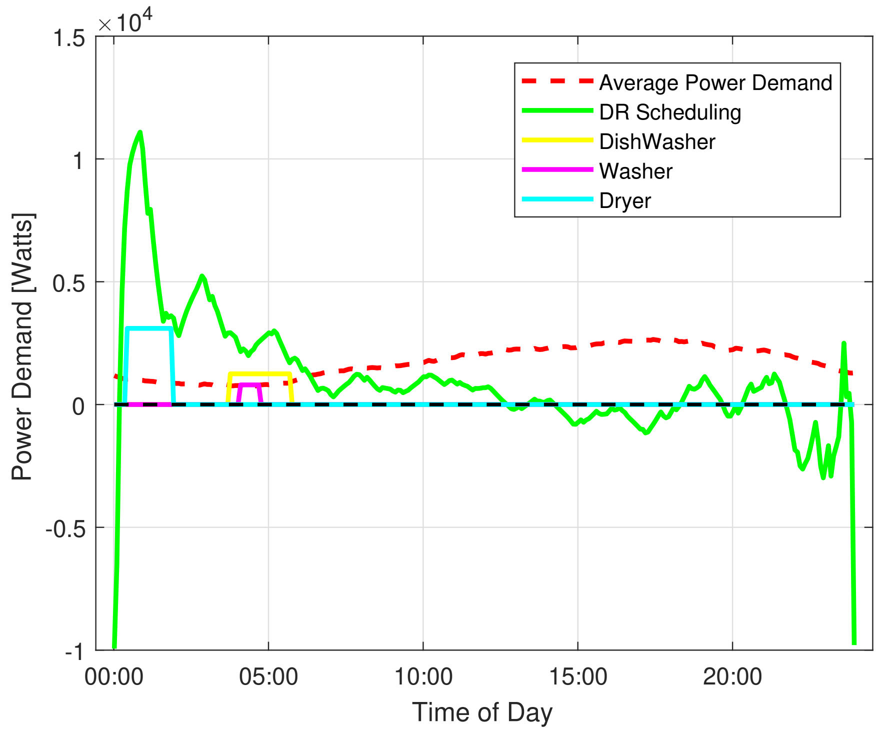


**Figure A.66:** Scenario 14 Appliance Scheduling

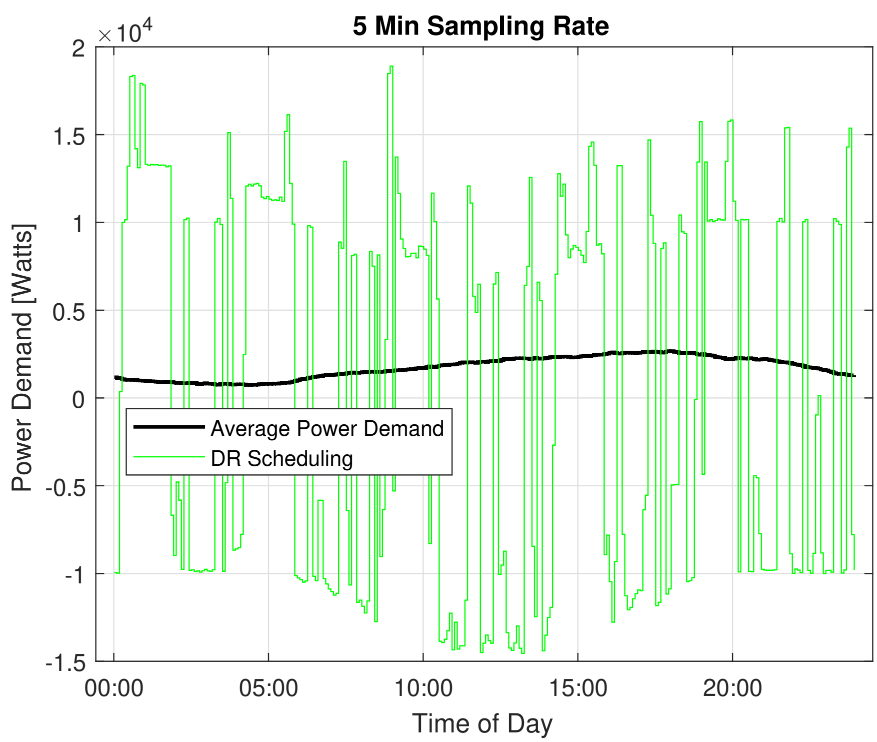


**Figure A.67:** Scenario 14 5 min. Sampling

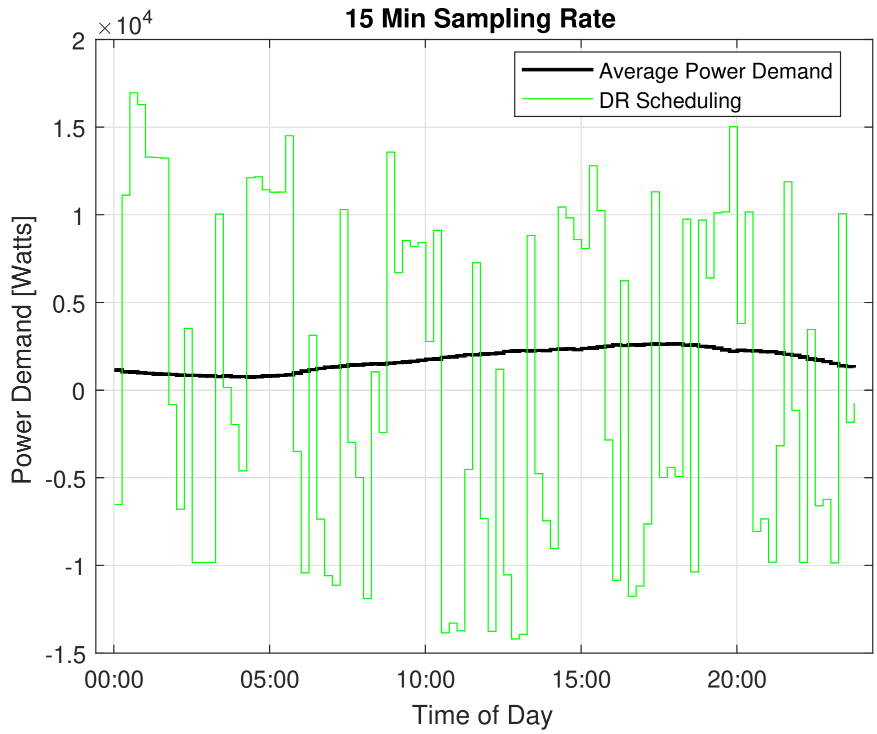


**Figure A.68:** Scenario 14 15 min. Sampling

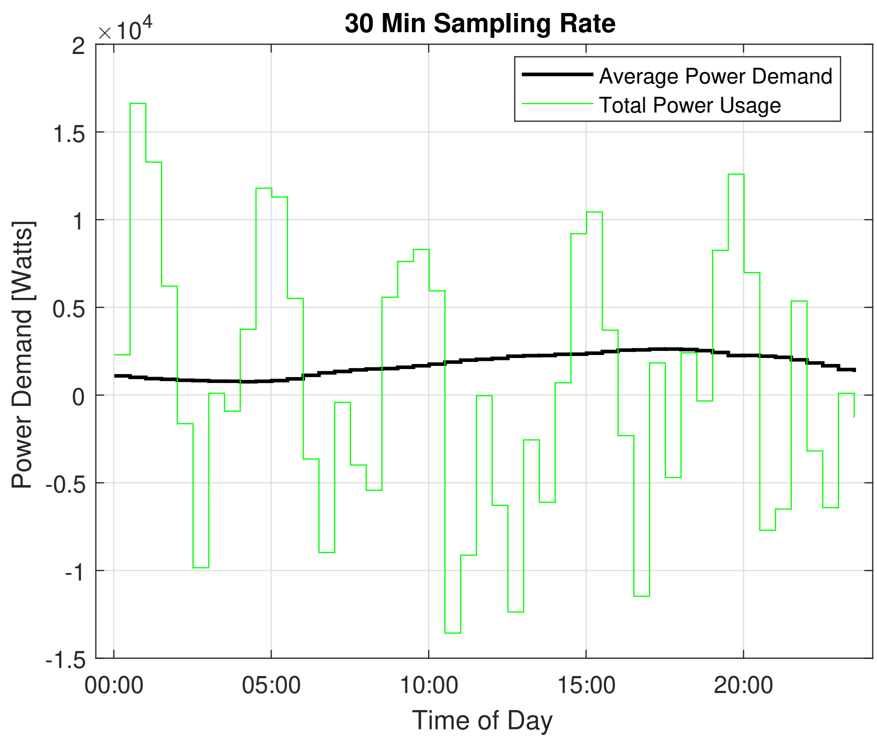


**Figure A.69:** Scenario 14 30 min. Sampling

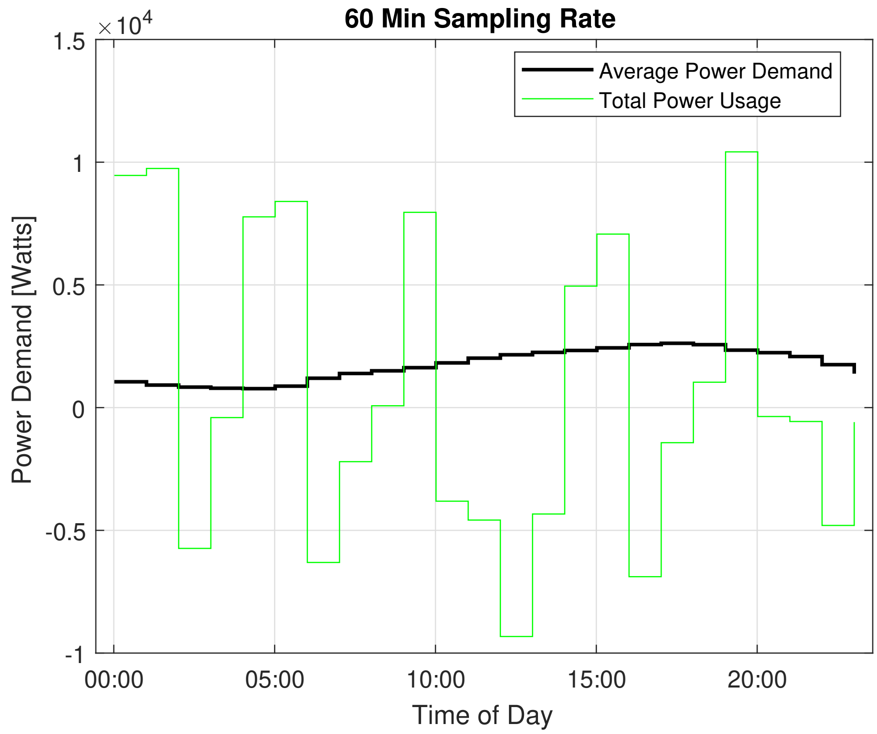


**Figure A.70:** Scenario 14 60 min. Sampling

# B Supporting Tables

**Table B.1:** Data for Radial Distribution System shown in Fig. 4.1

| | | Fault Location | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 |
| HOUSES | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 2 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 3 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 4 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 5 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 6 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 7 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 8 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 9 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 10 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 11 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 12 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 13 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 14 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 15 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 16 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 17 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 18 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 19 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |

**Table B.2:** Cont. Data for Radial Distribution System shown in Fig. 4.1

| | | Fault Location | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 |
| HOUSES | 21 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 |
| | 22 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 23 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 24 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 1 |
| | 25 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 |
| | 26 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| | 27 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 28 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |

**Table B.3:** Data for Radial Distribution System shown in Fig. 4.2

| | Fault Location | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| HOUSES | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 4 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 6 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 7 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 8 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 9 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 10 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 11 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 12 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 13 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 14 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 15 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 16 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 |
| 17 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| 18 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| 19 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |
| 20 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 |

**Table B.4:** Cont. Data for Radial Distribution System shown in Fig. 4.2

| | | Fault Location | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 |
| HOUSES | 21 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| | 22 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| | 23 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 24 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 25 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 26 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 27 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 28 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 29 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 30 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 31 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 32 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 33 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

# Vita

Albraa Bahour was born in Nashville, TN. He received a Bachelor of Science degree in Electrical Engineering from Tennessee State University in 2015. In 2016, he began graduate studies at the University of Tennessee toward a Master of Science in Electrical Engineering with a focus on Power Systems. His interests include smart grids, demand response, power system stability, power system planning, energy economics, and grid optimization.