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Internet of Things and Intelligent Technologies for Efficient Energy Management in a Smart Building Environment

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INTERNET OF THINGS AND INTELLIGENT TECHNOLOGIES FOR EFFICIENT ENERGY MANAGEMENT IN A SMART BUILDING ENVIRONMENT

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by
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ABSTRACT

Internet of Things (IoT) is attempting to transform modern buildings into energy efficient, smart, and connected buildings, by imparting capabilities such as real-time monitoring, situational awareness and intelligence, and intelligent control. Digitizing the modern day building environment using IoT improves asset visibility and generates energy savings. This dissertation provides a survey of the role, impact, and challenges and recommended solutions of IoT for smart buildings. It also presents an IoT-based solution to overcome the challenge of inefficient energy management in a smart building environment. The proposed solution consists of developing an Intelligent Computational Engine (ICE), composed of various IoT devices and technologies for efficient energy management in an IoT driven building environment.

ICE's capabilities viz. energy consumption prediction and optimized control of electric loads have been developed, deployed, and dispatched in the Real-Time Power and Intelligent Systems (RTPIS) laboratory, which serves as the IoT-driven building case study environment. Two energy consumption prediction models viz. exponential model and Elman recurrent neural network (RNN) model were developed and compared to determine the most accurate model for use in the development of ICE's energy consumption prediction capability. ICE's prediction model was developed in MATLAB using cellular computational network (CCN) technique, whereas the optimized control model was developed jointly in MATLAB and Metasys Building Automation System (BAS) using particle swarm optimization (PSO) algorithm and logic connector tool (LCT), respectively. It was demonstrated that the developed CCN-based energy

consumption prediction model was highly accurate with low error % by comparing the predicted and the measured energy consumption data over a period of one week. The predicted energy consumption values generated from the CCN model served as a reference for the PSO algorithm to generate control parameters for the optimized control of the electric loads. The LCT model used these control parameters to regulate the electric loads to save energy (increase energy efficiency) without violating any operational constraints.

Having ICE's energy consumption prediction and optimized control of electric loads capabilities is extremely useful for efficient energy management as they ensure that sufficient energy is generated to meet the demands of the electric loads optimally at any time thereby reducing wasted energy due to excess generation. This, in turn, reduces carbon emissions and generates energy and cost savings. While the ICE was tested in a small case-study environment, it could be scaled to any smart building environment.

DEDICATION

The dissertation work is dedicated to the 1.3 billion people around the world who do not yet have access to electricity. I hope that my work can be a step in achieving the goal of providing access to clean, affordable, sustainability electricity to meet the growing electricity demands around the world.

ACKNOWLEDGMENTS

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The Clemson University Holcombe Department of Electrical and Computer Engineering has given me many opportunities for professional development, which I greatly appreciate. Furthermore, my labmates were a constant source of encouragement during the dissertation process. Their friendship and willingness to always lend a helping hand makes the Real-Time Power and Intelligent Systems Laboratory a special place to work. I would also like to acknowledge the gracious support I received from Clemson Facilities, Johnson Controls, and ProtoConvert as I set up my building case study environment.

I would like to thank my family and my wife for their love and support. They inspired me to aim for excellence and gave me confidence that I could achieve my goals and aspirations.

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TABLE OF CONTENTS

Page

Table of Contents (Continued)

Page

Table of Contents (Continued)

Page

LIST OF TABLES

LIST OF FIGURES

List of Figures (Continued)

Figure Page

List of Figures (Continued)

Figure Page

CHAPTER ONE

INTRODUCTION

Overview

In 1999, Cherry Murray of Bell Labs stated: “In the next century, planet earth will don an electronic skin. It will use the Internet as a scaffold to support and transmit its sensations” [1]. The next major advancement with the Internet and the web that would impact our lives significantly is the Internet of Things (IoT). IoT is the connection of everyday objects in the physical world to the Internet. It imparts intelligence to the current devices and equipment using sensors and software that are networked together through the Internet. Literally every physical entity on earth, like appliances, goods, objects, machines, buildings, vehicles, plants, animals and even us humans, can be the “things” in IoT [2].

IoT is attempting to transform modern buildings into energy efficient, smart, and connected buildings. IoT imparts capabilities, such as real-time monitoring, situational awareness and intelligence, and control to transform the modern buildings into smart buildings, which are more energy efficient. Additionally, digitizing the modern day building environment using IoT improves asset visibility, eliminates energy wastage, reduces carbon emissions, and creates cost savings [3].

IoT has a significant impact on smart building environments and offers several opportunities for growth and development. The advancements in computational intelligence capabilities can evolve an intelligent IoT system by emulating biological

nervous systems with cognitive computation, streaming and distributed analytics including at the edge and device levels [3].

Energy Efficient Buildings

There are a number of energy efficient buildings around the world. Each of these buildings have incorporated certain innovative technologies for improving energy efficiency. The following are the examples of some of the top energy efficient buildings and their respective technological innovations (Fig. 1.1) [4]:

- Glumac (Fig 1.1(a)) in Shanghai, China features an indoor air monitoring system, five air purification systems, and a planted green wall. It is the first building in Asia to apply for a Living Building Challenge Certification.
- The Edge (Deloitte HQ) (Fig 1.1(b)) in Amsterdam, Netherlands features world's most efficient aquifer thermal energy storage system, water-efficient trickle-down rainwater toilet water system, human powered gym, and smart LED light panels across a floor reporting temperature and humidity measurements. With the BREEAM sustainability score of 98.4%, Edge is the greenest building in the world.
- Legion House (Fig 1.1(c)) at Liberty Place in Sydney, Australia features chilled beam technology-based air conditioning, which uses 100% fresh outside air for maintaining a very high level of indoor environment quality for the building occupants. The Green Building Council of Australia has certified the Legion House with a 6-Star Green Star-Office v3 Design rating.

- DPR Construction (Fig 1.1(d)) in San Francisco, CA features photovoltaics (PV) panels, ultra-energy efficient ceiling fans, rooftop solar thermal water heating system, living horticulture wine bar, intelligent electrochromic windows, and the first-ever-deployed LEED dynamic plaque in Northern California. It is the first commercial office space to receive NZEB certification in the city of San Francisco.

Fig. 1.1. Examples of energy efficient buildings around the world: (a) Glumac in China, (b) The Edge in Netherlands, (c) Legion House in Australia, and (d) DPR Construction in USA [4]

IoT for Energy Efficient Buildings

With IoT, modern buildings can be transformed into energy efficient, smart, and connected buildings. A smart building environment is comprised of IoT sensors and actuators for communication, control, and visualizations. IoT imparts real-time feedback

capabilities to the smart building administrators, which function to better serve building occupants through enhanced monitoring and control functionalities [2]. The IoT framework provides a technology-driven architecture for integration of building infrastructure and resources, and thus provide mechanisms to optimize their use and provide an efficient, informed, and equitable distribution of services, which benefits the building occupants in multiple ways. Three of the major benefits include improved energy efficiency of a smart building environment, active monitoring of the building environment, and enhanced social well-being of the occupants [5, 6]. IoT presents numerous opportunities in smart buildings having a significant economic, environmental, and societal impact.

IoT Sensors

IoT sensors play an important role in improving the energy efficiency of smart buildings. With IoT sensors, the building administrators can actively optimize energy supplies as needed to avoid energy waste. IoT sensors also contribute to building environment monitoring by actively detecting the presence of pollutants or other harmful gases in the building environment and alerting the building occupants to take corrective measures in a timely manner. Additionally, IoT sensors enhance the social well-being of smart building occupants by bringing more comfort and convenience in their lives [6]. The different types of IoT sensors are listed below [3, 6].

IoT Smart Building Occupancy Sensors

With IoT smart building occupancy sensors, the building administrators can monitor all movements in and around the building, thereby helping to protect the building from criminals and vandals. These sensors also reduce energy waste by controlling lighting in an area dependent on its occupancy. The different types of IoT smart building occupancy sensors include motion sensors, open/close sensors, and perimeter sensors [7-9].

Motion sensors monitor movements inside the building. With motion sensors, the building administrators can detect unexpected movements in the building and detect the presence or absence of people in a particular area and control the lights to turn on/off accordingly [7, 9]. Examples of motion sensors include passive infrared sensors, microwave sensors, ultrasonic sensors, area reflective sensors, dual sensors, video sensors, wireless sensors, vibration sensors, and pet immune sensors [10].

Open/close sensors monitor the opening or closing of cabinets, doors, and windows. Open/close sensors can also automatically turn on the lights when a door is opened [7, 9]. Examples of open/close sensors include glassbreak sensors, passive infrared sensors, and door and window sensors [10, 11].

Perimeter sensors provide the extra layer of security by detecting any vehicles or persons approaching the building [14, 16]. Examples of perimeter sensors include active infrared sensors, capacitance sensors, vibration sensors, radar sensors, fence sensors, driveway sensors, and electric field sensors [18].

IoT Smart Building Environmental Sensors

The building administrators can create a comfortable living environment for the occupants inside the building with IoT smart building environment sensors [7]. IoT smart building environmental sensors include temperature and humidity sensors, leak and water sensors, smoke and air sensors, and light sensors [9].

Temperature and humidity sensors monitor unexpected changes in heating, cooling, and the amount of water vapor inside the building. Temperature and humidity sensors also reduce energy waste by turning off the cooling or heating in an area where there is no person present [7]. Examples of temperature sensors include resistive temperature devices, thermometers, thermocouples, infrared sensors, bimetallic devices, silicon diode, and change-of-state sensors [12]. Examples of humidity sensors include resistive sensors and capacitive sensors [13].

Leak and water sensors alert the building occupants as soon as a leak is detected, thereby helping to prevent damaging floods that can be costly to repair [7]. Examples of leak and water sensors include under carpet leak detectors, rope-style sensors, spot leak detectors, and hydroscopic tape-based sensors [14].

Smoke and air sensors monitor the air quality inside the building. With smoke and air sensors, the building occupants can detect the presence of smoke, carbon monoxide or any other harmful gas in the building [7]. This would in turn help the building occupants to take corrective measures before any serious harm happens to anyone inside the building. Examples of smoke and air sensors include photoelectric sensors, ionization

sensors, dual sensors, aspirating sensors, projected beam sensors, video sensors, and heat sensors [15].

Light sensors monitor the lighting levels inside the building. These sensors automatically adjust the lighting inside the building depending on the ambient natural lighting from the sun [7]. This helps enhance the lifetime of the light bulbs and reduce energy wastage. Examples of light sensors include photo-junction sensors, photoconductive sensors, and photovoltaic sensors [16].

IoT Smart Building Power Monitors

IoT smart building power monitors keep track of the amount of energy used by each appliance or any other device inside the building [7]. Using these power monitors, the building occupants can be more conscious of their energy usage, adjust their energy usage behaviors to reduce energy wastage, and ensure that all appliances and other devices operate efficiently and not consume too much power. There are four types of power monitors including readout and history monitors (e.g., Wattvision power monitor), instant readout monitors (e.g., Blue Line PowerCost monitor), plug in monitors (e.g., Kill a Watt EZ electricity monitor), and circuit by circuit measurement monitors with both history tracking and instant readout capabilities (e.g., eMonitor) [17].

Other IoT Smart Building Sensors

Some of the other IoT smart building sensors that are currently on market and have not been listed above include dry contact sensors to detect contact between two wired contact points; smart plugs to enable building administrators to turn on/off the

appliances or other electronic devices remotely using their smartphones; current transformers to monitor the electricity flow inside the building; AC/DC voltage sensors to determine the powered state of equipment and alert the building administrators if voltage levels exceed the device ratings; power synching sensors to create customized triggers in response to changing state of the plugged-in device (e.g., the building administrator can have the conference room projector set the lighting level in the room when turned on); and smart home monitoring kits, which are made by incorporating some of the above-mentioned IoT sensors in a single package, to provide the homeowners with a more advanced and affordable way to monitor and stay connected to their house from anywhere and at all times [7, 8].

Fig 1.2 shows different types of IoT sensors with their leading suppliers, which are currently on the market for smart building applications.

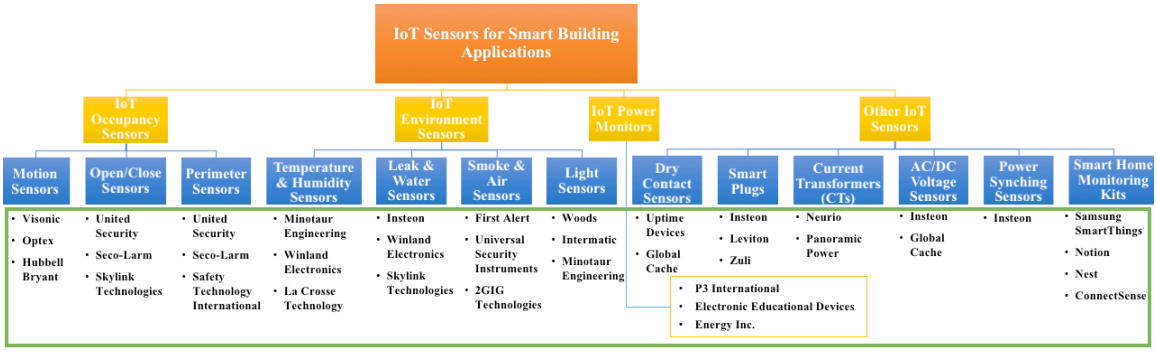


Fig. 1.2. IoT sensors on the market with their leading suppliers for smart building applications [3].

Economic Impact

McKinsey Global Institute has estimated that by 2025, the per year global economic impact of IoT for the different smart building environments will be as follows [18]:

- Smart homes: $200 billion - $350 billion
- Smart retail: $410 billion - $1.2 trillion
- Smart offices: $70 billion - $150 billion
- Smart factories: $1.2 trillion - $3.7 trillion
- Smart worksites: $160 billion - $930 billion

The market for IoT sensors for smart buildings is undergoing a favorable progression as well and offers numerous opportunities for growth and development. Driven by reduction in cost and energy per sensor, IoT sensors are now becoming more popular for industrial and consumer applications [19]. Transparency Market Research has estimated the increase in global market for IoT sensors from $9 billion in 2012 up to $21.60 billion by 2019, growing at a CAGR of 12.2 percent (Fig. 1.3) [20]. ABI Research has estimated an increase in the market value of enterprise IoT analytics from $4.2 billion in 2014 to $23 billion by 2020, indicating the increasing investment in IoT analytics [21].

While there are considerable opportunities for increased revenue in smart buildings, these impressive statistics must be balanced with the costly investments companies must make upfront when employing novel IoT devices and technologies. Nevertheless, the surplus generated will outweigh the initial expenses. Additionally, IoT

technologies can be deployed in existing devices and infrastructures, further minimizing expenses [3].

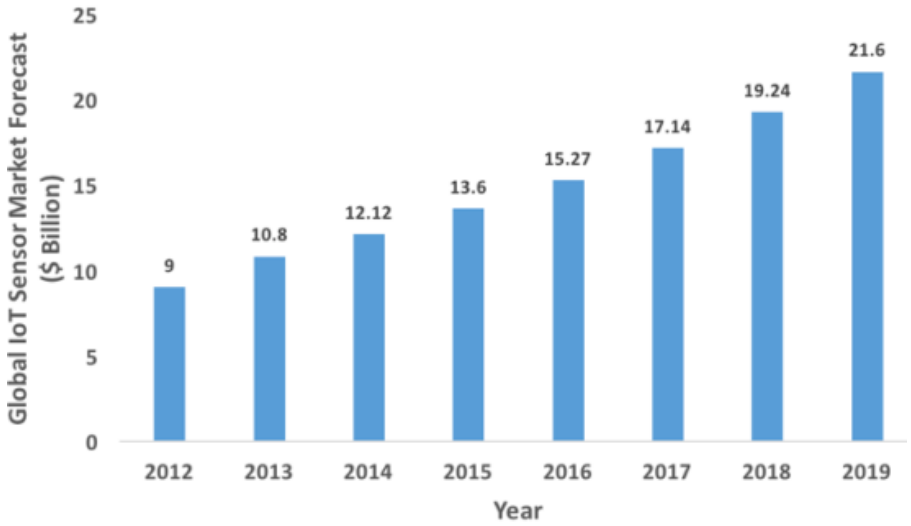


Fig. 1.3. Global IoT sensor market forecast ($ billion) (adapted from [20]).

Environmental Impact

With IoT deployed in smart buildings, energy is utilized more efficiently. Also, control systems are optimized for maximum power absorption from renewable sources (solar and wind) [22]. This has a positive impact on the environment in terms of less energy waste and reduced carbon dioxide (CO_2) emissions. By 2020, 2 Gigatons annual decrease in CO_2 emissions is expected [23].

Societal Impact

As world's population continues to grow, it becomes increasingly necessary for its inhabitants to care for the available resources. With rising living standards globally, health, convenience, and comfort have become personal priorities. IoT can meet all of

these needs and desires through its abilities to sense, collect, transmit, analyze, and distribute big data [3].

To meet these demands, organizations and institutions will deploy IoT in building environments, leading to increased energy efficiency and greater control and auditing capabilities. However, with greater amounts of personal data collected from smart meters to decrease energy waste (e.g., energy usage data and user movements and activities tracking data), personal security could be jeopardized if the meter is hacked. For instance, a hacker could determine if a user is in the building or not or if a child at home alone [3]. While there are cyber-security and privacy risks associated with IoT deployment in smart buildings, there are overwhelming societal benefits including lifestyle convenience, public safety, energy conservation, expense reduction, and a healthy living environment [24]. Individuals and corporations must decide the optimal use of the technology for their needs based on these tradeoffs [25].

IoT deployment cannot be pushed onto the society and expected to be readily accepted. People like to take responsibility for their well-being. Considering the numerous benefits of the deployment of IoT technology, a lot of people might be willing to try it out. But there will be some people who will resist this technology, even after being aware of its benefits. For them, IoT technology might not be the need of the hour, or they might just fear the unknown. Additionally, the competition between nations to excel at IoT device manufacturing and technology development makes it difficult for a company to establish a base in a foreign country and utilize its resources [3]. An instance of this was reported recently in [26] where GE launched its digital foundry in Shanghai

and is facing tough competition from the Chinese local firms. In any case, people's choices must be respected, and they should not be forced down a path that makes them uncomfortable.

Intelligence for IoT and Energy Management

Modern building owners are enamored by the possibility of being able to reduce monthly energy bills and resource usage by monitoring and having control over their building at all times without having to be physically present. IoT is making this concept a reality and transforming simple building energy management into smart building energy management. With IoT, every physical object present inside the building will be networked over the internet through sensors and software enabling these objects to communicate with one another and with the user over the internet. Some of the applications of a smart building energy management include improved energy efficiency, access control, lighting control, fire/leak detection, heating, ventilation, and air conditioning (HVAC) monitoring and temperature control, and improved building security [6].

Some of the leading building energy management system (BEMS) developers include Schneider Electric, Honeywell, Siemens, and Johnson Controls [27]. The BEMS developed by these companies are computational systems with capabilities including automated and real-time energy consumption monitoring and control and advanced building analytics using historic and real-time data. Situational intelligence (SI) must be incorporated into these computational systems to transform them into computational

systems thinking machines [28] to overcome current energy challenges. SI imparts capabilities including security and stability limit prediction with contingency analysis, load and generation forecasting, cyber security, and real-time/predictive visualizations [28]. SI can be implemented by integrating historical IoT sensor data with real-time IoT sensor data (equation 1.1).

Intelligence (near-future) = (history, current status, some predictions) (1.1)

Fig. 1.4 shows a block diagram of a smart building computational systems thinking machine that imparts intelligence for IoT and energy management in a building environment by providing communication (sense-making), computation (decision-making), and control (adaptation) capabilities [28].

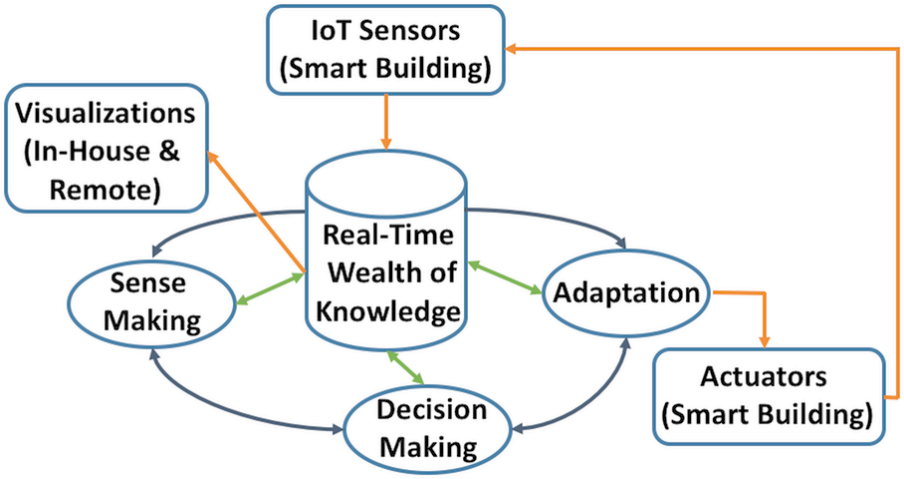


Fig. 1.4. Computational systems thinking machine for smart building environment (extended from [28])

A wide variety of IoT sensors (e.g., motion sensor, lighting sensor, and temperature and humidity sensor) impart monitoring capabilities to the existing building appliances and make them better aware of their surroundings. The wireless communication technologies (e.g., Bluetooth, Zigbee, IPv6, and Wi-Fi) impart connectivity capabilities to the building

appliances to transfer sensor data to the cloud, the control system, and other building appliances. Additionally, these wireless communication technologies enable remote monitoring and control of the building appliances in smart building electric energy management. The control system includes devices such as remote control, tablet, and smartphone, which utilize the sensor data to generate the appropriate control signal and transmit it to the building appliance (actuator) using the wireless communication technology. The building appliance uses this control signal to adjust its current state of operation to account for any deviations in the operating parameters. One such computational systems thinking machine [28] called the Intelligent Computational Engine (ICE) is developed in this dissertation and is described in Chapter 3.

Contributions of This Dissertation

The contributions of this dissertation are as follows:

- Detailed review of the role, impact, and challenges and recommended solutions for implementing IoT in building environments (Chapters 1 and 2) [2, 3, 6, 29]
- Development of a general framework of a control architecture for the Intelligent Computational Engine (ICE) to overcome current energy challenges in an IoT driven building environment (Chapter 3) [30]
- Development of building case study environment (i.e., Real-Time Power and Intelligent Systems (RTPIS) Laboratory) with integration of IoT devices and technologies) (Chapter 4) [31, 164]

- Development of energy consumption prediction models viz. exponential model and Elman recurrent neural network (RNN) model and their comparison to determine the most accurate model for use in the development of ICE's energy consumption prediction capability (Chapter 5) [31, 164]
- Development of ICE's cellular computational network (CCN)-based energy consumption prediction capability (Chapter 6) [30]
- Development of ICE's optimized control of electric loads capability using particle swarm optimization (PSO) algorithm and logic connector tool (LCT) (Chapter 7) [30]
- Deployment and dispatch of ICE's energy consumption prediction and optimized control of electric loads capabilities in the RTPIS laboratory to demonstrate energy savings (increased energy efficiency) (Chapter 7) [30]

Summary

IoT for smart buildings presents an exciting area of innovative growth and development. The important role of IoT in transforming modern day buildings into energy efficient, smart, and connected buildings was presented in this chapter. Digitizing the building environment using IoT reduces wasted energy and improves the energy efficiency of the building environment. The economic, environmental, and societal impact of IoT for smart buildings was also presented in this chapter. Furthermore, IoT sensors for smart building environment were discussed in this chapter. The contributions of this dissertation were enumerated in the last section.

CHAPTER TWO

CHALLENGES AND RECOMMENDED SOLUTIONS FOR IMPLEMENTING IOT IN SMART BUILDINGS

Introduction

As discussed in Chapter 1, deploying IoT in smart buildings has several advantages including improved system efficiency, reduced energy cost, increased energy savings, enhanced user comfort, increased return on investment, and reduced carbon emissions. However, some associated technical and non-technical challenges exist. Technical challenges include sensing, connectivity, power management, big data, computation, complexity, and security [3]. Technological innovations are necessary to overcome these challenges to ensure continued growth of IoT for smart buildings (Fig. 2.1).

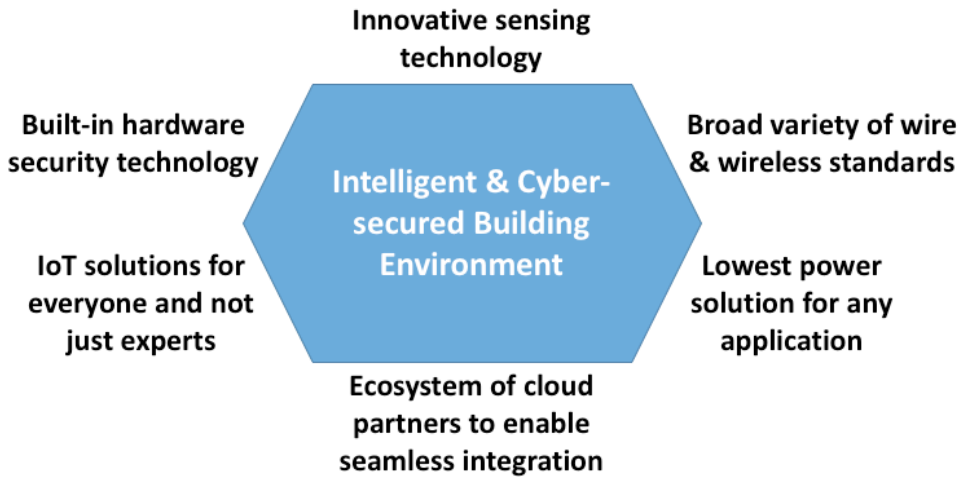


Fig. 2.1. Technological innovations for intelligent & cyber-secured building environment (adapted from [2]).

Non-technical challenges include need for behavior change and influence of social attitudes for uptake of the technologies and buy-in regarding smart buildings from consumers in order to realize the benefits of deploying IoT technologies in smart buildings [29]. Thus, it is important to employ science to consider not only the actual benefits of the technologies under laboratory conditions but also how the technologies will affect the real lives and communities of human users. Human behavior change and social attitudes will prove to be a driving factor of the penetration of IoT technologies in smart buildings [29].

Therefore, studying the implementation of IoT in smart buildings is complex because it involves not only measuring quantitative success but also consumer perceptions and satisfaction. To gain a rich, multi-dimensional, synergetic understanding, quantitative and qualitative data should be integrated [32]. Mixed method research designs have the capacity to capture the experiences, emotions and motivations of individuals as well as the objective measures of the successful deployment of IoT technology in the smart building.

Fig. 2.2 shows the recommendations for successful implementation of IoT devices and technologies in smart buildings. As presented in the figure, the key entities including people, IoT devices, and environment overlap or interact with one another and therefore, should not be treated as distinct entities. Each overlapping region has its associated impact and innovation needs. In order to realize this transformation goal, the innovation needs must be fulfilled [29].

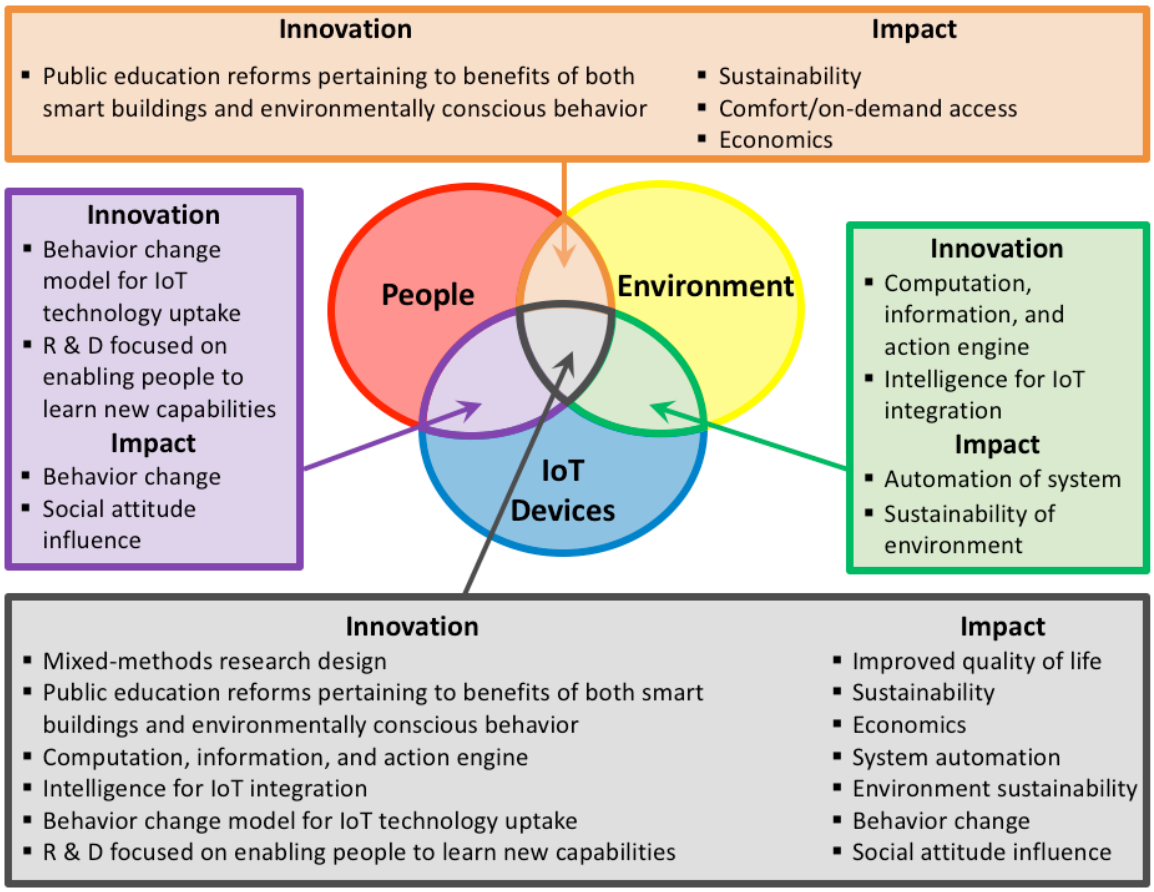


Fig. 2.2. Recommendations for successful implementation of IoT in smart buildings [29]

The different challenges (technical and non-technical) and some of the recommended solutions to overcome these challenges are described below. Also described below are some of the recommendations for mixed-methods research design for successful implementation of IoT in smart buildings.

Sensing

Advancements in sensor technology have resulted in IoT sensors becoming more powerful, cheaper and smaller in size. This, in turn, has led to their large scale deployment in building environments. Current IoT sensors lack some critical features viz.

situational intelligence, efficient power management, and enhanced cyber security, which must be incorporated into future IoT sensors to enhance their functionalities [33].

As discussed in Chapter 1, near-future situational intelligence can be implemented by integrating historical IoT sensor data with real-time IoT sensor data. Benefits of implementing near-future situational intelligence in IoT sensors include security and stability limit prediction with contingency analysis, load and generation forecasting, cyber security, and real-time/predictive visualizations [28]. For efficient power management, solutions include using arrays of low-accuracy sensor modules with subsequent data fusion to generate high-accuracy information, employing energy harvesting solutions (e.g., light, heat, RF, and vibration) to prolong battery life, and using digital circuits to design low power sensor nodes [34]. Cyber security solutions include embedding hardware security features and adding more layers of security [35-37].

Connectivity

Need for Comprehensive Connectivity Standards for IoT

There are many connectivity standards for IoT applications that can broadly be classified into three categories: service-related, communications-related, and data-related [38]. The service-related connectivity standards provide definitions for common services to support IoT applications. They provide definitions for common capabilities, their respective access interfaces, and the protocols employed over these interfaces in a manner that enables different IoT applications to gain access to these capabilities across protocol stacks developed by different standard organizations (e.g., International

Telecommunication Union [39], European Telecommunication Standards Institute [40], oneM2M [41]). Additionally, the service-related connectivity standards develop access-independent interface standards (e.g., [42] by Telecommunications Industry Association), addresses carrier portability matters (e.g., [43] by ATIS), and network security concerns (e.g., [43] by ATIS) for IoT applications. The communications-related connectivity standards provide definitions for efficient communication mechanisms for supporting IoT applications. They provide application guidelines to fit the operation of particular standards, like Transport Layer Security, in an IoT setting (e.g., [44, 45] by Internet Engineering Task Force (IETF)). They also define additional protocols, like RPL (pronounced "ripple") routing protocol for 6LowPAN, to fill gaps in the protocol solution set for IoT (e.g., [46] by IETF). They also provide support for multiple vertical application domains (e.g., [47] by IEEE). The data-related connectivity standards provide definitions for generic mechanisms for supporting versatile data usage and interoperable data exchange in IoT applications. They provide technology-independent interfaces for generic data definition and access (e.g., [48] by Open Geospatial Consortium, and [49] by Object Management Group). Additionally, they provide flexible mechanisms for defining object identity information and exchanging this information with other administrative domains (e.g., [50, 51] by OASIS, [38]).

Interoperability between all the different standards available for IoT applications is critical to support the integration of different types of data generated from a variety of sources. Interoperability enables the IoT devices to support the curation, provenance and exposure of data to third party applications enabling rapid innovations in the application

and service ecosystems [38, 52]. Without interoperability, there will be challenges with data representation formats, data dissemination mechanisms, and data management platforms. The diverse physical and virtual assets can no longer remain disparate entities in a smart building environment. They must be interoperable entities across IoT applications. These challenges along with the continuously increasing number of IoT devices demand the development and implementation of comprehensive connectivity standards that will be critical in achieving interoperability and seamless transitions between the physical and virtual domains of IoT [38, 52].

With the emerging 5G cellular communication standard, low-cost and efficient communication with increased network coverage and bandwidths are expected to support a sheer scale of IoT devices, the continuously increasing multimedia applications, and an exponential increase in wireless data [53].

Coexistence Challenge

IoT application in a smart building environment utilizes several connectivity protocols (e.g., Wi-Fi, Bluetooth, ZigBee, and BLE) for data transmission [54, 55]. Such heterogeneous connectivity scenarios are faced with the coexistence challenge i.e., interferences resulting from interaction between wireless connectivity protocols that share the same (2.4 GHz) frequency band. These interferences significantly degrade the network's quality of service [54].

A solution for overcoming the coexistence challenge is with a wireless convergence module since it can handle multiple connectivity protocols simultaneously using advanced coexistence algorithms. Fig. 2.3(a) shows a smart building scenario

where the wireless convergence module handles different connectivity protocols, enabling data transfer between IoT sensors and the cloud. An example of a wireless convergence module is Redpine RS9113, which supports the heterogeneous connectivity scenarios of IoT and addresses coexistence challenges through its innovative coexistence algorithms (Fig. 2.3(b) and Fig. 2.3(c)) [54]. Other solutions for overcoming the coexistence challenge include fair channel assignment [56] and dynamic licensed spectrum sharing [57]. The fair channel assignment approaches ensure fair allocation of radio resources to links or flows to achieve seamless transmission [56]. The dynamic licensed spectrum sharing approaches allow mobile operators to make use of underutilized licensed spectrum bands based on service level agreements [57].

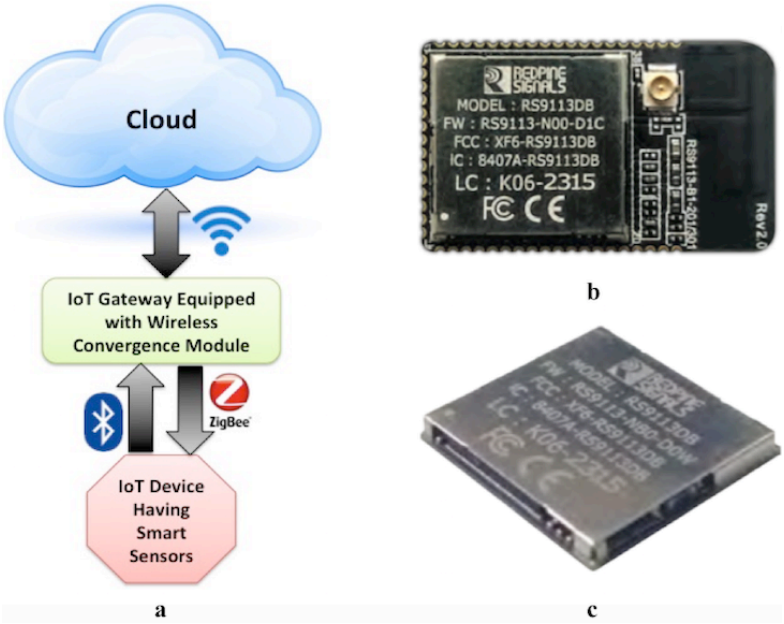


Fig. 2.3.(a) Application of wireless convergence module in a smart building scenario [6], (b) Redpine RS9113 module with built-in antenna [54], and (c) Redpine RS9113 module without built-in antenna [54].

Power Management

Incorporating power management is critical for an IoT device to perform its designated functions. Based on the position and functionality of IoT devices in a smart building environment, their power collection methods vary. This makes it challenging to incorporate power management in IoT devices [3]. The recommended solutions to overcome the power management challenge in IoT devices are discussed below.

Energy Harvesting System

IoT devices in a smart building may be installed in locations that are not easily accessible (hazardous, toxic, or hard-to-reach areas) making grid connection or battery replacement a complex and expensive approach to power these devices. In such scenarios, an energy harvesting system can be a promising alternative to prolong the lifetime of the IoT device and reduce their dependency on the grid or battery [58].

The energy harvesting system comprises of three components: energy source, harvesting architecture, and load (sink for the harvested energy) [59]. An energy source is the source of energy to be harvested. The energy sources that are present in the surrounding environment are called ambient energy sources, for example solar, wind and vibrations. Energy may also be harvested using body movements of humans and is called human power. Human power can be active or passive depending on whether the body movements are controllable by the user or not. Examples of active human power include finger motions and footfalls; and examples of passive human power include exhalation, breathing, and blood pressure. In general, energy sources can either be controllable or non-controllable. Controllable energy sources can be harvested as needed. There is no

need to predict energy availability before harvesting them. Examples of controllable energy sources include finger motions and footfalls. Non-controllable energy sources must be harvested whenever they are available. Prediction models are needed for non-controllable energy sources to forecast their availability to plan the next recharge cycle. Examples of non-controllable energy sources include (solar, wind, and vibrations) [59]. Out of all the different energy sources, solar energy emerges as the most promising harvestable energy source due to the following reasons [58]:

- Solar energy is freely available and easily accessible energy source
- The amount of energy harvested from solar is 24mW/cm^2
- It is uncontrollable but predictable
- Solar panels can be made small enough to fit the form factor of wireless IoT sensor nodes

A harvesting architecture is a mechanism to collect and convert ambient energy to electrical energy. It either harvests the source energy for just-in-time use (harvest-use architecture) or stores the harvested source energy for future use (harvest-store-use architecture). The energy conversion mechanism in the energy harvesting architecture depends on the energy source being harvested. For example, solar panels are used to convert solar energy into electrical energy; piezoelectric elements are used to convert mechanical energy sources such as walking, paddling, pushing buttons/keys, into electrical energy; and rotors and turbines are used to convert wind energy into electrical energy [59].

Employing energy harvesting systems exclusively to power IoT devices that have low-energy requirements can make these devices truly portable and self-sustaining in addition to helping reduce the carbon footprint [58, 59]. Studies have shown that an energy harvesting system has the potential to prolong the lifetime of low-power IoT sensor nodes when deployed in randomly distributed multi-hop topology and uniformly distributed ring topology [60]. Although energy harvesting systems offer promising benefits, they also have the following associated drawbacks [58]:

- The random and intermittent nature of the renewable sources of energy (e.g., solar and wind) for energy harvesting systems makes it challenging to provide a stable power source to the IoT devices.
- RF Energy harvesting systems have very low efficiencies (around 16.3 percent [61]).

Therefore, there is a need to overcome these drawbacks for successful deployment of ambient energy harvesting solutions to power the IoT devices. A solution to account for the intermittent nature of renewable sources of energy is to employ storage technologies (e.g. NiMH batteries, Li-ion batteries, and supercapacitors) to store the harvested energy [59].

Energy-Efficient Communication Networks

Energy consumption in communication networks is increasing at a tremendous rate, which is attributed to the rapid rise in the number of IoT devices with networking capabilities and the progressive growth of information and communication technology. Therefore, effective power management solutions need to be developed to overcome this issue. Energy-efficient communication networks for a smart building environment can be

achieved by incorporating power management in both peripheral (e.g., IoT sensor nodes and smartphones) and access (e.g., base stations, switches, and routers) network equipment of the communication network. This section discusses the energy-efficient communication techniques for wireless, wired, optical, and optical-wireless communication networks [62].

Energy-Efficient Wireless Communication Networks

Cellular networks including 3G, 4G, 5G (yet to be launched), WiMAX, ZigBee, and Wi-Fi are utilized in wireless communication. The metric for energy efficiency in wireless networks is "bits-per-joule" and is a measure of throughput with regards to unit energy consumption [62]. The following power management solutions can be incorporated in wireless communication networks to make them energy-efficient:

- Employing the relaying technique using mobile relays between IoT entities that are geographically spread, resulting in shorter transmission range requiring low transmission power [63, 64]
- Using the cooperative communication technique for IoT entities that have different channel conditions (channel diversity) [63]
- Placing the base station (BS) in sleep mode during low traffic volume since they account for 60–80% of the whole power consumption in a wireless network [65, 66]
- Using the coordinated multi-point technology, where the function of the base station is separated into baseband unit and remote radio unit parts. By doing so, the distance between the user and antennas decreases, resulting in reduced system transmission power consumption [67].

- Adoption of the power saving mode by IEEE 802.11 standards that allow the wireless nodes to go into sleep mode when they are neither receiving nor transmitting [68]
- Employing networks like ZigBee [69] and ultra-low power Wi-Fi [70], which are inherently energy efficient, for home area network
- Connecting IoT devices in mesh topology to improve power efficiency and communication capability [71]
- Using radio frequency energy harvesting to power the wireless communication networks [72]
- Deploying turbo codes in energy-constrained wireless communication applications can help decrease RF bandwidth requirements and/or increase information bit rates significantly, without having to increase the transmission energy consumption [73].

Energy-Efficient Wired Communication Networks

Power line communication (PLC) and Energy Efficient Ethernet (EEE) are utilized in wired communication [62]. The following power management solutions can be incorporated in wired communication networks to make them energy-efficient:

- Incorporating spectrum sensing scheme in PLC to reduce its power consumption [74, 75]
- Incorporating green resource allocation scheme in PLC that optimizes data allocation to the available channels [76]
- Adoption of the power saving mode by HomePlug Alliance (PLC standard for Smart Grid applications) within its Green PHY 1.1 definition [77]

- Employing low-power cycles in EEE with periodic refresh intervals to maintain the transmitter-receiver alignment and save energy [78]

Energy-Efficient Optical Communication Networks

Fiber optical communication networks offer several advantages including high speed, large bandwidth, and a high degree of reliability. These networks follow a hierarchical organization consisting of core (providing coverage ranging from a few hundred to a few thousand kilometers), metro (providing coverage ranging from a few tens to a few hundred kilometers) and access (providing coverage ranging over a few kilometers) domains [62]. The following power management solutions can be incorporated in optical communication networks to make them energy-efficient:

- Turning off the network equipment (e.g. switches, line cards or the links) that is in its idle state during low traffic volume [79, 80]
- Employing lightpath bypass technique over lightpath non-bypass technique to provision survivable demands with minimized power consumption in IP-over-WDM networks [81, 82]
- Incorporating techniques like multi-path selection [83], multi-granular switching [84], and energy-aware routing [85] to save energy
- Employing energy-efficient access technologies such as passive optical networks [86], Ethernet passive optical networks [87, 88], long-reach passive optical networks [89], and point to point optical networks [90]

Energy-Efficient Optical-Wireless Communication Networks

Optical-wireless communication networks, commonly known as fiber-wireless (Fi-Wi) communication networks, combine the ubiquity, coverage and flexibility of wireless communication networks with the speed and the reliability of optical communication networks. To make the optical-wireless communication networks energy-efficient, the optical network unit (ONU) module of a joint ONU-BS node can be placed in sleep mode during low traffic volumes. In this case only the BS module from the joint ONU-BS node handles data forwarding to the peers [62, 90].

Big Data

Hundreds of IoT devices connected across a smart building environment generate large amounts of data (or big data), making it challenging to store, track, analyze, capture, cure, search, share, transfer, secure, visualize, and interpret the generated data [91]. It is challenging to process big data using traditional data processing applications due to the following unique characteristics that are associated with big data [92]:

- Large volume/quantity of generated data
- Variety in the type of generated data
- Different velocity/speed of data generation
- Variation in the veracity/quality of source data
- Data inconsistency/variability

Big data must be transformed to actionable/intelligent information, knowledge, and understanding to extract value from it. Understanding is a process by which

individuals attach meaning to an experience. Understanding of what matters must be a priority, especially for critical operations. Additionally, understanding must be gained from a shared view due to the interconnected (spatial and temporal) nature of the electric power grid dynamics [28].

A recommended solution to overcome big data storage and processing challenge is Apache Hadoop – an open-source software framework. Hadoop utilizes large clusters of commodity servers to enable distributed processing of big data. Hadoop has a number of advantages including hardware infrastructure scalability, cost efficiency, data type flexibility, and fault tolerance, which makes it a leading candidate for storing, managing, and processing big data [92]. It is important to note that Apache Hadoop works well for smart grid markets days or weeks ahead, but does not work well for real-time application scenarios like smart buildings. Hence there is a need for real-time big data solutions for smart building like application scenarios. A prospective solution to overcome the real-time big data handling and storage challenge involves a collaborative effort from all leading cloud providers to develop a new IoT cloud ecosystem [91].

IoT Computational Requirements and Capabilities

As compared to human brain, IoT infrastructure is not that complicated. In a human brain, there are 100 billion neurons with each neuron connected to 10,000 other neurons [93]. Imparting computational capabilities to the IoT devices and the network-edge devices (e.g. gateways and routers) have resulted in a paradigm shift from connected/networked IoT devices to intelligent IoT devices.

The advancements in computational intelligence capabilities can evolve an intelligent IoT system by emulating biological nervous systems with cognitive computation, streaming and distributed analytics including at the edge and device levels. Cognitive computation emulates biological thinking, analysis, and strategy, serving as a learning mechanism for the entire IoT ecosystem. It can identify patterns from large and diverse data sequences in real-time by weighing the incoming data against the long-term information and making strong decisions. Several companies such as Intel and CognitiveScale are exploring intelligent interactions by combining sensors, contextual data, and cognitive computing to drive new strategies for various industries including home automation, healthcare, and traffic management. Streaming analytics mimics the biological spinal cord by controlling the reflex actions that do not need extensive computations to make decisions in real time. It weighs the incoming analytical data with historical information in real time to make quick decisions (very low latency). The decision making with streaming analytics is much faster than batch processing large amounts of data. There are several cloud solutions (e.g. Amazon Kineses and Azure Streaming Analytics) and cloud-based, open source or on-premise applications (e.g. Apache Spark and Apache Storm) that support streaming analytics. Edge and device computation mimics biological nerves and neurons that filter the incoming data, retain the data that can be processed locally in the edge devices (impacting only a small part of the IoT ecosystem), and forward the remaining data to be processed in the cloud (impacting a larger part of the IoT ecosystem). An example of a small and inexpensive edge computing device is Raspberry Pi [94, 95].

The number of IoT devices and applications are continuously growing leading to a significant increase in IoT data volume. ABI Research has estimated the IoT data volume to grow from 233 exabytes in 2014 to 1.6 zettabytes in 2020 [96]. The different IoT devices and applications generating real-time data are dispersed over large geographical areas and support a variety of use cases and domains. A centralized computation and storage solution (e.g. cloud) for real-time heterogeneous IoT data is not ideal. IoT applications have strict requirements like high throughput during short time periods, very low latency, and prompt decision making based on real-time data analytics, which cloud computation cannot satisfy. With all the IoT devices and applications sending service requests to the cloud, it would be challenging to serve these requests in real-time resulting in inefficient service-provisioning and increased latency. Additionally, IoT ecosystems are constrained in terms of low power communications, scarce energy, and lossy communications, which necessitates localized computation and storage solutions for processing, analyzing, and storing IoT data [97-101].

Two approaches for overcoming the IoT data computation challenge are discussed below viz. fog computing and IoT data footprint reduction methods. Deploying these solutions in the IoT ecosystem will drive the smart building operations using hard evidence and statistical probabilities rather than relying on soft opinions and intuitions.

Fog Computing

The term fog computing was coined by Cisco Systems, Inc. in 2012 [102]. Fog computing is a distributed computing infrastructure that provides computational and

storage capabilities to the network devices located at different levels in the IoT hierarchy viz. endpoint level, gateway/server level, and cloud level [97].

Fog computing is based on the principle of edge computing where IoT application service requests, requiring low latency, support for mobility, and real-time data analysis with decision making abilities (e.g. smart grid, smart traffic monitoring, and smart parking), are processed locally within the fog computing devices (e.g. gateways, routers, and access points). Alternatively, the requests that demand extensive analysis involving historical data-sets, or semi-permanent and permanent storage (e.g. social media data, photos, videos, medical history, and data backups), are forwarded to the cloud by the fog computing devices [97].

Therefore, fog computing and cloud computing are not competing computational technologies, but are instead complementary. Together they support the IoT applications' real-time and low latency service requests at the network edge, as well as applications requiring complex analysis and long-term data storage in the cloud [97, 100, 101].

The following are the advantages of employing fog computing in the IoT ecosystem. Many of these advantages are a result of the proximity of fog computing devices to consumers, their dense geographical distribution, and mobility support [98, 103]:

- Refining the generated IoT data by distributing it among the edge devices [96]
- Lowering latency and saving bandwidth by processing IoT applications' service requests at the network edge [96, 98]
- Improving availability through local storage and analytics [96]

- Providing location awareness, improved quality of service, heterogeneity support, fault tolerance, scalability, and reliability [103]
- Reducing network traffic by increasing the operational size of the network [104]
- Maximizing security and compliance by encrypting critical data packets at the source [96]
- Saving both time and cost of transmitting the locally generated IoT data to the cloud over the Internet (high latency network) [105]
- Optimizing the total cost of ownership by reducing the connectivity costs and increasing the lifetime of battery-operated IoT devices [96]

Although there are several advantages, associated challenges with fog computing also exist:

- Handling data generated from dissimilar sources because of different protocols and data formats [104]
- Cyber attacks (e.g. node-compromised attack and man-in-the-middle attack) and privacy concerns (e.g. data protection and data management issues) [105]
- The unpredictability of the computational availability of the edge devices [106]
- Increased costs and energy consumption at a Fog node due to additional resource requirement by migrating Fog applications [107].

Several fog computing techniques have been proposed to overcome these challenges including software defined network and network functions virtualization [103], schema-less database record [104], task execution by idle edge resources [106], and smart shadow technique [108].

IoT Data Footprint Reduction Methods

As mentioned before, centralized computation and storage are not ideal for IoT applications. The increased IoT data velocity and volume from the growing scale of IoT devices can elevate the stress on the communication network resources to a point where resource starvation occurs. Therefore, it is critical to minimize the traffic inserted into the communication network. One way to reduce the data traffic is by appropriately distributing the data between the network elements based on their computation capabilities and available resources. Another way to reduce the IoT data footprint is dimensionality reduction method. This method relies on the global awareness and knowledge of the IoT ecosystem for eliminating redundancy and filtering out the noise from IoT data packets. The drawback with the dimensionality reduction method is that it does not address the impact of IoT data exchanges on the communication network. Data filtering methods are used to address the impact of IoT data exchanges at an operational level. These methods are distributed throughout the communication infrastructure, monitoring the IoT data in transit for significant events. Once a significant event is detected, data filtering methods label them with critical local information (e.g. network load) resulting in a more efficient treatment for these events at the operational level. The IoT data footprint on the communication networks can be further reduced by employing both data filtering and data processing methods within the same IoT node [104]. Neural Networks can also be employed to reduce data size during transmission over the communication network (Fig. 2.4) [109].

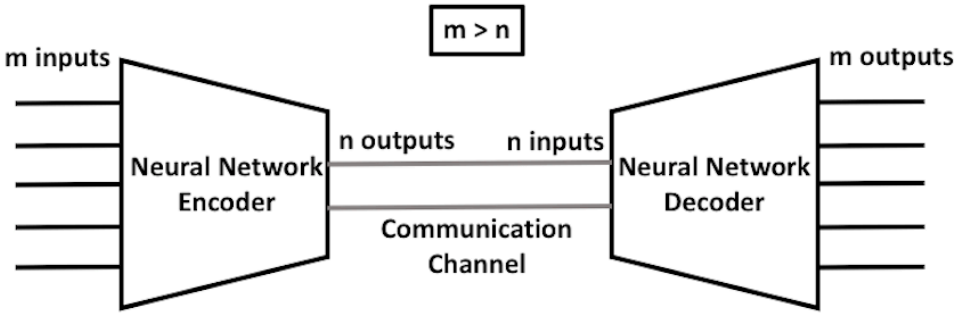


Fig. 2.4. Neural Networks used for reducing data size

Complexity

The expansion of network infrastructure due to the wide penetration of IoT devices has resulted in increased network size, heterogeneity (different vendors providing services, equipment, and applications), and complexity [110, 111]. For a lot of these devices, networked connectivity is a brand new feature. To continue this trend of adding more IoT devices with networked connectivity that seamlessly integrate with a smart building environment, IoT device design and development must be simplified [91, 55]. Further, the wireless capabilities must be encapsulated and instead easier to understand reference designs, modules, and on-chip connectivity stack and development environment must be provided [91].

The traditional approaches for network optimization, configuration, and troubleshooting are cumbersome, error-prone, and have proved to be inefficient in resolving the complexity issue [110]. For example, autonomous system based approaches have resulted in suboptimal performance, local optimization methods have resulted in conflicting operations, and the lack of inbuilt programmability, flexibility, and support

has resulted in service interruptions while implementing new ideas [112-114]. Additionally, the development, implementation, and testing of new methods for network optimization, configuration, and troubleshooting takes several years before they can be deployed, which may render them useless [115, 116]. A promising solution to manage the growing network complexity is software-defined networking (SDN) [110, 111].

The Open Networking Foundation defines SDN as "an emerging network architecture where network control is decoupled from forwarding and is directly programmable [117]." SDN decouples the control plane from the data plane. The data plane includes devices such as routers and switches that follow the controller rules to perform packet forwarding. The control plane includes controllers that oversee the network operations and provide a platform for the implementation of different network services and applications. The main advantage of SDN is that it offers the rapid implementation and deployment of innovative solutions (e.g., network security, network virtualization, and green networking) in the form of software. Additionally, SDN uses the cross-layer information and global network view in the logical centralization of feedback control to make better decisions. Therefore, SDN provides enhanced network configuration, improved network performance, and higher network flexibility to accommodate innovative architectures and operations [110].

Although SDN provides many benefits to overcome the complexity issue, it also has some associated challenges including SDN interoperability issues with legacy network devices, performance and privacy concerns with centralized control, and lack of

experts for technical support. Additionally, the shift from traditional networking to SDN can be disruptive [110].

Security

"A cyber security vulnerability is a weakness in a computing system that can result in harm to the system or its operation, especially when this weakness is exploited by a hostile actor or is present in conjunction with particular events or circumstances [118]." Cyber security is a potential issue for a smart building environment. Recent cyber attacks on IoT devices include the distributed denial of service (DDoS) attack on Dyn's managed domain name system infrastructure using Mirai botnet affecting over 100,000 endpoints [119], ransomware for smart thermostats that lock the user out and demand bitcoins to release the thermostat [120], Bluetooth smart locks that are easily hacked [121], DoS attacks by a lightbulb that froze the controls of the entire smart home [122], and the ease by which a neighbor was able to unlock the resident's front door smart lock, connected over Apple HomeKit, and gained entry into the house by simply issuing the unlock voice command to Siri [123].

Security solutions developed for IT computer systems will typically be inappropriate for a smart building environment. The attack incident taxonomy used by Computer Emergency Response Team (CERT) to describe security incidents is shown in Fig. 2.5 [124]. This taxonomy provides uniform terminology and useful framework to the security research community. Incidents consist of a set of attacks that are executed to achieve the desired objectives. Attacks produce unauthorized results by using tools to exploit system/network vulnerabilities. An attack consists of a sequence of events. Fig.

2.6 shows a modified attack taxonomy that adapts this approach to the smart building environment. As before, attackers use tools to exploit the vulnerabilities of the IoT devices in the smart building and launch attacks against targets to obtain unauthorized results.

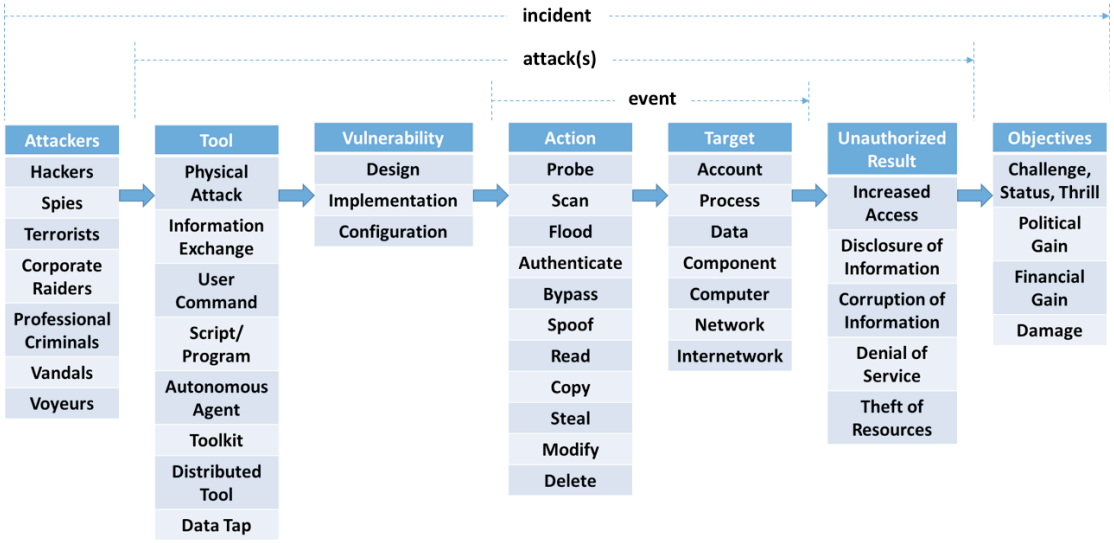


Fig. 2.5. Attack taxonomy by CERT [124].

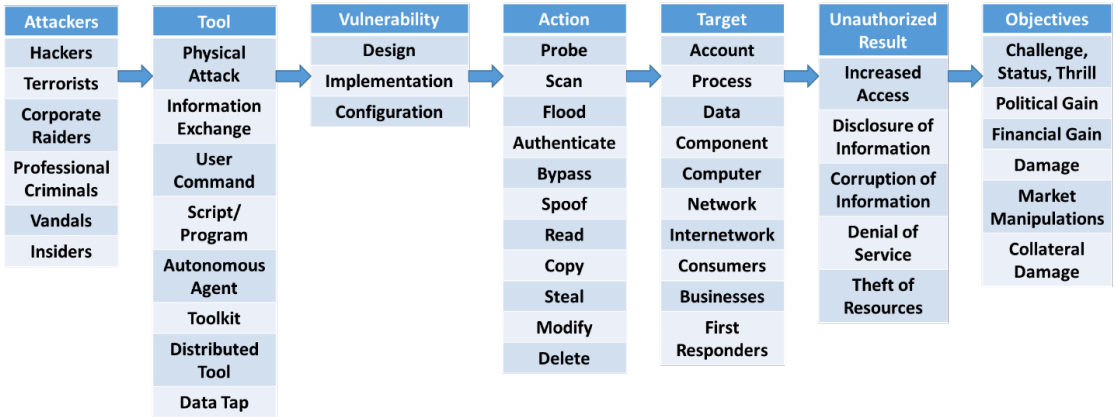


Fig. 2.6. Modified attack taxonomy for a smart building environment [3].

There are four general classes of attacks for the integrity, availability, confidentiality, access control, authentication, and nonrepudiation security aspects [125, 126]:

- Interruption: Asset availability is disrupted
- Interception: Unauthorized asset access
- Modification: Unauthorized asset tampering
- Fabrication: Fictitious asset creation

Security solutions are needed to overcome these risks and protect the IoT devices, networks, and sensitive data from security breaches and unauthorized access. Discussed below are some of the security challenges and recommended solutions for IoT devices in smart buildings [127].

Interruption Attacks

An interruption attack includes both hardware-based DoS attack or sabotage and software-based DoS attack [128].

Sabotage and Countermeasures

IoT device hardware or infrastructure sabotage (e.g. cutting a cable or inflicting damage to a physical IoT device) results in the disconnection of the device from the network. An example of sabotage in a smart building environment includes inflicting physical damage to smart meters [129-132]. These attacks can be reduced by limiting access to critical IoT infrastructure.

DoS Attacks and Countermeasures

In DoS attacks, the attacker compromises several machines (or zombies) and consumes network resources, which overloads the bandwidth of the target and results in slowed or dropped legitimate traffic (also known as distributed DoS (DDoS)). For instance, DoS attacks on smart building devices (e.g. smart meters) relying on the real-time measurement data cause delayed or lost measurements from these devices. This results in inaccurate demand predictions or complete failure of network measurement devices. Other examples of DoS attacks include network layer attacks, transport layer attacks, Local Area Network Denial attacks, and teardrop attacks [133]. In teardrop attacks, the attackers transmit fragmented packets to a target. Due to a bug in TCP/IP fragmentation reassembly, the target is not able to reassemble the received packets resulting in overlapping packets, which crash the target network device [134]. DoS attacks have the capability to inflict serious damage to the smart building environment and therefore, must be reduced by using network security techniques such as air gapped network, anomaly detection approaches, big pipes, and traffic filtering.

An air gapped network is a network security technique that physically isolates a secure computer network from other insecure networks (e.g. public Internet or an insecure local area network). It eliminates any communication with the machines not connected to the local segment. However, there is a drawback to this technique in terms of the high costs associated with building separate network infrastructures for the smart building environment.

Anomaly detection approaches are used to detect DoS attacks on a smart building environment. Experimental results have shown that the detection performance is inversely proportional to the network utilization. Also, the optimal detection parameters have a strong dependence on the network utilization [135].

Big pipes are large bandwidth network connections that can absorb attack traffic to mitigate the DoS attack on a smart building environment. However, there is a drawback to this technique in terms of the high costs associated with it.

A less expensive approach to mitigate DoS attacks on a smart building environment is traffic filtering. This approach utilizes distributed or redundant infrastructure to redirect attack traffic [136]. However, there are a couple of drawbacks with this technique including the lack of documentation to support the claim of filtering DoS traffic from normal traffic and the difficulty of employing this technique, especially with large traffic volume [128-130, 136-142].

Interception Attacks

An interception attack gains access to the information that is traversing the network between the smart building devices (e.g. between IoT sensors and actuators). These attacks can either be passive or active. Two types of interception attacks, packet sniffing and side channel attacks, are discussed below [135].

Packet Sniffing and Countermeasures

Attackers can gain access to the contents of the smart meter Transmission Control Protocol (TCP)/Internet Protocol (IP) packets that are sent across the smart building

network using software programs such as Wireshark [128]. This is known as packet analysis or packet sniffing. In the absence of encryption, the attacker can see and harvest all the sensitive information in the data packet.

Packet sniffing can be mitigated by using a security gateway that sends packets through a virtual private network (VPN) tunnel, which is created by embedding an IP tunnel (with encryption) within the normal IP network payload. The encryption hides the data from the attackers, making the network private, in addition to being virtual [141]. The communications between VPNs are secured using the Transport Layer Security (TLS) protocol. The connections between different parties on the smart building network are secured using the X.509 certificates, which first authenticate users and subsequently exchange symmetric keys. However, there is a possibility that the X.509 certificates are compromised or are issued in error [130]. An instance of compromised certificates was reported in [143], where an imposter tricked VeriSign into issuing two certificates for Microsoft. Although using VPN tunnels provide smart building network security, they have associated implementation and design errors. For example, an attack on a VPN tunnel was reported in [130], where the Heartbleed bug was discovered in the OpenSSL cryptography library leaving around half a million supposedly secure web servers vulnerable to cyber attacks. Therefore, it is essential to verify the security of VPN tunnels during their implementation [130, 137, 141, 144]. Using pre-shared keys is usually effective. Also, Secure Sockets Layer certificates or TLS certificates, which are generated by a common root of trust controlled by a trusted entity, can be used.

Side Channel Attacks and Countermeasures

From the above discussion, even though VPN encryption provides security for network connections, side-channel attacks are still possible. In side-channel attacks, sensitive information can be extracted by observing implementation artifacts [127, 145]. An example side-channel attack is in [134], where the protocol information was extracted by using a timing side-channel vulnerability for secure shell – a cryptographic network protocol [146]. This could severely degrade the monitoring of the smart building environment as the attacker can stop parts of the system's feedback control and hide inefficiencies or instabilities in the smart building environment.

To counter side channel attacks on a smart building environment, the communication channel bandwidth could be saturated to disallow any new patterns to emerge. However, this approach has an extreme resource requirement and can only be used in extreme cases [147]. Additionally, the detection of saturated channels, which can potentially be side channels, helps mitigate side channel attacks in a smart building environment. Also, building a separate infrastructure for smart building device communications can help resolve side channel attacks, but it is an expensive approach [148].

Modification Attacks

Modification attacks exploit security vulnerabilities in a smart building environment for corrupting, highjacking, or altering a legitimate process. Examples of modification attacks include man-in-the-middle (MITM) attack, Structured Query Language (SQL) injection, and malicious code injection [127].

MITM Attacks and Countermeasures

In MITM attacks, the attacker poses as the legitimate target to both the legitimate client and server during the protocol session. In other words, if A and B are communicating with each other, the intruder I disguises itself as B in front of A and as A in front of B, thereby replacing the AB link with two links AI and IB [127]. Some of the MITM attack methods include route table poisoning, modified packet source and destinations, and compromised certificates [127]. An instance of compromised certificate of Hypertext Transfer Protocol (HTTP) over TLS (HTTPS) connection was reported in [149], where the authors used fake certificates to initiate a MITM attack.

To counter the MITM attacks, the network traffic should be encrypted using security gateways [145]. The security gateway creates a VPN tunnel (unsecure network) connecting two secure networks. To ensure that the sensitive data is protected when passing through the VPN tunnel, the security gateway encrypts the data at the source and decrypts the data at the target. This encryption is typically done in hardware and can be efficient. Security gateways support smart building communications and interoperability by employing the Internet Protocol Security (IPsec) protocol. IPsec secures the communication link by ensuring that the data stays authentic, unaltered, and confidential throughout the communication process [145]. Additionally, to mitigate MITM attacks, both the system client and server need to be authenticated [144]. TLS protocols have in-built public key cryptography mechanisms that can promptly detect and correct any errors to avoid the occurrence of MITM attacks [128-130, 137, 139, 144, 150].

SQL Injection and Countermeasures

In SQL injection, the attacker alters the database by inserting new script commands [127]. Smart meters continuously send energy usage data to the utilities and the users, which is stored in a database. The SQL injection occurs if the queries formulated by the user are not properly validated before inclusion in the SQL query [151]. This attack can send malicious queries to the database management system to add, delete, or modify the database contents and take control of the system. This can disrupt the smart building operations as the attacker can indicate a normal operation state even when it's not, which might eventually result in an outage.

SQL injection on smart building networks can be mitigated by using measures including input type checking, positive pattern matching, penetration testing, static code checking, limiting database access to remote users, and avoiding dynamic SQL use [152, 153]. In input type checking, the characters that can be abused, like ";", are filtered out by the programmer to avoid any malformed input. This is not simple; authors in [154] have shown that most existing tools for sanitizing inputs have errors. In positive pattern matching, the user input is matched with the format of a good input. In penetration testing, SQL injection is attempted on the interface to ensure that these attacks are properly detected. In static code checking, the program is checked for correctness using code checking tools. Limiting database access to remote users means that the remote users should have limited rights on the database and all their inputs should go through an application program interface (API). Dynamic SQL use should be avoided and user inputs should be forced to use static templates and existing tables [130, 152, 153].

Fabrication Attacks

In fabrication attacks, the attacker creates a fictitious asset on the smart building network that transmits fabricated data across the network, which may be accepted by other network assets if not properly authenticated. Data spoofing – a type of fabrication attack is discussed below [127].

Data Spoofing and Countermeasures

The accuracy of data in the smart building network is critical for its efficient and reliable operation. In data spoofing, fabricated (inaccurate) data is injected into the control centers. Data spoofing severely degrades the smart building operation, stability, security, and reliability, which may result in an outage.

To counter data spoofing, the authors in [129] advise using a single data feed. Additionally, multiple/redundant smart building devices (smart meters) can be used to monitor the same electrical transmission bus to reduce data spoofing [83]. Other approaches to mitigate data spoofing include collaboration among GPS receivers to efficiently detect any spoofing [155] and synchronizing measurements using the network time protocol (NTP) across different locations in real time [156]. A combination of NTP and GPS is recommended to limit the modification of timestamps through GPS spoofing [124, 129-131, 137, 139, 141, 157].

Need for Behavior Change

Behavioral change is critical for realizing the impact of IoT in smart buildings. For behavior change to occur, it is necessary to understand the factors that influence a

person's decision-making process, lifestyles, and intensions. One way of motivating people to desire the behavior change necessary to adapt to smart buildings is through interventions where the people are educated about the benefits of smart buildings (e.g. reduced greenhouse gas emissions, revenue generation, and improved quality of life (QoL)). Because human beings are complex creatures, behavioral change usually occurs as part of a process [158].

This section discusses five stages of behavior change as described by the Transtheoretical Model (TTM) of Behavior Change (Fig. 2.7). TTM is a biopsychosocial, integrative model that conceptualizes the intentional behavior change process. It was originally developed by Prochaska and DiClemente in 1983. TTM uses stages of change to integrate processes and principles of change across major theories of intervention development, behavior change, and counseling [159]. It has been widely applied in problem behaviors (e.g. smoking cessation, alcohol abuse, drug abuse, weight control, medical compliance, and stress management) and has been considered in the context of IoT technology as well [158, 160].

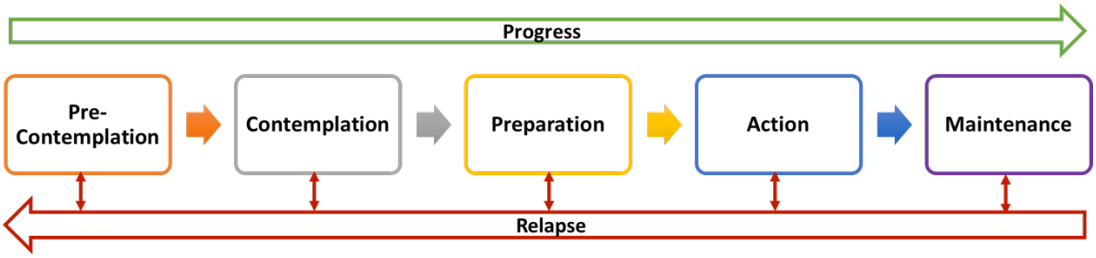


Fig. 2.7. Transtheoretical Model of Behavior Change [29]

Pre-Contemplation

In the pre-contemplation stage, the person is not aware that he/she needs a change in behavior. As applied to smart buildings this group includes people who are not aware of IoT technologies nor of their benefits for smart buildings [29].

To make this group of people interested in and excited about being part of a smart building, it is necessary to focus on improving communication and raising awareness that highlights the benefits of IoT technology and its impact on smart buildings. The information that is shared with this group should be clear, easy to understand, and tailored to their needs [161]. This information can be disseminated through social media outlets (e.g. Facebook and Twitter), testimonials from locals they know and trust, and news stories. By doing so, this group of people will hopefully progress to the contemplation stage [29].

Contemplation

In general, when people have reached the contemplation stage they realize they need a behavior change. In the context of smart buildings, these people acknowledge the existence and benefits of IoT technologies for smart buildings and desire to be a part of one such building [29].

At this stage it is necessary to foster "self efficacy" in the people by helping them move from a desire or goal to believing their desire or goal can actually become a reality. This could be accomplished by empowering people with practical tangible knowledge for helping them realize how IoT technology can make them energy efficient and save money in the long run as well as with the idea that they themselves can indeed learn to

use the new technological devices. It is important to provide enough information to the people but not to overwhelm them with too much information at this stage in order to hopefully move into the preparation stage [29].

Preparation

When reaching the preparation stage, people prepare for action. These people have the desire and are preparing to be a part of a smart building. These preparations can include understanding the different resources and IoT technologies available to them, budgeting these resources to meet their needs, and motivating their neighbors or finding a group of people that is interested in building or converting to a smart building. With a myriad of IoT devices available from various vendors, it would be helpful for the people in this stage to be able to consult with experts to determine the IoT devices and technologies that best fits their constraints [29].

Action

The action stage is when people actually begin changing behavior. They become a part of a smart building and start availing IoT devices and technologies. There is much enthusiasm associated with the novelty of this stage as well as a learning curve for operating the IoT devices. For instance, IoT technologies are implemented and people begin to see their effects in their day to day lives in terms of saving time, energy, and money; and improving their QoL. To engender a community of practice where participants share information and knowledge, users must be given important feedback that connects their individual home use with the community as a whole. Giving

community members the power to enact change through data-driven choices will provide a fertile context for exploring their relationships with energy resilience and smart systems [29].

Maintenance

The maintenance phase is about maintaining the behavior change. People in this phase are already availing IoT devices and technologies and are living in a smart building. The goal of this phase is to maintain the "smart nature" of their building on a daily basis so as not to terminate the behavior and to revert the smart building back to its "non-smart" state. Once people are reaping the benefits of IoT devices and technologies in smart buildings, they should feel good about their decision to avail these technologies. These feelings will motivate the people to continue using IoT technologies and remain excited to be a part of a smart building. It is vital that the IoT technologies are updated periodically (software and hardware) to ensure the best user experience. Additionally, the community has to work together as a society and help its residents stay motivated and keep up the spirit [29].

The success of the implementation of IoT technologies in smart buildings will be largely determined by their use by consumers. Thus, understanding the stages of behavior change can be insightful for industries and researchers in developing solutions to motivate and sustain behavior change. An important influence that could motivate personal behavior change related to deploying IoT technologies in smart buildings is social attitudes toward IoT [29].

Influence of Social Attitudes

Social attitudes will greatly influence the health and penetration of IoT in smart buildings. Members of smart buildings work toward energy resilience using system information, which involves issues of self-sufficiency, responses to and recovering from emergencies, and adapting to changing conditions. Achieving energy resilience is crucial for the vitality of the smart building [29].

One aspect that may greatly influence the development of energy resilience in smart buildings is the perception of Quality of Life (QoL) among its occupants. As smart systems change the built environment, the built environment affects the well-being of its residents. The introduction of smart buildings has the potential to affect the well-being of its residents, which will be evidenced by their attitudes and behaviors in their interactions with the smart system and with one another, especially around the topic of energy use. The social attitude of the building must be supportive of individual and community behaviors that collectively enhance QoL [29].

According to authors in [162] who conducted expert interviews and public deliberative workshops in two locations in the United Kingdom regarding smart home adoption, the public saw many social benefits, including better QoL due to aspects such as the potential to increase leisure time, save money, make life easier, and provide support for assisted living as people age. Concerns were also raised, however, regarding social barriers such as loss of control and apathy; reliability issues; perceiving smart technology as divisive, exclusive, or irrelevant; privacy and data security; cost; and trust.

These benefits and issues are relevant to the development of smart buildings since smart homes are a subset of smart buildings and directly impact the daily life of their occupants.

With the growth in the development of IoT devices and technologies, there is a burgeoning need for research and development focused on how people learn to use these new capabilities to change their minds and improve their knowledge. In order to increase the penetration and health of smart buildings, it is necessary to determine the motivators and initial attitudes that impact the willingness of users to engage with their smart environment [29].

Recommendations for Mixed-Methods Research Design Study for Implementing IoT in Smart Buildings

Researching the Implementation of IoT

The availability of IoT technology will not necessarily guarantee its uptake and use in achieving its benefit to society. People often do not progress through the steps outlined in the TTM of Behavior Change, and it is possible that persons may also regress. For researchers interested in studying the implementation of IoT in smart buildings, it is paramount that qualitative data be collected to determine the technological success, but it is also necessary to garner qualitative data that takes into account the complexity of the initiative due to many social and behavioral considerations. Therefore, employing mixed methods research designs can be beneficial. Currently, IoT technology developers rely primarily on quantitative data to ensure the IoT devices they develop help reduce electricity waste and generate savings for people using them. As these devices penetrate

deeper into society, studying the objective outcome measures alone is not sufficient for understanding factors that will majorly influence the widespread adoption of IoT technology. The integration of qualitative methods of data collection and analysis into this research will involve exploration and understanding of individual and group behavior, organizational dynamics, and cultural influences [32].

Methods for Collecting and Analyzing Data

Data is collected similarly in the quantitative and qualitative arms of a mixed methods study in that a sampling criteria and variables or constructs of interest must be carefully considered. There are three major types of mixed methods study designs (convergent parallel, exploratory sequential, and explanatory sequential) [32, 163]. The type of design chosen informs whether the quantitative or qualitative data is collected first or both datasets are collected simultaneously.

The qualitative research arm of the mixed methods study would likely utilize focus groups, key informant interviews, and surveys to identify barriers and facilitators related to the IoT deployment in smart buildings. Structured interviews can be used to generate a wide range of ideas and topics, whereas focus groups can be used to observe issues around which there seems to be consensus as well as topics that generate disagreement [32]. Surveys are often used to generate a large representative sample of data in order to generalize to the population [163]. Regardless of the chosen data collection method, a primary goal of the qualitative research would be to use the information learned to develop interventions that address the priorities and concerns of the residents.

Considerations for Mixed Methods Research Designs

Before employing a mixed methods design, it is important that researchers carefully consider the purpose of their research and the intended use of their findings in order to limit external validity issues. For example, it is especially important to consider the difference in focusing on representativeness versus seeking out information rich cases [32]. Before pursuing mixed methods research, researchers should also consider their budget to ensure that there are sufficient resources for this type of design since it is generally costlier in terms of time, labor, and resources. Mixed methods research also requires a flexible, dynamic, and often multi-disciplinary team that is willing to learn from one another and from the data they are collecting. Team members must value the mixed methods approach, share a common goal, and effectively communicate with one another in order for the collaboration to be successful [32].

Summary

The technical and non-technical challenges associated with implementing IoT in smart buildings were described in this chapter. The technical challenges included sensing, connectivity, power management, big data, computation, complexity, and security. The non-technical challenges included the need for behavior change and influence of social attitudes. Some of the viable solutions to overcome these challenges were recommended. Additionally, recommendations for mixed-methods research design to realize the potential of IoT for transforming modern buildings into smart buildings were presented in this chapter.

CHAPTER THREE

INTELLIGENT COMPUTATIONAL ENGINE

Introduction

With the growing world population, the demand for access to affordable, clean and sustainable energy is increasing. Currently, we are faced with problems including inefficient energy management, wasted energy resources, and expensive energy costs that make it very difficult to meet the growing energy demands [164]. As discussed in Chapter 1, the existing building energy management systems need to be transformed into computational systems thinking (CSTMs) by incorporating situational intelligence [205] to overcome current energy challenges. One such CSTM has been developed in this dissertation and is called the Intelligent Computational Engine (ICE). A general framework of a control architecture for ICE in an IoT driven building environment is described in this chapter. Also described in this chapter are the features and impact of ICE.

Features and Impact of ICE

The purpose of developing ICE is not only to overcome the above-stated problems, but also to make life more convenient, safe, and comfortable. Fig. 3.1 shows a block diagram of ICE with IoT technologies integration. ICE is a computation, information and action engine, which receives operational data from IoT sensors, processes it, and generates actionable information for IoT actuators. This data can be accessed using smartphone, tablet, or personal computer. Additionally, ICE controls the

switching of the electric power from the electric grid to optimally supply energy to the electric loads in a smart building environment. This, in turn, saves energy, reduces carbon emissions, generates cost savings, improves system efficiency, and enhances user comfort [31].

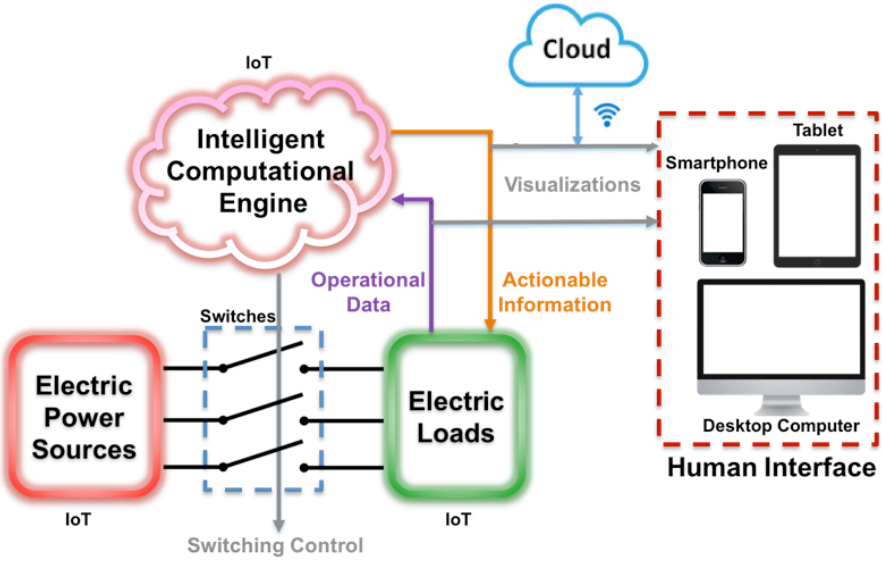


Fig. 3.1. ICE with IoT technologies integration [29]

General Control Framework for Smart Buildings

Fig. 3.2 shows the general control framework of ICE for efficient energy management in an IoT driven building environment. It comprises of sensing, communication, computation, control, and visualization blocks. The sensing block includes IoT sensors that record operational data (e.g. energy consumption, temperature, occupancy, etc.) and communicate it to the computation block. The computation block uses historic operational data to develop a prediction model/algorithm, which is used for analyzing the forecasted/real-time operational data to generate energy consumption

prediction values. The prediction values are communicated to the control block, which includes a control model/algorithm that uses the predicted energy value as a reference to compare the measured energy value (obtained from IoT sensors) to generate optimized control parameters. These parameters are communicated to the IoT actuators, which optimally regulate the operation of the electric loads to reduce energy waste (improve energy efficiency). The IoT sensor data and the energy consumption prediction values can be visualized, both in-house and remote, using the visualization block. The communication block facilitates data exchange between all the blocks [30].

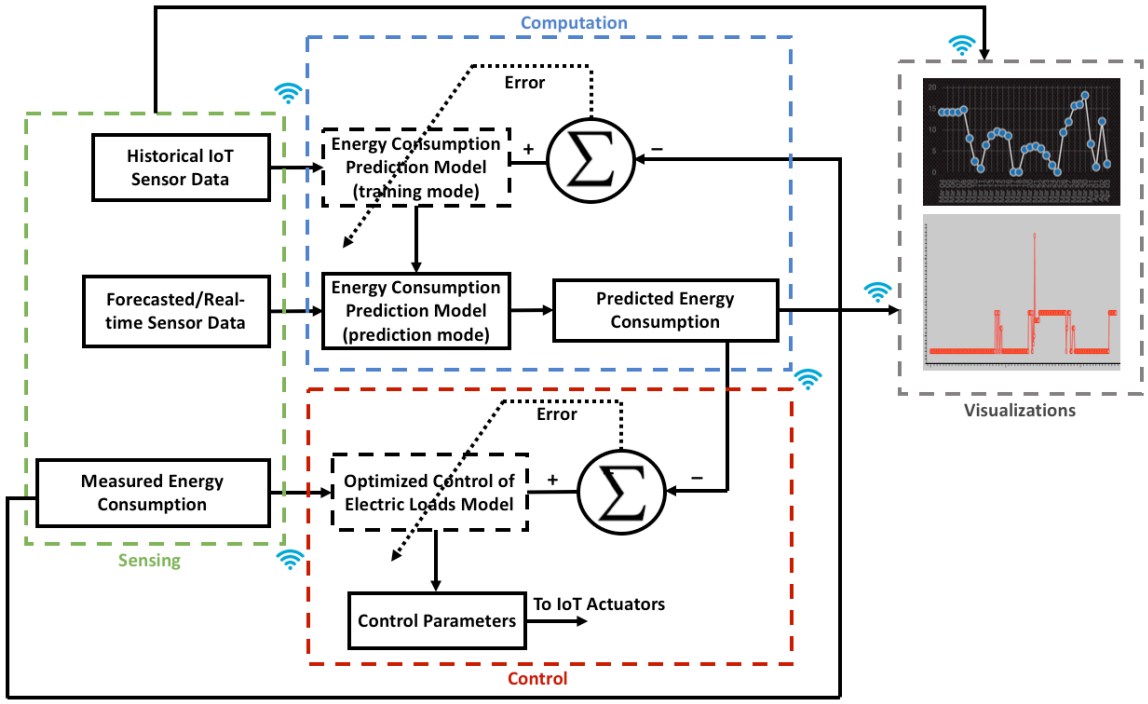


Fig. 3.2. General control framework of ICE for efficient energy management in an IoT driven building environment [30]

The general objective function for generating control parameters for optimized control of the electric loads in a smart building environment is given by (3.1) [165] subject to constraint (3.2).

$$\max\left(\sum_{i=1}^{N} P_i . L_i\right) \tag{3.1}$$

where P_i is the electric load priority weighting and L_i is the electric load magnitude (kWh) for a particular electric load i. N represents the total number of electric loads.

$$MEC \leq SF \times Ref \tag{3.2}$$

where *MEC* is the measured/actual energy consumption, *SF* is the safety factor, and *Ref* is the reference to guide the optimization procedure

In the subsequent chapters, the proposed ICE framework is deployed and dispatched in an IoT driven building case study environment to test for its effectiveness in terms of reduction in the amount of energy wasted (or improved energy efficiency).

Summary

A solution to overcome the inefficient energy management problem in a building environment was proposed in this chapter. The solution involves the development, deployment, and dispatch of ICE for efficient energy management in an IoT driven building environment. A general control framework providing an overview of ICE's capabilities along with its features and impact were discussed. ICE is scalable and flexible, providing the capability to adapt it for use with any IoT driven building environment.

CHAPTER FOUR

IOT DRIVEN BUILDING CASE STUDY ENVIRONMENT

Introduction

The building case study environment for implementing ICE is the Real-Time Power and Intelligent Systems (RTPIS) laboratory integrated with intelligent monitoring and control capabilities using IoT devices and technologies. The electric loads under consideration include heating, ventilation, and air conditioning (HVAC) units and light panels. The different IoT devices and technologies and their deployment in RTPIS laboratory are described in this chapter. Also described in this chapter is the methodology for data measurement.

Real-Time Power and Intelligent Systems Laboratory

The Real Time Power and Intelligent Systems laboratory is a premier world class research, education and innovation-ecosystem laboratory for smart grid technologies. It is housed in the sub-basement of Riggs Hall at Clemson University, Clemson, South Carolina, USA. The RTPIS laboratory comprises of the following three specialized laboratories each housed in a separate zone [166]:

- Zone 1 (SB002): Real-Time Grid Simulation Laboratory
- Zone 2 (SB003): Situational Intelligence Laboratory
- Zone 3 (SB007B): Digital Laboratory

The layout of the RTPIS laboratory is shown in Fig. 4.1.

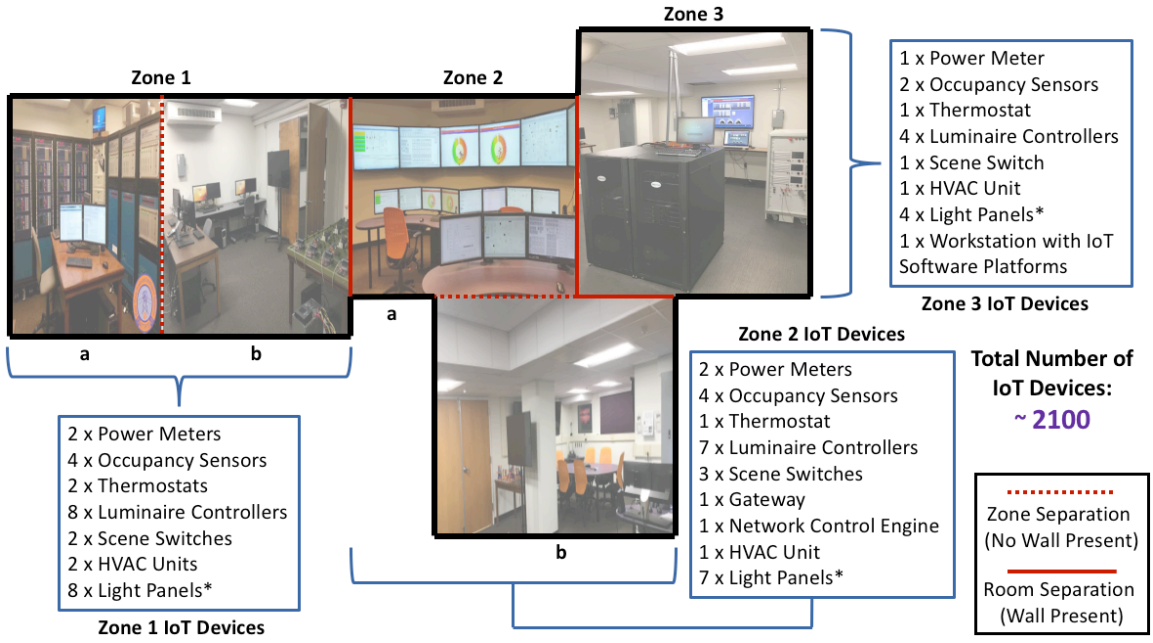


Fig. 4.1. RTPIS laboratory layout [31]

Deployment of IoT Devices and Technologies in RTPIS Laboratory

IoT Devices and Technologies

The IoT devices and technologies deployed in the RTPIS laboratory include smart power meters, occupancy sensors, smart thermostats, smart luminaire controllers, smart switches, gateways, and a network control engine (NCE) (Fig. 4.2) for monitoring and optimized control of the electric loads viz. HVAC units and light panels (Fig. 4.2). Each HVAC unit and light panel has a dedicated thermostat and luminaire controller, respectively. A brief description of each installed IoT device is provided below.

Energy consumption data from the electric loads in the RTPIS laboratory was measured using the Setra Power Patrol power meters [167]. These are three-phase power

meters that work with Rogowski Coils and communicate either through Ethernet (Building Automation and Control Network (BACnet) IP/ Modbus TCP) or through RS-485 serial connection (BACnet MS/TP / Modbus). The Power Patrol BACnet/Modbus Power Meters offer the following benefits:

- Small form factor that makes it easy to mount inside or outside the panel
- Rogowski and CT compatible, providing added flexibility
- Easy to configure through computer's USB port
- Supports both BACnet and Modbus-based communication
- No external power required since power meter is line powered from 80-600V

Johnson Controls thermostats [168] measured zone temperatures and controlled switching off and on of the HVAC units based on user-specified temperature setpoint. These thermostats offer the following benefits:

- Remote monitoring and temperature setpoint management
- Remote wireless occupancy scheduling
- Programmable temperature and control schedule
- BACnet compatible
- Maintenance-free operation
- Reliable zone comfort
- Enhanced energy economy
- Maximized energy savings without sacrificing user comfort

Each light panel in the RTPIS laboratory had an Audacy luminaire controller [169] installed in it, which controlled the switching on and off as well as 0-10V dimming

of lights. The luminaire controllers are AC-powered, BACnet compatible, operate in highly reliable 915 MHz spectrum, and easy to install.

Audacy scene switches [170] were wall-mounted in each zone of the RTPIS laboratory. These switches were pre-configured with four custom scene settings/light levels (0, 30%, 60%, and 100%) for each room, which allowed on-site occupants to instantly adjust the light levels according to their preference. The scene switches operate in highly reliable 915 MHz spectrum, easy to install, and wireless.

RTPIS laboratory's occupancy state was measured using the Audacy ceiling-mount occupancy sensors [171]. Additionally, the occupancy sensors controlled the light panels switching on and off by communicating the occupancy state of the rooms in the RTPIS laboratory with the luminaire controllers over BACnet protocol. These sensors offer the following benefits:

- Infrared devices capable of detecting occupancy and/or vacancy
- BACnet compatible
- Easy to mount

The central processing hub included the Audacy gateway [172], the ProtoConvert gateway [173], and the Johnson Controls Network Control Engine (NCE) [174]. Operational data from occupancy sensors, weather station, thermostats, and power meters is wirelessly transmitted to the workstation using the central processing hub, where the data is processed to generate actionable information. This actionable information is wirelessly transmitted to thermostats and smart luminaire controllers using the central processing hub. All communications take place over the BACnet protocol.

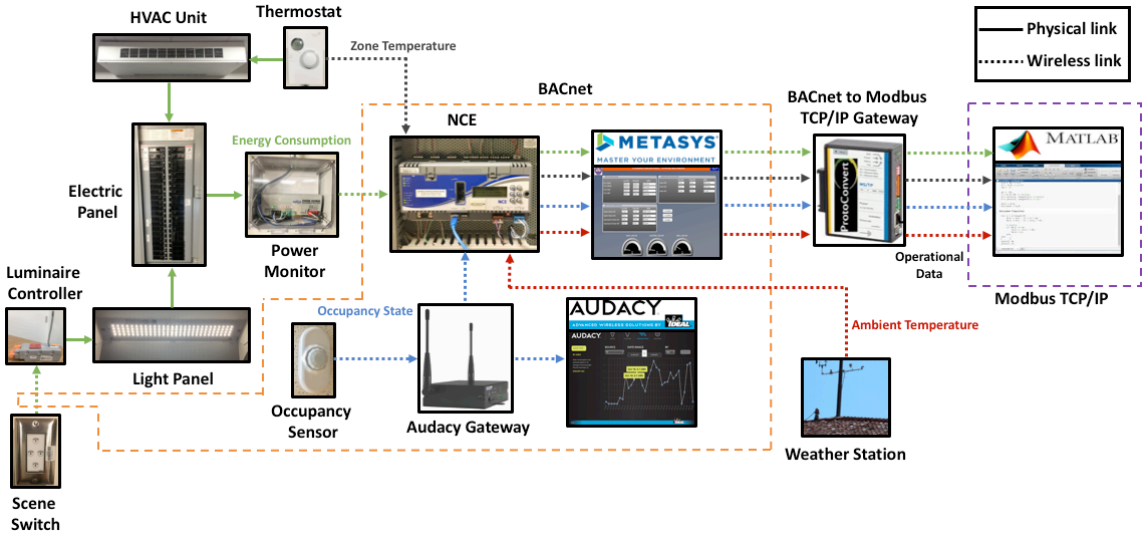


Fig. 4.2. Integration of all the IoT devices and technologies and software platforms using BACnet protocol for data measurement in RTPIS laboratory [30]

Software Platforms

The software platforms used to manage and drive the IoT devices deployed in the RTPIS laboratory include Metasys Building Automation System software, online Audacy Interface, and MATLAB (Fig. 4.2). A brief description of each software platform is provided below.

Metasys Building Automation System software [175] by Johnson Controls is the state-of-the-art software platform for modern building energy management. It is a world-class, intelligent technology system that connects the electric loads and IoT devices in the RTPIS laboratory, enabling them to communicate the desired information that makes their optimized control possible. This results in increased energy efficiency and enhanced occupant's comfort, safety, and productivity. The following are some of the features and benefits of Metasys Building Automation software:

- Web accessible with full capabilities from laptops, tablets, and smart phones
- Easy space-based navigation
- Intuitive design that reduces learning time
- Shows space-by-space status info that makes troubleshooting relatively easy
- Easy to compare equipment performances though single-view equipment summary
- Increased interoperability through support for BACnet protocol
- Follows government and industry best practices for continuous security improvements

Online Audacy Interface [176] provides a convenient access, monitoring, and control platform for wireless lighting control using Audacy IoT devices. It comprises of three primary sections viz. IoT device upload, IoT device scheduling and control, and electric energy consumption profile. Audacy IoT devices can be uploaded to the online interface during installation from the IoT device upload section via the mobile app or desktop computer. Once the IoT devices are uploaded and activated, their preferred control and scheduling settings can be instantly configured from the IoT device control section to achieve the desired light intensity levels across the building environment. Sliders are available in the user interface of the IoT device scheduling and control section to set dim levels and decide timeout delays for the light panels. The lighting load energy consumption profiles can be visualized from the electric energy consumption section. Energy consumption profiles can be broken down by date, room, range, or time period and can be easily exported for performing further analytics. The following are some of the features and benefits of Online Audacy Interface:

- Easy to program and customize
- Flexible scheduling
- Accessible from Apple devices through the mobile app
- Supports BACnet protocol

MATLAB or matrix laboratory [177] is a proprietary programming language that was developed by MathWorks. It is the state-of-the-art multi-paradigm numerical computing environment with professional mathematical, graphical, and programming toolboxes and interactive apps that are scalable to run on clusters, GPUs, and clouds. In this research, MATLAB was used to analyze operational data from the IoT devices and develop optimization algorithms to create optimized control models for the IoT actuators controlling the electric loads in the RTPIS laboratory.

BACnet Protocol

BACnet protocol [178] is an internationally recognized and accepted protocol. It is an American national standard, European standard, national standard in more than 30 countries, and ISO global standard. BACnet protocol was developed by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE). Its increasing use is attributed to the following benefits:

- Single operator workstation for all systems
- Competitive System expansion
- Eliminates fear of being “locked in”
- Possibility of integrating all building automation and control functions

- Interoperability to facilitate efficient data sharing, alarm and event management, scheduling, and remote device and network management

Data Measurement

Fig. 4.2 shows a circuit diagram with the different data sources (IoT devices) used for this research and their integration with software platforms using the BACnet protocol for recording measurement data for different parameters. Energy consumption data from the HVAC units and light panels is measured using the power monitors, which transmit this data to the network control engine (NCE). The zone temperature (ZT) and ambient temperature (AT) data is measured using the thermostats and the weather station temperature sensor, respectively, which transmit this data to the NCE. The occupancy state (OS) data is measured using the occupancy sensors, which transmit this data to the NCE via the Audacy gateway. The NCE transmits all the received data (operational data) to the Metasys BAS software, where it can be visualized. The operational data is subsequently transmitted to MATLAB via a BACnet to Modbus TCP/IP gateway where it is analyzed to obtain actionable information [30].

Summary

This chapter provided a description of the development of the building case study environment (i.e. RTPIS laboratory) for implementing ICE. Also described in this chapter were the various IoT devices and technologies and software platforms that were deployed

in the RTPIS laboratory over the BACnet protocol. Finally, the measured data for the research experiment was presented in this chapter.

CHAPTER FIVE

ENERGY CONSUMPTION PREDICTION – I

Introduction

Current energy challenges including inefficient energy management, wasted energy resources, and expensive energy costs need to be addressed to meet the growing demand for clean, affordable, and sustainable energy [179-182]. Energy generation is currently controlled based on energy demands of electric loads in near real-time. In this case, maintaining reserve energy resources operational at all times for generating and supplying excess energy to account for sporadic increases in energy demands is an inefficient and unsustainable approach. Electric energy consumption prediction capabilities are needed to reduce the amount of energy wasted from maintaining reserve resources operational at all times. With prediction capabilities, the electric energy consumption can be estimated for the near future and thus, the required amount of energy can be generated and supplied as needed to meet the demands of the electric loads, which minimizes wasted energy, reduces carbon emissions, and generates energy and cost savings [164].

The development of two energy consumption prediction models viz. exponential model and Elman recurrent neural network (RNN) model have been described in this chapter. The developed prediction models were compared with each other to determine the most accurate model for use in the development of ICE's energy consumption prediction capability, which is described in chapter 6.

Problem Definition

The problem definition (Fig. 5.1) for this study involves measuring historic data for ambient temperature, occupancy state, and energy consumption over a period of seven weeks (October 18 – December 5, 2017) and utilizing this data to build both Elman RNN and exponential prediction models that recognize a relationship between the net energy consumption by the electric loads (HVAC units and light panels) in the RTPIS laboratory and the laboratory's ambient temperature and occupancy state. These models can be used for real-time and near future electric energy consumption estimation and prediction based on the forecasted ambient temperature data and scheduled building occupancy state data. For validating the models, the electric energy consumption was predicted for the period December 6 – 12, 2017 and compared with the measured (actual) electric energy consumption data for the specified period [31].

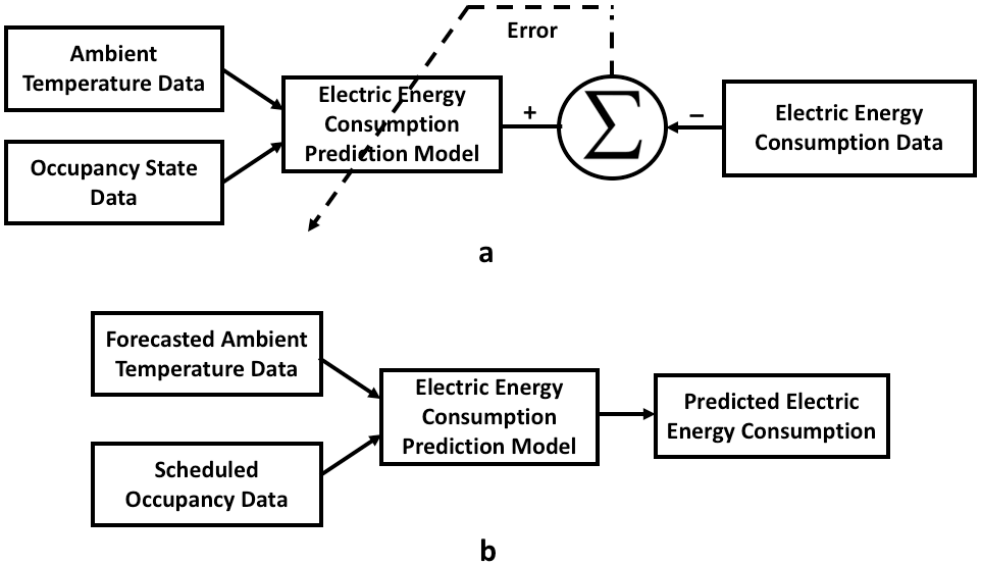
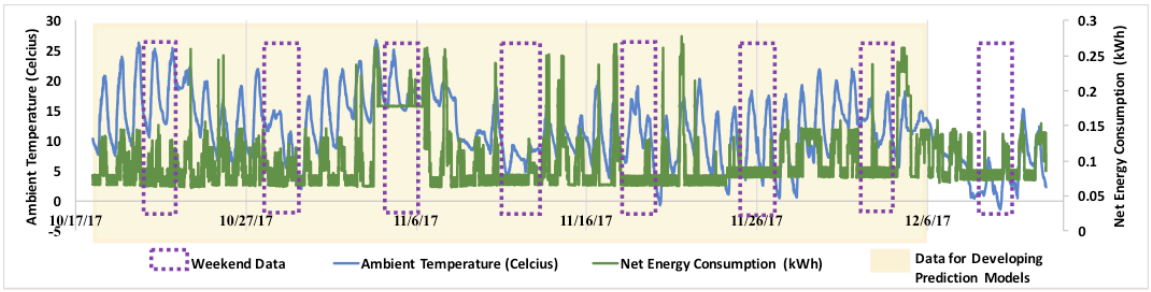


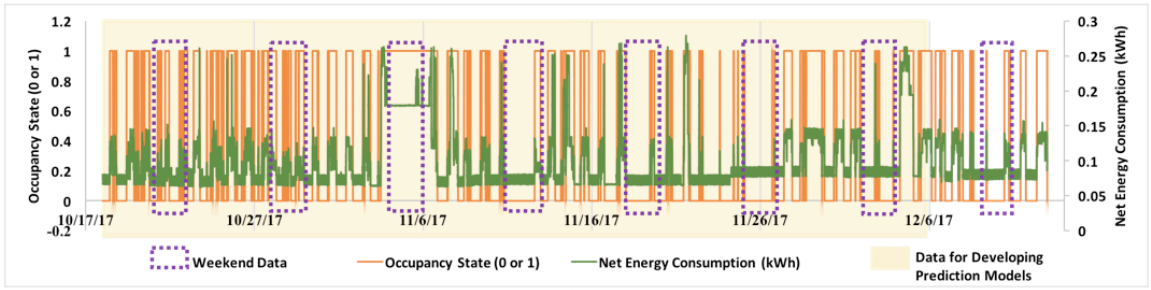
Fig. 5.1. Problem definition. (a) Electric energy consumption prediction model under development and (b) developed model used in prediction mode [31]

Measurement Data

The ambient temperature, occupancy state, and electric energy consumption data was measured over a period of eight weeks (October 18 – December 12, 2017) and had a resolution of 10 minutes, which makes it a total of 8064 data points (Fig. 5.2). This measured data was divided into two categories: (1) data used to develop the electric energy prediction models and (2) data used to test the prediction accuracy of the developed models. Seven weeks of data (October 18 – December 5, 2017) (7056 data points) was used to develop both Elman RNN and exponential models for energy consumption prediction. This data was further separated based on weekday data (thirty-five weekdays = 5040 data points) and weekend data (fourteen weekend days = 2016 data points) for improving the accuracy of electric energy consumption predictions as trying to predict electric energy consumption for the weekend using weekday data or vice versa is not ideal. The remaining one week of data (December 6 – December 12, 2017) (1008 data points) was used to test the developed models' energy consumption prediction accuracies [31].



a



b

Fig. 5.2. (a) Temperature and (b) occupancy data vs. net energy consumption data for October 18 – December 12, 2017 [31]

Elman RNN Model

Elman RNN was conceived and first used by Jeff Elman in 1990 [183]. It is usually a two-layer backpropagation network where the output of the hidden layer in the previous time step (*k-1*) is fed back as an input to the hidden layer in the current time step (*k*). This feedback is the recurrent connection in the Elman RNN that gives the neural network a short term memory that allows it to generate and recognize spatial and temporal patterns [184, 185]. The hidden/recurrent layer in an Elman RNN has a hyperbolic tangent sigmoid (*tansig*) or log-sigmoid (*logsig*) transfer function whereas the output layer has a linear (*purelin*) transfer function [184].

The Matlab function used to create an Elman RNN is *newelm* [184, 186]. The default parameter settings when using *newelm* include Nguyen-Widrow layer

initialization (*initnw*) function for initializing the weights and biases of each layer, *tansig* and *purelin* transfer functions for hidden and output layers respectively, BFGS quasi-Newton backpropagation (*trainbfg*) function for backpropagation training, gradient descent with momentum weight and bias learning (*learngdm*) function for backpropagation weight/bias learning, and mean squared normalized error performance (*mse*) function for performance. The mathematical equations for *tansig* (5.1), *purelin* (5.2), and *mse* (5.3) functions are as follows [177]:

$$tansig(n) = \frac{2}{(1+e^{-2n})} - 1 \tag{5.1}$$

$$purelin(n) = n \tag{5.2}$$

$$mse = \frac{1}{N}\sum_{i=1}^{N}(error_i)^2 \tag{5.3}$$

There are two Matlab functions that can be used for training Elman RNN viz. *train or adapt* [184]. The following happens at each epoch when using the *train* function: The network is presented with the input sequence for which the outputs are calculated. Next, an error sequence is generated by comparing the outputs with the target sequence. Once the error is known, error gradients for each bias and weight are determined by backpropagating this error sequence. It is important to note here that the value of the gradients is an approximation since in Elman RNN the biases and weights contributions to error through the delayed feedback or recurrent connection are ignored. Finally, the weights are updated using the approximate gradient with a backpropagation training function. The gradient descent with momentum and adaptive learning rate backpropagation (*traingdx*) function is recommended and generally used. In the case of the *adapt* function, the following happens at each time step: The network is presented

with the input vectors and an error is generated. Next, error gradients for each bias and weight are determined by backpropagating this error. As with the train function, the value of the gradients in this case is an approximation. Finally, the weights are updated using the approximate gradient with a learning function. The gradient descent with momentum weight and bias learning (*learngdm*) function is recommended and generally used. Since the training and adaption in an Elman RNN occurs using the error gradient approximation, this network is not as reliable as some other kinds of networks. A solution to overcome this drawback and give an Elman RNN the best chance at learning and solving a problem is to have more neurons in the hidden layer than is typical for any other network to solve a similar problem [177, 184].

A two-layer Elman RNN model was developed and used for electric energy predictions. It comprised of two input neurons, ten hidden layer neurons, and a single output layer neuron (Fig. 5.3). For training the Elman RNN model, the measured weekday and weekend training data (described above) was divided into three datasets viz. the input, target, and sample dataset. The input dataset included the ambient temperature and occupancy state data, the target dataset included the measured electric energy consumption data, and the sample dataset included the forecasted temperature and scheduled occupancy state data for electric energy consumption prediction. To avoid overfitting, the data in each dataset was randomly divided into three subsets: 70% of the data was used for training, 15% for validation, and 15% for testing [31].

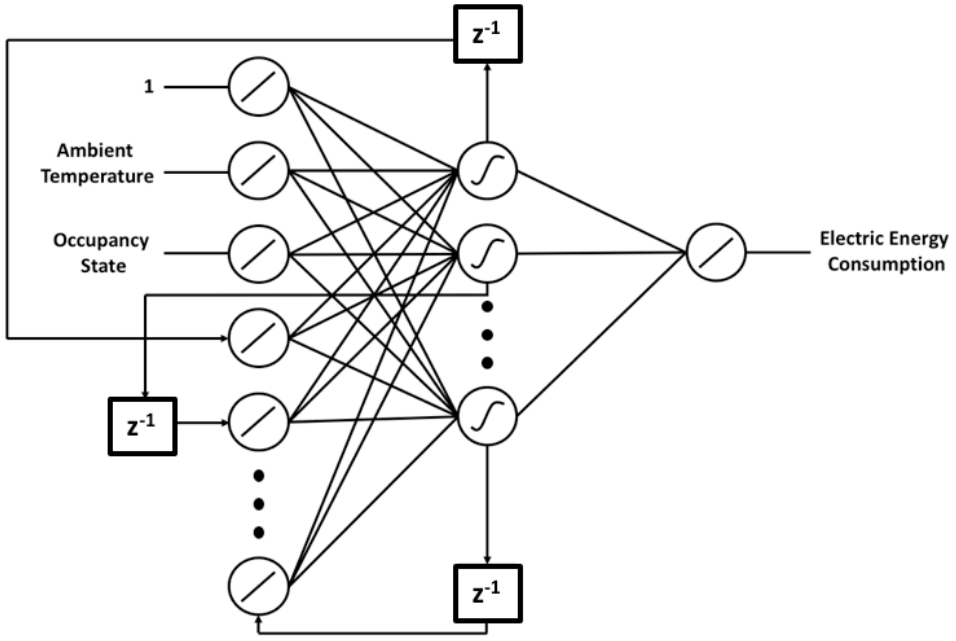


Fig. 5.3. Elman RNN model for electric energy consumption prediction [31]

TABLE 5.1. ELMAN RNN TRAINING PARAMETERS [31]

Parameter	MATLAB Implementation	Value
Maximum number of epochs to train	*net.trainParam.epochs*	1000
Performance goal	*net.trainParam.goal*	0
Learning rate	*net.trainParam.lr*	0.01
Ratio to increase learning rate	*net.trainParam.lr_inc*	1.05
Ratio to decrease learning rate	*net.trainParam.lr_dec*	0.7
Maximum validation failures	*net.trainParam.max_fail*	1000
Maximum performance increase	*net.trainParam.max_perf_inc*	1.04
Momentum constant	*net.trainParam.mc*	0.9
Minimum performance gradient	*net.trainParam.min_grad*	10^{-5}
Maximum time to train in seconds	*net.trainParam.time*	infinite

Table 5.1 shows the parameters used for training the Elman RNN. Initially, the specified parameters were set to the standard, default values, which were then further refined by trial-and-error until the desired network performance was achieved. The

network was trained separately for weekday and weekend data to obtain the corresponding weights and biases. The performance (*perf*) derivatives with respect to the bias and weight variables *X* were calculated using backpropagation. The gradient descent with momentum is used to adjust each variable (5.4) [177].

$$dX = mc*dX_{prev} + lr*mc*\frac{dperf}{dX} \quad (5.4)$$

where,

dX_{prev} = previous change to bias or weight

mc = momentum constant

lr = learning rate

After each epoch, the network *perf* is evaluated and the learning rate (*lr*) is updated accordingly. If the *perf* decreases towards the goal, *lr* is increased by *lr_inc*. If the *perf* increases beyond the *max_perf_inc* value, *lr* is decreased by *lr_dec*. The Elman RNN training stops when any of the following conditions hold true [184]:

- Maximum number of epochs is reached
- Maximum time to train is exceeded
- Performance goal is achieved
- Performance gradient falls below *min_grad* value
- Validation performance increases more than *max_fail* times since the last time it decreased

The developed Elman RNN model was used to generate the RTPIS laboratory's electric energy consumption predictions for the period December 6 – 12, 2017 using the forecasted temperature and scheduled occupancy state data. The electric energy

consumption for the specified period was predicted for weekdays and weekends, separately using their respective weights and biases. The predicted values were then compared with the measured net electric energy consumption values for these days and the $\%\,Error$ was calculated using (5.5). The results are shown and discussed in the Experiment Results and Discussions section below.

$$\%\,Error = \left(\frac{|Predicted\ Energy\ Consumption\text{-}Measured\ Energy\ Consumption|}{Measured\ Energy\ Consumption}\right) X100 \tag{5.5}$$

Exponential Model

Particle Swarm Optimization

In summary, PSO utilizes a particle population where each particle is given a velocity with which it flies through the problem hyperspace. After each iteration, the velocity for each individual particle is adjusted stochastically depending on its historic best position and the best position of the swarm. PSO algorithm is referred to as the global (*gbest*) PSO or local (*lbest*) PSO depending on whether the neighborhood of a particle is the entire swarm or whether a smaller neighborhood is used. The best positions of both particle and neighborhood are obtained from a user defined fitness function [187-189]. Therefore, movement of each particle evolves towards an optimal solution.

A particle i in a swarm is represented by its current position (x_i), current velocity (v_i), and personal best position (y_i). If f denotes the objective function, then the personal best position of a particle i at time k is updated according to (5.6) [190].

$$y_i(k+1) = \begin{cases} y_i(k) & if\ f(x_i(k+1)) \geq f(y_i(k)) \\ x_i(k+1) & if\ f(x_i(k+1)) < f(y_i(k)) \end{cases} \tag{5.6}$$

The global best particle's position vector ($\hat{y}$) is given by (5.7) [190].

$$\hat{y}(k) \in \{y_0, y_1, \dots, y_s\} = \min\{f(y_0(k)), f(y_1(k)), \dots, f(y_s(k))\} \quad (5.7)$$

where s= size of swarm.

For the *lbest* model, the neighborhood best particle's position vector ($\hat{y}_j$) is given by (5.8) [190].

$$\hat{y}_j(k+1) \in \left\{N_j | f\left(\hat{y}_j(k+1)\right) = min\{f(y_i(k))\}, \forall y_i \in N_j\right\} \quad (5.8)$$

where each neighborhood, $N_j = \{y_{i-l}(k), y_{i-l+1}(k), \dots, y_i(k), y_{i+1}(k), \dots, y_{i+l-1}(k), y_{i+l}(k)\}$ (5.9)

These neighborhoods can either be determined using particle indices [191] or topological neighborhoods can be employed [192].

The velocity v_i of a particle i is updated according to (5.10) [190]:

$$v_{i,j}(k+1) = wv_{i,j}(k) + c_1 r_{1,j}(k)\left(y_{i,j}(k) - x_{i,j}(k)\right) + c_2 r_{2,j}(k)\left(\hat{y}_j(k) - x_{i,j}(k)\right) \quad (5.10)$$

where,

$j \in 1, \dots, N_d$

N_d= dimension of the problem

$v_{i,j}$= j-th element of the velocity vector of the i-th particle

w= inertia weight [192]

c_1 and c_2= acceleration constants

$r_{1,j}, r_{2,j} \sim U(0,1)$

It is possible to clamp velocity updates at a user defined value of maximum velocity (V_{max}). This is done to prevent their explosion, which in turn avoids premature convergence [193].

The position x_i of a particle i is updated according to (5.11) [190]:

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{5.11}$$

The equations listed above are updated with each iteration of the PSO algorithm until a stop condition is reached. This stop condition may either be that the algorithm has reached its specified number of iterations or that the velocity updates are nearly zero. The optimality of the achieved solution is measured using a fitness function. Fig. 5.4 shows the general pseudo code for PSO algorithm.

```
1: Initialize no. of particles, no. of iterations, and no. of dimensions
2: Initialize velocity and position range and objective function
3: Initialize inertia weight and acceleration constants
4: for each particle i do
5:       Randomly initialize position (x_i) and velocity (v_i)
6: end for
7: Iteration (k)=0
8: while stopping criteria is not reached
9:       for each particle i do
10:              Evaluate particle fitness using objective function
11:              Update pbest and gbest values using (5.6) and (5.7)
12:              for each dimension j do
13:                      Update velocity (v_{i,j}) using (5.10)
14:              end for
15:      Update position (x_i) using (5.11)
16:      end for
17: k=k+1
18: Until convergence criteria satisfied
```

Fig. 5.4. Pseudo-code for PSO [165]

There are several advantages of PSO that make it very effective for a variety of optimization problems [194-197] that are similar to the one considered in this paper. Some of the advantages of PSO include [189, 198, 199]: (1) PSO is relatively simple and easy to implement with fewer parameters to adjust; (2) it has effective memory capability to store individual particle's and neighborhood's best values; (3) PSO is less sensitive to

the objective and the parameters; (4) it is efficient to maintain swarm diversity; and (5) PSO produces high-quality stable solution with low computational cost. Therefore, PSO is the chosen candidate for the proposed methodology. The authors in [189] have performed a detailed review of the basic concepts, different structures, and variants of the PSO computational intelligence technique.

Objective Function Formulation

To solve the above-mentioned pattern recognition problem using PSO-based algorithm, it is essential to formulate its objective function. For this study, the objective function does the following: (1) gathers the RTPIS lab's ambient temperature and occupancy state historic data over a period of one week (December 6 – December 12, 2017), (2) calculates the net energy consumption of the RTPIS laboratory based on this data, and (3) compares the calculated net energy with the measured net energy and calculates the error [31].

The mathematical formulation of the objective function is shown below (equations 5.12-5.14) [31].

$$P_{net} = A.(Temp) + B.((Temp)^2) + C.\left(e^{-(Temp)}\right) + D.occupy + E.((occupy)^2) + F.\left(e^{-(occupy)}\right) + G \quad (5.12)$$

where,

P_{net}= instantaneous net RTPIS lab power consumption (kW)

$Temp$ = ambient temperature (°C)

$occupy$= occupancy state of the RTPIS lab

$A, B, and\ C$= decision variables for ambient temperature data having units of kW/ºC, kW/ºC^2, and kW, respectively

$D, E, and\ F$=decision variables for occupancy state data, all having units of kW

G=constant (kW)

All decision variables and the constant are determined using the proposed PSO algorithm and are shown in the Results and Discussions section below. The net energy consumption of the RTPIS lab over time T can be calculated using equation (5.13) [31].

$$E_{netc} = \int_{t=1}^{T} P_{net}\, dt \tag{5.13}$$

where,

E_{netc}= calculated net energy consumption (kWh)

Using (5.12) and (5.13), electric energy consumption was predicted for the period December 6 – 12, 2017 using the same forecasted temperature and scheduled occupancy state data as used in the Elman RNN model. The electric energy consumption for the specified period was predicted for weekdays and weekends, separately using their respective parameters. The predicted values were compared with the measured net energy consumption values for the period, and the % $Error$ was calculated using (5.14) [31]. The results are shown and discussed in the Experiment Results and Discussions section below (Table 5.2).

$$\%\ Error = \left(\frac{|E_{netc} - E_{netm}|}{E_{netm}}\right) X100 \tag{5.14}$$

where,

E_{netm}= measured net energy consumption (kWh)

PSO Algorithm to Determine Decision Variables

PSO algorithm was used to generate values of the decision variables $A, B, C, D, E, F, and\ G$ while minimizing $\%error$. A flowchart representing the proposed PSO algorithm is shown in Fig. 5.5. The parameters specified in the proposed PSO algorithm are as follows [31]:

- Number of particles = 20
- Number of iterations = 500
- Number of dimensions = 7
- Particle velocity (v_i) and position (x_i) range = [-100, 100]
- Inertia weight (w) = 0.729
- Acceleration constants $c_1 = c_2 = 1.49$

Initially, the specified PSO parameters were set to the standard, tested values, which were then further refined by trial-and-error until the convergence was achieved. For example, the inertia weight of PSO was initially set at 0.9 and reduced to 0.729 with iterations.

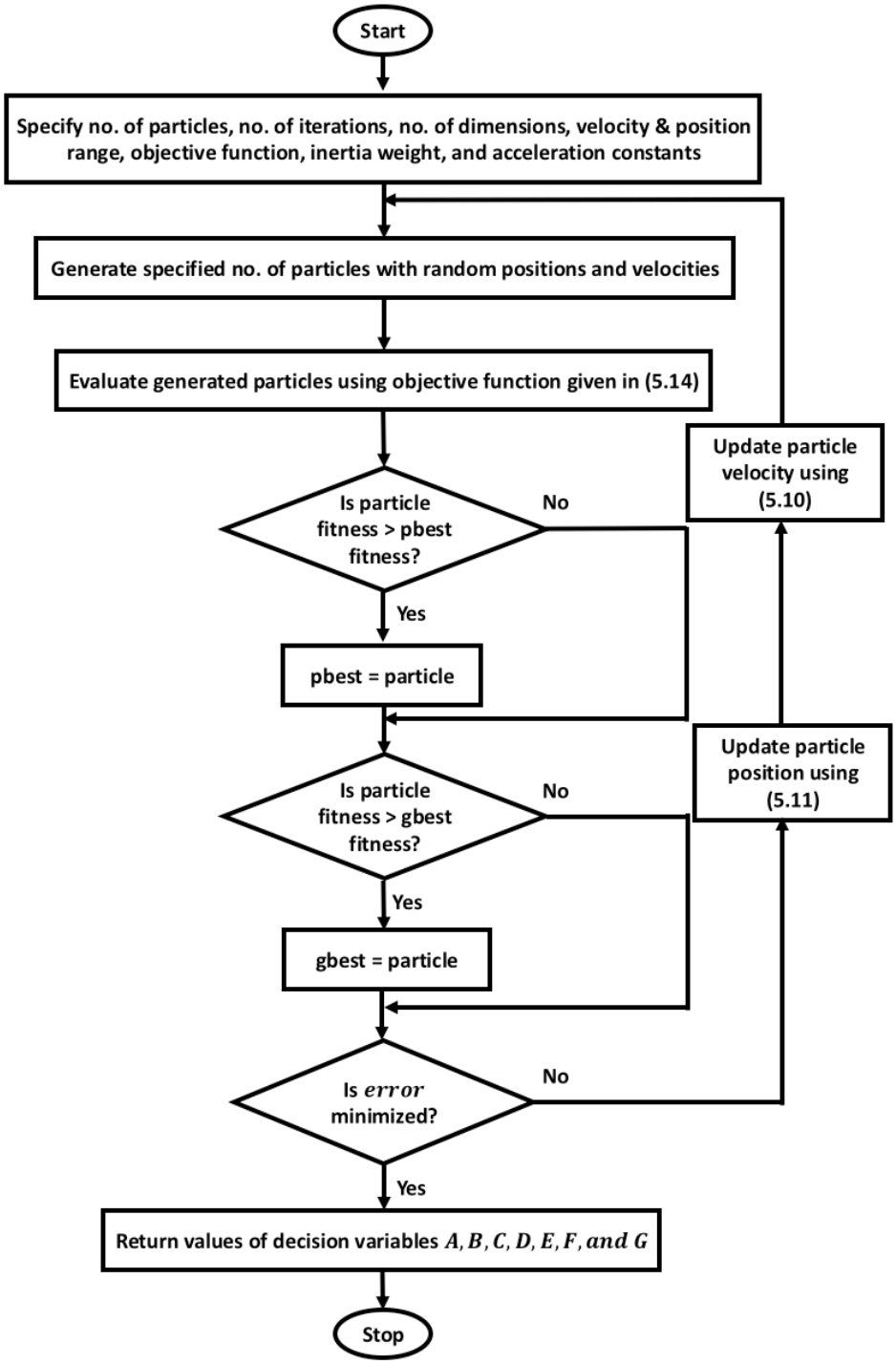


Fig. 5.5. Flowchart of the proposed PSO algorithm to generate values of the decision variables [31].

Experiment Results and Discussions

Decision Variables for Exponential Model

TABLE 5.2. VALUE OF THE DECISION VARIABLES, CONSTANT, AND MINIMUM ERROR FOR WEEKDAY AND WEEKEND DATA [31]

Parameter	Value for Weekday Data	Value for Weekend Data
A (kW/°C)	0.0022	0.0382
B (kW/°C^2)	-0.0002	-0.0027
C (kW)	0.3244	-0.0806
D (kW)	0.2291	0.1350
E (kW)	0.1407	0.1275
F (kW)	0.2342	0.1200
G (kW)	0.2459	0.2764
Minimum Error (gbest)	98.1959	74.4046

Prediction Results

The comparison of the predicted and the measured net electric energy consumption values using Elman RNN and exponential models, along with the % Error values are tabulated in Table 5.3 and shown in Fig. 5.6. From the small % Error values, it can be inferred that the predicted and measured net electric energy consumption values are very similar for all the days. This validates the developed Elman RNN and exponential models and shows they work well for electric energy consumption prediction in a smart building environment.

From the comparison between the Elman RNN model and the exponential model, it is clear that the Elman RNN model outperforms the exponential model on six out of seven days of electric energy consumption predictions, thereby making it a more efficient approach for use in the development of ICE's energy consumption prediction capability.

TABLE 5.3. PREDICTED ENERGY CONSUMPTION AND MEASURED NET ENERGY CONSUMPTION USING ELMAN RNN AND EXPONENTIAL MODELS [31]

Date	Measured Net Energy Consumption (kWh)	Predicted Energy Consumption with Elman RNN Model (kWh)	Predicted Energy Consumption with Exponential Model (kWh)	%Error with Elman RNN Model	% Error with Exponential Model
December 6, 2017	16.7333	16.2696	15.0489	2.7709	10.0656
December 7, 2017	15.4564	15.4205	14.6196	0.2323	5.4135
December 8, 2017	13.1197	12.4325	14.1332	5.2381	7.7244
December 9, 2017	12.1032	11.8417	11.2118	2.1609	7.3650
December 10, 2017	12.8876	12.6478	11.1339	1.8606	13.6083
December 11, 2017	14.0726	13.5625	13.5831	3.6246	3.4781
December 12, 2017	16.2459	15.9942	15.0152	1.5496	7.5755

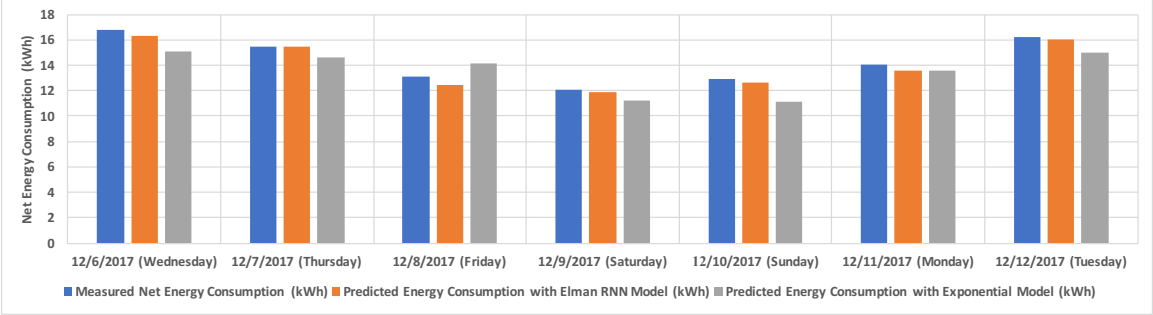


Fig. 5.6. Predicted and the measured net energy consumption values using Elman RNN and exponential models [31]

Summary

An Elman recurrent neural network model and exponential model were developed and applied to the RTPIS laboratory for real-time and near future electric energy consumption estimation and prediction. The developed prediction models were compared

with each other to determine the most accurate model for use in the development of ICE's CCN-based energy consumption prediction capability. From the comparison between the Elman RNN model and the exponential model, the Elman RNN model emerged as the more accurate model. Although developed for the RTPIS laboratory at Clemson University, the Elman RNN and exponential models are scalable and flexible, providing the capability to adapt these models for usage with any IoT driven building environment.

CHAPTER SIX

ENERGY CONSUMPTION PREDICTION – II

Introduction

The cellular computational network was used to develop ICE's energy consumption prediction capability. CCN is a distributed and scalable architecture, which can be used for implementing large networked systems with faster learning [200]. It is a dynamic recurrent network (DRN) consisting of interconnected cells that have the capacity to communicate with one another [201, 202]. The cell connections are modeled, or mapped, after the complex network topology [203]. Each cell in a CCN has a computational, learning, and communication unit (Fig. 6.1). While the type of computational unit varies for different applications, it is usually some form of the many computational intelligence (CI) and non-CI paradigms. The computational unit in a cell performs the following task: It receives information either directly or from its neighbors, processes it, and generates an output to enhance its performance over time. In other words, each cell gains experience over time. This task is facilitated by the learning unit, which provides the cell's performance evaluation measure through supervised, unsupervised, or reinforcement-based learning. The communication unit facilitates CCN's collaborative learning system where each cell interacts with its neighbors by transmitting and receiving information through an input/output interface according to a predefined rule [200, 204, 205].

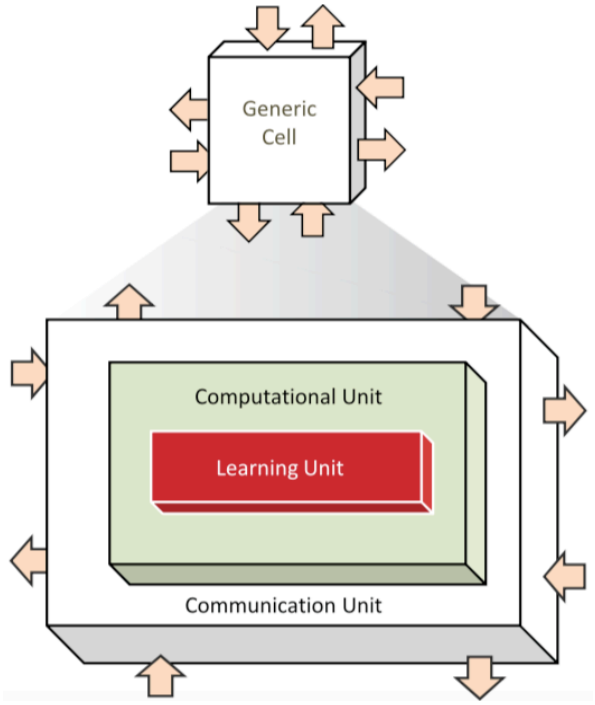


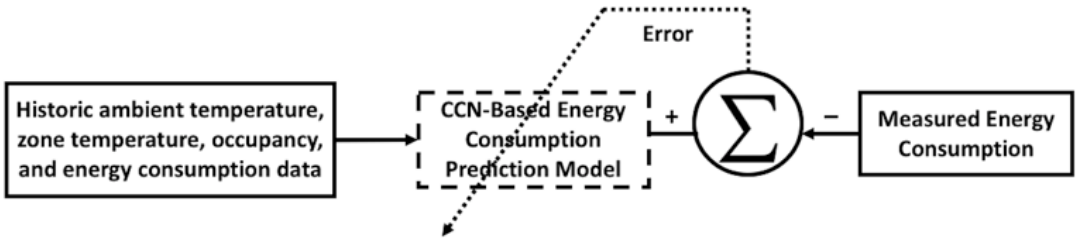
Fig. 6.1. CCN cell internal unit [204]

The major benefits of using CCN for prediction applications over other traditional approaches include distributed framework and dynamic communication capabilities. The distributed framework allows the computational load to be distributed amongst the individual cells in the CCN. With the dynamic communication capability, each cell can update its state and exchange this information with neighboring cells, thereby making the cells better aware of their surroundings [206]. These capabilities enable cooperative or synchronous operations amongst neighboring cells resulting in better prediction accuracy.

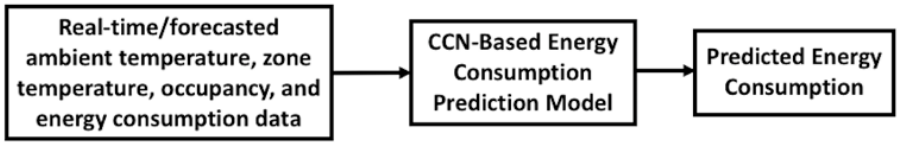
Problem Definition

The problem definition (Fig. 6.2) for the energy consumption prediction experiment involves the following: (1) measuring historic data for various parameters

including ambient temperature, zone temperature, occupancy, and energy consumption data, (2) using the measured data to develop a CCN-based prediction model that recognizes a relationship between the measured energy consumption by the electric loads and the rest of the parameters, and (3) using the developed model for real-time and near future energy consumption estimation and prediction based on the forecasted data of the various parameters. For validating the model, the energy consumption was predicted for the period March 4 – 10, 2018 and compared with the measured (actual) energy consumption data for the specified period [30].



(a)



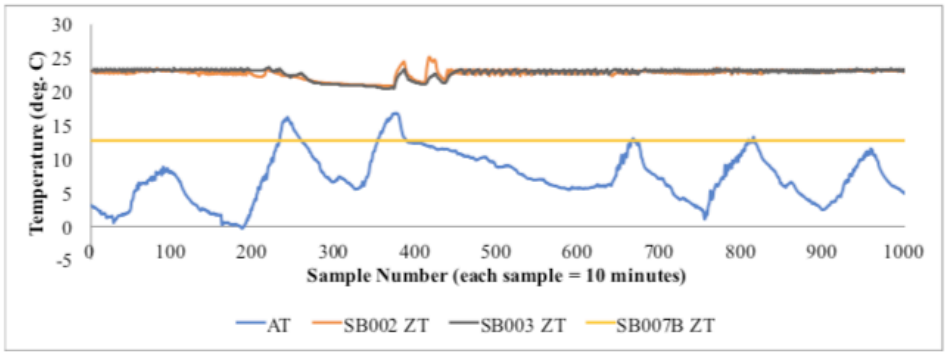
(b)

Fig. 6.2. Energy consumption prediction problem definition: (a) Model in development mode; (b) developed model operating in prediction mode [30]

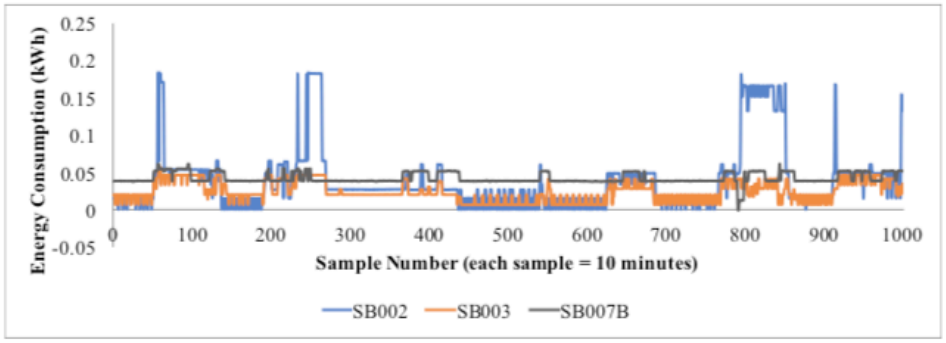
Measurement Data

A total of 15,475 data samples were measured for each parameter over a period of six months (October 2017 – March 2018). The data samples have a resolution of 10 minutes. Out of these data samples, 14,468 data samples were used for developing (or

training) the CCN prediction model, and the remaining 1007 data samples were used to test the prediction accuracy of the developed model. Fig. 6.3 shows an example of the data samples for the different parameters measured over a period of one week (1007 data samples) [30].



(a)



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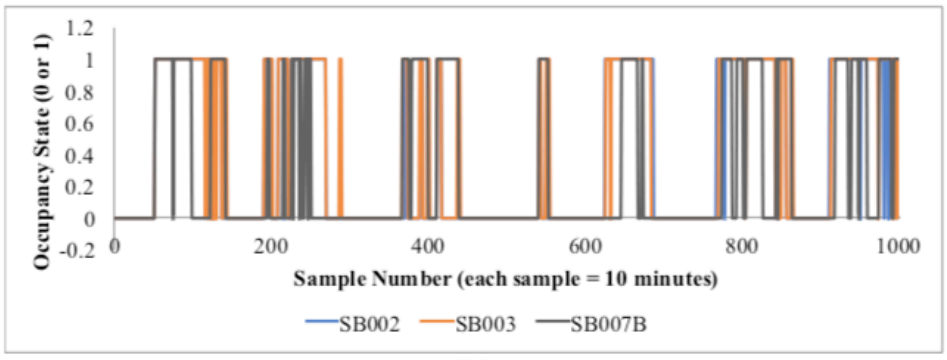


(c)

Fig. 6.3. Example of the data samples for (a) ambient and zone temperatures, (b) energy consumption, and (c) occupancy state over a period of one week [30].

CCN-Based Energy Prediction Model

The CCN-based model (Fig. 6.4) was developed, deployed, and dispatched for energy consumption prediction in the RTPIS laboratory. In this model, each laboratory zone is represented as an individual cell. Each cell receives two kinds of input parameters: (1) direct input parameters viz. AT, ZT, OS, and measured energy consumption (MEC) from the temperature sensors, thermostats, occupancy sensors, and power meters, respectively in each room (or cell), and (2) shared input parameters viz. ZT and predicted energy consumption (PEC) from the neighboring cells. *k* represents the current time step and *k*+1 represents the next (future) time step. Sharing input parameters between the neighboring cells make them better aware of their surroundings, which in turn, results in high accuracy energy consumption predictions [30].

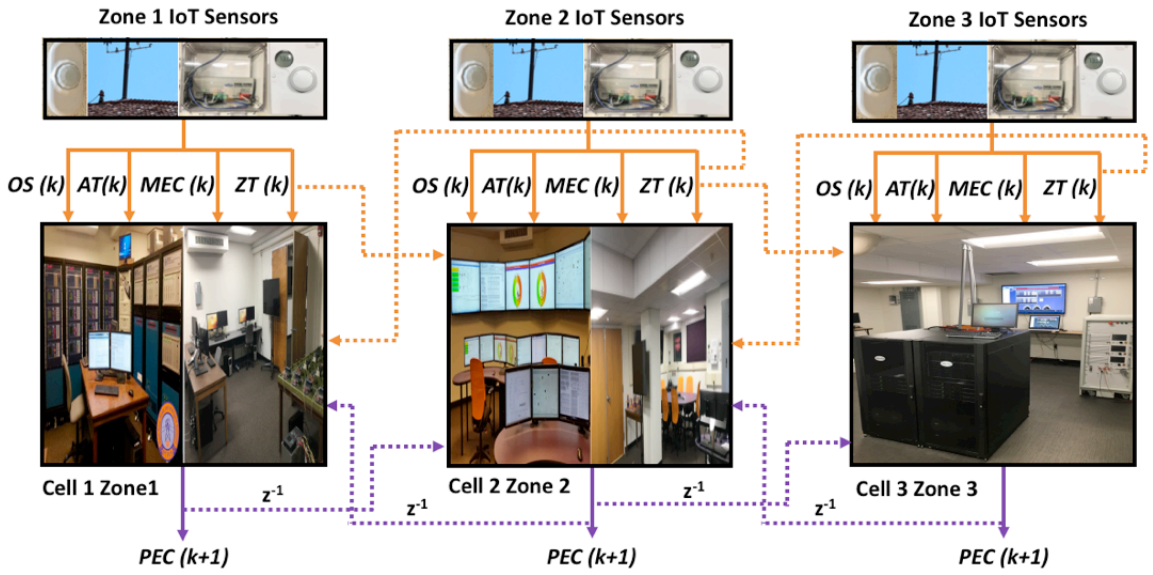


Fig. 6.4. CCN-based energy consumption prediction model [30]

Each cell of the CCN-based energy consumption prediction model is a two-layer Elman Recurrent Neural Network (RNN) with six, eight, and six input neurons for cells

1, 2, and 3, respectively; ten hidden layer neurons; and one output layer neuron. The hidden layer output in *k-1* time step is fed back as hidden layer input in *k* time step providing a short-term memory to the Elman RNN (Fig. 6.5) [184, 185]. Tangent sigmoid (*tansig*) and linear (*purelin*) transfer functions are used for the hidden and output layers, respectively. Mathematically, *tansig* and *purelin* transfer functions are represented using equations (6.1) and (6.2) [204].

$$tansig(n) = \frac{2}{1+e^{-2n}} - 1 \tag{6.1}$$

$$purelin(n) = n \tag{6.2}$$

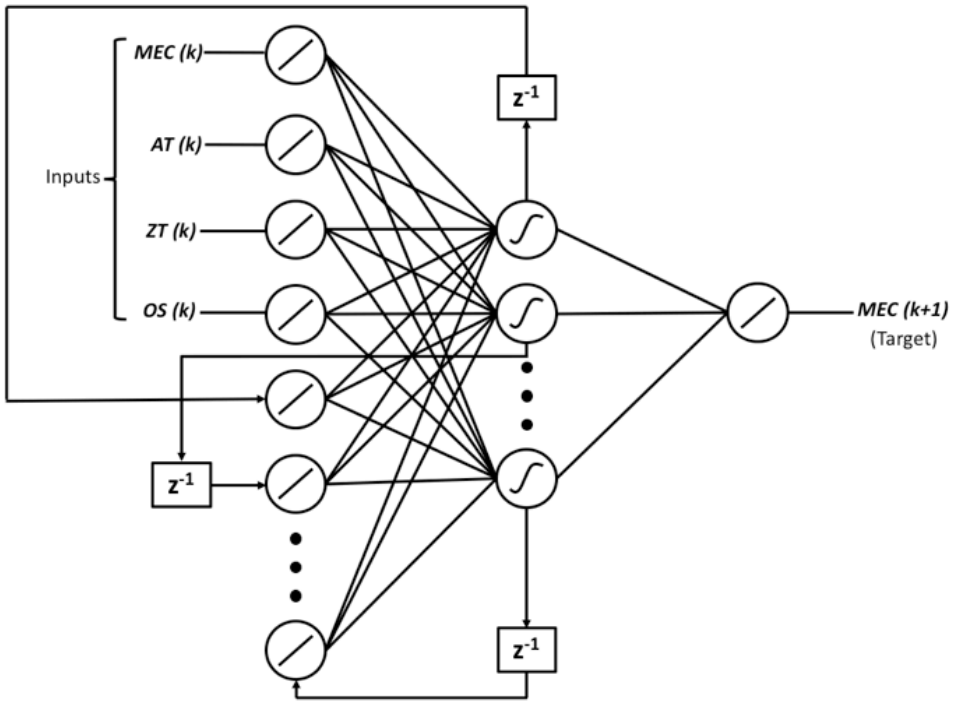


Fig. 6.5. Elman RNN for each CCN cell [30]

Elman RNN is created using the *newelm* Matlab function [184, 186]. By default, Nguyen-Widrow layer initialization (*initnw*) function is used for weights and biases initialization of each layer, BFGS quasi-Newton backpropagation (*trainbfg*) function is

used for backpropagation training, gradient descent with momentum weight and bias learning (*learngdm*) function is used for backpropagation weight/bias learning, and mean squared normalized error performance (*mse*) function is used as network performance metric (equation (3)).

$$mse = \frac{1}{n}\sum_{i=1}^{N}(error_i)^2 \tag{6.3}$$

Elman RNN is trained using the *train* function [184]. The measurement data was divided into three datasets viz. the input, target, and sample dataset. The input dataset included AT(*k*), ZT(*k*), OS(*k*), and MEC(*k*) data; the target dataset included the MEC(*k+1*) data; and the sample dataset included the real-time/forecasted input data at time step (*k+d-1*) for generating PEC at time step (*k+d*). To avoid overfitting, the data in each dataset was randomly divided into three subsets: 70% of the data was used for training, 15% for validation, and 15% for testing. At each epoch, an input sequence is presented to the neural network and the corresponding output sequence is calculated. The output sequence is then compared with a target sequence to generate the error sequence. This error sequence is then backpropagated to determine performance (*perf*) derivatives with respect to the bias and weight variables *X*, which are subsequently used to update weights and biases in accordance with equation (4) using the gradient descent with momentum and adaptive learning rate backpropagation (*traingdx*) function [184, 177].

$$dX = mc*dX_{prev} + lr*mc*\frac{dperf}{dX} \tag{6.4}$$

where,

dX_{prev} = previous change to bias or weight

mc = momentum constant

lr = learning rate

After each epoch, the network *perf* is evaluated and the *lr* is increased or decreased depending on if the *perf* decreases towards or increases beyond the goal, respectively.

The developed CCN-based model was used to generate the RTPIS laboratory's PEC for the period March 4 – 10, 2018 using the real-time/forecasted AT, ZT, OS, and MEC data. The predicted values were then compared with the measured energy consumption values for these days and the $\%\,Error$ was calculated using (5) [30]. The results are shown and discussed in the Experiment Results and Discussions section below.

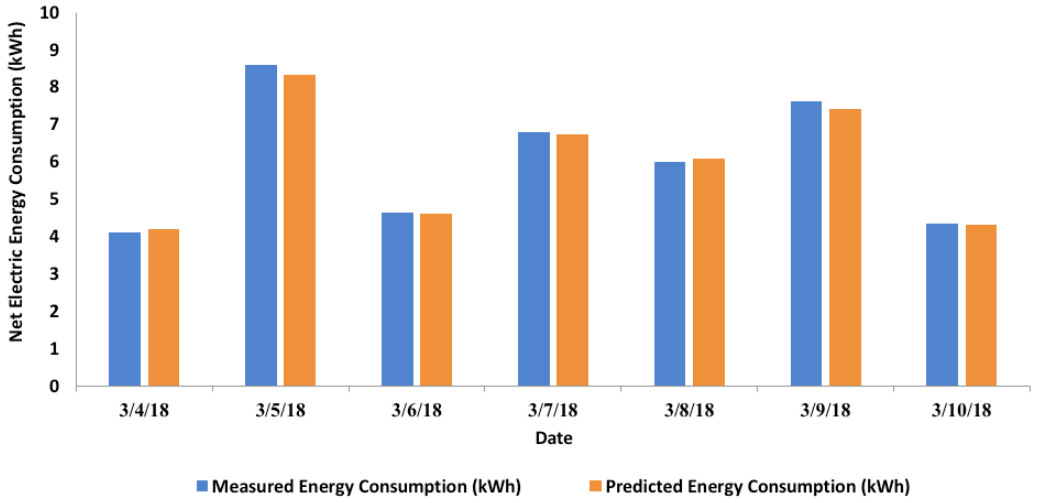
$$\%\,Error = \left(\frac{|PEC\text{-}MEC|}{MEC}\right) X100 \tag{6.5}$$

Experiment Results and Discussions

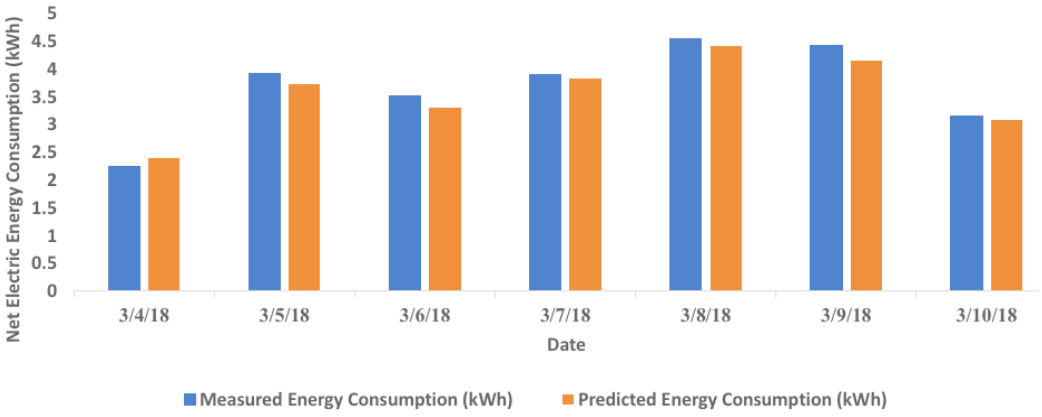
The comparison of PEC and MEC values obtained from the CCN model, along with the % *Error* values for all three cells from March 4 – 10, 2018 are tabulated in Table 6.1 and plotted in Fig. 6.6. Fig. 6.7 shows both the PEC and MEC waveforms for all three cells for the week under consideration. From the small % *Error* values, it can be inferred that the PEC and MEC values are very similar for all the days. This validates the developed CCN model and shows that it works really well for the real-time and near future energy consumption estimation and prediction in an IoT driven building environment [30].

TABLE 6.1. PEC AND MEC VALUES FOR ALL THREE CELLS USING CCN-BASED ENERGY CONSUMPTION PREDICTION MODEL [30]

	Cell 1 (Zone 1)			Cell 2 (Zone 2)			Cell 3 (Zone 3)		
Date	**MEC (kWh)**	**PEC (kWh)**	***%Error***	**MEC (kWh)**	**PEC (kWh)**	***%Error***	**MEC (kWh)**	**PEC (kWh)**	***%Error***
3/4/18	4.096	4.182	2.097	2.243	2.395	6.762	5.632	5.663	0.538
3/5/18	8.578	8.297	3.272	3.911	3.727	4.708	5.733	5.752	0.338
3/6/18	4.627	4.602	0.540	3.504	3.301	5.809	5.850	5.832	0.318
3/7/18	6.766	6.719	0.694	3.888	3.820	1.764	6.146	6.063	1.360
3/8/18	5.972	6.053	1.358	4.545	4.414	2.879	6.580	6.469	1.691
3/9/18	7.598	7.404	2.556	4.415	4.142	6.183	5.965	5.930	0.593
3/10/18	4.312	4.286	0.609	3.152	3.077	2.374	6.229	6.080	2.390



(a)



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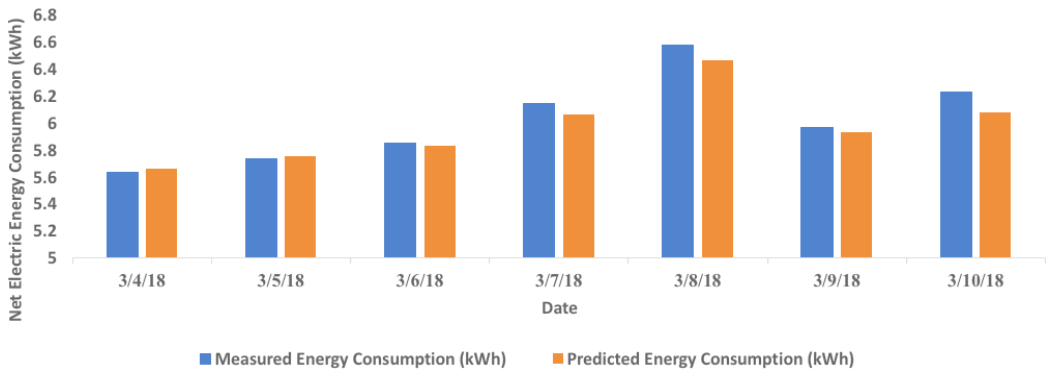
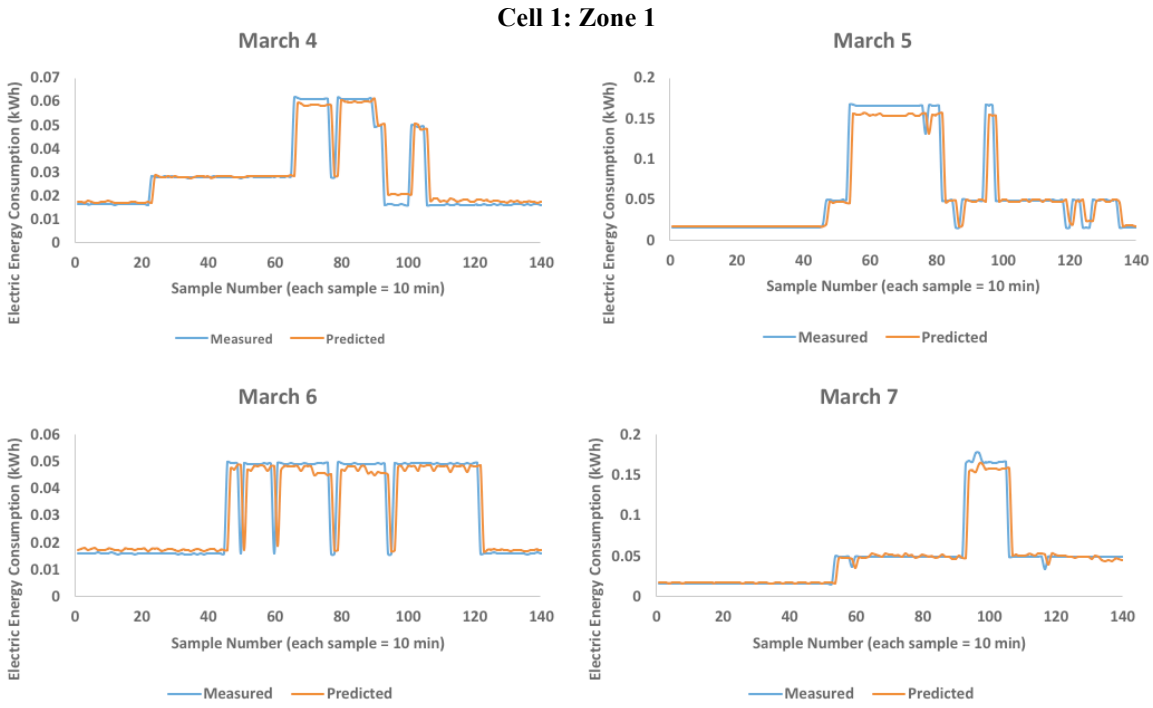
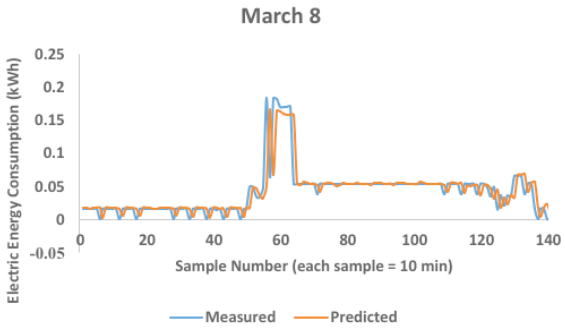
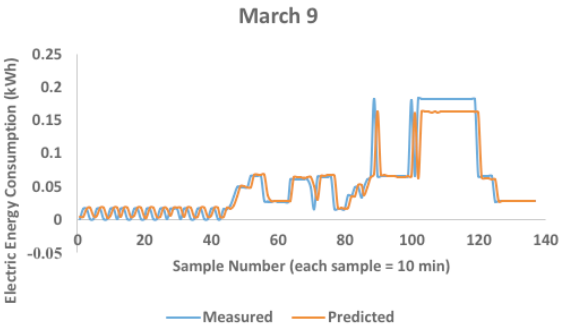


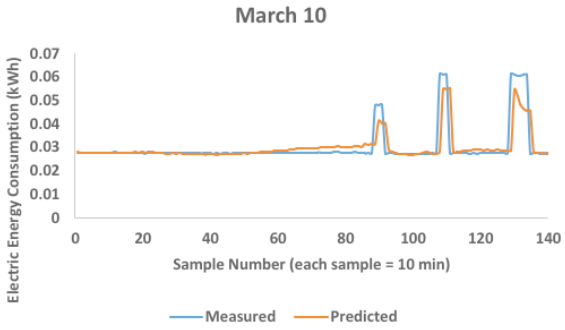
(c)

Fig. 6.6. PEC and MEC values for (a) cell 1, (b) cell 2, and (c) cell 3 using CCN-based energy consumption prediction model [30]

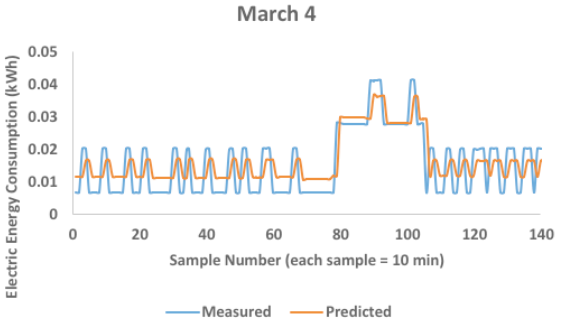


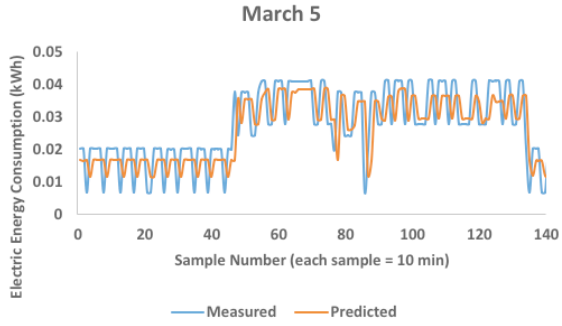

March 8
Electric Energy Consumption (kWh)
0.25
0.2
0.15
0.1
0.05
0
-0.05
0 20 40 60 80 100 120 140
Sample Number (each sample = 10 min)
Measured
Predicted

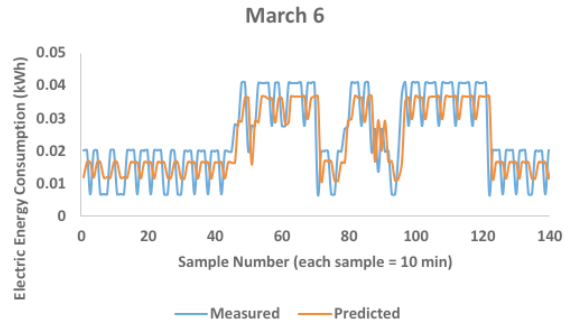

March 9
Electric Energy Consumption (kWh)
0.25
0.2
0.15
0.1
0.05
0
-0.05
0 20 40 60 80 100 120 140
Sample Number (each sample = 10 min)
Measured
Predicted

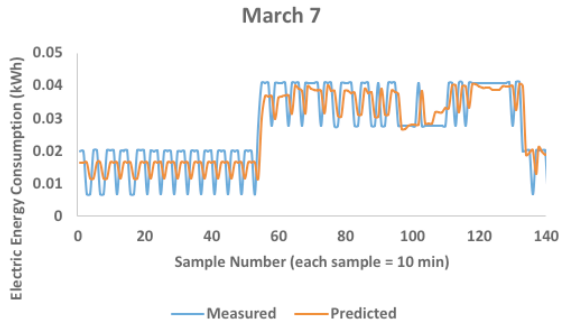

March 10
Electric Energy Consumption (kWh)
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140
Sample Number (each sample = 10 min)
Measured
Predicted

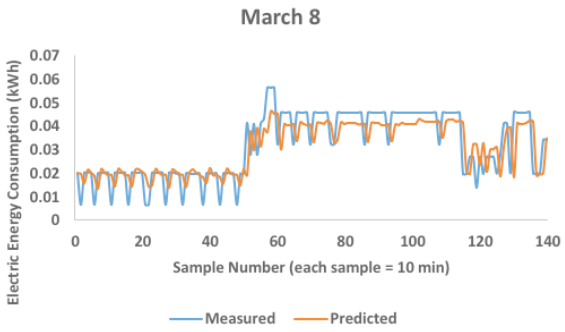
Cell 2: Zone 2

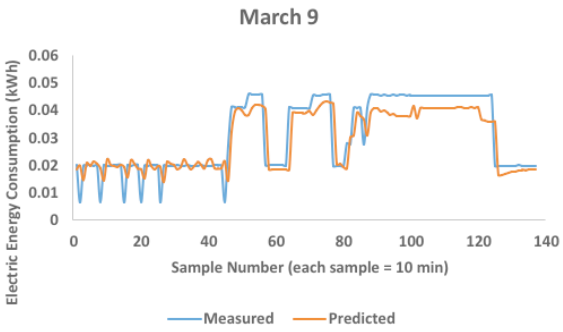

March 4
Electric Energy Consumption (kWh)
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140
Sample Number (each sample = 10 min)
Measured
Predicted

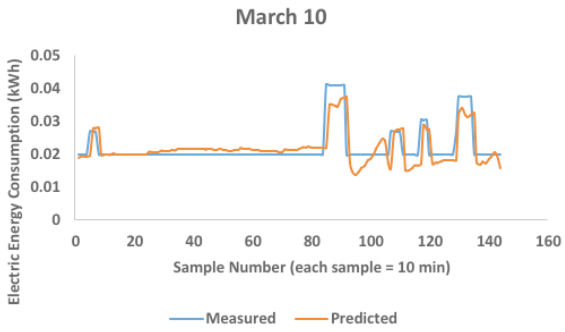

March 5
Electric Energy Consumption (kWh)
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140
Sample Number (each sample = 10 min)
Measured
Predicted


March 6
Electric Energy Consumption (kWh)
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140
Sample Number (each sample = 10 min)
Measured
Predicted

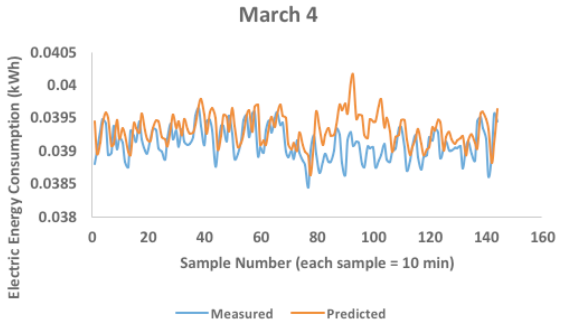

March 7
Electric Energy Consumption (kWh)
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140
Sample Number (each sample = 10 min)
Measured
Predicted

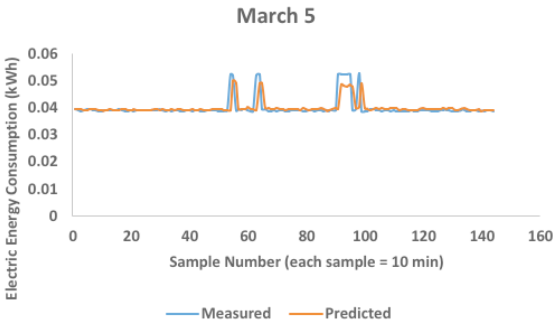

March 8
Electric Energy Consumption (kWh)
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140
Sample Number (each sample = 10 min)
Measured
Predicted

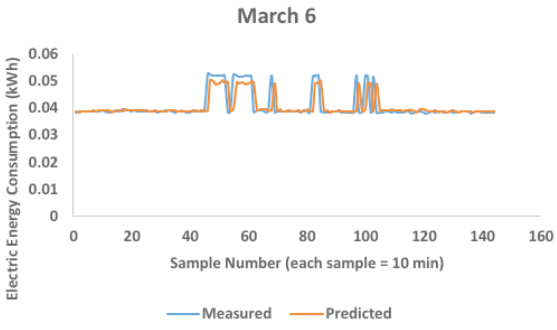

March 9
Electric Energy Consumption (kWh)
0.06
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140
Sample Number (each sample = 10 min)
Measured
Predicted

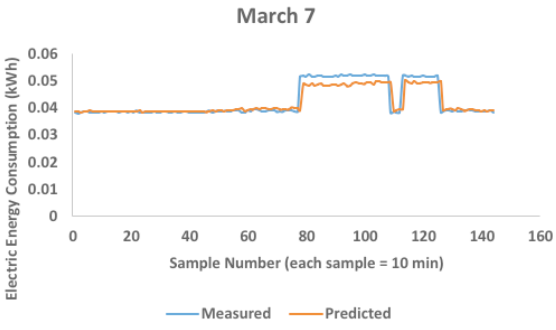

March 10
Electric Energy Consumption (kWh)
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140 160
Sample Number (each sample = 10 min)
Measured
Predicted

Cell 3: Zone 3


March 4
Electric Energy Consumption (kWh)
0.0405
0.04
0.0395
0.039
0.0385
0.038
0 20 40 60 80 100 120 140 160
Sample Number (each sample = 10 min)
Measured
Predicted


March 5
Electric Energy Consumption (kWh)
0.06
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140 160
Sample Number (each sample = 10 min)
Measured
Predicted


March 6
Electric Energy Consumption (kWh)
0.06
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140 160
Sample Number (each sample = 10 min)
Measured
Predicted


March 7
Electric Energy Consumption (kWh)
0.06
0.05
0.04
0.03
0.02
0.01
0
0 20 40 60 80 100 120 140 160
Sample Number (each sample = 10 min)
Measured
Predicted

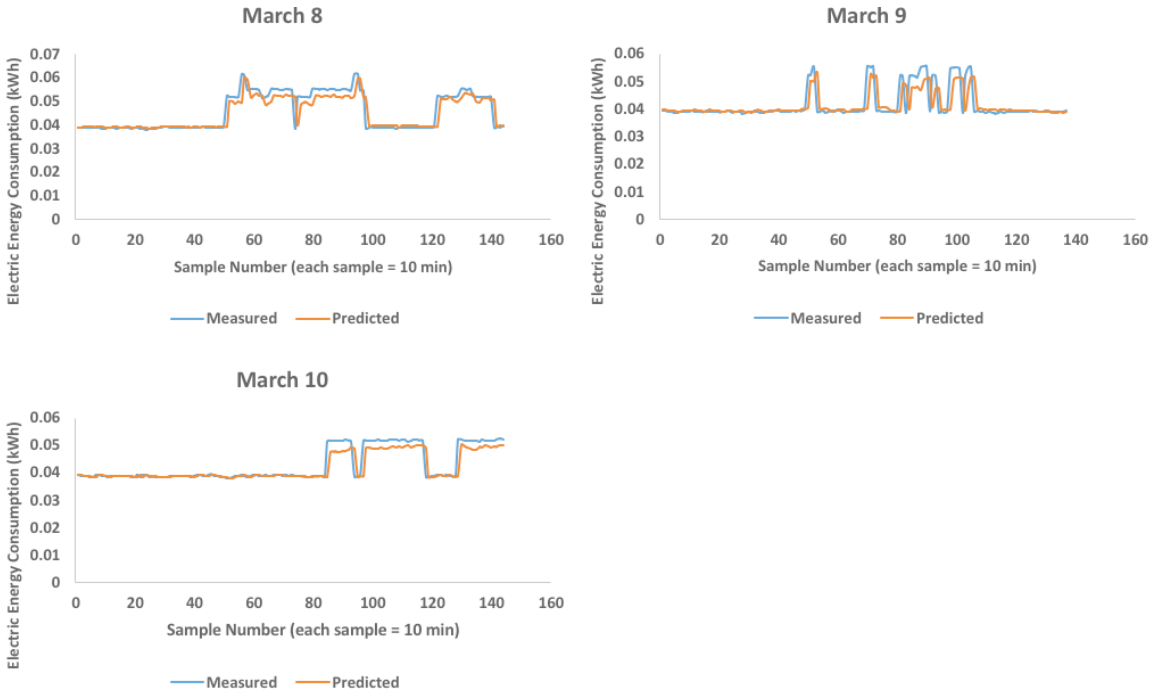


Fig 6.7. PEC and MEC waveforms for all three cells (or zones) for the period March 4 – 10, 2018 [30]

Summary

ICE's CCN-based energy consumption prediction capability was developed in this chapter. The CCN model was built in MATLAB, where it received certain input parameters (AT, ZT, MEC, and OS) from the IoT sensors (temperature sensor, thermostat, power meter, and occupancy sensor) and generated PEC values. The developed CCN prediction model was tested for accuracy by comparing PEC and MEC data over a period of one week. Low error % were obtained from this comparison, which indicates the developed CCN-based energy prediction model was highly accurate. Although developed for the RTPIS laboratory, ICE's CCN model is scalable and flexible,

providing the capability to adapt this model for usage with any IoT driven building environment.

CHAPTER SEVEN

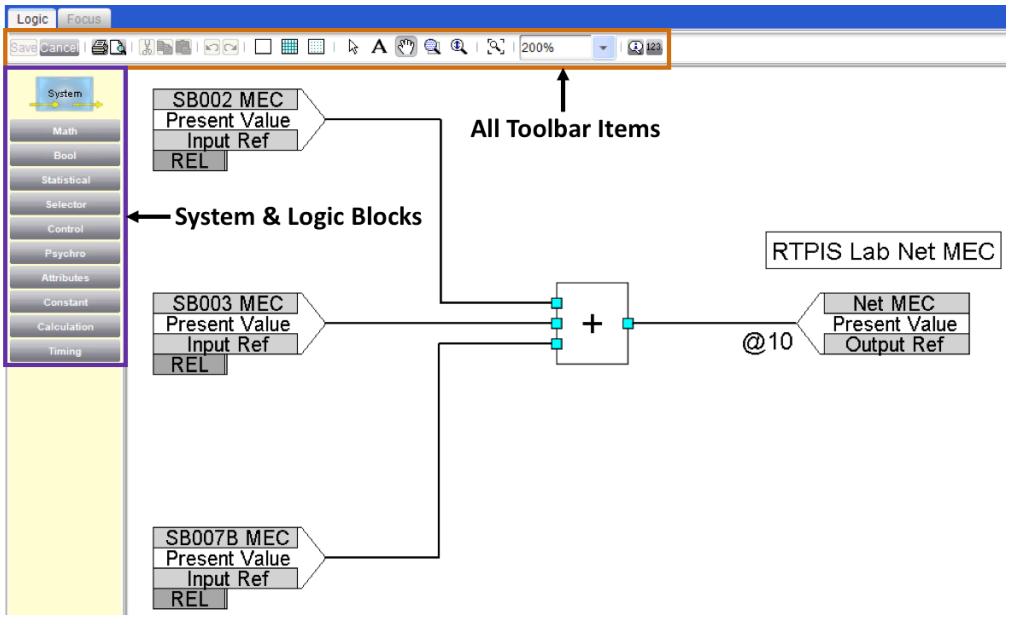
OPTIMIZED CONTROL OF ELECTRIC LOADS

Introduction

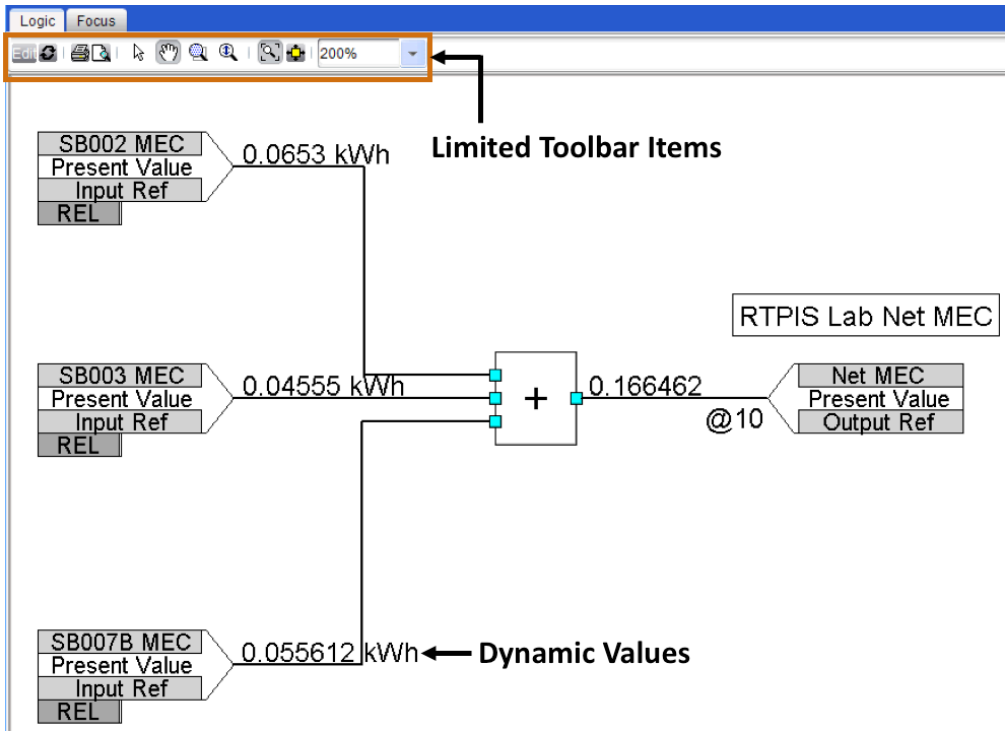
This chapter presents an Internet of Things (IoT)-based solution to overcome the challenge of inefficient energy management. The solution involves development, deployment, and dispatch of Intelligent Computational Engine (ICE) capabilities viz. energy consumption prediction and optimized control of electric loads. The development CCN-based energy consumption prediction capability was described in chapter 6. The particle swarm optimization (PSO) algorithm along with Metasys Building Automation System (BAS) logic connector tool (LCT) were used to develop ICE's optimized control of electric loads capability. The general PSO algorithm has been described in Chapter 5.

LCT is used to create a control system logic using graphical presentation. The control system logic comprises of three components: system blocks, logic blocks, and math category. The system blocks reference other control system logics. They support drag and drop functionality and allow configuration of control system logics. System blocks are useful with developing a complex control system logic by supporting nested control system logics. The logic blocks represent various functions that are performed on objects. Similar to system blocks, logic blocks also support drag and drop functionality. The logic block functions include mathematics, boolean, statistics, multiplexer, control, psychrometrics, attributes, constant, calculation, and timing. The math category performs calculations on input. The math category functions include multiply, divide, add, subtract,

negative, absolute, square root, cosine, sine, tangent, arc tangent, arc cosine, arc sine, exponent, natural log, log, and X^Y [207].



(a)



(b)

Fig. 7.1. Metasys BAS LCT graphical user interface in (a) edit mode and (b) view mode

LCT runs either in edit mode or view mode, which allows editing or viewing a control system logic through Metasys BAS. In edit mode (Fig. 7.1a), access to all toolbar items, system blocks, and logic blocks are made available. Control system logic is created or edited in this mode. In view mode (Fig. 7.1b), access to a limited number of toolbar items is made available. The system and logic blocks do not appear in this mode. Dynamic values are displayed on the connection line between two logic blocks in view mode. Also, commands to input reference blocks can be sent in this mode [207].

Having ICE's energy consumption prediction and optimized control of electric loads capabilities is extremely useful for efficient energy management as they ensure that sufficient energy is generated to meet the demands of the electric loads optimally at any time thereby reducing wasted energy due to excess generation. This, in turn, reduces carbon emissions and generates energy and cost savings [30].

Problem Definition

The problem definition (Fig. 7.2) for optimized control of electric loads experiment involves the following: (1) using the real-time IoT sensor data with the developed CCN-based energy consumption prediction model to generate the PEC value for the next time step, (2) using the PEC value as a reference for the PSO algorithm to generate optimized control parameters, (3) using the generated control parameters in the LCT model for regulating the electric loads operation (i.e. load shedding/reduction) to save energy. For validating the model, the energy consumption data was recorded for a period of one week (April 16 – April 22, 2018) with the optimized control model and

compared with the energy consumption data for the week of April 2 – 8, 2018 without the optimized control model to demonstrate energy savings [30].

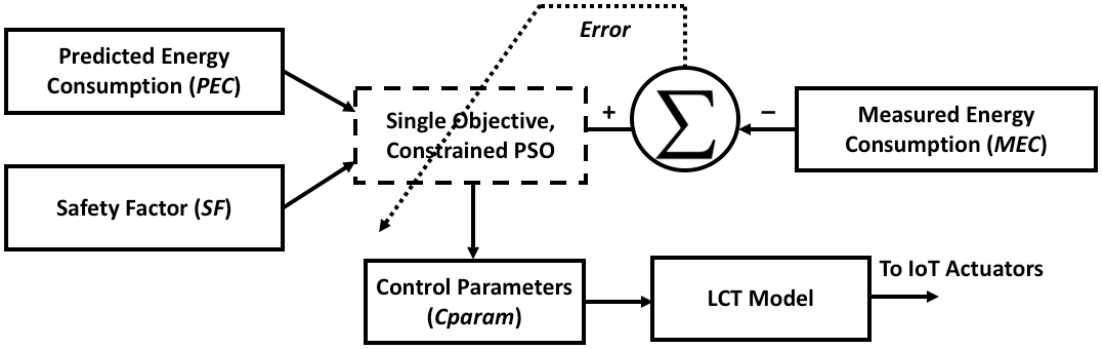


Fig. 7.2. Optimized control of electric loads problem definition [30]

PSO-Based Optimized Control Parameters

Objective Function

The general objective function in (3.1) and constraint in (3.2) were adapted for use in the RTPIS laboratory for generating control parameters for optimized control of the HVAC units and light panels. The RTPIS laboratory specific objective function and constraint are given by (7.1) and (7.2):

$$max[A(P1\times L1) + B(P2\times L2) + C(P3\times L3) + D(P4\times L4) + E(P5\times L5) + F(P6\times L6)] \quad (7.1)$$

where *A, B, ..., F* = [0 or 1] are the control parameters to be determined using PSO. Electric loads energy consumption magnitudes *L1, L2, ..., L6* correspond to zone 1 light panels, zone 1 HVAC1, zone 1 HVAC2, zone 2 light panels, zone 2 HVAC, and zone 3 light panels. The electric load energy consumption values are obtained from Metasys (BAS) LCT model via the BACnet to Modbus TCP/IP gateway (Fig. 7.3). The logic diagram for the generation of the electric load energy consumption values is shown in

Fig. 7.4. Each load is assigned a specific priority (*P1, P2, ..., P6*) as described in the next section (see Table 7.1).

$$MEC_i \leq SF_i \times PEC_i \tag{7.2}$$

where MEC_i is the measured energy consumption, PEC_i is the predicted energy consumption, and SF_i is the safety factor for room i. i is 1, 2, and 3 for zone 1, zone 2, and zone 3, respectively. The energy consumption prediction error percent ($\%error$) for each zone is calculated as described in Chapter 6 (6.5), and its values for each zone during each day of the study period are tabulated in Table 6.1. The safety factor for this model is calculated as shown in (7.3).

$$SF_i = \frac{100\% - \max(\%error_i)}{100} \tag{7.3}$$

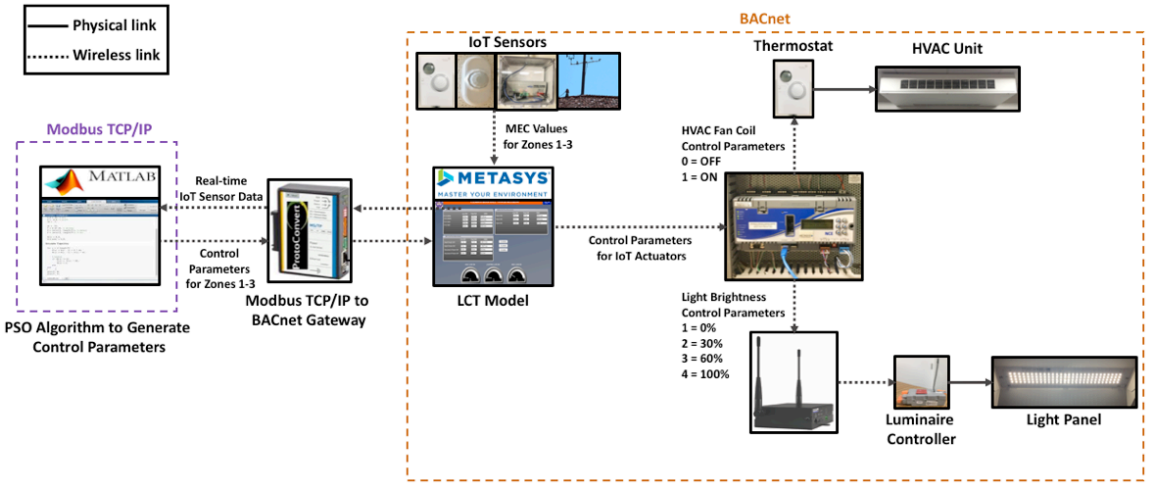


Fig. 7.3. Communication link between the Metasys BAS LCT model and PSO algorithm developed in MATLAB [30]

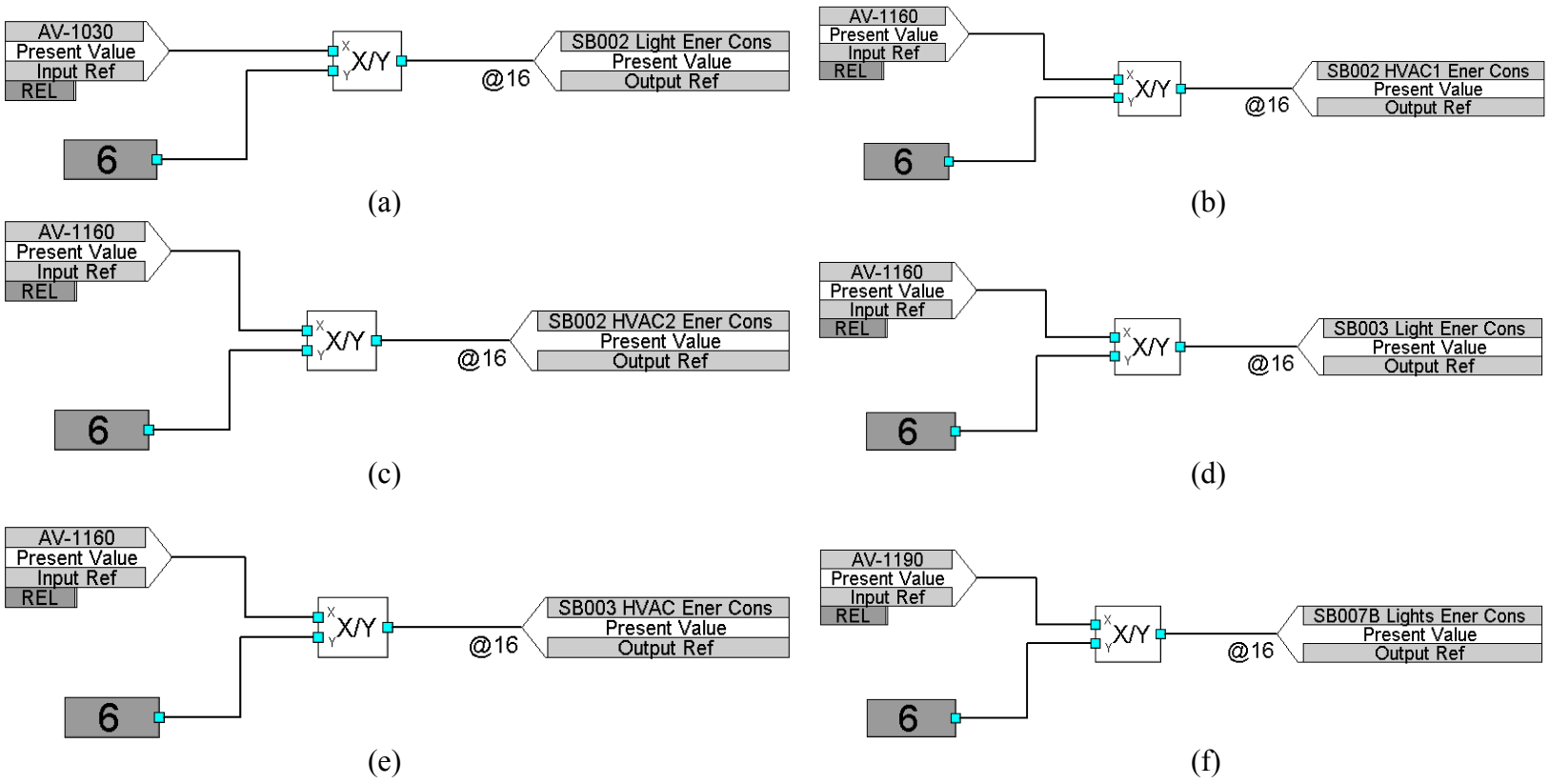


Fig. 7.4. LCT model for electric load energy consumption magnitude (in kWh) inputs to PSO algorithm from (a) zone 1 light panels, (b) zone 1 HVAC 1, (c) zone 1 HVAC 2, (d) zone 2 light panels, (e) zone 2 HVAC, and (f) zone 3 light panels

Electric Loads and Priority Weighting

The priority weighting for load shedding/reduction was set manually and is shown in Table 7.1. The electric load zone 1 HVAC1 was given highest priority (priority weighting = 4) because this area contains large equipment, including real-time digital simulators and phasor measurement units. It is important to keep this area cool to maintain the equipment, but it is not a required to keep the load on constantly. The electric loads zone 1 lights and zone 2 lights were assigned the second highest priority (priority weighting = 3), and the electric loads zone 1 HVAC 2 and zone 2 HVAC units were given third highest priority (priority weighting = 2). Since they are the main work areas and are often occupied, lighting was given the higher priority since it is difficult to work if there is poor lighting. It is still possible to continue working comfortably if the HVAC units are temporarily suspended. The electric load zone 3 lights were given lowest priority (priority weighting = 1) because this area contains a high performance computing cluster and is not a common work area. It requires constant cooling, but lighting is not a critical need for this area. Note that the zone 3 HVAC unit is a critical/must load and was kept on constantly.

TABLE 7.1. ELECTRIC LOAD MAGNITUDE AND PRIORITIES [30]

Electric Load	**Zone 1 Lights**	**Zone 1 HVAC 1**	**Zone 1 HVAC 2**	**Zone 2 Lights**	**Zone 2 HVAC**	**Zone 3 Lights**	**Zone 3 HVAC**
Case 1: Magnitude (kWh)	0.0497	0.0118	0.0149	0.0324	0.0132	0.0226	0.0388
Case 2: Magnitude (kWh)	0.0345	0.0118	0.0153	0.0278	0.0132	0.0161	0.0390
Case 3: Magnitude (kWh)	0.0345	0.0118	0.0149	0.0068	0.0132	0.0131	0.0387
Priority Weighting	3	4	2	3	2	1	Critical/Must Load

Cases 1, 2, and 3 represent three different operational scenarios varying by light intensity (Case 1: High intensity, Case 2: Medium intensity, and Case 3: Low intensity) for which the optimized control parameters of the electric loads were generated using the PSO algorithm. The results are shown in Tables 7.2 and 7.3 in the Experiment Results and Discussions section.

LCT Model

The LCT model for regulating the electric loads (i.e. load shedding) based on the optimized control parameters is shown in Fig. 7.5. The optimized control parameter values obtained using the developed PSO algorithm in MATLAB are transmitted to Metasys BAS via the Modbus TCP/IP to BACnet gateway (Fig. 7.3). The LCT model uses these optimized control parameter values as inputs to the IoT actuators (thermostats and luminaire controllers) to regulate necessary electric loads to reduce the energy consumption under the set reference (7.2) without violating any operational constraints (Fig. 7.5). The different control parameters for the thermostats and luminaire controllers are shown in Fig. 7.3. This saves energy and improves energy efficiency of the RTPIS laboratory [30].

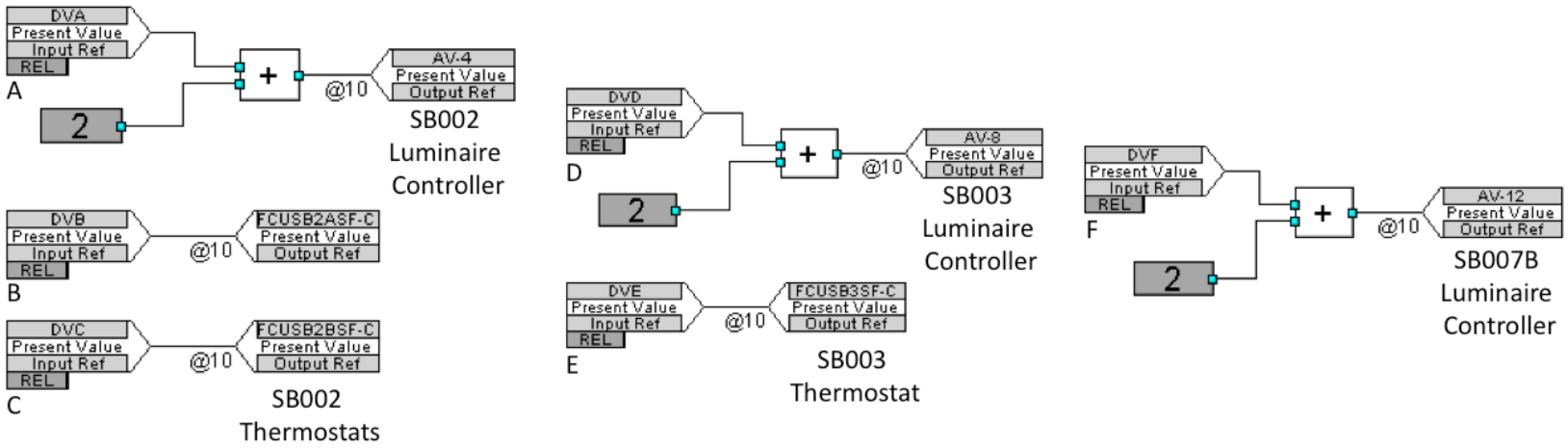
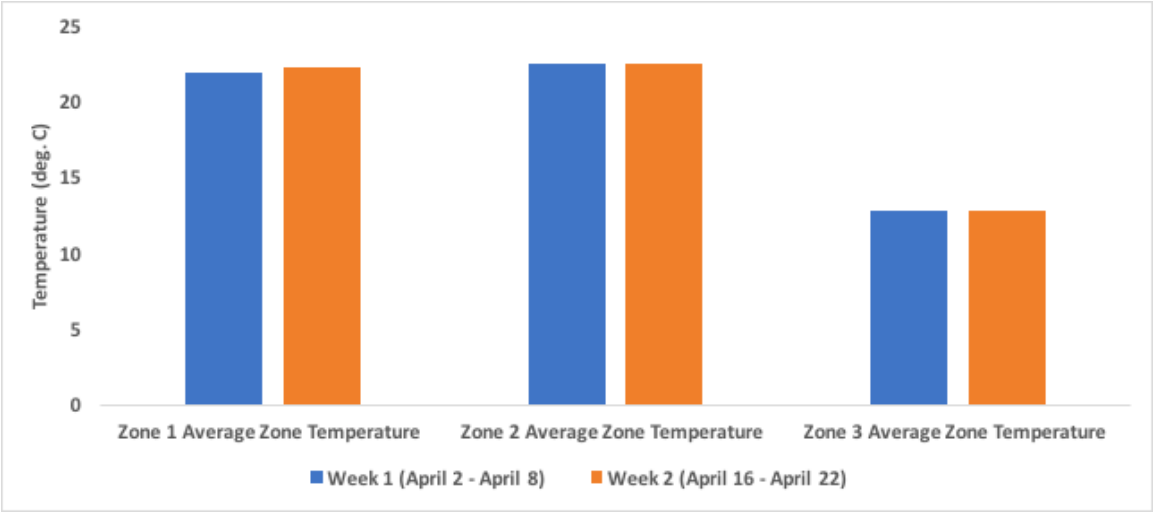
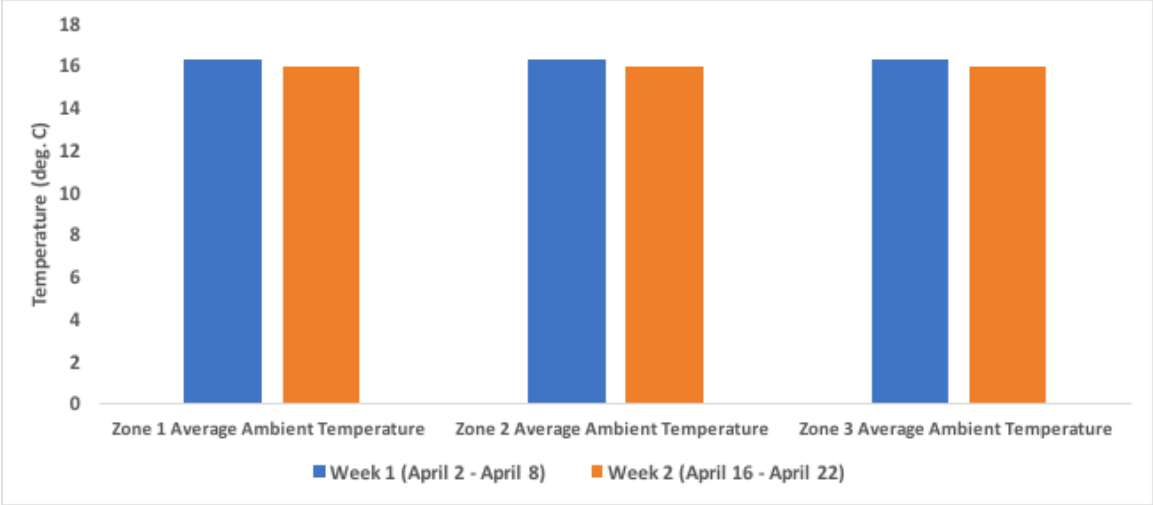


Fig. 7.5. Metasys BAS LCT logic diagram for optimized load shedding/reduction. A, B, C, D, E, and F are the optimized control parameters from the PSO algorithm

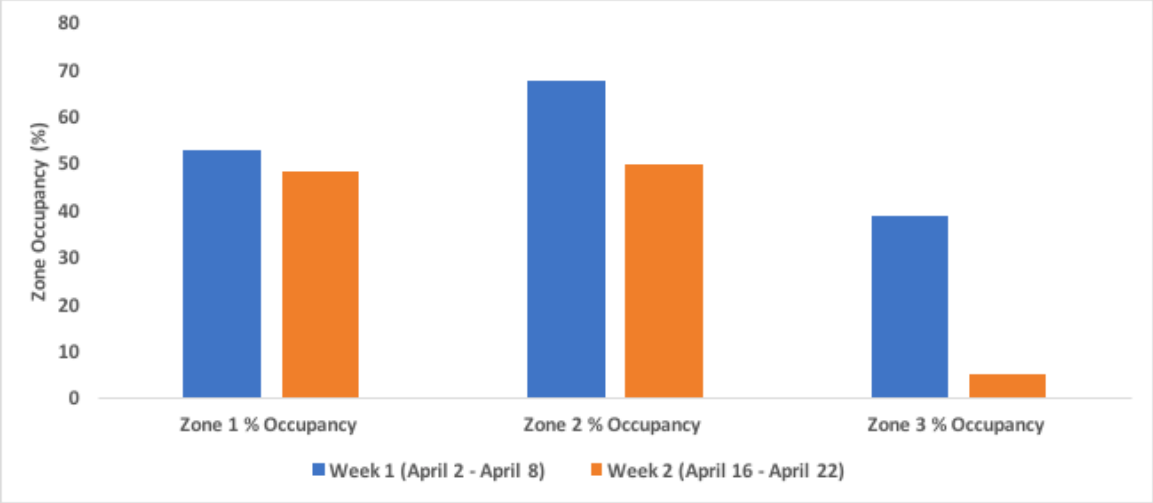
An experiment was conducted in the RTPIS laboratory for a period of two weeks (April 2 – 8, 2018 and April 16 –22, 2018) to test the optimized control of electric loads for managing energy efficiently. The selection of the time period for testing the optimized control model was done such that the input parameters (viz. ambient temperature, zone temperature, and occupancy state) of the three zones were comparable during the test period (Fig. 7.6).



(a)



(b)



(c)

Fig. 7.6. Comparison between (a) zone temperature, (b) ambient temperature, and (c) occupancy state for all three zones for week 1 (April 2-8) and week 2 (April 16-22) [30]

For zone 1, all the conditions for weeks 1 and 2 are almost identical. For zone 2, the zone temperature and ambient temperature comparisons are almost identical, but there is a slight variation in the occupancy comparison for weeks 1 and 2. Zone 3 comparisons are almost like zone 2 comparisons, but there is a major variation in the occupancy comparison for weeks 1 and 2. This is a real-world experiment with an actual building, loads, people, and environment. Therefore, slight variations are likely and expected from one week to the other. Furthermore, the low occupancy % for zone 3 during week 2 is normal as it houses a high performance computing cluster, which requires constant low temperature environment to be maintained (HVAC always 'ON'), and is therefore not a conducive working environment. The occupancy % for zone 3 was higher during week 1 as it was necessary for the author to work in that zone to develop the optimization algorithms on the workstation (also housed in zone 3). The occupancy, therefore, only included the author and its variation didn't have much effect on the experiment outcome.

The developed CCN prediction model, PSO algorithm, and LCT model was dispatched during the week of April 16 – 22. The net energy consumption data was recorded during this period (*energyOC*) and compared to the week of April 2 – 8 (*energyN*), a period during which the laboratory operated under similar conditions but without the integration of the optimized control model. $\%\,Savings$ obtained with the integration of the optimized control model was calculated using (7.3) [30]. The results are shown and discussed in the Experiment Results and Discussions section below.

$$\%Savings = \left(\frac{|energyOC\text{-}energyN|}{energyN}\right) \times 100 \tag{7.3}$$

Experiment Results and Discussions

PSO Generated Control Parameters

The control parameters (A, B, …, F) given in (7.1) were generated using the PSO algorithm. Table 7.2 presents the control parameters that were generated based on the total predicted and measured energy consumption of the RTPIS laboratory using PSO to solve equation (7.1) and satisfy constraint (7.2). Table 7.2 also presents the loads that were shed/reduced based on the generated control parameters. Table 7.3 supplements Table 7.2 in that it presents the predicted energy consumption, safety factor, and measured energy consumption for individual rooms in the RTPIS laboratory.

TABLE 7.2. CONTROL PARAMETERS GENERATED USING PSO [30]

Case	Total PEC (kWh)	Total $SF \times PEC$ (kWh)	Total MEC (kWh)	*Min. Load to Shed (kWh)	PSO Control Parameters	Loads Shed/Reduced	Comments/Justification
1	0.1381	0.1325	0.1834	0.0509	[1 1 0 1 0 0]	Zone 1 HVAC2, Zone 2 HVAC, Zone 3 Lights	The optimal loads to shed were of the lowest two levels of priority and their magnitude was equivalent to the amount needed to be shed without any excess
2	0.1482	0.1423	0.1577	0.0154	[1 1 0 1 1 1]	Zone 1 HVAC2	If based on priority alone, zone 3 lights would have been reduced since that is the lowest priority. But, that would only maximize priority weighting and not the objective function. Therefore, zone 1 HVAC2 was shed since it maximized the objective function and was of the second to lowest priority level.
3	0.1305	0.1254	0.1330	0.0076	[1 1 1 0 1 1]	Zone 2 Lights	Similar to Case 2, reducing zone 2 lights maximized the objective function and of was third in terms of lowest priority

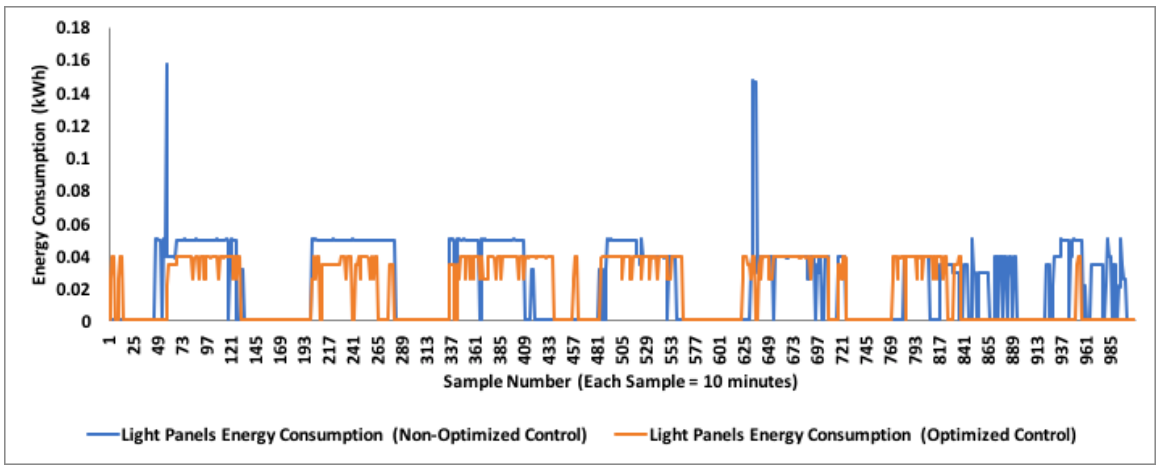
*Values have been rounded to the fourth decimal place, although the devices and software are more precise.

TABLE 7.3. MEASURED VS. PREDICTED ENERGY CONSUMPTION ALONG WITH THE SAFETY FACTORS FOR EACH ROOM [30]

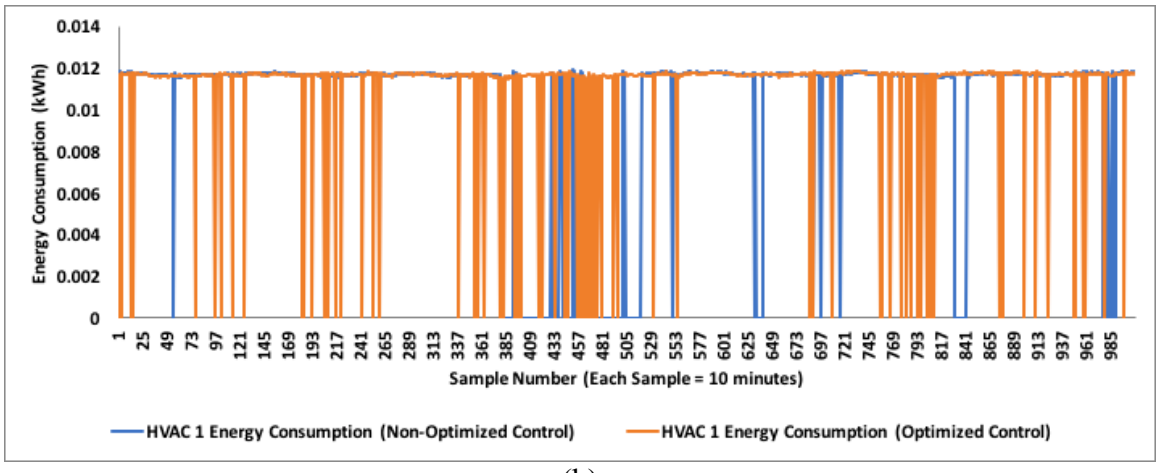
Case	Zone	PEC (kWh)	SF	$SF \times PEC$	MEC (kWh)
1	1	0.0418	0.97	0.0405	0.0764
	2	0.0367	0.93	0.0341	0.0456
	3	0.0596	0.97	0.0578	0.0614
2	1	0.0605	0.97	0.0587	0.0616
	2	0.0355	0.93	0.0330	0.0410
	3	0.0522	0.97	0.0522	0.0551
3	1	0.0516	0.97	0.0500	0.0612
	2	0.0289	0.93	0.0269	0.0200
	3	0.0500	0.97	0.0485	0.0518

Parameter Waveforms With and Without Dispatch of Optimized Control Model

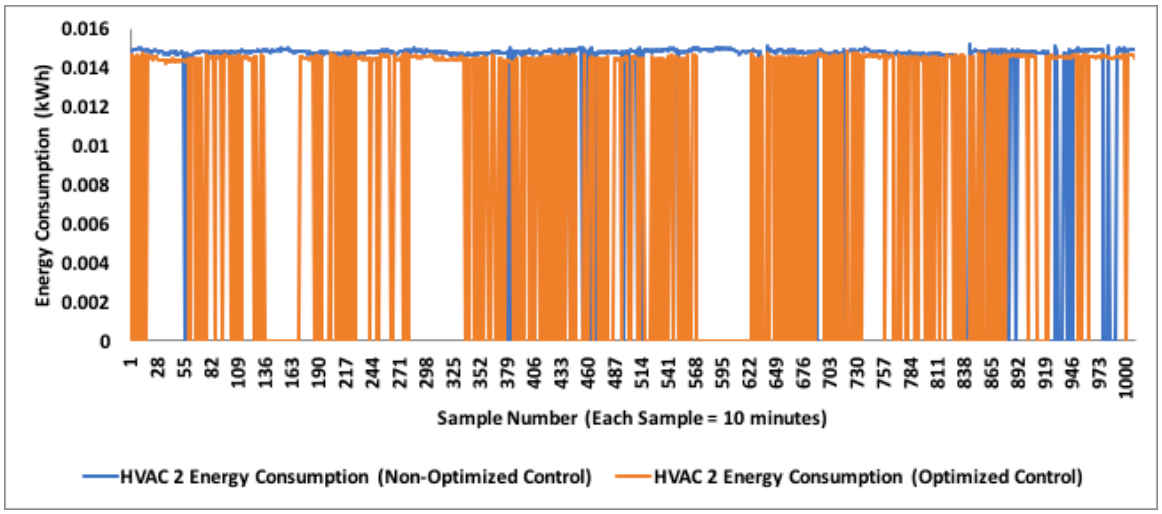
The waveforms of the various parameters viz. energy consumption by the electric loads (light panels and HVAC units), zone temperature, occupancy state, and ambient temperature for all three zones with and without the dispatch of optimized control model are shown in Fig. 7.7 – Fig. 7.9. The ambient temperature waveform is shown once (Fig. 7.7(f)) since it has the same values for all three zones.



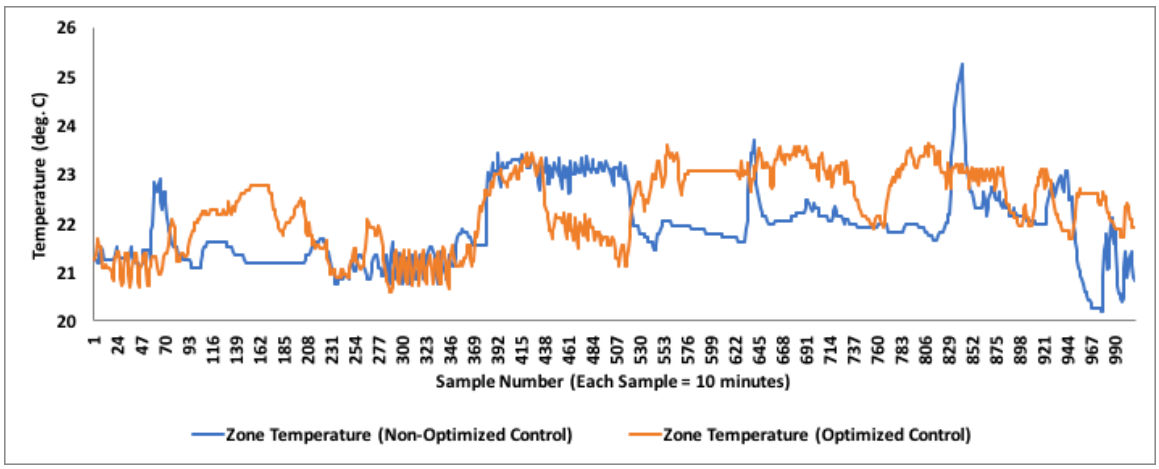
(a)



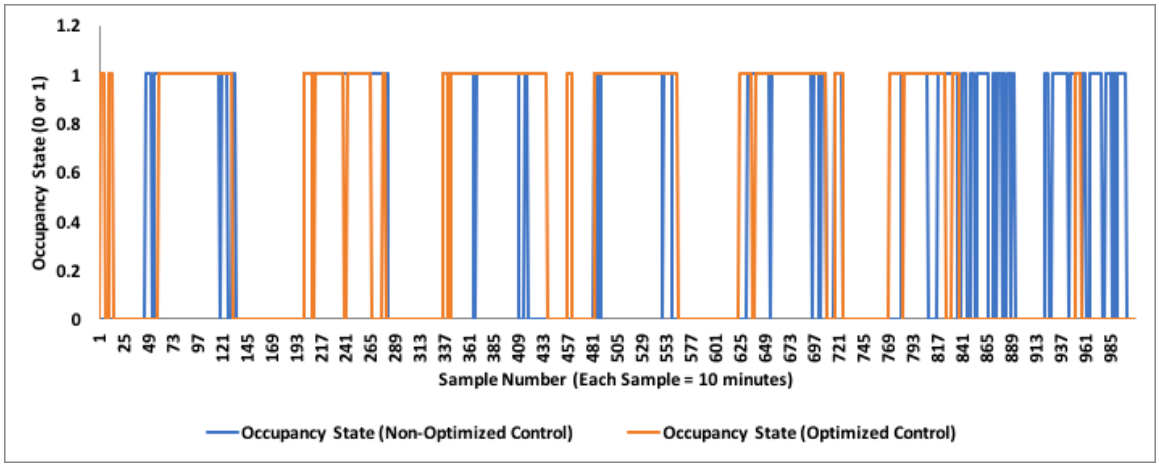
(b)


Energy Consumption (kWh)
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
1 28 55 82 109 136 163 190 217 244 271 298 325 352 379 406 433 460 487 514 541 568 595 622 649 676 703 730 757 784 811 838 865 892 919 946 973 1000
Sample Number (Each Sample = 10 minutes)
HVAC 2 Energy Consumption (Non-Optimized Control)
HVAC 2 Energy Consumption (Optimized Control)

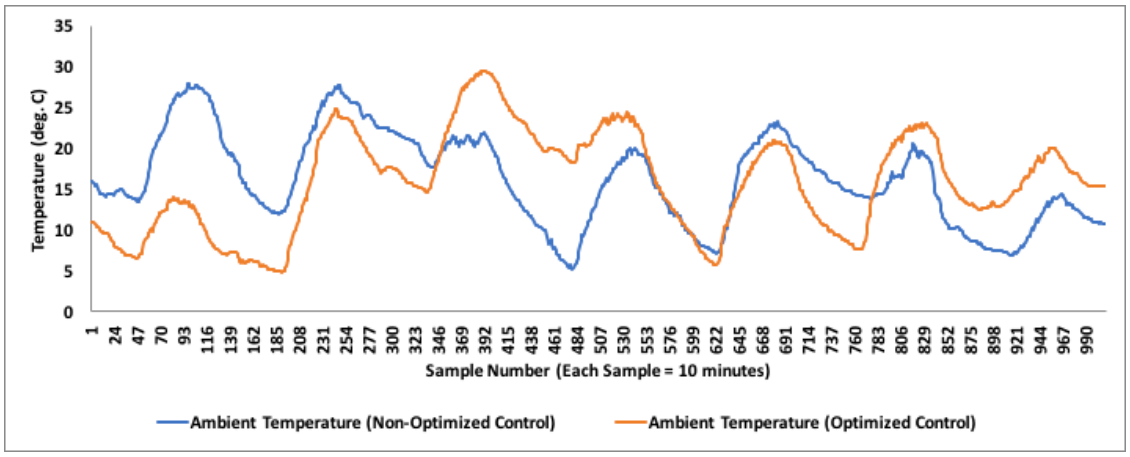
(c)


Temperature (deg. C)
26
25
24
23
22
21
20
1 24 47 70 93 116 139 162 185 208 231 254 277 300 323 346 369 392 415 438 461 484 507 530 553 576 599 622 645 668 691 714 737 760 783 806 829 852 875 898 921 944 967 990
Sample Number (Each Sample = 10 minutes)
Zone Temperature (Non-Optimized Control)
Zone Temperature (Optimized Control)

(d)

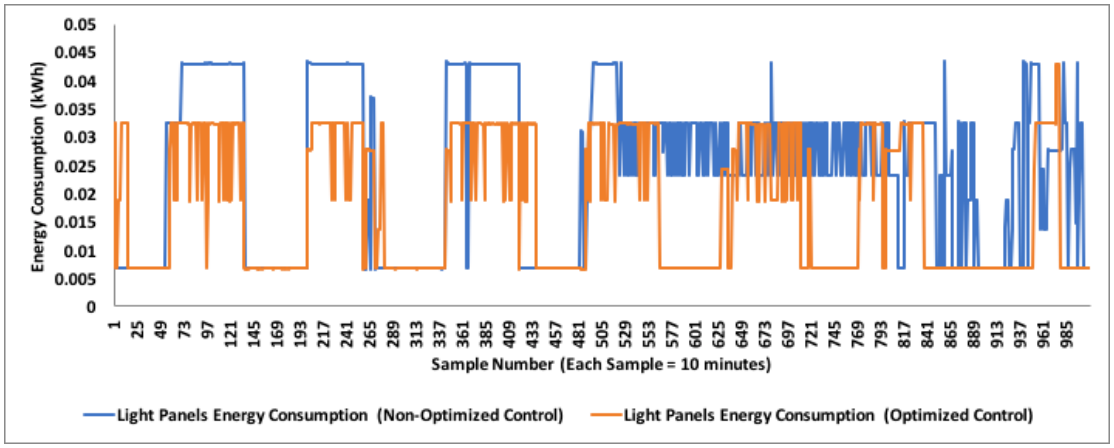

Occupancy State (0 or 1)
1.2
1
0.8
0.6
0.4
0.2
0
1 25 49 73 97 121 145 169 193 217 241 265 289 313 337 361 385 409 433 457 481 505 529 553 577 601 625 649 673 697 721 745 769 793 817 841 865 889 913 937 961 985
Sample Number (Each Sample = 10 minutes)
Occupancy State (Non-Optimized Control)
Occupancy State (Optimized Control)

(e)

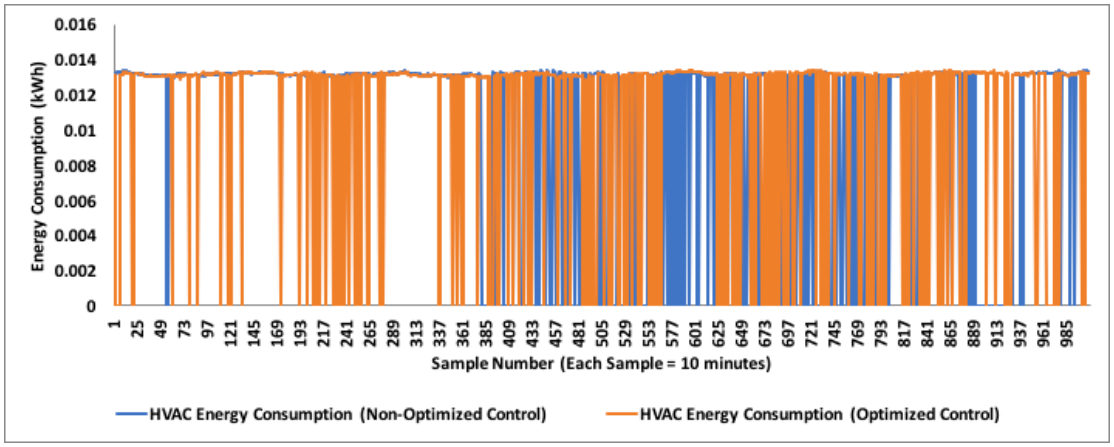


(f)

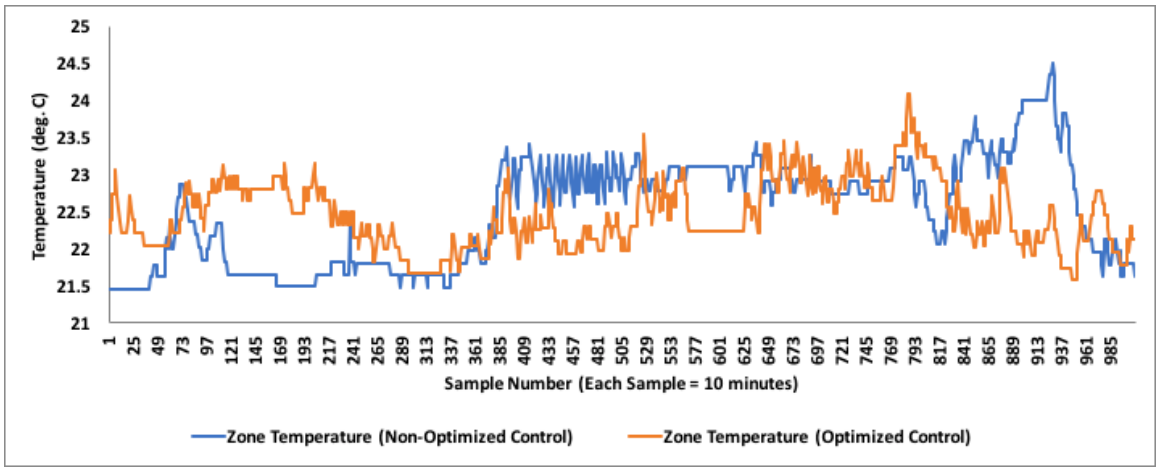
Fig. 7.7. Waveforms of (a) light panels energy consumption, (b) HVAC 1 energy consumption, (c) HVAC 2 energy consumption, (d) zone temperature, (e) occupancy state, and (f) ambient temperature for zone 1 with and without the dispatch of optimized control model [30]



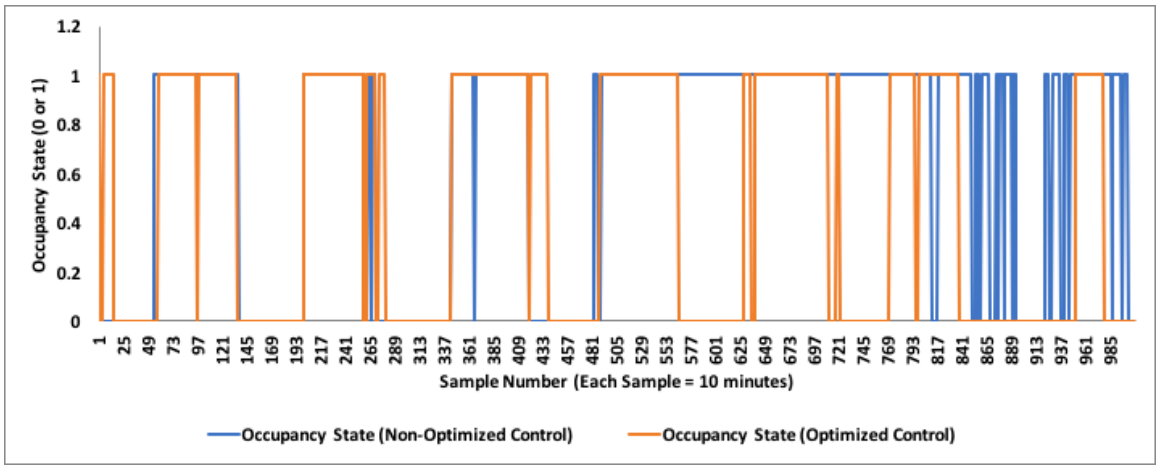
(a)



(b)

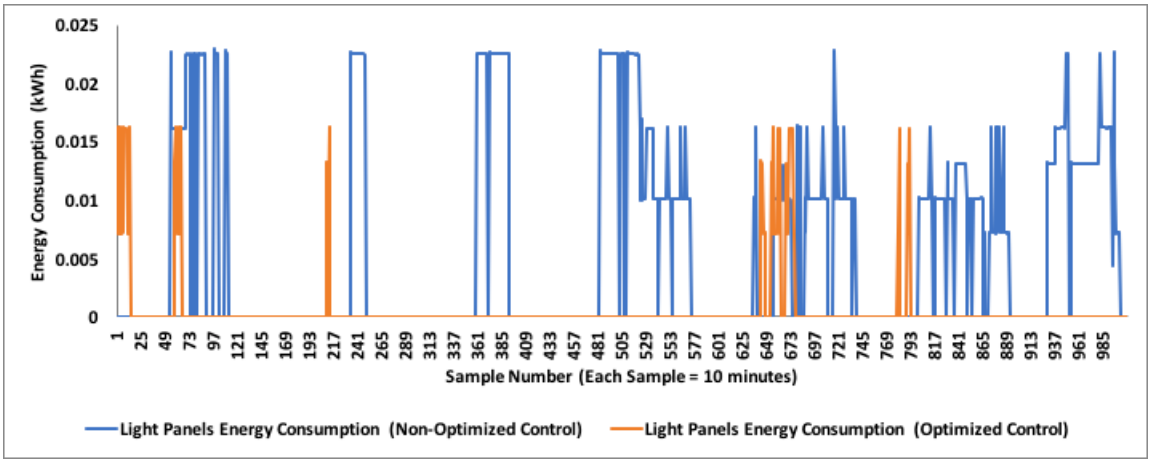


(c)

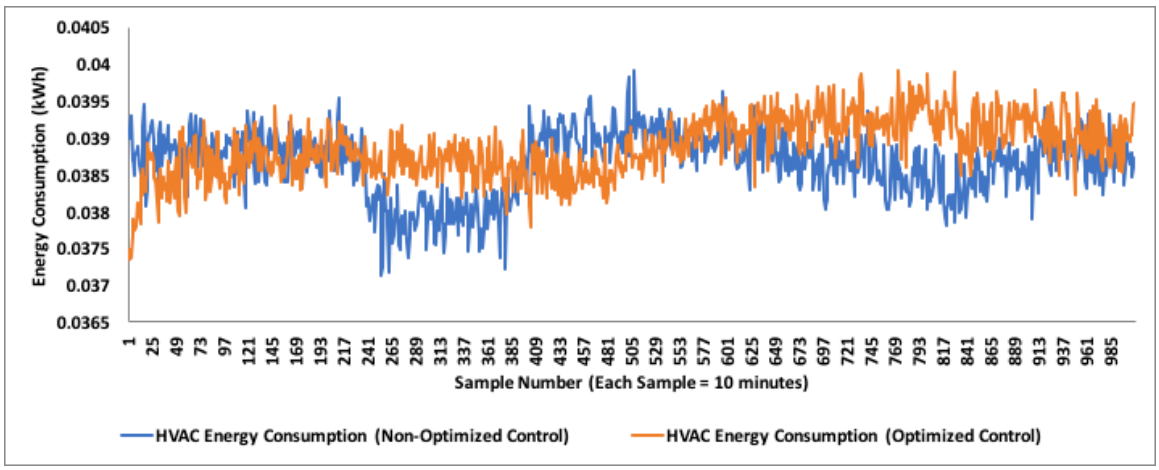


(d)

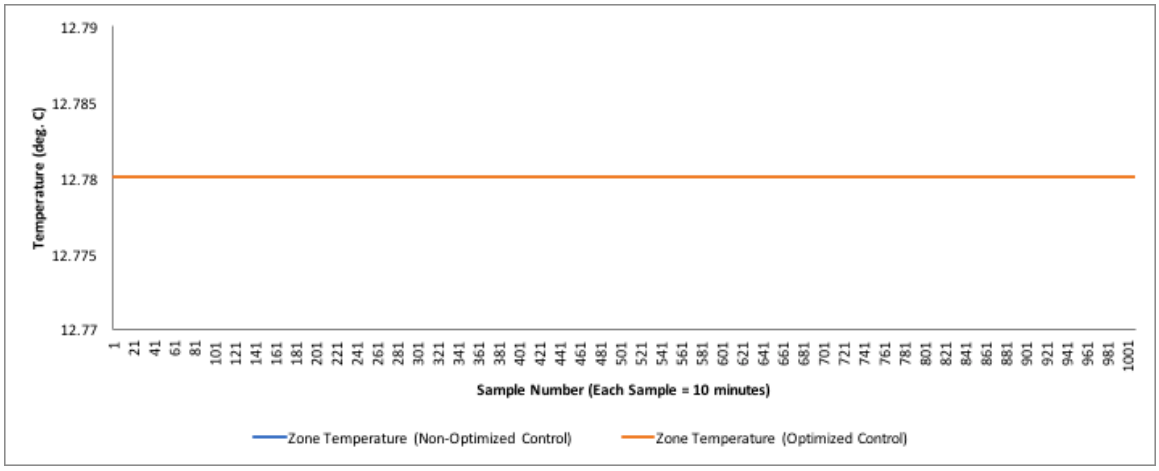
Fig. 7.8. Waveforms of (a) light panels energy consumption, (b) HVAC energy consumption, (c) zone temperature, and (d) occupancy state for zone 2 with and without the dispatch of optimized control model [30]


Energy Consumption (kWh)
0.025
0.02
0.015
0.01
0.005
0
Sample Number (Each Sample = 10 minutes)
Light Panels Energy Consumption (Non-Optimized Control)
Light Panels Energy Consumption (Optimized Control)

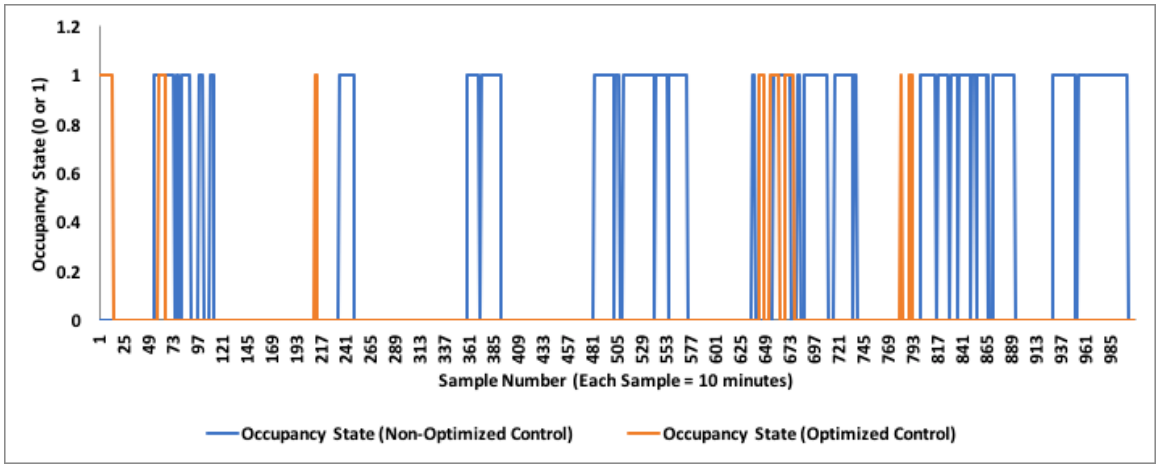
(a)


Energy Consumption (kWh)
0.0405
0.04
0.0395
0.039
0.0385
0.038
0.0375
0.037
0.0365
Sample Number (Each Sample = 10 minutes)
HVAC Energy Consumption (Non-Optimized Control)
HVAC Energy Consumption (Optimized Control)

(b)


Temperature (deg. C)
12.79
12.785
12.78
12.775
12.77
Sample Number (Each Sample = 10 minutes)
Zone Temperature (Non-Optimized Control)
Zone Temperature (Optimized Control)

(c)



(d)

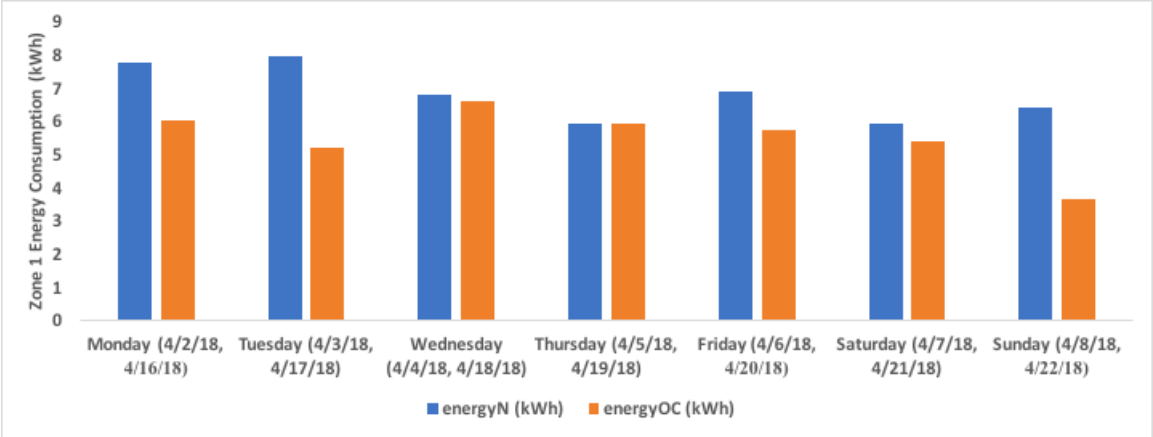
Fig. 7.9. Waveforms of (a) light panels energy consumption, (b) HVAC energy consumption, (c) zone temperature, and (d) occupancy state for zone 3 with and without the dispatch of optimized control model [30]

Energy Savings With Dispatch of Optimized Control Model

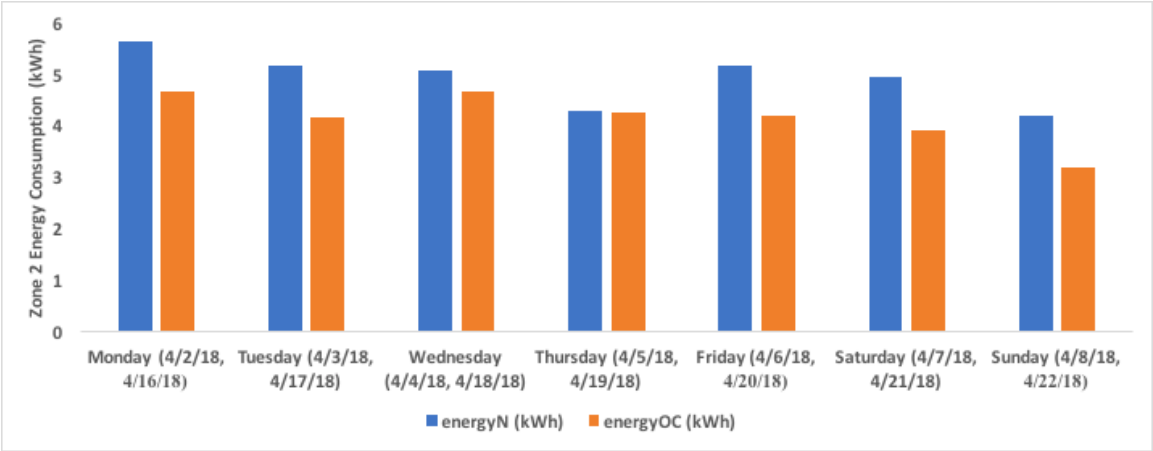
The comparison of *energyOC* and *energyN* values obtained from the optimized control model, along with the % *Savings* values for all three zones are tabulated in Table 7.4. Fig. 7.10 shows the net *energyOC* values for the period April 16 –22, 2018 and the net *energyN* values for the period April 2 – 8, 2018 for all three cells (or zones). The waveforms for the *energyOC* and *energyN* values are shown in Fig. 7.11. From the significant % *Savings* values obtained from the integration of ICE's capabilities, it is successfully demonstrated that the developed optimized control of electric load model and CCN-based energy consumption prediction model can reduce energy waste and enhance energy efficiency when dispatched in the RTPIS laboratory. Therefore, the CCN and optimized control models working together constitute an efficient energy management system for an IoT driven building environment [30].

TABLE 7.4. *energyOC*, *energyN*, AND *%Savings* VALUES FOR ALL THREE CELLS USING OPTIMIZED CONTROL OF ELECTRIC LOADS MODEL [30]

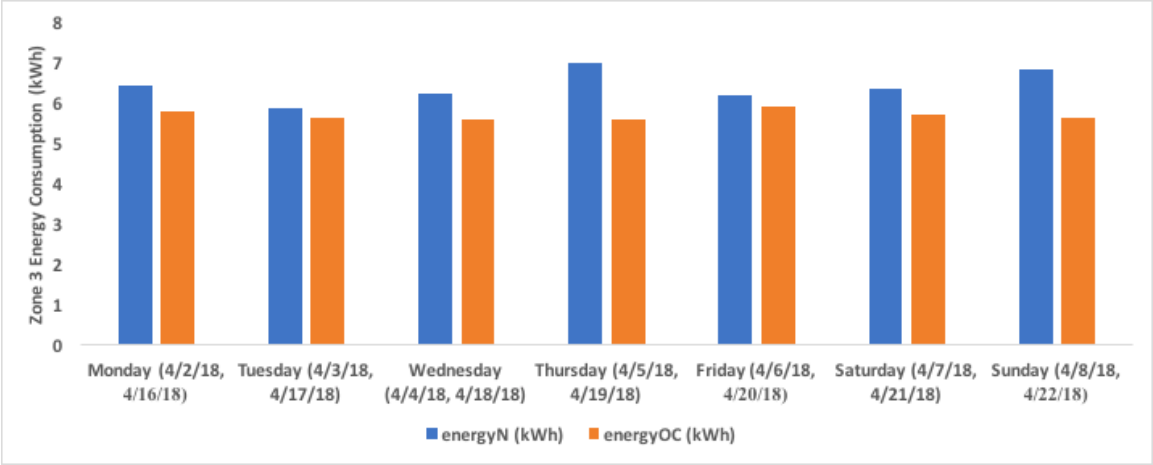
	Cell 1 (Zone 1)			Cell 2 (Zone 2)			Cell 3 (Zone 3)		
Date	***energyN* (kWh)**	***energyOC* (kWh)**	***%Savings***	***energyN* (kWh)**	***energyOC* (kWh)**	***%Savings***	***energyN* (kWh)**	***energyOC* (kWh)**	***%Savings***
4/2/18	7.763	-		5.645	-		6.404	-	
4/3/18	7.953	-		5.158	-		5.880	-	
4/4/18	6.763	-		5.089	-		6.228	-	
4/5/18	5.918	-		4.293	-		6.983	-	
4/6/18	6.878	-		5.173	-		6.194	-	
4/7/18	5.902	-		4.934	-		6.347	-	
4/8/18	6.371	-		4.189	-		6.805	-	
4/16/18	-	6.022	19.33%	-	4.664	15.65%	-	5.798	11.24%
4/17/18	-	5.163		-	4.177		-	5.618	
4/18/18	-	6.583		-	4.678		-	5.561	
4/19/18	-	5.890		-	4.268		-	5.574	
4/20/18	-	5.721		-	4.186		-	5.914	
4/21/18	-	5.365		-	3.909		-	5.710	
4/22/18	-	3.613		-	3.203		-	5.628	
Total	47.548	38.357		34.481	29.085		44.841	39.803	
RTPIS Lab Net Energy %Savings	**15.47%**								



(a)

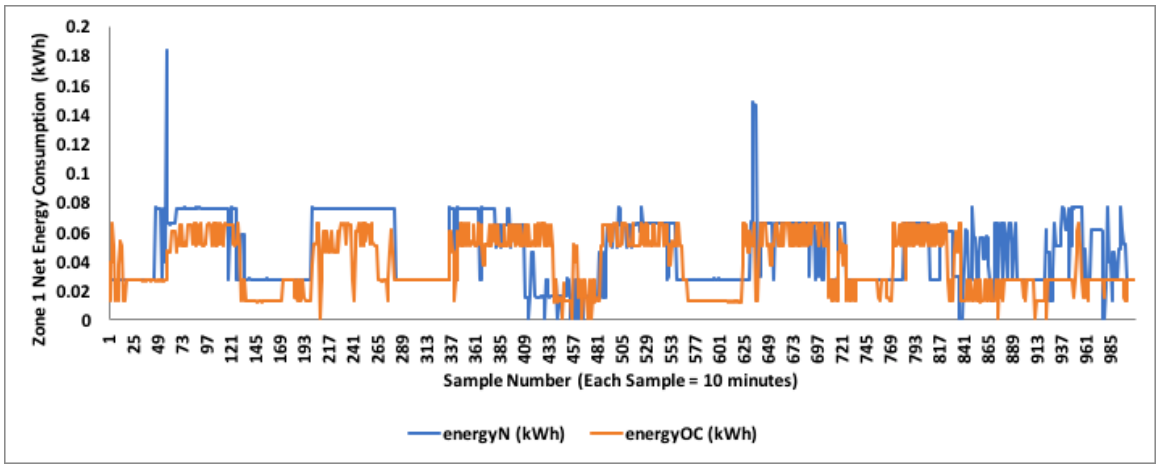


(b)

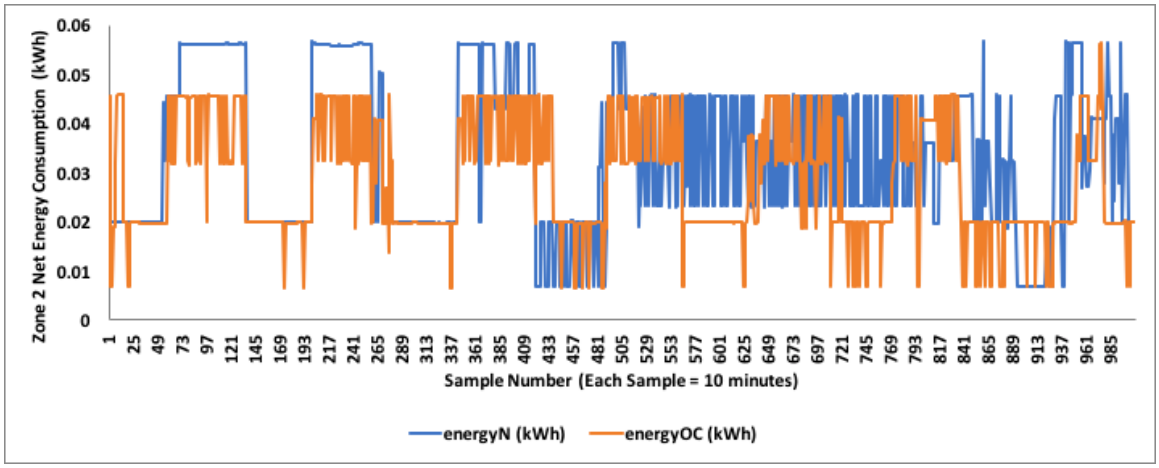


(c)

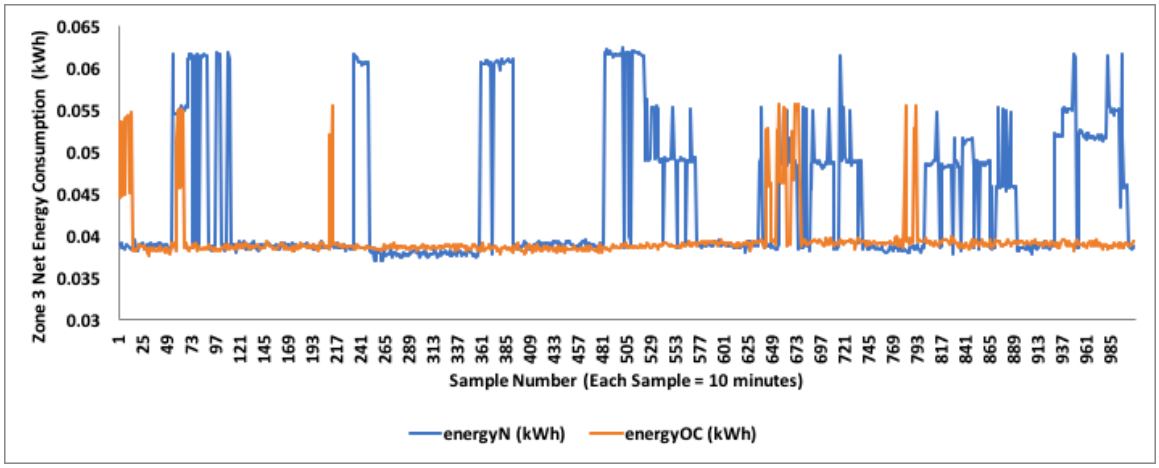
Fig. 7.10. Net *energyOC* and *energyN* values for (a) zone 1, (b) zone 2, and (c) zone 3 for the period April 2 – 8, 2018 and April 16 – 22, 2018, respectively [30]



(a)



(b)



(c)

Fig. 7.11. Net *energyOC* and *energyN* waveforms for (a) zone 1, (b) zone 2, and (c) zone 3 for the period April 2 – 8, 2018 and April 16 – 22, 2018, respectively [30]

Summary

ICE's optimized control of electric loads capability was developed in this chapter. The PSO algorithm was developed in MATLAB where it used the PEC value generated from the CCN model as a reference to generate the optimized control parameters. The LCT model was built in Metasys BAS, where it used these control parameters to perform

optimized load shedding of the electric loads without violating any operational constraints. It was successfully demonstrated that ICE's CCN prediction and optimized control models together served as an efficient energy management system that enhanced the energy efficiency by saving energy in the RTPIS laboratory. Just like ICE's CCN model, the optimized control model, although developed for the RTPIS laboratory, is scalable and flexible, providing the capability to adapt this model for usage with any IoT driven building environment.

CHAPTER EIGHT

CONCLUSIONS

Introduction

This chapter serves as the summary of the entire dissertation. The dissertation comprises of seven chapters (not including this chapter) that present a detailed review of IoT for building environments; the development of ICE, an efficient energy management system for smart buildings; the development of an IoT driven case study environment for the implementation of ICE; and the development, deployment, and dispatch of ICE's energy consumption prediction and optimized control capabilities for reducing energy waste (improving energy efficiency) when applied to the IoT driven building environment.

Research Summary

The summary of research work presented in each chapter is enumerated below.

Chapter 1 presented a detailed review of the role of IoT in transforming modern buildings into energy efficient, smart, and connected buildings. Also presented in this chapter, were the economic, environmental, and societal impacts of IoT for smart buildings. Finally, the main objectives and contributions of this dissertation were enumerated in chapter 1.

Chapter 2 presented a detailed review of the challenges (both technical and non-technical) and recommended solutions for overcoming these challenges for successfully implementing IoT in smart buildings. Additionally, recommendations for mixed-methods

research design to realize the potential of IoT for transforming modern buildings into smart buildings were presented in this chapter.

Chapter 3 presented Intelligent Computational Engine (ICE), an efficient energy management system for IoT driven building environment. The features and impact of ICE along with a general control framework providing an overview of ICE's capabilities were discussed in this chapter.

Chapter 4 provided a description of the development of the building case study environment (i.e. RTPIS laboratory) for implementing ICE. The various IoT devices and technologies and software platforms that were deployed in the RTPIS laboratory over the BACnet protocol were also described in this chapter. Finally, the methodology for recording measurement data for the research experiment was presented in chapter 4.

Chapter 5 described the development and application of two prediction models viz. Elman Recurrent Neural Network (RNN) model and exponential model for predicting energy consumption in the RTPIS lab. The objective of this chapter was to determine which of the two models was superior in terms of better prediction accuracy for use in the development of ICE's Cellular Computational Network (CCN)-based energy consumption prediction capability. Elman RNN model emerged as the more accurate energy consumption prediction model of the two.

Chapter 6 described the development, deployment, and dispatch of ICE's CCN-based energy consumption prediction capability in the RTPIS laboratory, which resulted in high accuracy energy consumption predictions.

Chapter 7 described the development, deployment, and dispatch of ICE's optimized control of electric loads capability in the RTPIS laboratory. It was successfully demonstrated that ICE's CCN prediction and optimized control models together served as an efficient energy management system that enhanced the energy efficiency by reducing energy waste in the RTPIS laboratory.

The conclusions of this dissertation including the chapterwise research summaries, recommendations, and future work was presented in **Chapter 8**.

Main Conclusions

IoT for smart buildings presents an exciting area of innovative growth and development. This dissertation presented a detailed review of the role, impact, and challenges and recommended solutions for implementing IoT in building environments.

A solution to overcome the inefficient energy management problem in a building environment was proposed in this dissertation. The solution involved the development, deployment, and dispatch of ICE for efficient energy management in an IoT driven building environment. Several IoT devices and technologies were integrated with the RTPIS laboratory to transform it into an IoT driven building environment, which served as the building case study environment for this research. The proposed ICE framework was deployed and dispatched in the RTPIS laboratory to test for ICE's effectiveness in terms of reduction in the amount of energy wasted (or improved energy efficiency).

Energy consumption prediction models viz. exponential model and Elman RNN model were developed and compared to determine the most accurate model for use in the development of ICE's energy consumption prediction capability.

The capabilities of ICE that were developed included a CCN-based energy consumption prediction model and an optimized control of electric loads model using PSO algorithm and LCT. The CCN model was built in MATLAB, where it received certain input parameters (AT, ZT, MEC, and OS) from the IoT sensors (temperature sensor, thermostat, power meter, and occupancy sensor) and generated PEC values. The developed CCN prediction model was tested for accuracy by comparing PEC and MEC data over a period of one week. Low error % were obtained from this comparison, which indicates the developed CCN-based energy prediction model was highly accurate. The optimized control model was built partly in MATLAB (PSO algorithm) and partly in Metasys BAS (LCT), where it used the PEC value generated from the CCN model as a reference. The MEC was compared with the PEC and optimized control parameters were generated to regulate the electric loads (HVAC units and light panels) without violating any operational constraints. It was successfully demonstrated that ICE's CCN and optimized models together served as an efficient energy management system that enhanced the energy efficiency by reducing energy waste in the RTPIS laboratory. Although developed for the RTPIS laboratory, ICE's CCN and optimized control models are scalable and flexible, providing the capability to adapt these models for usage with any IoT driven building environment.

Suggestions for Future Research

The detailed review of the role, impact, and challenges of IoT for smart buildings presented in this dissertation work will be beneficial for both academic and industrial

researchers and engineers getting started in the smart building energy management domain.

The ICE developed in this dissertation has unique capabilities that can overcome challenges including inefficient energy management, wasted energy resources, and potentially expensive energy costs to meet the growing energy demands. The ICE is a computational systems thinking machine that is flexible, scalable, adaptable, and self-learning, which makes it convenient to deploy and easy to use in any smart building scenario.

Recommendations for future work include scaling the developed ICE for use in a larger building environment and testing the efficiency of its energy management operation; incorporating privacy and security solutions in ICE to make it more resilient to attacks; and integrating qualitative methods of data collection and analysis into this research to explore and understand individual and group behavior, organizational dynamics, and cultural influences that are necessary to guarantee its uptake and use in achieving its benefit to society.

Summary

The entire dissertation is summarized in this chapter. Chapterwise summaries, main conclusions, and recommendations for future research have been highlighted.

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