Chapter 1

Introduction

1.1 Background and Motivation

1.1.1 Energy Management System (EMS) for Smart Buildings

Electricity demand in residential buildings is increasing day by day due to population growth, the standard of living, and technological development. Different types of technologies such as Information and Communication Technologies (ICTs), Internet-of-Things (IoT), Artificial Intelligent (AI), Advanced Metering Infrastructure (AMI), and scheduling techniques considering Demand Response (DR) are used by Energy Management System (EMS) of Smart Residential Buildings (SRBs). For making DR program effective, utilities have introduced different pricing schemes, such as, Real-time Pricing (RTP), guideline pricing, day ahead pricing, and Time of Use (ToU) pricing are widely used pricing schemes in the electricity market. Further, with the integration of Distributed Energy Resources (DERs) [2, 3], EMS of the SRB can reduce the energy demand or minimize the energy cost.

Figure 1.1 shows the energy consumption in residential, transportation, industrial, commercial, and other sectors [4]. It shows that about 27% of the global demand is from the residential sector, 75% of which is from residential buildings [5]. Figure 1.2 depicts that the number of Smart Home (SH) users around the world is increasing rapidly [6]. According to the worldwide forecast [6], the number of smart home users was 150 million in 2017 and is expected to reach 500 million by 2025. Therefore, the number of smart home users will be increased by nearly around 350 million in 8 years. Figure 1.3 shows

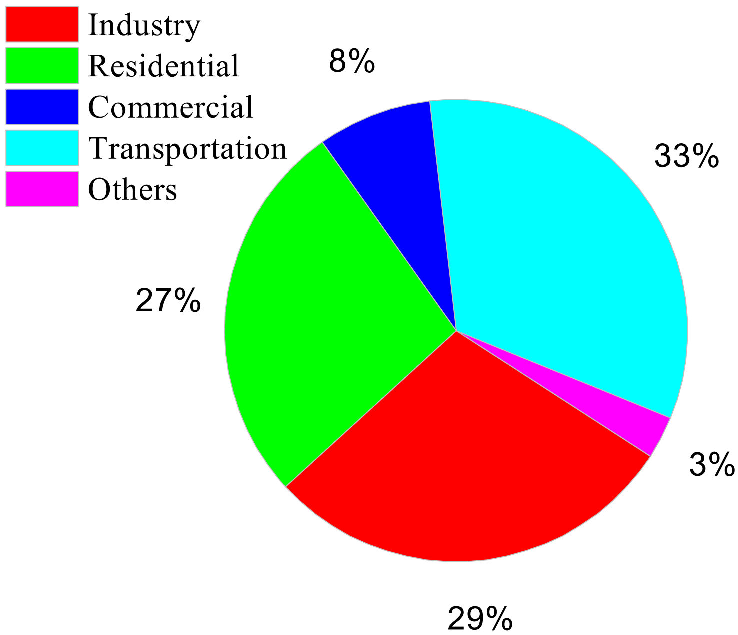

Figure 1.1: Sectorial Energy Consumption

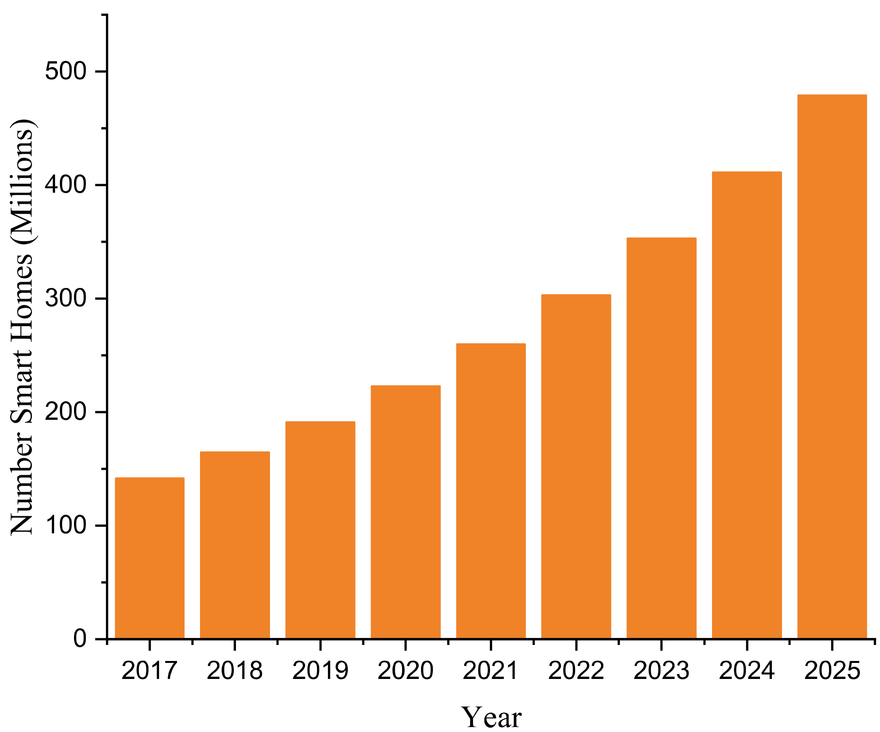

Figure 1.2: Number of SH Growth Statistic

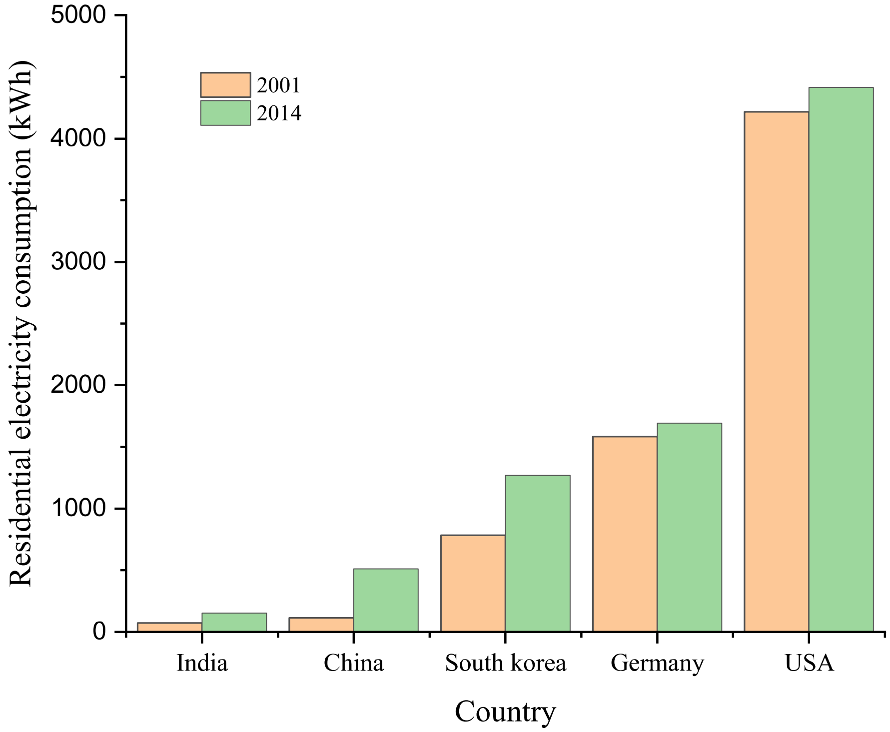

Figure 1.3: Residential electricity consumption

per-capita Residential Electricity Consumption (REC) for different countries in the year 2001 and 2014 [7]. It shows that the USA tops in residential electricity consumption.

In smart grid architecture, electricity utilities consider Demand Side Management (DSM) as the most promising technique to encourage residential consumers to reduce their energy cost or energy consumption [8]. It includes different types of programs such as Demand Response (DR) programs and fuel substitution programs, and energy conservation and energy efficiency programs [9]. In the DR programs, consumers are encouraged to participate in the electricity market and directly interact with the utility. Consumers alter their demand pattern according to the time-varying price to reduce their electricity bill, i.e., reduce the energy consumption during peak hours or shift the demand to non-peak hours. Residential consumers can respond to price-based or incentives-based DR programs to alter the energy consumption pattern during peak hours. In the context of smart grids, the utility ensures that the residential consumers schedule their SH appliances to reduce the electricity bill and reduce Peak To Average ratio (PAR) based on DR programs. The researchers have observed that DR programs yield significant reduction in the cost and consumption of energy [10–13].

1.1.2 Distributed Energy Resources (DERs) in Smart Buildings

Distributed Energy Resources (DERs) are small-scale generation units and locally connected resources that can be aggregated to provide the regular power demand. Combined Heat and Power (CHP) Generator, Battery Storage System (BSS), Renewable Energy Sources (RESs) such as roof-top solar Photovoltaic (PV), and Wind Turbines (WTs) are generally considered as DERs of smart residential buildings. In addition to power generation, Solar PV also provides solar water heaters, solar dryers, and solar coolers to smart home users [14]. Furthermore, as it is affordable with a low maintenance cost, the hot water produced by solar water heaters can be used in several home functions such as washing and cooking, which increases household energy efficiency [15]. Similarly, small WTs are installed on the smart residential building to increase the power supply. As the generation from RESs is of intermittent nature, residential buildings use BSS and CHP generators to avoid power supply interruptions. For space heating and water heating, the residential consumers directly use the heat energy produced from the CHP generator.

As solar and wind are Eco-friendly sources of energy are flexible in installation, their installed and production capacity is increasing day by day. Figure 1.4 shows the global annual growth of solar and wind power capacity over the past decade [16]. It shows that global solar and wind power generation in 2020 increased almost twice compared to 2015. Figure 1.5 depicts the energy generation from all RESs such as solar, wind, hydro, and other renewable resources. It shows that more than 50% of renewable energy generation comes only from solar and wind.

1.1.3 Cyber-attacks on Smart Building EMS

In a Smart Residential Building (SRB), EMS uses advanced technology such as Information and Communication Technology (ICT), Internet-of-Things (IoT), smart meters, and Advanced Metering Infrastructure (AMI) for two-way communication between utilities and consumers. Therefore, the control and operation of smart homes highly depends on computer networks, software, and advanced communication technologies. In a cyber-attack, a capable opponent can target elements of this critical infrastructure to bias the system in its favor. The cyber-attack are of different natures, such as gaining control access, spreading malware, stealing information, injecting false data, introducing error in

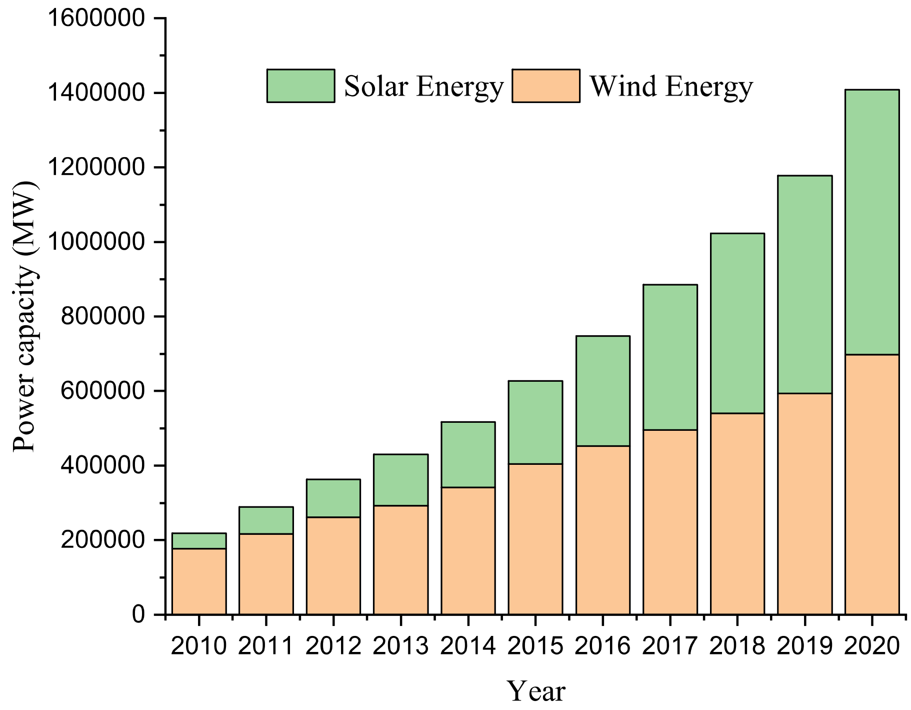

Figure 1.4: Renewable Energy Growth Capacity

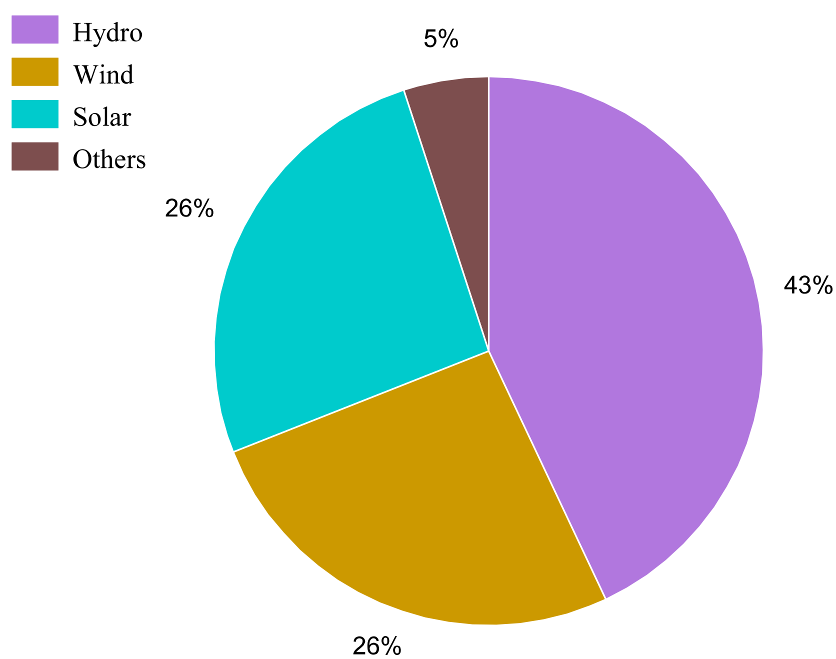

Figure 1.5: Renewable Energy Source

meter readings, and jamming the communication network [17].

Cyber-attacks have been ranked fifth in the 2019 global risk table [18]. Nearly 80% of IoT devices are vulnerable to different types of cyber-attacks. Some of these attacks are False Data Injection (FDI) attack, Denial-of-Service (DoS), Man-In-the Middle (MITM), Spear phishing, and Device hijacking. For example, an electricity distribution company in Ukraine was attacked in 2015 for a power outage [19]. From the above discussion, it can be noted that cyber-attack is a real threat for EMS of smart building infrastructures. As the usage of network terminology is increasing day by day the cyber-attack could be occur more frequently in near future. Since EMS is fully automated application, detection and defense strategy against cyber-attack must be either built in EMS or EMS should be robust.

1.2 Literature Review

This section provides a discussion on previous research work related to Smart Building Energy Management System (SBEMS) and cyber-attacks on such systems.

1.2.1 Smart Building Energy Management System

The electricity demand is increasing continuously due to increasing population density, diversification of city limits and environmental constraints. Smart grid technology requires Information Technology (IT), two-way communication and intelligent techniques for reduction of the energy consumption. The technological advancement of residential buildings has increased with the widespread use of smart residential components and integration of IT. Demand-Side Management (DSM) is used by utilities to reduce consumer's energy costs through Demand Response (DR) program [20]. The two types of Demand response programs are Real-Time Pricing (RTP) scheme and direct load control scheme. The real-time pricing scheme enables direct interaction of consumers with the utility electricity market [21, 22]. This interaction encourages consumers to shift their loads from peak hours to off-peak hours. In direct load control scheme, the service provider has the ON and OFF control facilities of the consumer's load [23, 24]. To reduce the price of conventional energy, the Renewable Energy Sources (RESs) like roof-top solar PV panels and small wind turbines are installed at the residential buildings by the utility [25, 26]. The power generation from RESs is intermittent. To reduce the power fluctuation of RESs, consumers use Battery Storage System (BSS). It is expected that the integration of RES will affect the real-time pricing. Therefore, in order to get the maximum benefit of RTP, and to maximize the use of RES, the smart components need to be properly scheduled.

A considerable amount of literature has addressed the different scheduling methods for minimizing energy costs in Smart Home (SH) system. A DSM scheme considering dynamic pricing has been proposed by Adika *et al.* [27] to reduce the energy cost of prosumers. A Game-theoretic algorithm [28] has been proposed to solve the energy scheduling problem in smart community infrastructure. In this problem, smart controllers are used to schedule various home appliances to reduce electricity bill of customers. A multistage smart Home Energy Management System (SHEMS) [29] has been proposed to minimize the energy cost of the consumer. Price forecasting, day-ahead scheduling, and real time implementations are the main stages in this proposed SHEMS. In this literature, Natural Aggregation Algorithm (NAA) has been used in SHEMS. Peak-to-average ratio minimization and operating cost minimization of smart home user are the objectives in day-ahead scheduling stage. In real-time implementation stage, deviation between day-ahead scheduled power and actual power demand has been minimized. A SHEMS [30] considering the uncertainties of RESs has been proposed to minimize the energy cost. Monte Carlo (MC) sampling technique has been used to model the uncertainties of RESs. In ref. [31], an improved Genetic Algorithm (GA) based SHEMS has been proposed to minimise the electricity cost and to maximize the utilization of renewable energy generation. Smart homes can introduce adjustments to the operation of home appliances to save on energy costs that may affect the Quality of Experience (QoE) of consumer. A QoE driven scheduling technique [32] has been used to minimize the energy cost for SHEMS. In the context of SHEMS, a multi-objective scheduling addressing cost minimization and privacy protection maximization has been proposed in ref. [33]. A hybrid algorithm having stochastic and deterministic search mechanisms has been used to solve the multi-objective scheduling [33]. Mathematical modelling of different home appliances and energy management considering energy cost minimization for smart home has been presented by Melhem *et al.* [34]. Huang *et al.* [35] has employed two-point estimation (2PE) method to assess the uncertainty related to the critical load variation in a smart home system.

A multi-objective energy management algorithm considering thermal comfort, energy saving and user convenience has been proposed in the article [36]. Similarly, an optimization technique has been proposed by the researchers to minimize the energy cost with consideration of consumer's comfort [37]. In this article, consumer waiting-time is considered as the comfort constraint. Researchers in [38] have proposed game-theory based scheduling of appliances to minimize the energy consumption in the residential buildings. In the said game formulation, each consumer has been considered as a player and scheduling of appliances has been considered as a strategy in the game. Market price based scheduling of appliances in automated home system has been presented in [39]. To avoid peaks in consumer demands during low price period, a penalty mechanism has been used for violation of threshold limit of power demand. Consumer comfort has also been taken care of while minimizing the electricity bill. Real-time pricing based combined charging/discharging strategy for EVs and BSS have been proposed to reduce the energy cost for a smart home [40]. This strategy ensures the users satisfaction and optimal utilization of RES and energy storage. A user comfort and cost saving based scheduling algorithm for thermostatically controlled loads has been presented in ref. [41]. In this article, the user comfort has been considered as a set of linear constraints in cost minimization optimization. Multi-agent based reinforcement learning have been proposed to take the optimal decision for the smart home appliances in decentralized manner [42]. A batch reinforcement learning has been used to minimize the energy cost considering the DR programs [43]. Monte Carlo method is used to predict the day-ahead power consumption.

In the article [44], a Particle Swarm Optimization (PSO) algorithm has been proposed to minimize the energy cost considering the consumer comfort in residential buildings. A genetic algorithm (GA) based single objective multi-variable optimization technique is used to minimize the energy cost in residential homes [45]. A multi-objective MINLP problem is formulated in [46] for minimization of energy cost as well as improvement of Peak-to-Average Ratio (PAR). A similar multi-objective problem is proposed in [47] considering multiple-users and load priority (MULP) algorithm. An MILP problem is formulated in [48] to minimize the energy cost considering a single load model with integration of different specific appliances. A hybrid Bat pollination optimization algorithm is used in [49] to reduce the energy cost and PAR of SH system. A dynamic pricing scheme is used in [50] to minimize the energy cost and PAR of SH system. S.L Arun and M.P. Selvan [1] proposed a smart building EMS using the minimum energy cost as objective function by using the dynamic demand response programs. They also described the steps for calculating the optimal size of energy generation resource components and number of batteries in a given system. The optimal sizing of DERs for a stand-alone system has been proposed in the literature [51]. In the article [52], the authors have proposed a hybrid solar-wind system and calculate the required number of different components for the given system. An automated home energy management system based on artificial intelligence is described in [53] to optimize the performance of the DG units in a residential applications. Researchers optimized the electricity bill in SH considering consumers' spending goals [54]. An energy-efficient scheduling algorithm has been proposed in [55] for the residential buildings considering uncertainties in the operating time of appliances, the intermittent nature of renewable energy sources, and battery storage systems. In the article [56], home energy management scheduling to reduce the electricity bill considering the varieties of specific appliance models and their integration into a single model is proposed. To reduce the PAR as well as electricity cost, authors have considered combined RTP and inclining block rate model in the article [57].

Coordinated DERs scheduling in smart residential buildings improves energy efficiency. A PSO technique considering coordinated scheduling of distributed energy resources has been proposed in [58]. A cooperative control scheme has been proposed in [59] for the smart residential building considering finite horizon scheduling problem. This work has used model predictive control (MPC) to combine forecast and newly updated information. For scheduling different loads and DERs, it is necessary to know the total load demand and generation.

In [60], researchers have attempted minimization of the operational cost of Smart Home Energy Management System (SHEMS) considering stochastic behavior of load and its consumption uncertainties. A priority-based and optimization-based algorithm for scheduling the demand of the smart building has been proposed in [61]. In this work, it is observed that the use of dynamic demand response programs results in the reduction of the electricity bill. In [62], the authors have proposed a Conditional Value at Risk (CVaR) optimization method for SHEMS to reduce the effect of risk of real-time exposure to energy price and uncertainty of RESs on the consumer. To approximate the solar power, the authors have used a Two-Point Estimation method (2PE) with CVaR.

In [63], to optimize customer satisfaction, a fatigue response index is used and authors have considered a stochastic model to describe the uncertainties of electric vehicles and RESs for SHEMS. Mixed integer Problem formulation is used in [64] for real-time electricity scheduling in the residential home energy management system to minimize the energy cost. The authors have also considered the uncertainties of RES in the objective function. In [65], authors have proposed a novel SHEMS to minimize the energy cost considering the human interaction factors, unavailability of power supply, consumers' preferences and priorities. In [66], the authors have studied the residential demand response programs through scheduling of the home appliances to minimize the energy cost using a Mixed Integer Nonlinear Programming (MINLP) Problem formulation. In the article [67], researchers have considered the battery scheduling to minimize the energy consumption cost of household appliances. In [68], authors have modeled the refrigerators and batteries using artificial neural networks. The authors have also shown that the domestic refrigerators could be modeled accurately by measuring power consumed and changes in the internal temperature. Real-time scheduling of home appliances and generation units, such as Photo-voltaic (PV) cell , Battery Storage (BS), Air Conditioner (AC), Electric Water Heater (EWH), cloth washer, and Plug-in Hybrid Electric Vehicle (PHEV), have been discussed in [69, 70].

In the literature discussed above, the researchers have not considered the degradation cost of the battery in the smart home appliance scheduling process. However, it is important to investigate the degradation cost of battery and its subsequent impact on the operational cost and practical aspects. In the article [71], authors have described the battery degradation cost in the grid-connected BSS . Authors in [72] have investigated the Depth of Discharge (DOD) of battery for each half cycle in a particular pricing scheme for BSS in electricity markets. In [73], authors have proposed a new algorithm to calculate the number of half or full cycle of the battery.

A lot of literature has discussed various scheduling methods to reduce the energy cost of smart homes (SHs) without considering the power exchange between Smart Buildings (SBs). In [74], authors have proposed a new controlled pricing scheme to maximize economic benefits in HEMS considering EV charging/discharging. Authors in [75] have proposed a multi-agent-based distribution system to reduce energy consumption in the intelligent community system. In [76], authors have proposed a three-level smart building energy management system by using artificial intelligent tool. Authors in [77] have proposed deep reinforcement learning for scheduling of appliances in SHEMS to minimize the electricity costs. Electric Vehicle (EV) are used as energy storage system in stochastic scheduling of smart home appliances to reduce the energy cost of the SHEMS [78]. In this article, authors mainly focus on the uncertainties of the EV energy storage system in a smart home. In [79], a hybrid robust-stochastic optimization approach has been proposed for SHEM considering profit maximization of a SH. In this hybrid approach, the uncertainty related to electricity price is modeled using robust approach and the worst-case PV generation is assumed using a stochastic approach. In this article author considered profit maximization as their objective. In ref. [80], the authors propose a stochastic energy management framework for a residential building containing various energy resources, such as CHP, EVs, RESs, heater, gas boiler and other thermal-electric loads. In this framework, the uncertainties related to loads, RESs, EVs, and electricity tariff have been considered using a stochastic model.

1.2.2 Cyber-Attack

Advanced Metering Infrastructure (AMI) is widely used in smart grid systems for two-way communication. These AMI's are having their own processor and these AMI's are further connected to computer networks through various wireless communication technologies (ZigBee, Wireless LAN), power line carriers, and optical fiber. Further, modern cyber-physical power systems are also equipped with advanced communication networks, IoT devices and sensors. These computer networks are prone to cyber-attacks. For example, an attacker can change information supplied to a state estimator by hacking a subset of sensors [81]. Once attacker gains control of the system, attacker can carry out a variety of attacks such as unauthorized access to meter and sensor data, modification in data and making bills unavailable [82–84].

Different cyber-attacks and their detection techniques at different levels of smart grid system have been studied in the literature. Security requirements, attack countermeasures, and secure communication protocol have been discussed in [85]. Researchers in [86] have analyzed the economic impact of an False Data Injection (FDI) attack in the electricity market of networked multi-microgrid systems. The authors in [87] have proposed a DC power flow method based approach to investigate cascading failures and cyber-attacks in an electrical Cyber Physical System (CPS). Three types of cyber attacks, i.e., Denial-of-Service (DoS), uplink-spoofing, and downlink-spoofing attacks, have been studied in this article. A comprehensive discussion on modeling of FDI attacks and their effects on the power system are presented in [88]. In a successful FDI attack, a competent attacker can modify the measurements from the grid sensor by introducing some undetected errors into the estimates of the state variables. To detect a random FDI in a communication network aiming to reduce network performance, a network estimator has been designed in [89]. In [90], the authors have examined the economic benefits to the attacker due to FDI attack. In this article, a bi-level programming based FDI attack vector is designed to modify the demand vector with the aim of increasing the operating cost in an economic load dispatch problem. The attack vector was featured with a zero sum, and a lower/upper limit.

Smart grid state estimation can be vulnerable to FDI attack and it is very important to detect and identify these attacks. In these cases, matrix separation method is used to detect the FDI attack on the state estimator. Matrix separation methods like Augmented Lagrange Multipliers (ALMs), double-noise-dual-problem ALMs, the low rank matrix factorization and Go Decomposition (GoDec) can be used to detect the FDI attack against the state estimator [91]. In [92,93], the authors have proposed matrix separation methods for detecting FDI attacks in smart grids. Authors have used sparse optimization and Kalman filter techniques in the matrix separation method to detect FDI attacks. In [94], authors have proposed a malicious data injection strategy onto the smart meters of the grids to bias the power system state estimation. Also authors have proposed a likelihood algorithm in smart grid state estimation to detect the malicious data attack. Authors in [95] have proposed an anomaly detection technique using a Kalman filtering and the temporal-based detection against the FDI attack. Similarly, the authors in [96] have proposed an anomaly detection technique in the smart grid against FDI attack. A centralized energy theft detection technique is proposed in [97] using the Kalman filter. Authors in [98], have proposed a cumulative sum algorithm for FDI attack detection in real time in a smart grid. Markov-Chain based analytical model has been developed in this article to characterize the behaviour of proposed algorithm.

In [99], the authors have proposed an attacking scheme for manipulating price signals in the electricity market. In this type of attack, the attacker jams the price signal and manipulates the price signal to make profit. Similarly, in [100] the effects of a jamming attack in a critical power system network have been discussed. In this article a detection technique has also been proposed to mitigate its effects. In [101], the authors have formulated a problem considering the FDI attack against state estimation to carry out the financial misconduct in a deregulated electricity market. In this article, the authors have also proposed a heuristic detection technique to detect this profitable attack. In [102], authors have proposed the optimal placement of feeder Remote Terminal Units (RTUs) considering cyber-security in distribution system. The placement of feeder RTUs has been decided using the cyber-security metrics based on the consumer historical load profile. Apart from above, smart digital devices in smart grid are also vulnerable to the malicious attacks. In [103], authors have proposed a resilient detection technique to protect DERs and modern grid from malicious attacks.

Interactions between smart home communities and utilities are also vulnerable to cyber-attacks, such as price attacks and energy theft attacks using FDI. Pricing-cyber attack can be defined as manipulation of price curve by an attacker. Through a manipulated price curve, the attacker can mislead SHEMS due to which householders may be forced to change their demand patterns. Changes in the demand pattern can alter the real-time price curve of the utility [104]. Energy theft can be defined as the modification of smart meter readings. An attacker can manipulate the smart meter reading in such a way that the attacker's smart meter will report low energy consumption while the victim's smart meter will report high energy consumption. In this way, the total energy consumption of the community will remain unchanged making it difficult to detect the attack. In [105], Partially Observable Markov Decision Process (POMDP) based detection technique has been developed for coordinated cyber-attack (both price attack and energy theft attack applying simultaneously). In [106], Denial-of-Service (DoS) and FDI attack models have been investigated in the context of SHEMS. In this article, interference with input data to the central controller (such as unavailability/modification in pricing data and load data input to the central controller) is considered to analyse the impact of cyber-attacks on scheduling. Different types of threat agents (attacks), motivation of cyber-attacks, and capability of threat agents have been classified in [107]. Authors in [108] have proposed short- and long-term detection strategies against pricing cyber-attacks in SHEMS. The short-term detection strategy based on binary logistic regression (binary categorization of input samples) compares the actual load profile with the estimated load profile, whereas, long-term detection strategy based on POMDP considers the number of detections in the short-term detection strategy. The aim of long-term detection is to optimize the decision of the utility by considering the financial loss due to cyber-attack and labour cost for on-site inspection. Main challenges and countermeasures to cyber-attacks in smart home have been discussed in [109, 110]. IoT technologies are widely used in the smart home which provide improved energy efficiency and user comfort. The wide use of IoT devices in home automation and smart grid requires security and privacy to exchange information. Cyber-risks and cyber-security analysis of IoT have been investigated in [111–115]. The impacts of a cyber-attack on SHEMS, and its possible detection and mitigation methods have been described in [116]. In [117], researchers have investigated the impacts of two pricing cyber-attacks with different motives. In this article, the two motives of cyber attacks are cascaded tripping of overloaded transmission lines and generators due to frequency imbalance. Detection techniques at the community level of SHEMS have also been proposed in [117]. The energy theft cyber-attacks in a SH networked community have been discussed in [118]. Bollinger bands (a data analysis technique) and POMDP based detection technique have also been proposed in [118]. In smart grid infrastructure, the DR program plays a vital role in balancing supply and demand. The authors in [119] have discussed the security concerns of DR implementation in home energy management systems and identified security concerns due to attacks and corresponding potential countermeasures.

To prevent AMI from cyber-attacks, an anomaly detection and prevention framework through on-site investigation has been proposed in [120]. Security of different layers of Cyber-Physical Systems (CPS) against the vulnerabilities have been discussed in [121]. Home automation security, smart devices security and hardware security are the three different layers of CPS. Home automation is an important component of smart grid infrastructure in which potential attack vectors can be introduced. Smart devices are the backbone of CPS which security vulnerabilities have been discussed in [121]. Similarly hardware security in CPS is another important component of CPS security which have discussed in this article. The thermostat is an important component of a home automation system. The authors of [122] describe how a spy can hack the thermostat in a smart home system and the authors also provide a secure hardware platform for the thermostat. Net metering is used by the utility to exchange the power from prosumers. In [123], authors have analyzed the impact of net metering on smart home cyber attack detection. Some researchers have conducted investigations on different types of cyber-attacks and their target systems, the summary of such investigation is presented in Table 1.1.

From the above literature survey, it can be concluded that the pricing attacks and energy theft attacks are the common cyber-attacks in the smart home community. As SHEMS handles small energy levels and deals mainly with scheduling of smart appliances, One of the perspectives with which the SHEMS can deal with the cyber-attacks would be to design the scheduling algorithm for smart home devices in such way that even in the presence of cyber-attacks, scheduling can be done satisfactorily within acceptance limits. The said SHEMS should not only make the scheduling resilient to such attacks but it should also be capable of detecting the cyber-attacks on the SHEMS or smart devices.

1.3 Research Gaps

In context of the above literature review, the following research gaps have been identified.

The attacker can mislead the SHEMS through manipulated price signals. The manipulated price signal can insist SHEMS to change the load profiles of the users. This can lead to a fall in the comfort of the users and increase in the electricity bill. In addition, the scheduling of multiple smart buildings at the community level can be effected through energy theft attacks. For example, in a game theoretic framework, the scheduling of a smart building depends on the price signals as well as the decisions of the other participating smart buildings. Therefore, manipulation of the energy consumption data of a smart building affects the scheduling of all buildings at the community level.

Further, the cyber-attack is a possible phenomenon in the scheduling of smart devices in SHEMS. Therefore, resilience constraints must be embedded in the scheduling algorithm in such a way that the scheduling done by the SHEMS becomes robust to any potential cyber-attack.

Table 1.1: Summary Types of Cyber-attack and Target System

Category	Subcategory		Attack Type	Attack Target	Ref.
Energy Management	Battery storage system		sequential data injection	battery terminal voltage	[124]
	PV Inverters	Commercial	short term data injection	VAR,Watt & pf of smart inverter	[125]
			MiTM short term data injection	data penetration in PV	[126]
			DoS attack	on Sensor	[127]
		Residential	coordinated MiTM	Reactive power information	[128]
			power injection attack	data penetration in power	[129]
	Smart Energy Management System		DoS, short term data & phishing	demand & pricing data	[106]
			long-term data injection	price data	[116]
Advanced metering infrastructure	Smart Meter		short term MiTM attack	energy level	[130]
			short term data injection	SM energy data	[131]
			privacy attack	load profile	[132]
			false load attack	energy consumption	[133]
			short term data injection	SM energy data	[134]
	Communication Network		DDos attack	Network	[135]
			MiTM attack	communication SMS	[136]

1.4 Objectives of the Thesis

The work presented in the thesis aims to develop an efficient Smart Building Energy Management System (SBEMS) under FDI attacks. The objective of EMS developed in this thesis is to schedule smart home appliances in such a manner that the scheduling remains resilient under cyber-attacks. To achieve this objective, the work is divided into the following sub-objectives.

1. The first sub-objective is to develop an Energy Management System (EMS) for a single smart home architecture to minimize energy and battery degradation costs while considering user comfort. For this a realistic pricing FDI attack model need to be developed. To mitigate the effects of FDI attacks in the scheduling process, a resilient scheduling is to developed considering consumer's past behaviour.

2. The second sub-objective is to develop an Energy Management System to minimize the energy cost for multiple smart buildings. Also the effects of cyber-attacks (pricing, demand and coordinated pricing and demand attacks) on the efficacy of scheduling is to be studied. In this context, a resilient scheduling is required to mitigate the effects of cyber-attacks.

3. Finally, the objective of the thesis is to develop a multi-smart building energy management system that considers the power exchange capacity between buildings to reduce energy costs and make effective use of DERs incorporating cyber-attack resilience.

1.5 Organisation of the Thesis

The above said objectives are met in the thesis and the thesis is organised in the following manner

- ***Chapter 2***: This chapter describes the modeling of various Distributed Energy Resources (DERs) such as solar PV, wind turbine, CHP generators, and Battery Storage Systems (BSSs). Similarly, different types of residential load models, such as Schedulable Loads (SLs), Temperature-Dependent loads (TDLs), and Unscheduled and Noninterruptible loads (UNLs) are discussed. The modeling of thermal and electric power of a CHP generator is discussed in this chapter. The modelling and description of different parameters of BSSs such as State of Charge (SOC), Depth of Discharge (DOD), discharging, and charging power are also discussed. At last, we have modeled a general FDI attack which occurres in the residential buildings.

- ***Chapter 3***: In this chapter, to minimize the energy cost the scheduling of energy generation resources and smart home loads have been performed considering battery degradation cost. In addition, price and bill prediction is made considering the past 90 days' price data. The proposed formulation presents the effects of pricing cyber attacks on scheduling. However, a resilient scheduling considering consumers' past behavior is proposed to nullify the effects of FDI attack in the scheduling of residential loads and resources. A case study considering single smart home is developed and discussed to verify the proposed framework.

- ***Chapter 4***: This chapter presents a non-cooperative game theoretic multi-smart building energy management system. Machine learning-based price and bill prediction is studied by considering price data for the past three months'. A pricing and demand cyber-attack detection scheme against FDI attack based on a bill change rate and maximum demand change has been developed and studied. Finally, resilient scheduling algorithm for energy resources and loads, taking into account the power exchange with the smart grid, is proposed. Finally, to show the efficacy of the proposed EMS algorithm, a case study consisting of three smart buildings has been performed.

- ***Chapter 5***: This chapter presents a Multi-Building Energy Management System (MBEMS) with power exchange capability among the buildings. Scheduling is based on forecasted price, calculated by considering the three-month historical price data using a regression machine learning model. Further, a detection scheme for pricing cyber-attacks is proposed considering the information available in the form of bill and maximum demand. Further, resilient scheduling based on power exchange among buildings is also developed and studied. A case study consisting of three smart residential buildings is performed to demonstrate the effectiveness of the proposed algorithm.

- ***Chapter 6***: In this chapter, the conclusions of the thesis are presented along with the future scope of the this.