Chapter 2

Modeling of Components of Smart Home

2.1 Introduction

Smart residential buildings can include a variety of smart appliances, renewable energy sources, battery storage systems, thermal storage system and CHP generators. This chapter presents steady-state models of various energy resources and smart appliances. In this chapter, we have discussed the modelling of the following components of smart home systems. (i) Distributed Energy Resources (DERs) viz. solar PV, Wind turbine, CHP generators, (ii) Energy Storage System viz. Battery Storage System (BSS), and Thermal Storage System (TSS), and (iii) Residential loads viz. Temperature Dependent Loads (TDLs), Unschedule and Noninterruptible Loads (UNLs) and Schedulable Loads (SLs). The models developed in this chapter shall be used in this studies reported in the subsequent chapters.

2.2 Modeling of Distributed Energy Resources

The following subsections describe the modeling of Distributed Energy Resources (DERs) such as solar PV, wind turbines, and Combined Heat and Power (CHP) generators.

2.2.1 Solar PV

Solar photovoltaic (PV) power generation modeling is an important tool for optimizing the use of solar energy in smart buildings. Solar PV systems generate electricity by converting sunlight into electrical energy, and can be integrated into smart building systems to reduce energy costs and reliance on non-renewable energy sources. To model solar PV power generation for smart buildings, several factors should be considered. The first factor is the location of the building and the amount of sunlight it receives throughout the year. The amount of sunlight available can be estimated using solar radiation models that take into account the latitude, longitude, and other geographic factors. The second factor is the size and orientation of the solar PV system. The size of the system can be optimized based on the building's energy demand and available roof space. The orientation of the system can also be optimized based on the building's location and the angle of the sun.

The third factor is the energy demand of the building. The power output of the solar PV system can be compared to the energy demand of the building to determine the amount of energy that can be provided by the system.

In addition to modeling solar PV power generation, the integration of solar PV systems into smart building systems can also involve the use of sensors and control systems to optimize energy use. For example, sensors can be used to measure the energy demand of the building and adjust energy consumption based on occupancy, weather conditions, and other factors. Control systems can be used to automatically adjust the operation of the solar PV system and other components of the smart building system to optimize energy use.

Overall, solar PV power generation modeling can be an important tool for integrating renewable energy sources into smart building systems and reducing reliance on non-renewable energy sources. By modeling the power output of solar PV systems and optimizing the use of solar energy, smart buildings can reduce energy costs and environmental impact. The solar PV model used in this work is taken from the existing literature [137].

The amount of power generated from solar PV depends on the solar radiation and the ambient temperature. The generated solar power, P^s, can be expressed as,

$$P^s = DF \times P_{STC} \times \frac{G_A}{G_{STC}} \times [1 + (T_C - T_{STC}) \times C_T]. \tag{2.1}$$

Here, DF is the derating factor (0.8), P_{STC} is the nominal PV array power in kW under Standard Test Conditions (STC), G_{STC} is the solar radiance at STC (1 kWm^{-2}), G_A is the global solar radiation in kW/m^2, T_{STC} is the temperature under STC (25^0C), C_T is the PV temperature co-efficient ($-0.0011/^0C$), and T_C is the solar PV cell temperature. The value of T_C depends on the ambient temperature (T_a), global solar radiation G on horizontal plane, and normal operating cell temperature NT (48^0C). T_C can be calculated as,

$$T_C = T_a + \frac{NT - 20}{0.8} \times G. \tag{2.2}$$

2.2.2 Wind Turbine

Wind turbine power generation modeling can be used for smart buildings to optimize the use of renewable energy and reduce energy costs. Smart buildings use advanced technology to optimize energy consumption and reduce energy waste, and renewable energy sources like wind turbines can be integrated into these systems to reduce reliance on non-renewable sources.

To model wind turbine power generation for smart buildings, a few additional factors should be considered, such as the energy demand of the building, the energy storage system, and the energy grid connection. The power output of the wind turbine can be compared to the energy demand of the building to determine the amount of energy that can be provided by the turbine. Energy storage systems can be used to store excess energy generated by the wind turbine, which can be used later when energy demand exceeds the wind turbine's output. The energy grid connection can also be used to supplement the wind turbine's output when necessary.

In addition to modeling wind turbine power generation, the integration of wind turbines into smart building systems can also involve the use of sensors and control systems to optimize energy use. For example, sensors can be used to measure the energy demand of the building and adjust energy consumption based on occupancy, weather conditions, and other factors. Control systems can be used to automatically adjust the operation of the wind turbine, energy storage system, and other components of the smart building system to optimize energy use.

Overall, wind turbine power generation modeling can be an important tool for integrating renewable energy sources into smart building systems and reducing reliance on non-renewable energy sources. By modeling the power output of wind turbines and optimizing the use of renewable energy, smart buildings can reduce energy costs and environmental impact.The wind turbine model used in this work is taken from the existing literature [138].

The power output of a small Wind Turbine (WT) depends on different parameters such as wind speed, swept area and air density. The extracted power from WT, P^w, in kW can be expressed as,

$$P^w = 0.5 \times C_P \times \rho \times A \times V^3. \tag{2.3}$$

Here, C_P is power co-efficient (0.25 to 0.45), ρ is the air density (1.255 kg/m^3), A is the swept area of WT, and V is the wind speed in m/sec.

2.2.3 CHP Generator

CHP (Combined Heat and Power) generators, also known as co-generation systems, are used in many different settings to generate electricity and thermal energy simultaneously. The thermal energy generated can be used for heating, cooling, or process heating in a wide range of applications. Here are a few examples of the use of CHP generators:

Hospitals: CHP generators are often used in hospitals to provide electricity and thermal energy for heating and cooling. Hospitals have a high demand for energy, and CHP generators can help reduce energy costs and improve energy efficiency by generating electricity and thermal energy on-site.

Data centers: Data centers require a lot of electricity and cooling to keep servers and other equipment running. CHP generators can provide electricity and thermal energy for cooling, reducing energy costs and improving energy efficiency.

Residential buildings: CHP generators can also be used in residential buildings to provide electricity and thermal energy for heating and cooling. They can be especially useful in large residential buildings, such as apartment buildings or high-rise buildings, where there is a high demand for energy.

Industrial applications: CHP generators are used in many industrial applications, such as chemical plants, paper mills, and food processing plants. They can provide electricity and thermal energy for process heating and cooling, reducing energy costs and improving energy efficiency.

Universities and colleges: CHP generators are used in many universities and colleges to provide electricity and thermal energy for heating and cooling, as well as for laboratory and research applications.

Overall, CHP generators are a versatile technology that can be used in a wide range of applications to generate electricity and thermal energy simultaneously, reducing energy costs and improving energy efficiency.

Among DERs, the use of Combined Heat and Power (CHP) generators is becoming in smart residential buildings as it provides both thermal as well as electrical energy to the user at the same time. In this way, CHP generator improves energy efficiency of a residential consumer. The block diagram of a fuel cell based CHP generator, commonly used in residential buildings, is shown in Figure 2.1. Part Load Ratio (PLR) is used to

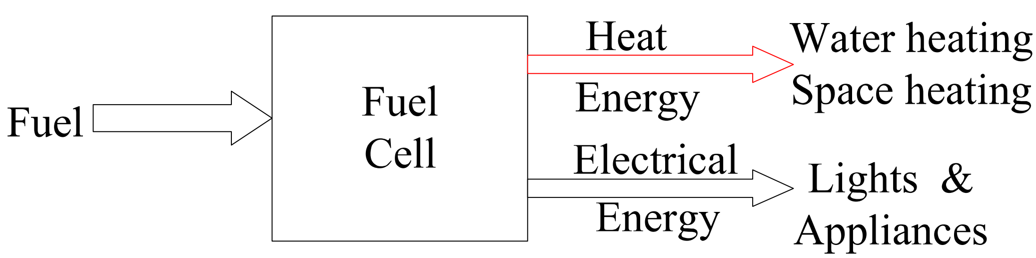

Figure 2.1: Fuel Cell Based CHP Generator

measure CHP generator utilization efficiency. The PLR can be defined as the ratio of electrical power obtained from the CHP generator to the power rating capacity of the CHP generator [139]. Mathematically, PLR can be written as ,

$$PLR(t) = \frac{P^{chp}(t)}{P_c^{chp}}, \tag{2.4}$$

and the total heat generated from CHP generator can be calculated as,

$$H^{chp}(t) = \frac{P^{chp}(t)}{P_{TE}}, \tag{2.5}$$

Where, P_c^{chp} and $P^{chp}(t)$ are the rated capacity and electrical power output of the CHP generator respectively, P_{TE} is the electrical power to heat ratio of CHP generator.

2.3 Modeling of Energy Storage Systems

The following subsections describe the modeling of Energy Storage Systems (ESSs) such as Battery Storage Systems (BSSs) and Thermal Storage Systems (TSSs).

2.3.1 Battery Storage Systems

Battery storage system modeling is an important tool for optimizing the use of renewable energy and reducing energy costs in smart buildings. Battery storage systems can be used to store excess energy generated by renewable energy sources such as solar PV and wind turbines, and can be integrated into smart building systems to provide backup power and optimize energy use. To model battery storage systems for smart buildings, several factors should be considered. The first factor is the capacity of the battery system, which refers to the amount of energy that can be stored in the battery. The capacity of the battery system can be optimized based on the energy demand of the building and the amount of renewable energy available.

The second factor is the charging and discharging rate of the battery system, which refers to the amount of energy that can be charged or discharged from the battery at any given time. The charging and discharging rate can be optimized based on the energy demand of the building and the available renewable energy. The third factor is the efficiency of the battery system, which refers to the amount of energy that can be stored or discharged relative to the amount of energy put into the battery. The efficiency of the battery system can be optimized based on the type and model of the battery.

In addition to modeling the battery storage system, the integration of the battery system into smart building systems can involve the use of sensors and control systems to optimize energy use. For example, sensors can be used to measure the energy demand of the building and adjust energy consumption based on occupancy, weather conditions, and other factors. Control systems can be used to automatically adjust the operation of the battery storage system and other components of the smart building system to optimize energy use.

Overall, battery storage system modeling can be an important tool for integrating renewable energy sources into smart building systems and reducing energy costs. By modeling the capacity, charging and discharging rate, and efficiency of battery storage systems and optimizing the use of renewable energy, smart buildings can reduce energy costs and environmental impact.

The Battery Storage Systems (BSSs) stores energy during surplus power periods and delivers energy during deficit power periods to meet the load demand. Different operating modes of BSSs (viz. charging, discharging, and idling) depend on the factors such as the availability of Renewable Energy Sources (RESs) generation, demand of consumer, electricity price, and Maximum Demand Limit (MDL). The State of Charge (SOC) level of battery available at given stage $(t+1)$, depends on the SOC level, power charged and power discharged at time t. This relation can be expressed as,

$$SOC(t+1) = (1-\sigma) \times SOC(t) + \Delta t \times \left(\eta^{ch} P^{ch}(t) - \frac{P^{dis}(t)}{\eta^{dis}} \right). \tag{2.6}$$

Here, $SOC(t+1)$ and $SOC(t)$ are the state of charge of battery at time $(t+1)$ and t respectively, σ is self discharging rate of battery, Δt is the time interval, $P^{ch}(t)$ is charging power of battery, $P^{dis}(t)$ is discharging power of battery, η^{ch} is charging efficiency, and η^{dis} is discharging efficiency of the battery.

Li-ion batteries used in smart homes degrade due to calendric and cyclic aging [140]. The main causes of cyclic aging are internal electro-chemical reactions and mechanical stresses, and these are influenced by the battery operating conditions [141]. The frequent charging/discharging operations have severe impact on its cyclic aging. Calendric aging is a self-discharge phenomenon that is influenced by environmental temperature, and cannot be avoided even when the battery is idle [140]. In [142], the authors have shown that with the aging of the battery, the internal resistance of the battery increases exponentially. Due to the presence of electro-chemical reactions, the battery degradation cost tends to be non-linear and this increases the complexity of the optimization problem.

Motivated by the degradation cost of battery as discussed in the literature, an attempt is made in this work to explore the impact of degradation cost in the SHEMS. The degradation cost accounts for the effects of discharging and Depth-of-Discharge DOD. Degradation cost due to discharging cycle at time t can be written as,

$$C_{dis}(t) = \frac{C_{in}}{n_{std}} \times \frac{P^{dis}(t)}{BC}, \tag{2.7}$$

Where, C_{in} is initial investment cost of the battery, n_{std} is the permissible number of charge or discharge cycles specified by the manufacturer, $P^{dis}(t)$ is the discharging power at time t and BC is rated capacity of the battery in kWh.

DOD of the battery gives percentage energy storage status of the battery which has been discharged from the maximum battery capacity, i.e., it shows the extent to which a battery is discharged and can be expressed as,

$$DOD(t) = 1 - SOC(t). \tag{2.8}$$

Life (days) versus DOD curve of Li-Ion battery can be approximated by the following equations [62].

$$L(D) = Z.D^{-Y}, \tag{2.9}$$

where, D is the average DOD, and the parameters Z and Y depend on the configuration of Li-Ion battery. The parameters Z and Y are considered as 1591.1 and 2.089 respectively in this thesis [62]. Now, the cost due to DOD level transition, C_{DOD}, can be defined as,

$$C_{DOD}(t) = C_{in} \times \Big(\frac{1}{L(DOD(t+1))} - \frac{1}{L(DOD(t))}\Big). \tag{2.10}$$

From the Eqs. (2.7) and (2.10), the total degradation cost of the battery, $C_{cyc}(t)$, at time t can be written as,

$$C_{cyc}(t) = C_{dis}(t) + C_{DOD}(t). \tag{2.11}$$

2.3.2 Thermal Storage Systems

Thermal storage system modeling is an important tool for optimizing the use of renewable energy and reducing energy costs in smart buildings. Thermal storage systems can be used to store excess thermal energy generated by renewable energy sources, such as solar thermal systems and geothermal systems, and can be integrated into smart building systems to provide backup heating and cooling and optimize energy use. To model thermal storage systems for smart buildings, several factors should be considered. The first factor is the capacity of the thermal storage system, which refers to the amount of thermal energy that can be stored in the system. The capacity of the thermal storage system can be optimized based on the heating and cooling demand of the building and the amount of renewable thermal energy available.

The second factor is the charging and discharging rate of the thermal storage system, which refers to the rate at which thermal energy can be charged or discharged from the system. The charging and discharging rate can be optimized based on the heating and cooling demand of the building and the available renewable thermal energy. The third factor is the efficiency of the thermal storage system, which refers to the amount of thermal energy that can be stored or discharged relative to the amount of energy put into the system. The efficiency of the thermal storage system can be optimized based on the type and model of the system.

In addition to modeling the thermal storage system, the integration of the system into smart building systems can involve the use of sensors and control systems to optimize energy use. For example, sensors can be used to measure the heating and cooling demand of the building and adjust energy consumption based on occupancy, weather conditions, and other factors. Control systems can be used to automatically adjust the operation of the thermal storage system and other components of the smart building system to optimize energy use. Overall, thermal storage system modeling can be an important tool for integrating renewable energy sources into smart building systems and reducing energy costs. By modeling the capacity, charging and discharging rate, and efficiency of thermal storage systems and optimizing the use of renewable thermal energy, smart buildings can reduce energy costs and environmental impact.

The SOC level of Thermal Storage System (TSS), SOC^T, available at given time interval $(t+1)$, depends on the SOC^T level, thermal power charged and thermal power discharged at time interval t. This relation can be expressed as,

$$SOC^T(t+1) = SOC^T(t) + \left(P^{chT}(t) \times \eta^{chT} - \frac{P^{disT}(t)}{\eta^{disT}}\right) \times \Delta t \tag{2.12}$$

Here, SOC^T is the SOC of TSS, P^{chT} and P^{disT} are charging and discharging power of thermal storage system respectively, η^{chT} and η^{disT} are the charging and discharging efficiency of TSS and Δt is the time duration.

2.4 Modeling of Loads

Residential load modeling is an important tool for optimizing the use of energy in smart buildings. It involves the analysis of energy consumption patterns and the identification of factors that influence energy use in residential buildings. Behavioral load modeling involves the analysis of human behavior and how it impacts energy consumption. It can be used to identify patterns in behavior, such as when residents are more likely to use energy-intensive appliances, and to develop strategies for reducing energy consumption by changing behavior patterns. Temperature dependent load models such as the refrigerator model and the air conditioner model used in this work are taken from the literature [68] and [69] respectively.

The scheduling of smart appliances (loads) considered in a SH depends on the users comfort. Therefore, it is necessary to model the loads in-terms of their operating parameters such as temperature set point, rating, and time of uses. Residential loads can be classified into three categories: (i) Temperature Dependent Loads (TDLs), (ii) Unschedulable and Noninterruptible Loads (UNLs), and (iii) Schedulable Loads (SLs). The modelling of smart appliances (loads) has been discussed in the following section.

2.4.1 Unschedulable and Noninterruptible Loads (UNLs)

The demand pattern of UNLs is highly associated with users' comfort. Light loads, TVs, laptop charging, fans etc. are the examples of UNLs. The UNLs can neither be interrupted nor be shifted from one time period to another. However, the total demand of UNLs varies according to the number of user in a SH and it also varies from day to day as per the user pattern. Therefore, the processing unit aggregates all the UNLs into a single load whose power varies continuously as per the comfort and convenience of users.

2.4.2 Temperature Dependent Loads (TDLs)

Air Conditioners (AC) and refrigerators are the most essential components in daily life. Around 60% of residential energy is consumed by these two components as compared to the other smart home components [143]. In this thesis, air conditioners and refrigerators are considered to be TDLs that fall under the cooling load types. Generally the energy consumption of cooling loads is more than the other types of home appliances like dish dryer, dish washer, washing machine, cloth washer and clothe dryer etc. Modeling of TDLs has been discussed as follows.

Refrigerator

The internal temperature of the refrigerator can be modelled as [68],

$$T^{in}(t+1) = \epsilon \times T^{in}(t) + (1-\epsilon) \times \left(T_O - \eta_{rf} \times \frac{P_{rf}(t)}{K_{rf}} \right), \tag{2.13}$$

where, $T^{in}(t)$ is the inner temperature of refrigerator at time interval t, $P_{rf}(t)$ is the power consumption of refrigerator at time interval t, and T_O is ambient temperature. System inertia, ϵ, efficiency of the refrigerator, η_{rf} and insulation constant, K_{rf} are considered as 0.95, 1 and 3.21 respectively.

The power consumed by the device for time interval t is calculated as

$$P_{rf}(t) = P_{rrf} \times S_{rf}(t), \tag{2.14}$$

where, P_{rrf} is rated power of refrigerator in kW and $S_{rf}(t)$ is ON/OFF status of refrigerator at time interval t. $S_{rf}(t)$ changes alternatively as follows.

$$S_{rf}(t) = \begin{cases} 0, & \text{if } T \leq T^{in,min}, \\ 1, & \text{if } T \geq T^{in,max}. \end{cases} \tag{2.15}$$

The set temperature range is considered as $4^oC - 8^oC$.

Air Conditioner (AC)

AC is an ON/OFF mode device where ON/OFF mode depends on the user activity and it runs at its rated capacity when it is in ON mode. For each time step t, room temperature for the air conditioner can calculated as [69],

$$T_r(t+1) = \epsilon_{air} \times T_r(t) + (1 - \epsilon_{air}) \times \left(T_{out} - \eta_{ac} \times \frac{P_{ac}(t)}{K_{air}} \right), \tag{2.16}$$

where, $T_r(t)$ is the room temperature, ϵ_{air} is the factor of inertia of air, T_{out} is temperature outside room, K_{air} is the thermal conductivity of AC in $kW/^0F$, $P_{ac}(t)$ is the consumed power in kW and η_{ac} is the co-efficient of performance of AC.

The power consumed by an AC for each time interval t is given as,

$$P_{ac}(t) = P_{rac} \times S_{ac}(t), \tag{2.17}$$

where,

$$S_{ac}(t) = \begin{cases} 0, & \text{if } T \leq T_r^{min}, \\ 1, & \text{T} \geq T_r^{max}. \end{cases} \tag{2.18}$$

P_{rac} is rated power of AC, $S_{ac}(t)$ is ON/OFF status of AC at time interval t. and the set temperature range is considered as $68^oF - 77^oF$.

2.4.3 Schedulable Loads (SLs)

SLs have pre-defined duration of operation. Loads falling under this category are dish washers, cloth washers, EV chargers, washing machines, dish dryers, cloth dryers etc.. Scheduling of this type of loads has an important role in minimizing the electricity bills of a smart home.

The total power consumption, $P_{SL}(t)$, of the SLs is given as,

$$P_{SL}(t) = \sum_{a_s=1}^{A} S_{a_s}(t) \times P_{a_s}, \tag{2.19}$$

where, P_{a_s} is the rated power of appliance a_s, $S_{a_s}(t)$ is a binary variable which represents the operating state of a_s^{th}, which can be written as,

$$S_{a_s}(t) = \begin{cases} 1, & \text{for ON state} \\ 0, & \text{for idle state.} \end{cases} \tag{2.20}$$

2.5 Cyber-attack

Scheduling for the smart home is accomplished through various sophisticated equipment such as smart meters, sensors and communication infrastructure. In this context, smart meter with advanced communication infrastructure may be targeted as possible nodal end-points for cyber-attack. In this thesis, FDI attack is considered in smart home architecture.

In case of FDI attack, the attacker injects the malicious data deliberately in a smart meter so that prices observed by the smart meter are corrupted. In present case smart meter is used to collect price data decided by the utility and data from the consumer including . Since the consumer is aware of both price data and load scheduling patterns, smart meters can be attacked by injecting false data into the price as well as load data for economic benefits. It can also disrupt the scheduling of the loads. This kind of attack can be modeled as

$$y(t) = h(t) \pm f(t), \tag{2.21}$$

where, $f(t)$ denotes the false injected data at time interval t, $h(t)$ is the actual smart meter data at time interval t before attack and $y(t)$ is the modified smart meter data at time interval t due to attack.

$$f(t) = \begin{cases} 0, & \text{when meter not under FDI attack} \\ \neq 0, & \text{otherwise.} \end{cases} \tag{2.22}$$

In this thesis, the false data, $f(t)$, is modeled using a regression model. Figure 2.2 depicts the modeling of attack vector. Past three month price data and corresponding attack vectors are used for training the regression models (linear regression, logistic regression, Gaussian process regression). In this work, Gaussian Process Regression (GPR) model is used for modeling the attack vectors, as the Root Mean Square Error (RMSE) in GPR is minimal compared to the other regression models. The GPR model generates N attack vectors corresponding to the N forecasted prices and error vectors are obtained with the help of forecasted prices and attack vectors. The mean, μ, and standard deviation, σ, of error vectors are used to model a Gaussian noise based FDI attack vector.

2.6 Summary

In this chapter, different types of DERs, energy storage systems and residential loads are modeled and discussed. The detailed modeling of solar PV, wind turbines, CHP generators, battery storage systems and thermal storage systems is presented for use in later studies. Based on user's comfort and convenience, residential loads are classified into Unschedulable and Noninterruptible Loads (UNLs), Temperature Dependent Loads (TDLs), and Schedulable Loads (SLs). The discussed models and classification of different SH components will be used for scheduling. The modelling of FDI attack vectors which will be used in further studies are also discussed.

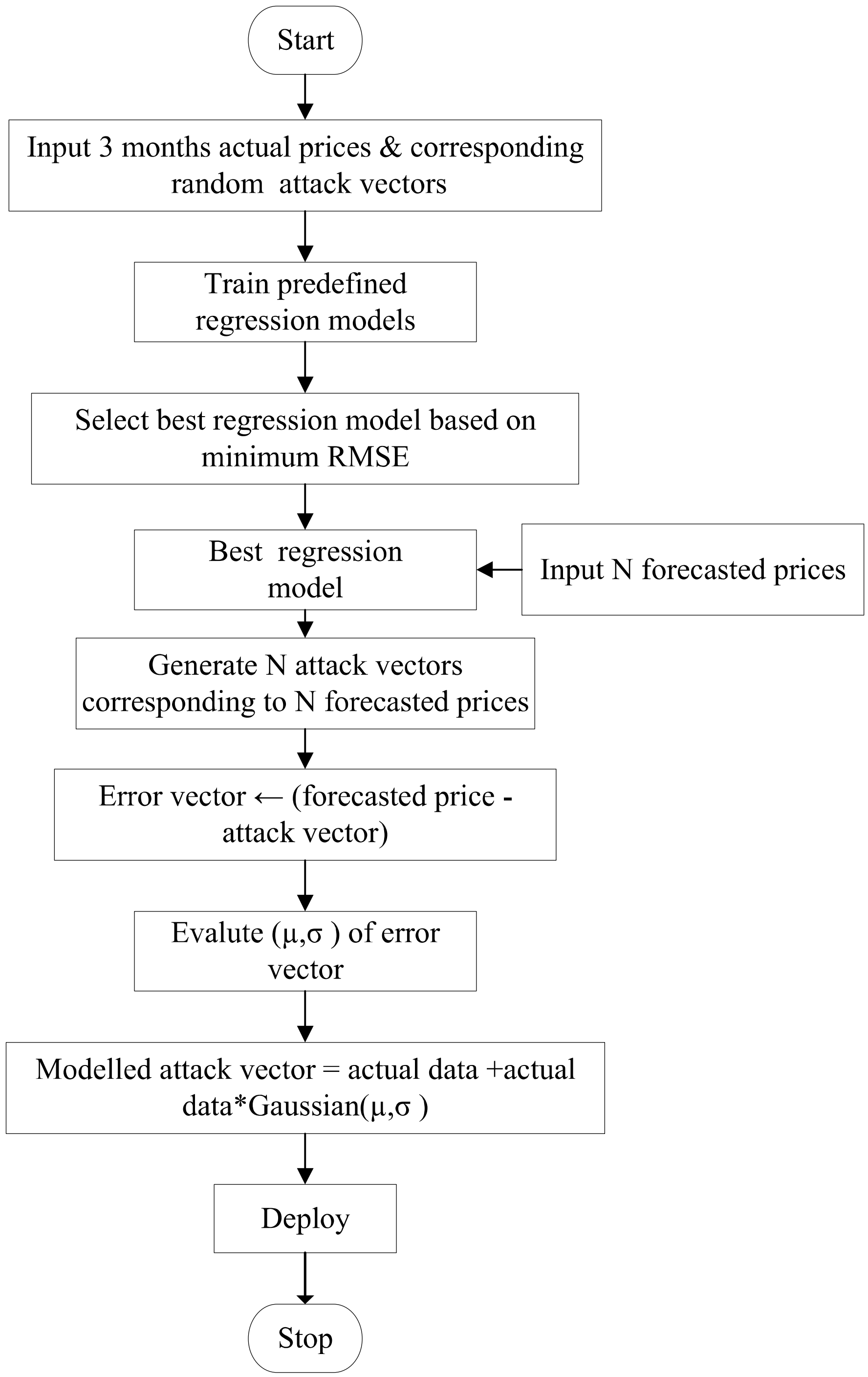

Figure 2.2: Flowchart of Attack Vector Modelling