# Cyber-Physical Smart Homes/Buildings

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**Abstract** This chapter investigates smart homes and buildings (SHBs) as cyber-physical systems. Initially, a discussion on the concept and role of SHBs is presented, considering the future evolution of the energy systems and other benefits of smartening efforts in energy infrastructure. An in-depth discussion of both the physical and cyber elements of the SHBs is then presented. Once the reader has an understanding of the elements, the following chapter explores models of the cyber elements and models of the physical elements, which combine to form the cyber-physical models. Control and management techniques of cyber-physical SHBs are outlined. Techniques include traditional model-based control and modern machine learning (ML) control using data. These techniques are addressed practically, with discussions of management and control systems and case studies considering aggregation and Model Predictive Control (MPC) for SHBs. Future research directions are also outlined.

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# 1 Introduction

## Concept of Smart Homes/Buildings

Traditionally a building interacts with grid services passively. The building's users consume natural gas, electricity and water, then utility providers are paid for these resources using predefined tariffs. Now, in the age of technology, previously distinct sectors of industry are connecting. Sitting in a taxi, requested by a phone application, someone can adjust the heat of their house using another mobile application, while the taxi parks using an auto-park feature based on sensors in the vehicle. These modern sensors and devices, which remotely interact with physical elements such as a car or boiler, are considered *smart devices*. Homes and buildings which contain smart devices are known as *smart homes* and *smart buildings* respectively, and in this chapter we will use SHBs for short. These SHBs when connected to the grid act similarly to smart devices incorporated in an SHB, so the grid can be considered a *smart grid*.

## The Role of Smart Homes/Buildings in the Future of Energy

Buildings represent 40% of the energy consumption in Europe and the USA, and 27.3% in China. The majority of the energy is used for space heating and water heating [1]. Buildings also account for 37% of the global $CO_2$ emissions as of 2020. With climate change and sustainable energy becoming mainstream concerns, many countries have developed goals to become net carbon zero by 2050. Buildings will need to reduce their $CO_2$ emissions by at least 90% to achieve this goal [2].

It is expected that for future energy systems, *distributed energy resources* (DERs) such as *photovoltaic panels* (PVs) will be included within the infrastructure of an SHB. The PVs use solar energy to provide a clean energy solution, and allow SHBs to generate their own energy resources and store them in *energy storage systems* (ESSs). This energy can also be sold back to the power grid providing users, in demand-side response schemes, with lower utility bills or even profits from the generated energy. This scheme would also benefit grid operators as stability is available across the power network. When SHBs interact with the grid in this way, they are known as *active buildings* or even *prosumers* since they both consume and produce energy for grid services.

As well as generating their own energy, SHBs can use the sensors and devices in *home/building management schemes* (H/BMS), an equivalent term is *building automation and control systems* (BACS), to both consume less total energy and to use energy consumed more efficiently. Buildings can use less energy by having increased insulation or air flow so that heating and cooling systems do not need to switched on for the same length of time. Additionally, energy can be used more efficiently by scheduling devices. At a national level, the load on the power network increases during the day and decreases at night. By scheduling building devices, consistent load values can be measured across the power network and less excess energy is produced to balance the load. Inside the building, money can be saved by scheduling devices to charge when energy prices are lower. Energy consumption can be reduced by storing generated energy in ESSs to be used at other periods of the day, for example, solar energy stored for use during the night when no solar generation occurs.

## The Concept of a Smart Home/Building Cyber Physical System

The integration of smart devices into SHBs has created an interconnection between embedded computers, cyber devices, and physical assets. This modern interconnected system is then a *cyber physical system* (CPS). As SHBs increase self-monitoring, measuring the physical asset performance using sensors, high amounts of data are generated. This data is then shared over computer networks to be processed. Using the processed data, automated building control systems with predefined objectives can send signals back to actuating devices of the building to adjust the buildings features and optimise the building's global objectives. The physical assets adjust their behaviour based on the received messages, and then sensors again collect data from these assets. This creates a closed loop control system of the building using computer systems or the *internet of things* (IoT) for communication. When a significant amount of sensor data is collected per cycle and modelled, it is possible to forecast key building parameters such as energy generation and system load. Forecasting building behaviour will lead to more efficient energy scheduling while maintaining user comfort levels and expectations.

To give an example, we consider an SHB, with a H/BMS, which is trying to autonomously regulate the temperature of a zone inside the building using heating and cooling devices. At a high-level perspective, the building has the objective to keep a zone's temperature between a certain predefined range. A sensor measures the ambient temperature of the zone and, the controller takes one of several actions, dependent on the measured value. If the temperature is too low then a message is sent which automatically increases the output of the heater. If the temperature is too high, then a different signal is sent which increases output from the cooler. If the temperature is measured within the range, then either no action is taken or active actions (cooling or heating) can be stopped. The physical assets complete the tasks of cooling and heating, but cyber devices automate the process. Additionally, depending on the measurement frequency of the sensor, energy can be managed efficiently as assets are only in operation when needed and there is no energy wastage from unnecessarily running appliances. Non-automated H/BMS would struggle with this, as the SHB users would not assess the ambient temperature as regularly and optimal actions would be missed.

## 2 Physical Elements of Smart Homes/Buildings

SHBs consist of multiple different elements. These range from boilers and lighting, found in nearly every building, to PVs and ESSs, found in more modern ones.

### Heating ventilation and cooling systems

Hot water and steam are distributed around European buildings from gas boilers. The largest portion of building energy consumption is from heating and cooling systems. To meet the target of 90% $CO_2$ emissions reduction for buildings, alternative solutions will need to be found. If using renewable electricity, heat pumps are a clean energy heat source. As well as providing heat in winter, the heat pumps can provide cool air in summer. The main benefit of the heat pump is its efficiency, where 1 unit of electricity energy can create $3-4$ units of heat energy [3]. For densely populated areas such as cities, district heating and cooling networks (DHC) could also phase out the reliance on natural gas by redistributing heat generation from industrial buildings and waste incineration plants to residential SHBs.

Generally, heating and cooling systems use a setpoint reference to determine a target temperature for heat sources. These set points are controlled throughout the day manually or autonomously scheduled. An industrial SHB will likely use high amounts of energy to heat or cool while the building is occupied, but use low energy at night when it is not. While a residential SHB will have no heating or cooling during the day when the occupants are away from home, but the reverse in the evenings when they return. Ventilation can be treated similarly to the heating and cooling systems which are together combined to form *heating, ventilation, air conditioning systems* (HVAC).

The main challenge of these devices is optimising energy efficiency while maintaining user comfort. In [4], a *building envelope* is described as the components which divide the indoor environment from the outdoor environment. Simply put, this is the walls, roof, insulation, etc. It is inefficient to heat a building with thin walls, as more heat energy will be lost to the outdoor environment than for a building with well insulated walls. It is impossible to avoid energy loss altogether, but good building envelope design (both passive or active), can reduce the building load by efficient insulation/ventilation while maintaining user comfort. This then reduces the energy costs of that building for its users.

### Distributed Energy Resources at Smart Homes/Buildings Level

DERs are small scale local generation devices which can connect to the smart grid through SHBs, a prime example of this is PVs placed on the rooftops. The amount of energy generated by a PV panel is given as

$$P = I \times \eta \times A$$

where $P$ is the power produced (W), $I$ is total solar radiance on the PV surface (W/m$^2$), $\eta$ is the total system efficiency and $A$ is the area of the PV panel (m$^2$) [5]. The amount of power produced by a panel is directly proportional to the amount of solar irradiance. As cloud cover, ambient temperature and solar cell efficiency are all uncertain factors, it is difficult to forecast solar energy production. With future decarbonisation plans, renewable generation sources like PVs are essential to the future of power systems but provide control challenges when incorporated in energy systems because of their unpredictability [6]. For other DER sources whose energy may be incorporated in an SHB, wind power is the most unpredictable.

A technique that can address uncertainty in DER generation is to pair complementing generation sources. Wind power can complement solar power, since factors which increase wind power generation often decrease solar power generation and vice-versa. By pairing together energy sources in this way, a more stable energy supply can be created that remains steady despite environmental uncertainties.

Another technique to address DER uncertainty uses ESSs. Any excess energy not being used by the SHB at time of generation can be stored in the ESS for later use. When the generation of the DER drops below the desired value, the ESS can supplement the DER generation with previously stored energy. Additionally for examples such as PVs, which does not generate energy at night, ESSs can supply energy to satisfy nighttime energy demand within the SHB.

## Plug-in Electric Vehicles and Charging Points

The demand for plug-in electric vehicles (EVs) is increasing substantially, with a need for EV sales to represent at least 40% of new vehicle sales by 2040 to achieve carbon net zero targets [7]. EVs and hybrid EVs can connect via charging points to the electricity network to recharge their batteries. The charging of one EV can be equivalent to the load of three houses on the power system [8]. Therefore, managing and controlling EV charging is essential to prevent overloading of the power system as EV penetration increases globally.

Some EV charging points can provide bidirectional charging functionality, allowing charge to enter and leave the vehicle on demand. For EVs using these chargers, they can be incorporated in demand-response services to help control power system stability. For example, in the case of a sudden large power loss event, SHBs can inject the energy stored in their EVs back into the smart grid to balance the supply-demand ratio for system frequency [9].

SHBs can contain multiple EV charging points in their network. As EVs are essentially moving ESSs, it is possible to incorporate them in the H/BMS of the building. It is possible to discharge the energy stored inside an idle EV to be used as a building energy source, under the assumption the battery will have sufficiently recharged before the next time it is required by the owner. Charge scheduling of EVs is therefore an important feature of a H/BMS to maintain EV user satisfaction when vehicles are used as energy sources.

### Smart and Controllable Home/Building Appliances

Aside from DER generation appliances and HVAC systems, various other SHB appliances can be controlled as part of the SHB infrastructure. Building appliances are becoming smarter, kitchen devices such as ovens, dishwashers, toasters can be scheduled. Sensors in clothes washers detect the weight of a washing load. Smart exercise bikes can automatically adjust resistance, and automated robotic vacuum cleaners can apply collision detection to clean the floor without colliding into objects.

Occupancy sensors can measure the number of people in a location, this data can then be used for security purposes, detecting intruders, or to determine temperature needs for occupied building zones. If a person with disabilities were to access the building, sensors may be able to detect the need for this person to have additional assistance and send out an alert or deploy special services. Occupancy sensors could also detect unoccupied rooms and turn lights off. Similarly, parking sensors can detect the number of free vehicle spaces available, and how many EV charging stations are unoccupied [10, 11].

For safety scenarios such as fires, sensors could detect the fire and then send alerts to local fire stations or warn building occupants of the danger and specifically where a danger is located.

## 3 Cyber Elements of Smart Homes/Buildings

As SHBs experience an ever growing amount of sensor and networked machine integration, CPS provides a smart infrastructure to manage the interconnections between the computational capabilities and physical assets. For the implementation of CPS in industry, clearly defined structures and methodologies of the system are required. In general CPS consists of two main points:

- Acquiring data from physical assets and relaying that information in real-time.
- Managing and analysing the system to provide system control and forecasting.

### Internet of Things Devices

Small embedded devices are increasing the capabilities of communication, sensing and identification, when connected they form the smart network known as the Internet of Things (IoT). IoT is the fastest growing area of telecommunications and the concept of the SHB originates from it, since appliances are monitored and controlled using a complex communication network.

The IoT is the medium with which the heterogeneous sensors and actuation devices can communicate together. The coupling of IoT, sensors and actuation is what can be described as Industry 4.0 [11]. IoT devices have lower energy consumption than other existing technologies, but equally satisfy user comfort levels. The IoT devices share data, interact with other IoT devices and act autonomously to heat, cool, regulate indoor air quality (IAQ), activate lights, manage water, interact with health sensors, among many other tasks.

To fully deploy IoT in an SHB, a standard architecture is required which is well-defined, scalable and secure. The CPS architecture complements building IoT by managing its distributivity, interoperability, scalability and security. The distributivity of the IoT refers to the number of different devices generating and processing data. These devices will be from different manufacturers and use different software requiring interoperability. The CPS architecture is scalable as it can manage the increasing number of smart devices incorporated within an SHB and also provides users with control over their home or building to avoid security fears that their home is run entirely by computers [12].

In the remainder of this section a detailed description of CPS architecture using the 5Cs architecture will be described that is suitable for the Industry 4.0 standards. These are the connection layer, conversion layer, cyber layer, cognition layer and configuration layer, as can be seen in Fig. 1 [13, 14].

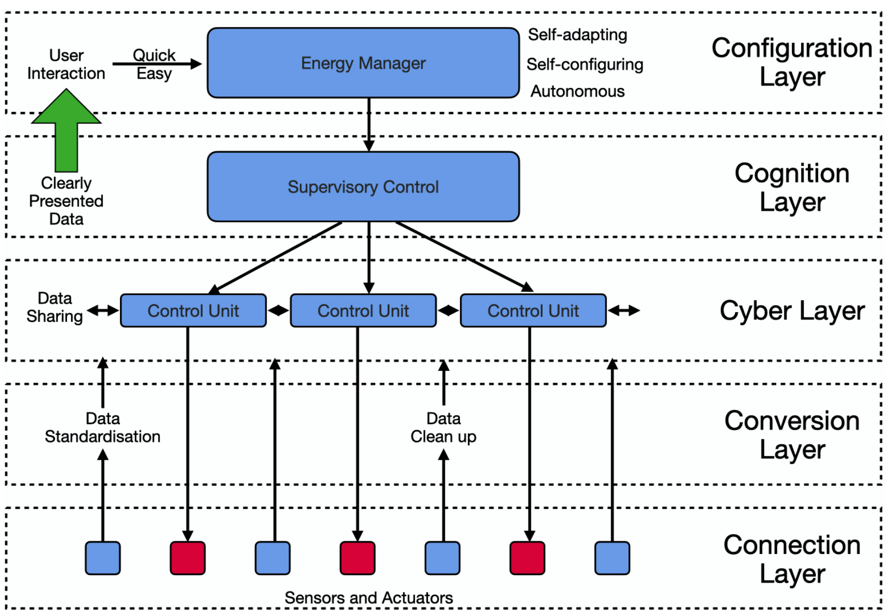


Fig. 1: CPS architecture

### Connection Layer

The connection layer consists of smart connection devices. These are the sensors which collect the system data from the physical assets and from the environment. This data then needs to then be transferred to a central server via IoT, wireless sensor networks (WSN) or machine to machine communications (M2M). The data will be used for predictive control in upper layers. This layer also consists of actuation devices which can influence the environment, such as HVAC systems and artificial lighting.

For the highest performance, sensors need to be used which can best monitor the condition of the machines and appliances within the SHB. On top of this, the data collected is sent in a unified data format. This way, the connection layer hides communication protocols and data formats used by underlying hardware to create an interoperable format for upper layers to control devices from different manufacturers or that use different software.

### Conversion Layer

At the conversion layer, the sensor data is cleaned, converted and standardised. For example, most data-driven techniques use numerical features so categorical data such as appliance OFF/ON needs to be first converted to a numeric representation (e.g. 0/1). Statistical data can be standardised.

$$Z = \frac{x - \mu}{\sigma}$$

where $Z$ is the standardised data, $x$ is the sensor data, $\mu$ is the mean value and $\sigma$ is the standard deviation. This converts to the data to center around 0 with a standard deviation of 1, making it easier to be analysed by some controllers.

During data conversion, low level analysis is also computed. This includes estimating the remaining lifespan of industrial machinery and other self-awareness tests. In this way, raw data can be mapped to events with contextual information which is easier for higher layers to interpret and understand. The conversion layer also forwards control signals coming from upper layers to lower layers.

### Cyber Layer

At the cyber layer, control devices can communicate with one another and share data. It may also be called the control layer. The goal of a control device is to maximise the effect of its assigned tasks, while maintaining global SHB objectives, e.g. heating a room to a setpoint value. The cyber layer implements the intelligence of the device, computing control actions and choosing the correct actuation signal to achieve it in the underlying hardware. The device data is analysed against other data from this time step.

Additionally historical data is analysed, the device looks for similarities in order to achieve behaviour forecasting. The prediction methods rely on modelling of the SHB, and these can be either *theoretical approaches* or *data-driven approaches* as discussed in Section 4. Although the control at this level is valuable and provides a solution to the control problem, it is usually not the optimal control.

## Cognition Layer

The cognition level forms data representations that clearly and accurately reflect what is going on in the system for use by the expert users that are operating it. By correctly representing data the users can support the decisions which need to be taken in the building.

It is also at this level that optimisation occurs. Automated building controls are implemented in the cyber layer but these may be sub-optimal. By accounting for stochastic uncertainties in the modelling, optimised building models can be used for control actions. In this regard the cognition layer can also act as a supervisory control layer, optimising the control of the cyber layer using rule based control (RBC) or model based control (MBC) techniques. These optimisation techniques can include *linear programming* for tractable problems, while intractable problems may use the *genetic algorithm* (GA), the most common meta-heuristic optimisation technique. The optimisation will attempt to minimise some cost function, dependent on this different control approaches may be taken. Different weights will be applied to different control objectives to maintain stability of the system.

## Configuration Layer

Finally, control decisions are communicated to the SHB and implemented, adjusting the physical assets as wanted. For some devices this will be a simple ON/OFF command, while for others setpoint values will be communicated for the asset to steer towards. The configuration layer influences the building as an energy manager in a way that is both self-adaptive and self-configuring.

The CPS can autonomously change its behaviour to better achieve the optimisation objectives. Additionally at this layer, user interaction occurs. The users can be notified when needed and also feedback from users is acquired in order to provide any correctives to the system. The H/BMS should be non-intrusive so interactions with the user must be quick and easy. This is done by providing an abstraction of the building which users interact with and leaving all details of implementations hidden.

## 4 Cyber-Physical Models of Smart Homes/Buildings

When describing an SHB as a CPS, there are 3 main aspects to be modelled. The first is the physical elements, these are the devices and physical assets within the system which each behave under different physical principles depending on their utility. The second is cyber devices, these are usually simple Single Input - Single Output (SISO) controllers that are used for basic control of the physical elements, or devices used for communication or cyber security. Thirdly, the whole SHB can be modelled as an Multi Input - Multi Output (MIMO) system, integrating both cyber and physical elements. This allows the SHB to be optimised by either a human operator or an automated *energy management system* (EMS). Each SHB will have its own bespoke model, this will depend on the different physical elements it holds, building location, climate and a variety of other factors [15].

### Models of physical elements

There are various physical elements present in the SHB, and each element may have its own system model that can be used to describe and control that element. In this section three of the main elements will be discussed; HVAC, onsite generation and energy storage.

#### HVAC System

HVAC is the primary energy consuming feature of an SHB. By reducing the energy consumption of HVAC systems, significant energy savings can occur. To achieve this, improvements in control algorithms will increase efficiency by a greater degree than replacing HVAC equipment with upgraded technologies. However, to improve HVAC energy efficiency, highly accurate models are required which fairly represent the discrete, highly nonlinear, highly constrained SHB characteristics. This includes incorporating heat loss and gain through the building's floors, walls and roof, managing a fresh air supply through the SHB and modelling humidity and air cleanness. The key factors for determining a valuable HVAC model are identification of model order and suitable parameter selection, this is also known as *system identification*. Identifying an appropriate system model allows a control algorithm to deal well with disturbances, uncertainty and time-varying system dynamics. There are three main types of HVAC system models, they are *white-box models*, *grey-box models* and *black-box models*.

White-box models are based on the fundamental laws of energy. This includes heat transfer, momentum and mass balance, which can each be converted to solvable mathematical equations representing the system. White-box mathematical models are mainly used at the early stages of HVAC system design to analyse and predict the behaviour of the system through simulations. Mathematical dynamic models are valuable for slow moving dynamics such as zone temperature and zone humidity. Static models are used for faster moving systems.

Black-box models use data-driven approaches. These models discover a relationship between inputs and outputs of the system using mathematical techniques such as artificial neural networks (ANN). There are nine different data-driven models that can be used for HVAC. These are state-space model, geometric model, stochastic model, frequency domain model, fuzzy logic model, statistical model, instantaneous model, data mining algorithm and case-based reasoning. When historical data is available for an HVAC system, then data-driven models can be formed by training this data.

Grey-box models are a hybrid approach to modelling HVAC. They combine white-box and black-box modelling techniques. The skeleton of the model is determined based on the physical equations which describe the elements of HVAC. However, the parameters of these values are chosen using parameter estimation algorithms of historical data. Grey-box models are particularly suitable when there is not enough data to run black-box modelling or for processes where white-box models start to diverge from real behaviour.

HVAC zone models are used to imitate the thermodynamic behaviour inside a zone, as well as the interactions between the zone and the external environment. As the number of zones increases, this task becomes increasingly challenging [16].

### Onsite Power Generation

PVs are the most common form of onsite power generation one might find connected to an SHB. The basic unit of a PV system is the PV cell. When connected in series these form PV modules and module strings are PV modules in series. Connecting module strings in parallel to one another creates the PV array, and increases the circuits current.

PV cells are often represented using equivalent circuit models. Of these the *five parameter circuit* (5-p model) with 1 anti-parallel diode, one series resistance and one parallel resistance, is the most commonly used. The outputs of the circuit, current ($I$), and voltage ($V$), are combined to form I-V curves. In the desirable scenario, the outputs from experiments will match the predicted or modelled output. The equation representing the 5-p model is as follows

$$I = I_{ph} - I_D - I_p = I_{ph} - I_0(e^{(V+IR_s/V_t)} - 1) - \frac{V + IR_s}{R_p}$$

where $R_s$ is the series resistance, $R_p$ is the parallel resistance, $I_{ph}$ is the photo current, $I_0$ is the diode saturation current, $V_t$ is the diode thermal voltage [17]. In general $R_s$ will affect the system power output while $R_p$ affects the available current. Other models are also available for PV modelling.

**Energy Storage**

As already discussed the energy storage in an SHB takes the form of connected EVs or ESSs which are used to store solar generated energy, but old EV batteries can also be repurposed as ESSs for SHBs [18]. For the purpose of this section we will treat ESS and EV modelling as the same. The term 'battery' will be used generally to describe a single cell, a battery module and a battery pack. From [19], batteries can be modelled in three ways - mathematical models, electrochemical models and electrical equivalent circuit networks.

Mathematical models can be analytical or stochastic. Analytical models are designed and based on a few equations which describe the physical concepts of battery properties. For example, the Kinetic Battery Model is developed based on chemical kinetic properties. Stochastic models are based on discrete-time Markov chains. This technique is used for random models, the model transitions between states depending on transition rules of the current state.

Electrochemical models use physics based methods that fully describe the internal electrochemical dynamics of the battery. These dynamics are described as a set of partial differential equations (PDEs). These models can describe the electrochemical reactions inside the cells and their potentials. Good electrochemical models are the most accurate of the different modelling techniques, due to their high level of detail.

To use electrochemical models in computers, a balance between model accuracy and model complexity is required. This lead to the development of electrical equivalent circuit modelling or equivalent circuit (EC) modelling. EC modelling is the most common technique used in EV battery models. They are constructed by building simple equivalent circuits to the battery and selecting appropriate parameters using a technique such as electrochemical impedance spectroscopy (EIS). Using these modelling techniques on ESSs and EVs provides the SHBs with an understanding of the battery range, capacity, discharge and charge rates, amongst others.

When modelling energy storage devices such as the batteries used in ESSs and EVs, one important factor to model is the degradation of the battery. As batteries spend the majority of their time idle, EVs are parked 90% of the day, the factor most affecting degradation is known as *calendar aging*. An equation used for modelling calendar aging is

$$Q_{loss,\%} = Ae^{(-E_a/RT)}t^{\frac{1}{2}}$$

where $Q_{loss,\%}$ is the percentage capacity loss, $E_a$ is the activation energy in Jmol$^-1$, $R$ is the gas constant, $T$ is absolute temperature and $t$ is the time in days [20]. In [21], it is shown that high battery state of charge (SOC), above 60% charge, and temperature, above 50°C both degrade the battery capacity and increase the battery impedance (which reduces power output). Cells which use graphite are particularly affected by these factors during *calendar aging* of the battery, however each cell's degradation can be different. Cells using LTO degrade faster with low SOC rather than high SOC, the opposite to the graphite based cells. Battery usage in an SHB will mostly involve supplementing insufficient power generation or providing smart grid demand-side response services. Understanding the longevity of the batteries aids SHB control mechanisms to model available energy that can be used. Additionally in [22], it is shown that discharging batteries for demand-side response services can slow the calendar aging, a mutually beneficial energy exchange for the ESS or EV and the SHB.

## Models of Cyber Elements

When discussing cyber elements inside a SHB, the elements described are ones that are used for security, communication and control purposes.

### Cyber Security Devices

As SHBs rely on IoT devices for various different aspects of their operation, the SHBs face both real and potential security risks. In [23], it was noted that 4 in 10 clients do not take steps to protect smart buildings from malicious cyber threats. There are four main reasons for security deficiencies in SHBs.

1. The interconnection of the various previously independent systems inside an SHB, provide a large attack surface of both physical and cyber aspects.
2. Engineers who do not understand security risks are in charge of the design, installation and maintenance of an SHB.
3. Open communication standards from industry are integrated in the SHB.
4. Small sensor devices do not have the ability to run or install the computationally intensive encryption and authentication security techniques.

Risk assessments are models that can be used to describe the security features and risks that an SHB may have. No building can be completely free of security risks, however risk assessments can identify vulnerable aspects of a system and the associated costs to mitigate them.

When conducting their own risk assessment of a smart university building, the authors of [23] found that there was not an established risk assessment process for SHBs, particularly with a focus on the technical elements of the buildings. Examples of technical elements include seperation of different information networks, penetration testing and data protection in databases and servers. The risk assessment should be conducted by experts in multiple fields as SHBs are cross-disciplinary in nature, and important building security features may go unrecognised by a non-technical assessor. Finally, for a large SHB with multiple stakeholders it is important to have clear systems ownership, where stakeholders hold responsibility over certain aspects of the SHB. In this way certain access aspects can be limited to only those with correct clearance and protect systems from malicious third parties.

**Pre-Processing Devices**

Most sensor devices provide an SHB with basic data. This could be humidity, lighting, ventilation or temperature. Edge computing described in [24], leverages these sensor devices and applications from IoT to complete some simple data processing, filtering and aggregation tasks at device level. These sensor devices are known as *edge nodes*.

Edge nodes can complete advanced computing tasks. With the increase in sensing devices present in SHBs, large amounts of data is being sent every second by different sensor devices. Edge nodes can pre-process this data to determine what information is useful to forward onto the higher levels of the system architecture, and what can be ignored or stored at device level. For example, it is not necessary to constantly send updates about device health, unless there is an issue. Instead, this data can be stored and a single message summary can be distributed daily.

**Control Devices**

Using edge nodes can also increase the performance of the SHB. Developments in big data processing mean that algorithms run on small devices are more efficient. Instead of sending data and waiting for a response before taking a control action, the device can react based on its own logic. Leveraging Moore's law and developments in communication from IoT devices, this is not expensive to implement as microprocessors are both cheaper and smaller.

The control devices in the system are fairly basic SISO controllers. There are two ways to model control devices in the SHB. These are *open loop control* and *closed loop control* devices. Open loop control responds to changes in the reference, in a specific predefined method. The open loop controller chooses an input signal that is sent to the system in question. This input manipulates the system, or plant, to produce a desired system output, as shown in Fig. 2. An examples of an open loop controller in an SHB is a controller for the lighting system.

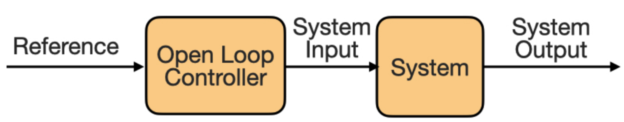


Fig. 2: Open loop feedforward control.

Closed loop control is similar to open loop control, except that sensors measure the system output and feed it back to the controller. The controller then calculates the error between the desired reference value and the actual system output. The controller then update the choice of system input in an attempt to minimise the error, see Fig. 3. Closed loop control can be used to track a reference signal and an example use is in thermal applications such as HVAC.

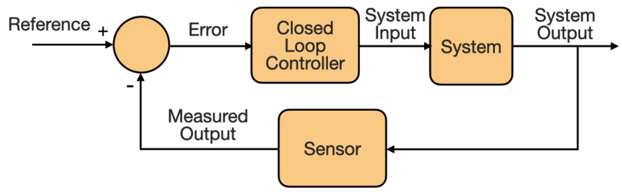


Fig. 3: Closed loop feedback control.

The control devices described in this section are not optimised with respect to the whole SHB. To do so would require a reference signal chosen by a higher level controller which has a full grasp of the interconnections of the different systems inside the SHB. These closed loop control devices are likely to implement ON/OFF control, the simplest and most common control method which turns a system ON or OFF to make the system output match the reference. A slightly more complex device may use PID control, as described in Section 5. Particularly powerful controllers at a local level may use self-tuning artificial intelligence (AI) or ML control techniques. These controllers can locally optimise their control response to match the reference using data-driven algorithms based. However, these are computationally intensive control techniques and only likely to be used for systems with significant amounts of uncertainty or nonlinearity, to leverage the predictive abilities of ML algorithms.

The performance of control techniques implemented at this level will inevitably worsen over time and increasingly underperform. The control techniques need to be regularly updated due to building repairs, seasonal variance or occupant preference changes. Therefore, it is necessary to have integrated models of cyber and physical building aspects combined, that can adapt to these variations.

## An integrated Model for Cyber-Physical Smart Homes/Buildings

Integration of the system elements is essential for performance optimisation. An optimised SHB can manage energy, which reduces operation costs, while maintaining occupant comfort levels and services. Additionally models that integrate cyber and physical elements can determine when an optimisation can be improved, and use prediction techniques to determine how the state of the SHB will evolve over time.

The supervisory control level is a term describing the cognition layer and configuration layer of the cyber elements architecture. At this level, there are two general automated control methods which can be used to control the elements inside the SHB, both methods are heavily reliant on sensors and actuators to directly control the system elements. The first is rule based control (RBC) and the second is model based control (MBC) [25].

An SHB can be modelled by describing the system as a set of constraints or rules. Essentially the details of the elements inside the model are abstracted away.

RBC uses *direct logic*, based on rules, to control the SHB elements. These rules are based on the states of the system. Depending on the current system states, different actions are taken to direct the system to a point where it satisfies the system logic. An example is a rule which states the temperature of a room must not exceed 20°C. If the temperature of that room breaks this rule, then an action is taken to turn on cooling devices. SHBs that use RBC are simple to implement relative to MBC, but rely on good rule selection to best describe the building.

An SHB can also be modelled based on details of the elements contained inside the building. MBC uses *indirect logic*, based on models which simulate building behaviour. Using the models, different control strategies can be compared and the best strategy is chosen. This makes the building adaptable to different situations but is also more complex than RBC. The complexity of using MBC means that there is longer processing time when choosing the best control strategy. However, a significant benefit of the MBC SHB model is that performance indicators such as energy, $CO_2$ emissions and cost can be described and used in the SHB control, and collected as data to present to users and owners of the SHB. MBC captures complex dynamics but can incorporate some of the RBC strategies for its control.

Both RBC and MBC are adaptive control techniques. This means they adapt to variance in the conditions as they evolve through out the day. For example, desired set point temperatures might be different, or HVAC optimal operational points might fluctuate, during the day compared to at night. By combining the adaptive control with predictive control, based on data-driven models, it is possible to create a self-learning control technique with reduction in error supported by the predictions. Without the prediction, the model may misinterpret input-output data and incorporate errors into the model, thinking they are being removed. Using prediction, it is possible for RBC to choose control parameters that satisfy the SHB rules, one technique for this is the *genetic algorithm* (GA), however RBC is still limited by the selection of rules which will not expect all possible SHB scenarios. Merging MBC with prediction, allows the SHB model to analyse different building scenarios, and use these to choose the optimal control technique for the SHB. Merging MBC with prediction is known as model predictive control (MPC) and will be discussed, along with GA, in Section 5.

MPC is the most promising SHB control and management technique, however there is still a discrepancy between predicted values of a system and real measured values. A strength of MPC is that it can adapt to the discrepancy and limit it. This discrepancy is often caused by uncertainties in the behaviour of the environment, uncertainties in the behaviour of the users or accuracy of the model being used for prediction. When discussing models used for prediction, three key types are available white-box models, grey-box models and black-box models [26]. These have been previously discussed when considering HVAC systems.

White-box models are based entirely of the detailed physical algebraic and differential equations of the SHB elements. The advantage of this is that the models are accurate and precise, with detailed descriptions of the phenomena present in the SHB. However, this makes them computationally difficult and it would not be possible to use white-box modelling for online real-time MPC calculations. Additionally, by describing all elements in the system there is a large degree on uncertainty in the model as it is impossible for all these different units to behave exactly as described in the equations. By simulating white-box models, the data is useful for defining advanced RBC rules.

Grey-box models are simplified version of white-box models. Using measured data, the grey-box model parameters are selected and the reduced model is a useful compromise to the heavy computations of white-box modelling. While increasing in computation speed, the grey-box model does suffer regarding accuracy compared to white-box models. These easy to calibrate models are useful for both MPC and RBC.

Black-box models are also known as data-driven models. These models rely entirely on empirical data and no understanding of the physical principles of the SHB it describes. These models require large amounts of available data of the system being modelled in order to predict future behaviour with accuracy under a similar set of conditions. These models are flexible and simple to compute, as well as providing MPC with accurate real-time predictions. The main difficulty using black-box models compared to white-box models is that they are application specific. Any significant changes to the SHB, such as new installations or repairs may require the black-box model to be recreated. If an old black-box model is used on a new system, there will be prediction errors as the two models do not sync, additionally it is not easy to adapt an existing black-box model like one might for a white-box model since there is no physical representation of the acquired predictions. Black-box models are increasing in popularity as ML techniques are becoming a future capstone of technology and data analysis. *Artificial neural networks* (ANN) and *support vector machines* (SVM) are both viable for learning input-output relationships to be used in black-box models.

Overall, it has been discussed that combining physical element models with cyber element models produce useful cyber-physical SHB models. These models can be used to control the SHB as a whole from a high level perspective. Adding prediction to the SHB models helps reduce the error between the desired output of the system and the measured output of the system due to adaptive control techniques which can self-learn to improve SHB response under fluctuating conditions. Of the prediction models, black-box models are the most beneficial for predictive control but are also application specific, due to their reliance on historical data, meaning they must be recalibrated when the SHB elements are significantly changed.

## 5 Control and Management Techniques

In this section, the control and management techniques mentioned in this paper will be described with more detail.

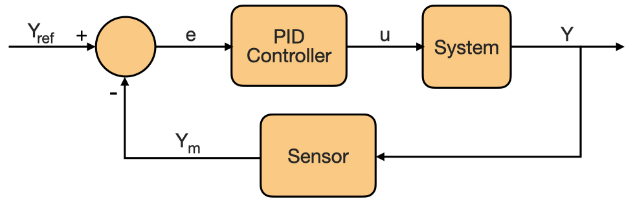


Fig. 4: A PID controller.

## PID control

Proportional, integral, derivative (PID) control is the most commonly used industrial control strategy. This is largely due to its simplicity as a closed loop controller. PID controllers use current and previous error measurements to direct the system output to match the desired reference signal. Tuning the system can be completed by adjusting the constants $P$, $I$ and $D$ in the controller equation

$$u(t+1) = Pe(t) + I\sum_{t=1}^{t} e(i) + D(e(t) - e(t-1))$$

where $e$ is the error, $t$ is time, $P$ is the proportional constant, $I$ is the integral constant and $D$ is the derivative constant.

In Fig. 4, an example system is shown with a PID controller. This could be a simple system discussed in Section 4. $Y_{ref}$ is the reference signal and $Y_m$ is the measured output of the system. The system error $e = Y_{ref} - Y_m$ at time $t$. The PID controller selects an input for the system which will direct the system output, $Y$, to be the same as $Y_{ref}$. In the next time step the sensor measures the new system output and the error is updated, allowing the PID controller to choose a new input for the system and minimise $e$ so $e_{t+1} \leq e_t$.

PID control is useful for SISO systems and uncoupled two input two output systems. For MIMO systems other techniques such as Model Predictive Control are more optimal [27].

## Model Predictive Control

MPC is a control technique that is one of the fastest growing in the world. This is due in part to the broad range of scientific fields which benefit from MPC control techniques. As previously mentioned, MPC is an MBC scheme, representing the system to control by a model and minimising a cost function associated to that model. The implementation of MPC can vary, and involves layers of freedom, but three consistent ideas are held.

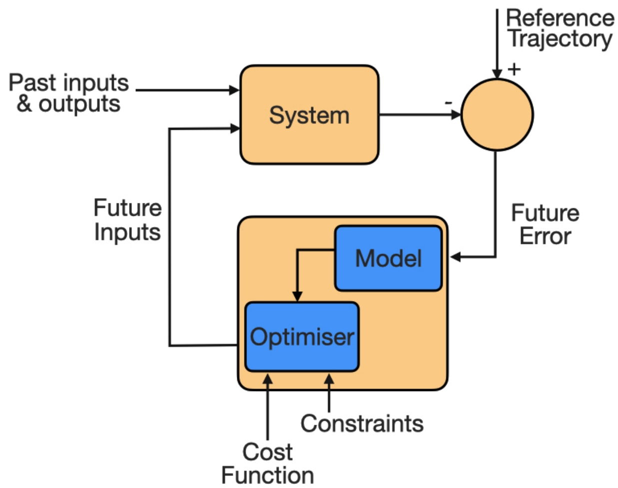


Fig. 5: Model predictive control approach based on a receding horizon.

Firstly, MPC uses a process model to create a prediction horizon. Secondly, MPC calculates a set of future control signals. Thirdly, MPC uses a receding strategy, the first value of the control sequence is chosen by the process as it moves forward in time, then all following values in the sequence are discarded and a new prediction horizon is created.

In Fig. 5, an MPC model is shown which predicts future system outputs. The set of future control signals is represented by $u(t+k \mid t)$ for $k = 0, \ldots, N$. The future system outputs are also known as the prediction horizon, $y(t+k \mid t)$ for $k = 1, \ldots, N$, where $t$ is the current time step, and $y$ is a set of future outputs for a time horizon, $N$. This is calculated using past control signals, $u$, past outputs, $y$, and predicted future control signals.

Using the set of future control signals, a control sequence is formed which minimises an objective function at each time step, $t + k$. The objective function consists of a cost function and a set of system constraints. The cost function measures the variance between future system outputs and the desired reference value, $w(t+k)$. The optimisation uses the minimised objective function value to choose the optimal system input value for the current time step.

The objective function consists of the sequence of manipulated values ($Z_k$), a cost function for tracking error ($J_y$), a cost function for manipulated variable tracking ($J_u$), a cost function for change in manipulated variables ($J_{\delta u}$) and a cost function for constraint violations ($J_\epsilon$).

$$J(Z_k) = J_y(Z_k) + J_u(Z_k) + J_{\delta u}(Z_k) + J_\epsilon(Z_k)$$

This optimisation and selection of system inputs is computationally intense. It can either be run online, in which case a processor with significant processing speed is required for MPC to compute real-time control. The optimisation can be computed offline and imported into the controller as a lookup table. The lookup table simplifies control as instead of reoptimising the model, the current model state can be looked up in the table and the optimised input values to pass to the system will be provided.

MPC is reliant on an accurate process model. MPC is computed *a priori*, with prior knowledge of the process. If the MPC model used has poor system dynamic accuracy, then the difference in the model and the real system will create discrepancies between the predicted control and the real control of the process. Although MPC is designed to adapt to errors in the model, the more significant the errors are the more difficult it will be for the MPC to correct them. In [28], a detailed description of MPC applications in SHBs are described, providing useful examples.

## Multi-Agent Approaches

An SHB can be described as a collection of smart devices which interact to provide a reliable service at low cost to users. This description decomposes an SHB into smaller structures or systems which interact with one another. Multi-agent systems (MAS) approaches support this framework.

MAS is a system composed of autonomous, interacting devices known as agents, the agents adapt to their environment and percieve and act to satisfy their needs and objectives. Edge nodes, as discussed in Section 4, are smart devices which can act as agents in the SHB multi-agent system.

Agents receive information from the environment through sensors, these sensors pass the information to the agent's logic which chooses an appropriate action to take based on this data. This choice is then passed to the agent actuators which influence the environment or system to complete the task. Actuating the system is likely to change the global state of the SHB.

As agents are distinct from the environment and act on their own logic, MAS is a distributed energy control technique. MAS is also proactive, as agents follow their own objectives, or global objectives that are beneficial to the agent as an entity. Agents are social and can interact via cooperation or competition. For MAS to be effective, agent-agent and agent-environment interactions must be understood.

There are three main types of agent. *Reactive agents*, which is the most basic, have minimal responses to environment precepts. They provide fast responses when needed and when modelled as a large group have useful results. An *intelligent agent* has more functionality than a reactive agent, it is able to use resources to achieve an objective. Finally, *learning agents* gain information by analysing the outcome of their actions. The learning agent will have a good grasp of the environment it is in, which it uses for decision making and prediction.

The MAS approach to control is bottom-up, agents have local knowledge and flexible interactions. The agents only know certain information, and this reduced data model transfers across the network, making MAS scalable. It is unnecessary for two distant agents that never interact to be aware of one another.

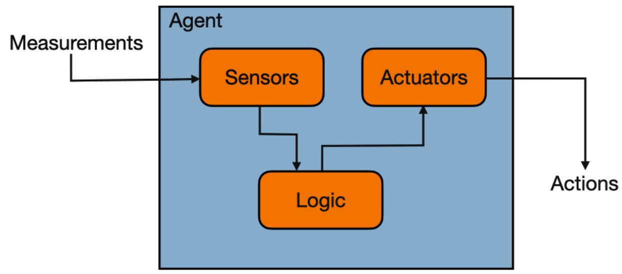


Fig. 6: A multi-agent system model of an agent.

Difficulties of MAS revolve around the proactivity of the system. As each agent has a local objective and groups produce global objectives, it may occur that competing objectives arise. These challenges make distributed control more complex than the centralised control approach where an action would be demanded to suit the global specification. As these agents are cooperating or competing with one another autonomously, the control approach required for the system is to distribute the control tasks between the agents. To help with this, a clear communication framework between agents and definitions of the agent roles are defined. Other system approaches rely on predicting network changes and having costs associated with maintenance or redesign of the SHB. MAS can avoid these costs. This also benefits future hardware that will be incorporated into the networks [29].

### Artificial Neural Networks

ANN were developed from the mathematical model of a synapse in the brain known as the *perceptron*. Perceptrons use binary values, by layering them on top of one another they can learn system behaviours. ANN are simple to implement and is used to predict a system output for any given input based on historical data of previous inputs and outputs.

Neural networks consist of three sections, see Fig. 7. Firstly, the input layer, where system inputs are received. These are then passed into the hidden layer, which has N-layers of neurons. Neurons in the first layer receive the normalised values from the input layer and compute an output which is passed to each of the neurons in the subsequent layer. Those neurons complete the same process as just mentioned until all layers have computed some output. The final values are fed to the output layer for an overall output prediction. If there are known errors in previous predictions, the ANN can adjust weightings associated with each layer to improve its performance, this is known as *backpropogation* [30].

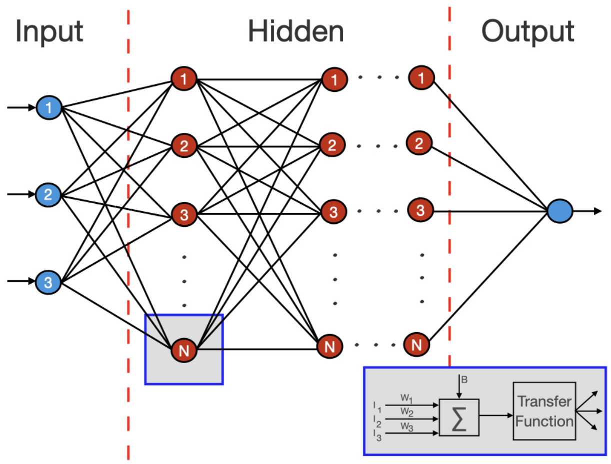


Fig. 7: Artificial Neural Network with multiple hidden layers. A representation of Eq. 1 is also shown.

$$y = tansig(B + \sum_{n=1}^{n} (I_n \times w_n)) \tag{1}$$

At an individual neuron equation calculated is shown in Eq. 1. $y$ is the neurons output, $B$ is a bias value, $I$ is the input and $w$ is the weight associated to the respective input. The product of inputs and weights is summed, then a bias value is added. This result is put into a transfer function such as $tansig()$ or $logsig()$, depending on the specifics of the desired algorithm.

To run the ANN algorithm, a large data set is required of measured input and output values. The data is divided into a training data set (majority of the data) and a validation data set (remaining data). The strength of ANN lies in the training algorithm, which decides the weights and the bias to apply to each neuron. The algorithm optimises the values of $w$ and $b$ for the data, using a mean square error or sum of errors in the process. Once the training has finished forming the model, the algorithm can predict the expected output values of a given input.

Occasionally, the ANN model focuses on smaller details present in the training set over the general trends of the input to output mapping. This is known as *overfitting* and to avoid this, validation data is used. The model is run using the inputs from the validation data, but the output values remain hidden. The model predicts outputs from the validation data that can be checked against the actual outputs from that data which had been hidden. If the there is a significant error in these predictions then it is likely that overfitting has occurred within the model, and the training should be redone.

### Support Vector Machines

SVM is an essential ML technique for data mining, and is used particularly for the classification of data points. SVM can be linear, an optimal hyperplane is identified that separates the data, or nonlinear, the data is first embedded in a nonlinear, higher dimensional state space before detecting the optimal hyperplane [31].

For linear SVM, a hyperplane is used to classify the data. The hyperplane is described by

$$\mathbf{wx} + b = 0$$

with vector **w** and constant parameter $b$. The *support vectors* are the boundaries of the hyperplane's margin - where the margin meets the data. There are two objectives with finding the optimal hyperplane parameters for the classification. The first is to minimise the labelling errors of the data, so data is not wrongly classified by the hyperplane. The second is to maximise the margin between the hyperplane and the data points. Linear SVM is easy to interpret, but has only limited value compared with nonlinear SVM.

Nonlinear SVM is useful for classifying data in a high dimensional data space. A larger set of features improves the classification algorithm. The SVM algorithm is improved by mapping the current data space to a nonlinear, higher dimensional data space. The nonlinear features add a new dimension to the feature space and building hyperplanes in this higher dimension make detecting separations easier. These separations can be mapped back to the original dimensional space, and reveal the optimal hyperplanes of that dimension. In essence, embedding the data in a higher dimensional space makes detecting data separations easier. The optimisation technique remains unchanged from that in linear SVM, the only difference is it is run in the new higher dimensional space.

### Genetic Algorithm

Parameter identification is a useful technique for when the control law of the system is known but the parameters are not. A useful meta-heuristic optimisation approach used for parameter optimisation is GA. The system is run and evolves over time. With each new generation, an improved set of parameters are identified. As the technique is based on evolutionary biology, the most optimal set of parameters in a generation can be called the fittest individual. An individual is a member of a generation, $k$, with parameter values chosen randomly. This parameter set is the individuals DNA, and described as a numeric sequence. The algorithm attempts to discover the system's optimal set of parameter values using *genetic rules*.

A cost function, a calculation of parameter selection error, is used to determine the fittest individuals of a generation. These individuals minimise the cost function relative to other individuals of their generation. Once a generation has been simulated, all individuals are ordered by cost function value. Relative to these values, the individuals are assigned a probability of selection for the next generation. A lower value will equate to a higher probability of being selected in generation, $k + 1$. Optionally, the top $x$ number of individuals can be immediately moved to $k+1$, with probability 1. This is known as *elitism*. Remaining individuals, those selected for generation $k + 1$ will undergo one of three genetic rules:

1. *Replication* - An individual is moved to generation $k + 1$ with no modifications.
2. *Crossover* - Two individuals swap a portion of their DNA before moving to generation $k + 1$.
3. *Mutation* - An individual's DNA is randomly modified before moving to generation $k + 1$.

Individuals from generation $k$ who were not selected are discarded. As the GA iterates through future generations, the fittest individuals should converge on the optimal parameters.

GA does not guarantee convergence on an optimal solution and the size of the population and the number of generations affect the algorithms performance However, GA is a useful technique since it does not require the iterations of a brute force algorithm and it scales to high dimension spaces.

## 6 Smart Homes/Buildings Management and Control Systems

### Introduction to H/BMS

An SHB is interconnected with its own generation source and a growing number of smart devices that consume energy. A system to manage and control these devices is essential. H/BMS is an intelligent, autonomous system that enforces efficient electricity use without compromising user comfort or preferences. For an H/BMS to be most effective, there are several functional and non-functional requirements that should be met [32].

Firstly, some SHB users have a fear of technology, they worry about loss of control and security implications. To encourage user participation, H/BMS is easy to deploy, and the interaction with users, the devices and the infrastructure all have low intrusiveness.

Secondly, H/BMS is suitable for settings such as large industrial buildings as well as residential homes. It is scalable with respect to devices but also increasing numbers of occupants and building zones. When new devices are added to the SHB, the H/BMS can extend to incorporate them and the system is interoperable so devices that use different software, or made by different manufacturers can communicate with one another.

H/BMS meets various functional requirements also. These fall under two main categories; 1) monitoring and control and 2) prediction and learning. For monitoring and control, the H/BMS is able to monitor energy consumption, and environmental conditions such as temperature and light. Sensors are also able to detect occupancy levels, and actions performed by the users. The H/BMS can interact with the user to optimise controlling the system and influencing the SHB environment.

As well as detecting the user behaviour, the H/BMS can begin to predict and learn the habits of appliances and users. The H/BMS can predict the energy consumption of appliances and also the effects of actuators when signalled to control the environment. Using these features, the H/BMS can reduce energy consumption while satisfying the user requirements on the system. Energy management is valuable as it reduces the energy costs of the SHB users.

## Centralised, Decentralised, and Distributed Frameworks for H/BMS

With the increase in smart devices and controllers embedded in SHBs, different frameworks have been developed to control an SHB as a single entity system. Traditionally any control aspects inside a building have been human operated and hardware based. For example, to control the temperature a user manually changes settings for the boilers or air conditioning units. Now with the benefits of IoT and smart devices this approach can be *centralised* or *distributed*.

In the centralised framework, control of the SHBs various systems (HVAC, lighting, energy storage, etc.) can be controlled from a central location. BMS provide either automated control techniques or an interface for users to control all building systems from a single location. This is beneficial to users for two reasons. Firstly, controlling all building systems from one location makes managing the systems easier. Secondly, the systems will pass their sensor data to a central controller which can analyse all building data collectively and choose the most optimal control actions to take. This will reduce economic costs of running the SHB by maximising energy efficiency. For the centralised controller to be effective it requires a powerful control algorithm. MPC is considered by many to be the optimal choice [33]. Additionally, hardware used for the controller must be able to process the large volumes of data that will be passed from all the sensors inside the SHB. As more and more sensors are added to buildings, choosing an optimal control action will take longer to calculate.

One solution to tackle the risk of overloading a centralised controller is the distributed control approach. The IoT has enabled sensors and devices to communicate with ease. By providing sensor devices with the processing power to make decisions, localised controllers distributed around an SHB can be formed which communicate with one another to collectively control an SHB. One suitable control technique is MAS, where each distributed controller would be treated as an agent in the system. The agents each have their own objectives to control the localised area they cover and can compete or coordinate with other agents to achieve a global SHB objectives defined by users for reducing SHB energy costs and optimising energy usage.

MPC can also be used in a distributed setting, where different MPC controllers are in charge of different building zones. In [34], centralised MPC is compared with a *decentralised* MPC approach and a distributed MPC approach. The significant difference between decentralised MPC and distributed MPC in this setting is that for distributed MPC the controllers can communicate directly with one another while for the purely decentralised approach they will act fully independently.

A hierarchical decentralised approach is not suitable for SHB systems. In a hierarchical decentralised approach localised controllers are in charge of the zones for a specific area and communicate and are directed by a central controller. The central controller is also used as a relay between different local controllers in order to satisfy the global SHB objectives. The reason this is not suitable as a control technique for the SHB is due to the relatively small size of SHBs. Even a relatively large building such as an office tower is likely to have only 200 kW of load that needs to be managed. Hierarchical decentralised control would instead be a suitable technique when considering a group of SHBs in a microgrid. An example is a university campus, an SHB can manage its own energy usage using a localised controller, and the collection can be managed by a central controller. For grid services the central controller can communicate with the SHBs so they share energy across the network.

## 7 Case Studies

We have now discussed in detail the components and architecture of cyber-physical SHB, in particular we discussed the different levels of control within the SHB. At the cyber layer basic controls are implemented which may apply to small SISO systems, while at higher layers supervisory controls such as MPC can apply to optimise the performance of the building as a whole.

In this section we will provide a case study demonstrating both of these control methods using an HVAC system. In an SHB the largest energy usage comes from the HVAC system. At the cyber layer we will consider a simple ON/OFF controller than is in charge of a single building zone and then afterward we will consider a seven zone SHB HVAC model where each zone has its own heat pump and an MPC scheme is used to accurately track a reference value in each room with disturbances.

### Modelling Aspects of Aggregation of Smart Homes/Buildings

Firstly, we will consider the scenario of a control device at the cyber layer which is in charge of one building zone or room. It would also be possible to consider this device as an edge node. The control device is simple and useful for an SISO model of a zone. The controller will receive the room temperature and then either switch the heating system ON or OFF depending on the current heating value. This forms a simple RBC strategy of the zone.

To define our single zone we will consider a grey-box model with 6 states; external wall temperatures: $T_{e1}$ and $T_{e2}$, internal wall temperatures $T_{AB}$ and $T_{AC}$, floor temperature $T_f$ and zone temperature: $T_A$. One input ($\dot{Q}_{HVAC}$) and seven disturbances; solar irradiance: $\dot{Q}_{sol,e}$, neighbouring zone temperatures: $T_B$ and $T_C$ (above the zone) and $T_D$, outside air temperature: $T_a$, ground temperature: $T_g$, and temperature gain from zone occupancy: $\dot{Q}_{gain}$.

We can describe the system using the following dynamic equations of a 3R2C building model where $C_x$, $R_x$, and $T_x$ are the capacitance, resistance and temperature of wall $x$. They are as follows:

$$
\begin{aligned}
C_{e1}\dot{T}_{e1}(t) &= \frac{T_a(t) - T_{e1}(t)}{R_{e1}} + \frac{T_{e2}(t) - T_{e1}(t)}{R_{e2}} + \dot{Q}_{sol,e}(t) \\
C_{e2}\dot{T}_{e2}(t) &= \frac{T_{e1}(t) - T_{e2}(t)}{R_{e2}} + \frac{T_A(t) - T_{e2}(t)}{R_{e3}} \\
C_{AB}\dot{T}_{AB}(t) &= \frac{T_B(t) - T_{AB}(t)}{R_{AB}} + \frac{T_A(t) - T_{AB}(t)}{R_{AB}} \\
C_{AD}\dot{T}_{AD}(t) &= \frac{T_D(t) - T_{AD}(t)}{R_{AD}} + \frac{T_A(t) - T_{AD}(t)}{R_{AD}} \\
C_f\dot{T}_f(t) &= \frac{T_g(t) - T_f(t)}{R_f} + \frac{T_A(t) - T_f(t)}{R_f} \\
C_A\dot{T}_A(t) &= \frac{T_{e2}(t) - T_A(t)}{R_{e3}} + \frac{T_{AB}(t) - T_A(t)}{R_{AB}} \\
&\quad + \frac{T_{AD}(t) - T_A(t)}{R_{AD}} + \frac{T_f(t) - T_A(t)}{R_f} + \frac{T_a(t) - T_A(t)}{R_{win}} \\
&\quad + \frac{T_C(t) - T_A(t)}{R_{ceil}} + \dot{Q}_{HVAC}(t) + \dot{Q}_{gain}(t)
\end{aligned} \tag{2}
$$

The temperature of the zone $T_A$ is what the controller uses to determine whether to turn the heating system on or off. For different periods of the day, the zone will experience varying levels of occupancy. For an SHB used as an office, the occupancy at night will be low compared with the occupancy during the day. For this reason a varying reference for temperature is useful. In this scenario we will consider a setpoint of $13°C$ when users are out of the building and $20°C$ when users are inside the building. The SHB is occupied from 9am until 6pm, but from 1-2pm the building is closed for lunch.

We treat surrounding temperatures as disturbances to our model, the outdoor temperature $T_a$ fluctuates from $-6°C$ to $8°C$. The neighbouring zones $T_B$, $T_C$ and $T_D$ are controlled at $16°C$, $14°C$ and $15°C$ respectively. The ground temperature is fixed at $2°C$ and there is heavy cloud cover so $\dot{Q}_{sol,e}$ is 0. Other constant values are found in Table 1.

The heat input that enters the system is calculated as:

$$\dot{Q}_{HVAC}(t) = m \times c_p \times (T_{supply}(t) - T_A(t))$$

Table 1: Values used for RBC control simulation.

| *Constant* | *Value* |
|---|---|
| $R_f, R_{ceil}$ | 4.38 |
| $R_{e1}, R_{e2}, R_{e3}$ | 0.084197 |
| $C_{e1}, C_{e2}$ | 9861100 |
| $R_{AB}, R_{AD}$ | 0.044014 |
| $C_{AB}, C_{AD}, C_f$ | 128560 |
| $CA$ | 100000 |

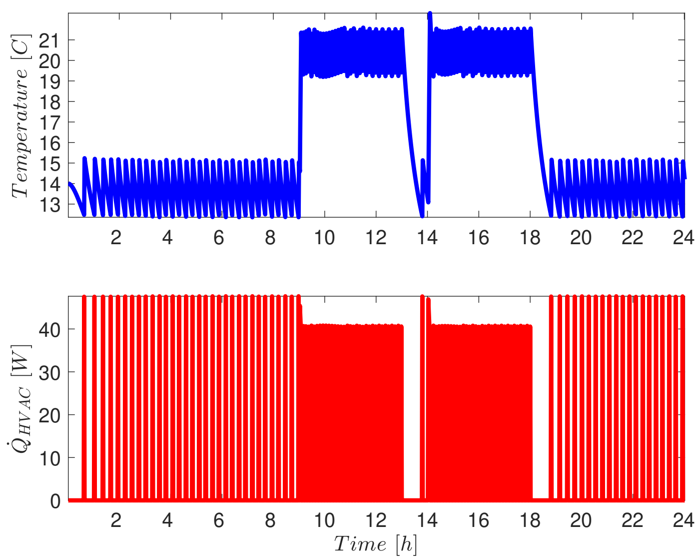


Fig. 8: RBC ON/OFF control of a single zone HVAC system.

where $m = 100$ is the mass of air in the zone (kg), $c_p = 1.005$ is the specific heat capacity of air (J/kg°$C$) and $T_{supply} = 60$ is the temperature of the supply air (°$C$).

We simulate the system for a period of 24 hours using the time step of 1 minute between measurements, as show in Fig. 8. The RBC controller uses a tolerance of $0 \pm 0.5°C$ around the reference. If the temperature is above the tolerance then the heater should be turned OFF, and if the temperature is below the tolerance then it should be turned ON. It is visible from the simulation that the heater fluctuates frequently between ON and OFF putting in a significant amount of work to track the reference. Additionally, it is noticeable that, although the mean zone temperature across an interval may remain at the desired reference, the temperature fluctuates between $19 - 22°C$ and $12.5 - 15°C$. This is a sizeable oscillation and may provide discomfort to users of the building zone. Although the control strategy is effective, it is not optimal as disturbances in the system are not minimised over time and for this other control techniques need to be implemented.

## Model Predictive Control to Provide User Comfort

Now we will try and attempt the same control but from a higher layer of the CPS architecture. At a higher level our control is able to consider the whole of the building and leverage dynamics as heat is exchanged between zones. In this way we consider an MBC approach. As the operator of the building we are also aware of some building features ahead of time and can use these to optimise our control strategy. In particular, the reference temperature for each hour of the day and in each zone is known ahead of time. Using an MPC strategy we can track this reference closely, and minimise the error when the reference point changes.

MPC is able to track a reference by predicting the building behaviour $N$ time steps in the future of current time step $t$. Using this prediction an optimal input can be selected for 1 time step ahead. The predicted values are then discarded and the process is repeated at time $t + 1$.

For this case, we consider a zone model as used for the single zone RBC control case. We then consider seven of these zones connected to one another across two floors of a building. Zones $A$, $B$ and $C$ are on the ground floor and zones $E$, $F$ and $G$ are on the first floor. Zone $D$ is a tall zone which is a member of both the ground floor and the first floor similar to a stairwell.

In this scenario we assume that we have a greater level of control over the heat transferred into each zone, compared with the single zone case where only a signal ON or OFF was used. The MPC controller in this scenario is also aware of all heat transfers between the different zones and so it can leverage heat being transferred from a neighbouring room in order to reduce the heat required from the HVAC system.

For this simulation we consider the same reference scenario to the single zone case, and consider this reference for all of the zones. We also consider a 24 hour time period with 1 minute measurements of the system. The disturbances used are random with a variance higher than that of a real-life scenario. In this way the control technique can be properly assessed. In Fig. 9, it can be seen that the MPC controller is able to closely track the reference for a single zone, it is also able to do this without turning ON and OFF the heating system nearly as regularly. Instead an approach of heating the zone with a high temperature and then reducing that heat is used. There is almost no fluctuating of temperature around reference value in this scenario so user comfort is unlikely to be compromised.

In Fig. 10, the complete MPC control of all seven zones can be seen. It is clear that depending on which zone is being controlled that different control inputs are necessary. This is due to the alignment of zones with their neighbours and the heat transfer occurring between the different zones. Overall it is clear that MPC provides optimal control to each zone, and that user comfort can be guaranteed.

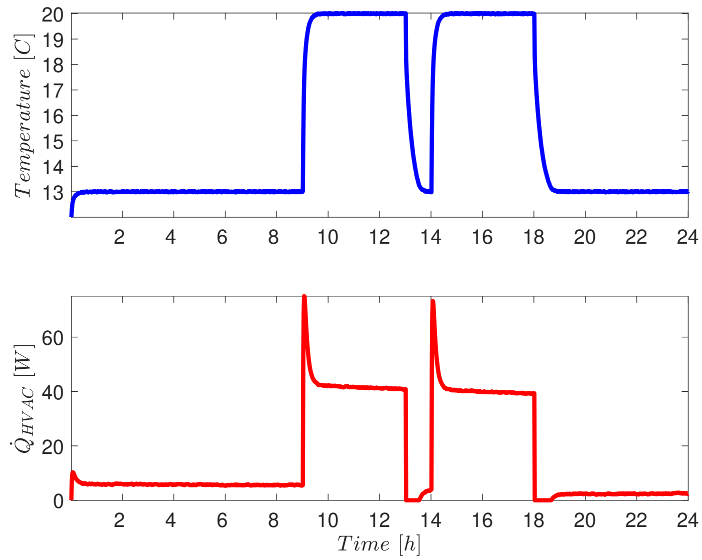


Fig. 9: MPC control of a single zone from the seven zone HVAC system.

One important point to note is that control under these constraints is perhaps too restrictive. In our model we only desire for the MPC model to track a reference value and no cost are associated to the energy usage. User comfort could still be guaranteed with a small deviation from this reference value. Therefore, future models can be created which incorporate energy costs to provide an optimal controller that both meets user comfort requirements and also attempts to schedule heating to satisfy heating cost constraints or even to achieve demand-side response to the wider smart grid.

## 8 Conclusion

To conclude, in this chapter we have discussed the concept of the SHB as a CPS. The CPS can be separated into a five level cyber architecture with both cyber and physical elements. Each of these elements can be modelled independently as well as being incorporated in larger models of systems which combine to form a cyber-physical SHB. Control devices can be used to maintain the well-being of SHB users, provide security to building assets and optimise the energy efficiency and costs involved with running such a building. To manage all the devices an H/BMS can be used which autonomously controls the different building components and interacts with users non-intrusively. We also provided a case study considering the HVAC system in the

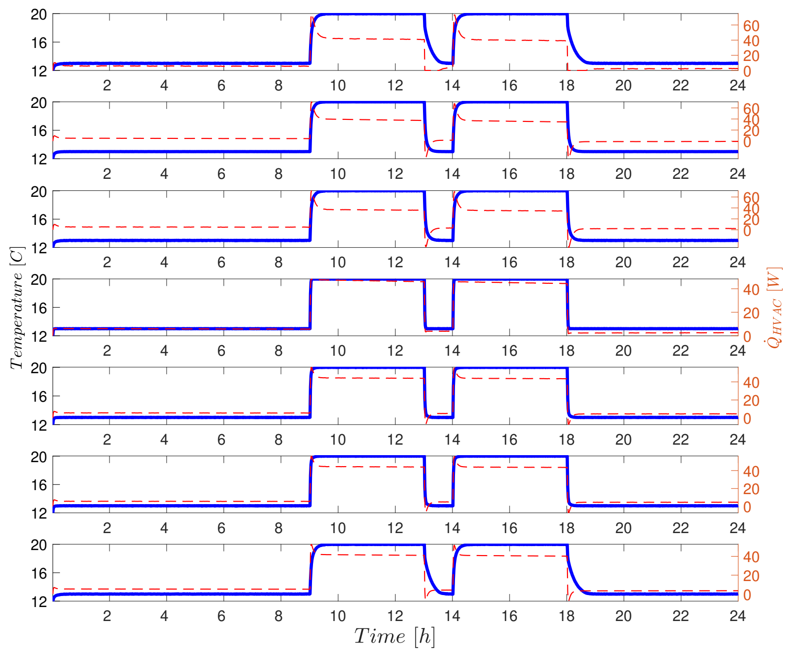


Fig. 10: MPC control of the seven zone HVAC system. The blue curve shows the zone temperature and the red dashed curve shows the HVAC input to the zone.

building for the control of a single zone and also for all the zones of a seven zone building considering reference tracking.

## Future Research Directions

There are a few future research direction to be considered after reading this chapter:

- From a security standpoint, different SHBs have different customer requirements and technical requirements depending on the assets contained within them. Having an established risk assessment process will allow an adequate degree of protection to valuable building assets or intellectual property. Without having such a process, SHB assessors may miss important technical requirements leading to high risk vulnerabilities in the SHBs.
- One challenge with building optimisation and control is that different users have different optimal references. Further research into solving competing user de-

mands and improving control to satisfy all individual user demands, is an interesting topic for future research.

- When optimising the control of a building there is a clear trade off required between factors. The most noticeable of these are cost and user comfort. However, other factors such as $CO_2$ emissions, air quality and demand-side response services are also important. These optimisation challenges make SHB designing difficult as the become bespoke and differ depending on the users, environment, location of the building, etc. Designing buildings that can adapt to different demands is a future topic necessary for the wider adoption of SHBs.

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