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Doctoral Dissertation

Design of Networked Control System using Distributed Wireless Sensors

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Abstract

Networked control systems have attracted a great attention in recent decades, and have been applicated in a wide range of areas. In a networked control system, the sensors, actuators and controllers are working in a separate manner in a network. By replacing the complex and burdensome wiring systems with wireless networks, the control system can achieve such benefits as flexibility, extended range, security and easier implementation.

However, it also creates new problems and challenges to adopt wireless networks in the control loops, especially in large scale systems. Due to the large number of devices, subsystems and the inter-communications between components, the control and feedback signals will greatly suffer the time delays in network, which decrease the control system's performance and even could destabilize the system. And the state estimation of the control target based on the data from the spatially distributed sensors, whose detection ability is always seriously restricted by the energy and communication constraints, over wireless networks is also an important but challenging task for stable networked control. Moreover, the dynamics of targets and the interactions between targets and distributed sensors are important for estimation and control, but they are always difficult to accurately modeled, because the scale and structure of networked control systems are always large and complicated. By addressing the three challenges above, this thesis focuses on effective control through networked control systems, and aims to provide a design of networked control system using distributed wireless sensors, and to applicate it in building energy consumption control.

The traditional centralized control strategy highly limits the system's stability and cannot handle large-scale systems due to the large time delays. To overcome such problem, the design and development of distributed networked control strategy are necessary. The thesis begins by designing a hierarchical distributed networked control system for large-scale power control system to realize demand and response in powe rgrid during peak hours. Plenty of sub-controllers are distributed in the proposed networked control system in charge of man-

aging the power balance in the local clusters. The sub-controllers are subject to local power consumption limits assigned from its upper layer. These form a series of local centralized control loops, whose scale can be maintained to be small enough to guarantee the local stable control. And a distributed control algorithm is also proposed, in which sub-controllers at higher layers determine appropriate local power consumption limits, which contributes to realizing the global objective of power reduction during peak hours. The numerical simulations with realistic parameters show that the proposed control network is scalable regardless of the size of the power system. Furthermore, a building-scale test-bed for power control system is implemented to confirm the effectiveness of the proposed scheme contributing to daily life power saving instead of high-cost planned blackouts.

Moreover, the fusion of observed data from spatially distributed sensors and the estimation based on them are important for stable networked control. To address such problem and further increase the efficiency of building energy usage in virtue of networked control systems, an LED lighting control system, which is based on user localization by using multiple distributed wireless battery-less binary human detection sensors, is also designed and implemented. To increase the accuracy of estimation of user location through the wireless network, a multiple-distributed-sensors-based user localization algorithm is proposed. And in the system, sensors can be flexibly located, e.g., as close to user as possible, by using a battery-less wireless sensor network, in which all sensors are activated by wireless power transmission and can be placed freely in the space with high energy stability. The lighting control is designed to reduce office lighting energy consumption and to satisfy user's illuminance requirement. And a verification experiment is conducted by measuring the practical illuminance and power consumption. Its results agree with design expectations. It shows that based on the estimation of user location, this LED lighting control system reduces the energy consumption significantly by 57% compared to batch control scheme without any loss of users illuminance requirement.

Proper models of system, such as sensing process and target dynamics, are also key factors for accurate state estimation and stable networked control. A recurrent neural network is designed to accurately represent how the target process and sensing processes evolve and interact with each other. It extracts the models from training data instead of theoretical and experiential assumptions. The performance analysis shows that both the performance of location estimation and lighting control gain a further increase in performance, compared to that using experiential models.

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Chapter 1

Introduction

In a networked control systems (NCS), all controllers, sensors and actuators work in a separate manner. The information of both control link and feedback link are transmitted through communication networks. The networked control system is a multidisciplinary field integrating control theory, information theory, wireless communication, computer science and physical plants in one system. The networked control system is a promising field, and has been widely used in many residential and industrial sectors, e.g., Smart Grids, building energy management system (BEMS), indoor navigation system, autopilot and manufacturing plants.

By using wireless networks, such as wireless sensors networks (WSNs), in control loops, networked control system can be applied for very large-scale systems in a distributed manner, e.g., the distributed energy control systems, which is difficult and even impossible to be stably controlled by the traditional one-to-one and one-to-many centralized control systems. By replacing the complex and burdensome wired networks with wireless networks, the systems can achieve benefits such as flexibility, extended range and easier implementation. However, it also creates new problems. This thesis aims to provide designs of networked control systems using distributed wireless sensors and their applications in building energy control. It focuses on the challenges for effective control through networked control systems mainly in three aspects: time delay of large-scale systems, state estimation based on distributed sensors and improvement of system dynamics models.

In the next section, the research backgrounds and motivations are discussed. And in the last of this chapter, the outlines of the thesis and the main contributions are given.

1.1 Background and Motivations

1.1.1 Wireless Technology in Control Systems

In order improve the life quality for people and improve the production efficiency for industry, many efforts have been made to look for the potential technological solutions. The advanced level of automations and more developed feedback control systems are two examples of such technological solutions for improvements.

With the development of high-performance, cost-effective and energy-effective wireless communication technologies, here comes a great opportunity to advance the automation and control to provide us more even further advantages.

For instance, in recent decades, the prices of communication equipments, sensors and actuators have a constantly decreasing trend thanks to the development of technologies in both theory and practice. Right now when the prices of such high-tech products drop lower than a certain affordable threshold, the cost of cables to build the wiring networks turns the standout among all costs. Moreover, wired connectors are not easy and convenient to wear and tear, and the failures of connector are also risks for the whole system. The use of advanced wireless communication technologies allows us to reduce or remove the burdensome cables, the costs and the risks of failures. It results in more efficient and reliable systems. Wireless technologies also allow devices to fast and reliably collect more information from the target physical processes. It becomes possible to sense what might not probably be able to sense in the past, or what might be not affordable to sense in the past. These more accurate and detailed information can be the key to obtain a better understanding of the state of the system for both targets and the properties of the system itself. This results in a higher performance feedback loop control.

The benefits of wireless communication technologies to control systems includes *flexibility, cost-effectiveness, security* and *reliability*.

Besides the merits of the conventional new advanced wireless communication technologies are expected to bring more unprecedented applications of networked control systems. On the other hand, here also comes new challenges. The following are some examples of such new wireless communication technologies.

- 5^{th} generation mobile networks (5G)

  In the 5G standardization, great efforts have been put on consistency and reduction of time delays in order to establish a wireless networked system in varieties of fields, such as industrial control, manufacturing, robot and wireless sensor networks [1]. By the communication with enhanced robustness against time delays and corresponding variations, 5G is even possible to support for applications that require the responding time at sub-millisecond level [2]. On the other hand, the radio shadowing in 60GHz may be a potential challenge, and needs for lower frequency band backup coverage, which may have worse delay performance [4].

- Internet of thins (IoT)

  The Internet of Things (IoT) envisions a world, in which through communication networks, e.g., Low Power Wide Area (LPWA) communication technologies, everything is connected. Electrical devices, software, sensors, and network connectivity are embedded into these large numbers of devices and are able to sense the state of the real world. This sensing information is especially valuable for many control systems, and provide us new prospects for the control application, such as, traffic control, environmental monitoring, and power management. But IoT systems are always highly spatially distributed and imposes control theoretic challenges, such as physical security, resilience, plugand-play sensors and algorithms, that we are unlikely to encounter in our usual application domains.[5]

1.1.2 Networked Control Systems

A networked control system can be described as a feedback control system in which the control link and feedback line are both through real-time communication networks, such as dedicated or shared networks, wired or wireless communication network. And all information exchanges among the controllers, sensors and actuators are through the communication network, as shown in Figure 1.1.

Exchanging information of control loop through the communication networks, which are always not dedicated communication systems and may be shared by numbers of sub-control systems and other individual systems, makes the design and analysis of networked control systems more complicated than the conventional control systems, because some basic assumptions in conventional control theory, e.g., perfect communication with zero time delay in control and feedback link, are not available anymore when wireless networks are introduced.

The networked control system is a multidisciplinary field including control theory, wire-

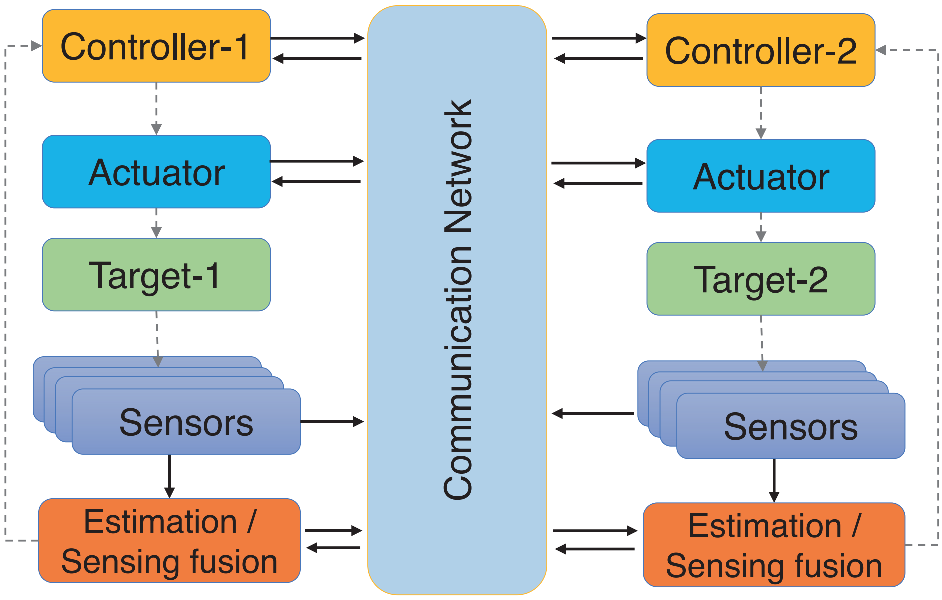


Figure 1.1 Networked control system

less communication, computer science, digital signal processing, automation and information theory. It well integrates all these advanced technologies together effectively and efficiently in one system. Therefore, networked control systems have many merits, such as low costs, less system complexity, decentralization of control, flexible implementation, easy maintenance, and scalability.

Through communication networks, networked control systems are able to combine and fuse the information from the large numbers of distributed sensing devices and to make decisions and operations over long physical distances. On the other hand, it also introduces new challenges. In the conventional control system, the control link and feedback link are all one-to-one or one-to-many connections, while in the networked control systems, because the information exchange are all through communication networks, the performance of control does not only depends on the control algorithm, but also highly related to the communication networks, such as time delays caused by communication networks which could be fixed or varying, distributed working manner of the system, and accurate state estimation by distributed sensors over communication networks.

The performance of a networked control system can be evaluated mainly by the following indices.

- *Reliability*:
  - Under the assumption that possible device failures drive a control system to an undesirable situation, failure-case performance, besides the normal-case performance, is taken into consideration.
  - Safety function against the assumed device failures is realized in redundancy existing in the normal-case control system. [26]
- *Stability*:

  The stability of a networked control system is often the most important metric to evaluate if the system is valid. Theoretically, a control system is stable, if the impulse response of the system approaches 0 when time approaches $+\infty$.
- *Scalability*:

  Generally, it is easier to design a small-scale networked control system than a large-scale system because of the delay caused by the network topology and constraint communication in the large-scale system. If a networked control system, which is on a very large scale, can still maintain the stable control of the target, it is a scalable control system. Obviously, it is necessary to co-design the control strategy and communication network in order to achieve the scalability.

In the following, a brief description of the some basic issues of interest concerning networked control system is given.

Constraint of time delays in networked control systems

Time delays are caused by communication networks, especially wireless communication networks, due to the large numbers of components in the system and the inter-communications among them. Time delays could decrease the control performance of the system and even may unstabilize the system. In the design and analysis of the networked control system, the assumption of zero-time-delay of information transmission in conventional control systems is not available anymore. Figure 1.2 shows varying time delays in both control link and feedback link of a networked control system. In it, the time delay in each transmission and reception process is time-varying. And in order to make sure of the message delivery, long period for each process is always left, which could further increase the system time delay.

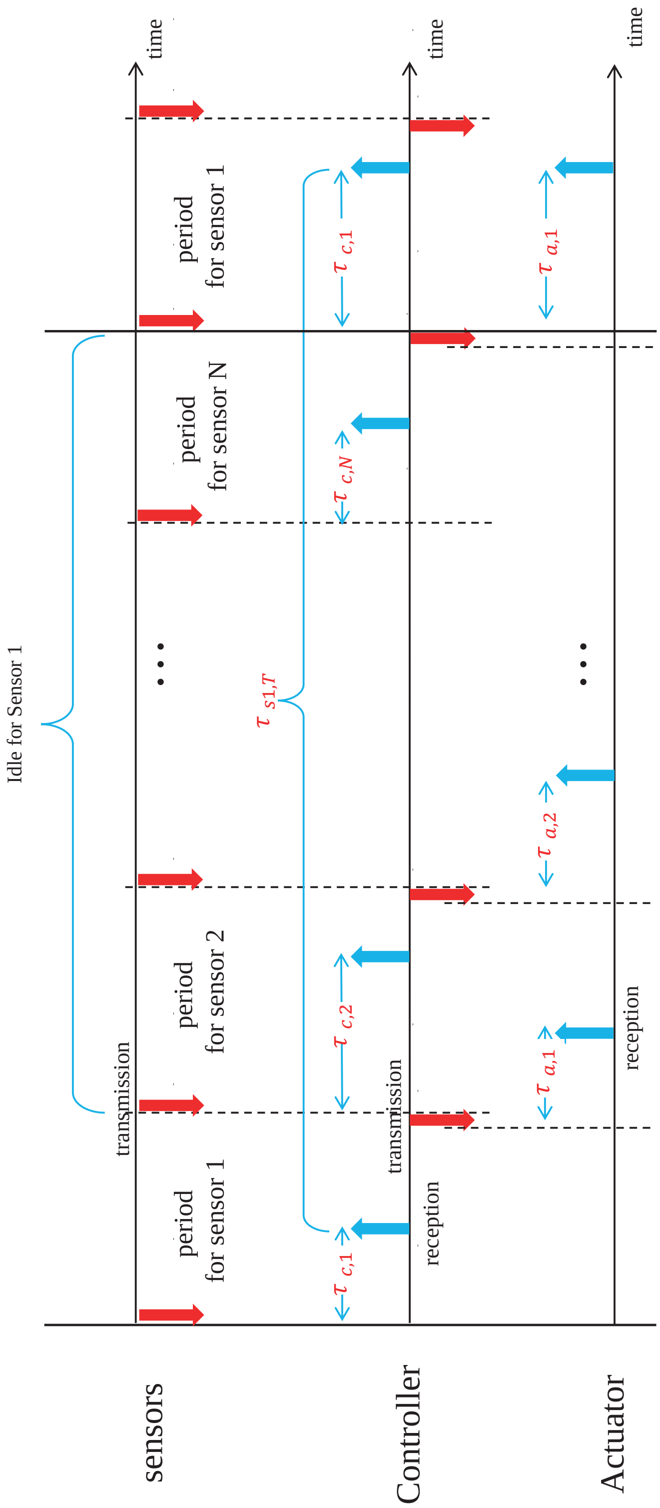


Figure 1.2 Time delays in networked control system.

For small-scale networked control systems, time delays can be made small and deterministic by good scheduling and giving some signals high priority, and in this case, the system can be treated as an ordinary deterministic time delay system. And time delays could be treated as a constant if the delay introduced by the network is less than the applications delay. But for large-scale systems, long time delays are always inevitable. Time delay affects the performance and the stability severely. The important factors which affect the time delay include the traffic amount of the network, the network scheduling, the network bandwidth and the message size. When designing the networked control system, time delays must be taken account into consideration. In the analysis of the stability of the networked control system, the time delay is usually modeled based on their statistics. A model which exactly characterizes the time delays of networks is difficult to obtain but generally, an acceptable model can be obtained.

Constraint of energy in networked control systems

Obviously, the performance of networked control systems greatly depends on the sensing observations from the spatially distributed autonomous nodes with sensing, communication and computation functionalities. The large numbers of sensors can be to be inexpensively and easily deployed in the target environment and have many advantages, such as flexible sensing scheme, high fault tolerance, and easy maintenance. However, all these benefits are achievable only if the employed sensors can highly efficiently use the available energy because they are always activated by batteries or they harvest energy from the surrounding environments. Basically, the approaches to increase the energy efficiency of sensors can be grouped into two categories: design of the energy-efficient control algorithm and design of the energy-efficient communication protocol.

Distributed networked control system

A networked control system can have one of the following structures as shown in Figure 1.3: centralized structure and hierarchical structure. In the centralized structure, the sensors directly transmit sensing data to the central controller, and the controller directly transmits the control commands to actuators through the communication network. The feedback link (transfer the sensing measurements from sensors to controllers), control link (transfer control commands from controllers to actuators), and the actuator network always share the same communication networks. It can highly reduce the complexity of the connections, especially by using wireless communication networks.[6]

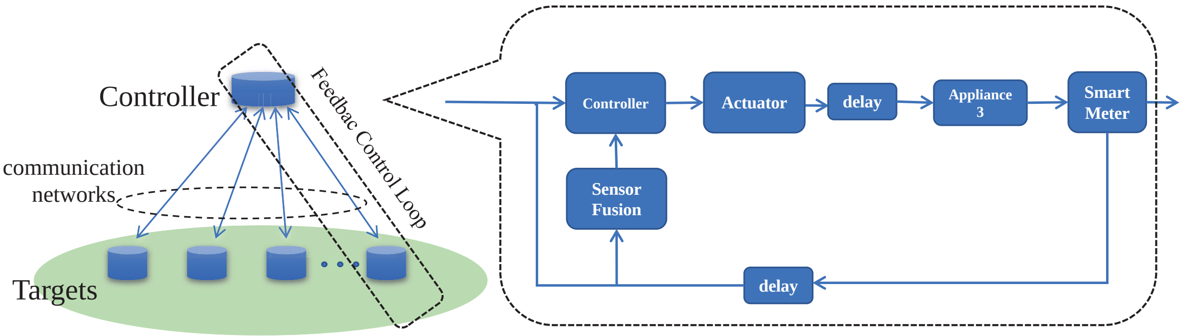
In the hierarchical structure, the whole system is divided into many layers and many subsystems in a hierarchical structure. Each subsystem is a complete feedback control loop, including sensors, actuators and controller. In this structure, the local controllers can communicate with the central controller and in some case communicate with each other. Coordinated by the central controller, sub-controllers in subsystems can achieve the global target by achieving their own local targets.

And because a large system, which contains a large number of components, is divided many subsystems, the scale of subsystems can be maintained to be a controllable size.

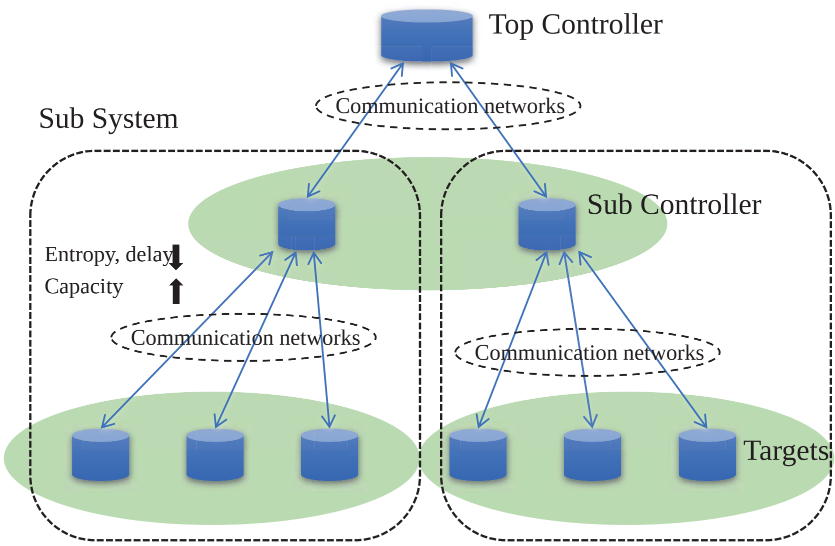
Target state estimation by distributed sensors

In a networked control system, there are always a series of distributed sensors deployed in the space. The large amount of data must be combined and fused to obtain the estimation, based on which the controller makes the control command. Therefore accurate estimation of target's state based on the measurement from distributed sensors is one of the determining factors on the performance of a networked control system. It is the process of combining sensing information from multiple distributed sensors pertaining to the same target, instead of the data from a single sensor. The reason for incorporating multiple information sources to collect information is that the aggregated data could be much more reliable (less noisy) and therefore can aid the controller in better understanding of the control targets under surveillance. Its objective is to produce a robust estimation of target's state for the controller to make decisions.

Rather than decisions toward hypothesis, when the estimation's objective is to compute numeric estimates of certain quantities (e.g., physical attributes like position and speed) from noisy observations, one of the most versatile estimation and fusion algorithms is the maximum likelihood estimation, which is a recursive linear estimator. Based on observations of the physical process, it calculates and update the estimation of the continuous states successively. An explicit statistical model of how the parameter to be estimated evolves across time (target model) and an explicit statistical model of how the observations are made (sensing model) are necessary.



(a) Centralized control.



(b) Distributed control

Figure 1.3 Structure of control

1.2 Motivated Applications

1.2.1 Networked Control for Energy Control

The energy control system is one of the best examples of the applications of very large-scale networked control systems.

Energy shortage is a worldwide problem, including Japan. For example, after the terrible earthquake and tsunami which hit the Tohoku areas in Japan on 11th of March 2011, Japan faced a serious shortage of power supply especially in Tokyo area. As a result, the load power consumed during peak hours was reduced by 10% to 15% as stated by the government. To avoid tremendous power blackout over the whole area due to power overload, area-by-area planned blackouts were conducted in Tokyo in 2011 and are planned to be conducted again in Osaka and some areas of Japan in 2012. However, the cost of such planned blackouts on our daily life and business is prohibitive, and in a long term, more radical solutions on this power saving issue should be more considered.

Network control system can be applied to solve the energy problems by its the capability of handling very large-scale systems, such as power systems, through communication networks. In such a networked control system for energy control and energy saving, the communication network should connect to the great number of the electrical appliances, in order to obtain power supply information about power consumption at the consumer side by using such sensors like devices called smart meter, and send control commands to each appliance to perform energy-saving operations.

The communication architecture of overlarge-scaled power control network such as Smart Grid is still an open problem. The first and the most major problem is how to guarantee the stability of the whole control system. As discussed above, in the small-scale control system, the time delay is small and the stability of the control system can be achieved simply. However, the time delay becomes considerably long in the transmission between the central controller and the large number of geographically distributed sensors and actuators in power control network, which can make the control system become unstable. The second problem is that the communication protocols standardized for Smart Grid, such as IEEE802.15.4/4g, are not subject to support control function but to achieve low-energy low-rate data network. For this reason, if the communication architecture is designed only base on the view of communication specifications, the control stability problem cannot be avoided. In the other words, the design of communication architecture for control network should be based on the view of both communication theory and control theory to realize the stable power control. However, to our best knowledge, the sophisticated design of such kind of communication architecture is not yet established.

1.2.2 Indoor Localization Systems by Multiple Sensor Fusion for Networked Control

Location and trajectory information of the control target are necessary for many indoor localized tasks of networked control systems, such as medical care, environment monitoring, guiding, robots, building energy management and so on. There are several kinds of solutions, such as radio-based and sensor based schemes, of which here we are interested in the sensor-based solutions.

In order to get accurate information of the target, multiple sensors, such as infrared sensors and ultrasonic sensors, are always spatially distributed in the target spaces. It is a challenging issue to accurately estimate or even predict target's position, since the localization information is obtained from sensors subject to detection errors which in some cases are very large. If this fact is not taken into account, it could lead to great uncertainty and incorrect estimation while performing the localization process, and result in wrong control decisions.

In order to improve the accuracy of the location estimation prediction, these different measurements from sensors must be well combined by appropriate algorithm which takes into account the different accuracy and noise levels of each sensor.[16–19]

1.3 Related Works

1.3.1 Distributed Networked Control for Power Control

Introducing communication networks to control system brings many benefits, but it introduces delays which are quite large and may unstabilize the control system. Hence, in order to achieve stable and effective control, the networked control system has to always take the delay as one of the key factors into its design and combine the control and communication networks together. In [7], the authors addressed analysis and implementation of a distributed control system on a network of communicating control unit via control system analysis in terms of sampling times and delays, mapping of control loops to computation/communication hardware components and scheduling analysis. And in [8–10], the goal was again to estimate suitable choices of scheduler periods or priorities with the aim of improving control performance. In [11], least squared (LS) error is used to adjust the estimate of the unknown time delays. In [12], for the optimization of the performance criterion, a feedback-feedforward loop was used to adjust the sampling period and delay. In [13], the authors adopted a control server to ease the latency, and different strategies, such as a feedback loop for sampling times, were also used to minimize jitter. In [14], the authors transformed the original control system into a mixed integer quadratic programming problem to achieve optimal control. In [15], the schedule is derived with an iterative procedure.

Large-scale power control system is a great application of networked control systems. In [36, 37], a theoretical bound of maximal allowable delay or minimum rate of communication was derived to guarantee stable control via a point to point communication network, but there was no discussion about designing of a point to multi-point network which can be applied for large-scale systems such as Smart Grid. Authors in [38] proposed how to design a smart message authentication system to reduce control delay time during peak hours, however, the DR was not included. On the other hand, [32] evaluated the performance of DR restricted in a small-scale Home Energy Management System, or commercially called home gateway, with negligible delay. However, delay becomes the most critical parameter in realizing stable control in large-scale feedback systems like Smart Grid. Implementing a simple star-typed centralized architecture consisting of a central controller and multiple sensors and actuators, since feedback delay increases with respect to the size of the network, leads to an unstable control as reported in [39, 40]. In addition, coverage of the network becomes limited in the case of wireless access in the centralized architecture. Although multi-hop architecture [41] can solve the problem of restricted coverage, it worsens feedback performance due to packet relay. Therefore, instead of the centralized control architecture, a distributed architecture with multiple controllers is a reasonable solution for large-scale networks. However, to the best of our knowledge its design criteria are not yet established.

1.3.2 Networked Luminance Control Based on User State Estimation

Building energy management system (BEMS) integrates both wireless communication network and real-time feedback control. The lighting networking control system for power saving in BEMS attracts our interests in this thesis. User occupancy is one of the key factors of an energy-efficient lighting control system [53]. In conventional occupancy-based batch lighting control systems, when the presence of any user is detected in an area, a controller switches all or several corresponding lights on, and when the absence is detected for a given delay period, it switches off the lights. Experimental study shows that in such system 20-26% energy can be saved compared with manual switching [54]. Occupancy sensors have been used for detecting user's presence or absence. In [55–57], user occupancy or position is detected using infrared sensors by dividing the space into partitions according to sensor coverages and then differentiating the single triggered sensor or the set of triggered sensors. In [58], multiple infrared sensors are integrated as a sensor node to increase the detection capacities. Ultrasonic sensors [59, 60], RFID [61] and surveillance cameras [62] are also employed to obtain more accurate information of user's occupancy.

1.3.3 System Dynamical Model for Networked Control by Neural Networks

The deep learning such as convolutional networks have gained lots of great successes in numbers of recognition and classification tasks, such as object recognition in computer science and nature language processing.[88, 90] It has much larger numbers of hidden layers, neurons and features than those of the conventional neural networks. By using these features, it can solve large and complex problems, which could be impossible to complete by conventional neural networks in the past. Recently, some efforts have been made to apply machine learning in some control systems, in which the system dynamics is difficult to be modeled by a theoretical model and the control strategy is hard to design by convolutional methods.

Some usages of multilayer perceptrons in control are explored, e.g., in [89], however, such methods is always used small controllers and only for simple tasks. Early experiments with neural network control represented both the system dynamics and policy as neural networks, so that the gradient of the policy could be propagated backward in time [89, 90]. However, this direct optimization approach may generate very unstable gradients, and is always unsuitable for learning the complex and detailed behaviors. More recent reinforcement learning methods instead attempt to improve the policy by using sample rollouts on the actual system, which avoids the need to propagate gradients through time [91] .However, such methods are still susceptible to local optima, and only work simple and linear policies with good performance.

Hence, rather than learning the whole control system, currently it is a good choice that the machine learning algorithm is only used to model the system dynamics and the controller still follow conventional mathematical way. In essence, system dynamics, including the targets dynamics and sensing model, are spatio-temporal sequences, which can be considered as a black-box with the sequence of past states and observations as input and the sequence of future states as output.

The development in deep learning, especially recurrent neural network (RNN), give some useful insights on how to tackle this problem. In [89], RNN is used to predict next frame in the video and gives good results. Let's recall the indoor localization and lighting control problem. Obviously, except for the temporal relation, the spatial correlation also must be taken into consideration. Hence convolutional layer should also be introduced to model the system dynamics.

Hand-designing networked control systems for some of the tasks with difficult system dynamics is very challenging and difficult to achieve high control performance, because the estimation and prediction of target state cannot be accurately performed due to the lake of system dynamical models and consequently the controller cannot make control commands performing best influence on the control target. However, these issues may be addressed by viewing the problem from the machine learning perspective. The deep learning such as convolutional networks have gained lots of great successes in numbers of recognition and classification tasks, such as object recognition in computer science and nature language processing.[88, 90] It has much larger numbers of hidden layers, neurons and features than those of the conventional neural networks. By using these features, it can solve large and complex problems, which could be impossible to complete by conventional neural networks in the past. Recently, some attempts have been made to apply machine learning in some control systems, in which the system dynamics is difficult to be modeled by theoretical models and the control strategy is hard to design by convolutional methods. Some usages of multilayer perceptrons in control are explored, e.g., in [89], however, such methods is always used small controllers and only for simple tasks. Some research tries to use neural network control to reproduce the system dynamics and control policy [89, 90]. However, this kind of direct optimization approach could always generate very unstable gradients, and is always unsuitable for learning the complex and detailed control policies. Some reinforcement learning algorithms are used to improve the control strategies in the control systems, which try to avoid the gradients propagation [91]. However, such methods are still easy to be disturbed by to local optimization instead of the global optimization. Moreover, they show the effectiveness only in simple and linear control strategies. The development in deep learning, especially recurrent neural network (RNN), give some useful insights on how to tackle this problem. In [89], RNN is used to predict the next frame based on current and previous frames in the video and gives good results.

1.4 Outline and Contributions of Thesis

As discussed above, networked control systems have attracted a great research attention in recent decades and been applied in a wide range of areas. In a networked control system, the sensors, actuators and controllers work in a separate manner in networks. By using wireless networks in control loops, the systems can achieve benefits such as flexibility, extended range and easier implementation. However, it also creates new problems. This thesis aims to provide designs of networked control systems using distributed wireless sensors and their applications in building energy control. It focuses on the challenges for effective control through networked control systems mainly in three aspects: time delay of large-scale systems, state estimation based on distributed sensors and improvement of system dynamics models. And the applications of networked control system in energy control are also studied and implemented to evaluate the performance of the designed networked control systems. The outline and contributions of this thesis is described as follows:

- This thesis is briefly introduced by Chapter 1 in its background, motivation, and main contributions. The chapter serves a preparation and overview to the whole thesis.
- In Chapter 2, the conception of networked control systems and estimation by distributed sensors over wireless networks, which is the theoretical background of this thesis, are given. And specifically, two wireless communication network structures for the implementation of networked control systems are introduced. They will be employed in the application of the design in Chapter 3 and Chapter 4.
- The traditional centralized control strategy cannot handle large-scale systems due to time delays caused by the large number of subsystems and the inter-communications. To overcome such problems, in Chapter 3, the thesis begins by designing a hierarchical distributed networked control system for large-scale power control system to realize demand response during peak hours. Not only the numerical simulation is done, we also practically build a testbed hardware to evaluate the effectiveness of it. The testbed is a

completed scenario where wireless communication network, control server and actuator networks are all involved. And both of the numerical simulations and experiments both show that stable control for power saving can be archived regardless of the size of the power system.

- And the state estimation based on the sensing data from distributed sensors over wireless networks is also important for effective controls. In Chapter 4, an LED light networked control system, which is based on user localization by using multiple distributed wireless battery-less binary human detection sensors, is designed and practically implemented in order to further increase the efficiency of building energy usage in virtue of networked control system and distributed sensors. Results of experiment in the real office environment prove the effectiveness of control that 57% energy can be saved without loss of any user satisfaction.

- Proper dynamical models of systems, such as sensing process and target dynamics, are also key factors for accurate state estimation and stable networked control. In Chapter 5, a recurrent neural network is designed to accurately capture system dynamics from training data instead of theoretical assumptions. Performance analysis shows that both the performance of location estimation and lighting control gain a further increase compare to using experiential models.

- Finally, Chapter 6 concludes the thesis.

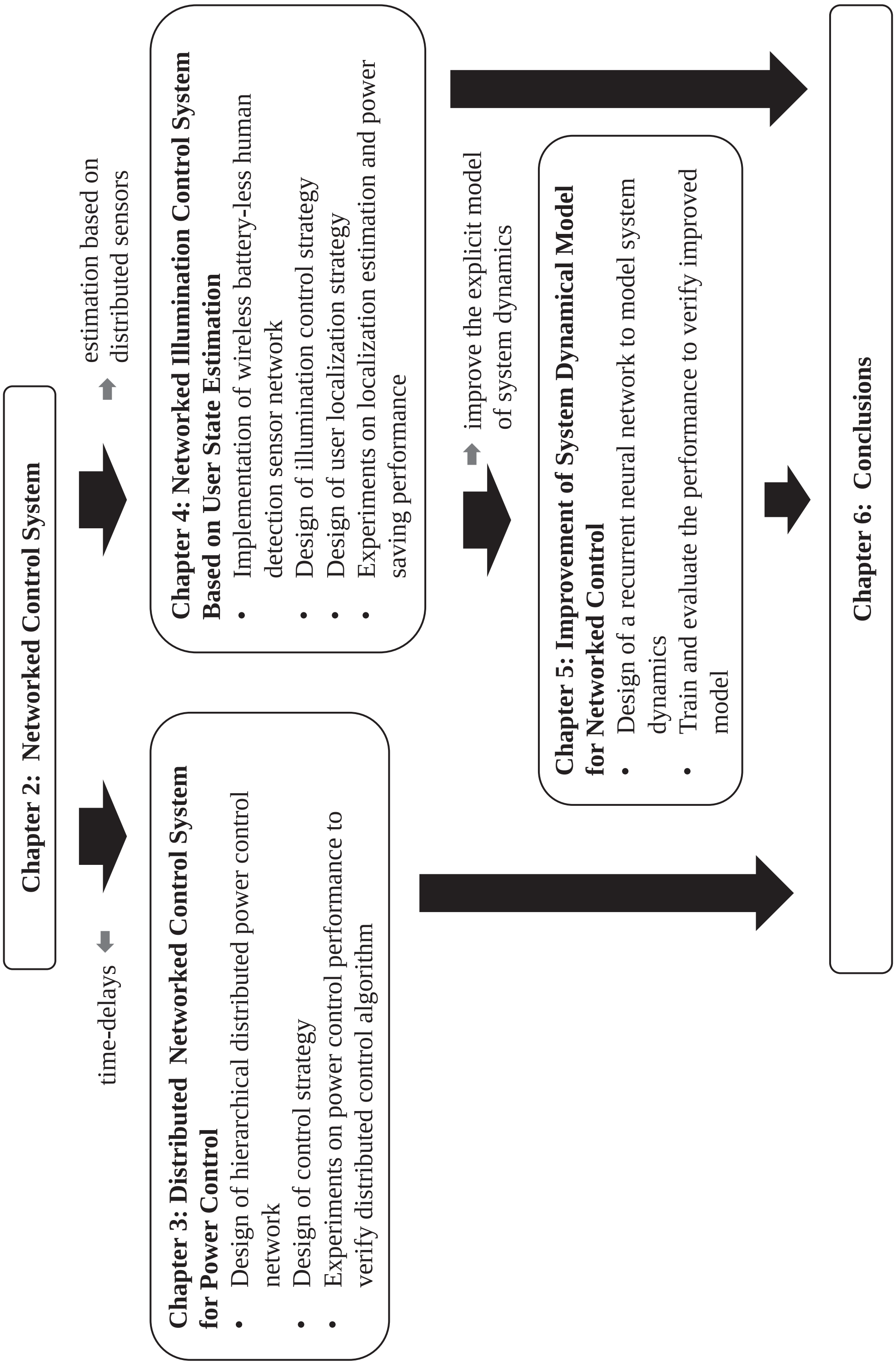


Figure 1.4 Thesis structure.

The results of Chapter 3 are published in

- K. Sakaguchi, V.K. Nguyen, T. Yu, G.K. Tran, K. Araki, Distributed Power Control Network and Green Building Test-Bed for Demand Response in Smart Grid, IEICE Trans. Fund., VOL.E96-A, NO.5 MAY 2013.

The results of Chapter 4 are published in

- T. Yu, Y. Kuki, G. Matsushita, D. Maehara, S. Sampei, K. Sakaguchi, Design and implementation of lighting control system using battery-less wireless human detectionăsensor networks, IEICE Trans. Comm., Vol.E100-B, No.6,Jun 2017.
- T. Yu, Y. Kuki, G. Matsushita, D. Maehara, S. Sampei, K. Sakaguchi, Deployment of LED light control system using battery-less wireless human detection sensor networks, RFID-TA 2015, IEEE, 2015.

The results of Chapter 5 are under submission.

Chapter 2

Networked Control System

In this chapter, basic concepts and some theoretical background which are needed in later chapters are introduced and described. First, an introduction to feedback control systems with emphasis on distributed control system is given. Next, the concept of estimation by distributed sensors for networked control is introduced. In the last, specifically, two communication network structures of wireless networks for networked control system are introduced.

2.1 Distributed Control over Wireless Networks

2.1.1 Classic Single Controller Model

Figure. 2.1 shows the model of a classic single control system. A control system generally comprises a controller, an actuator, a control target and an optional sensor. Here, the actuator has to adjust the control target following the commands from the controller, and meanwhile, the sensor sends the feedback of the state of the control target to the controller for the next

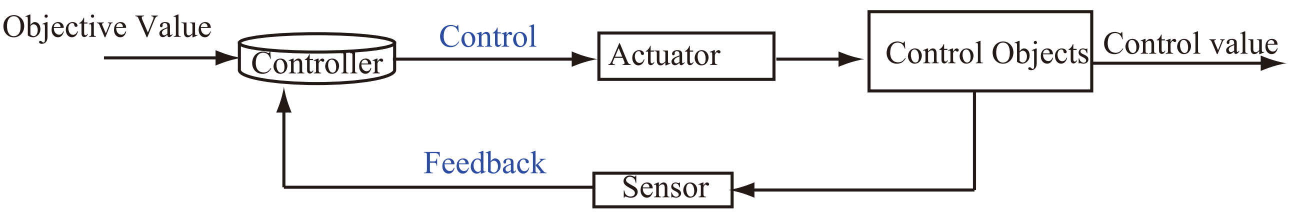


Figure 2.1 Feedback control loop single controller model

processing step. The mission of the control system is to adjust the control value (output of control target) to the desired objective value (input of controller). If the difference between the control value and the objective value is constantly kept smaller than a specific amount, the control is effective and the control system is stable. In contrast, if the control value is varying so differently from the objective value, the control system is said to be unstable.

2.1.2 Feedback Loop Control System

Control systems are divided into 2 main groups: open-loop control system and feedback loop control system.

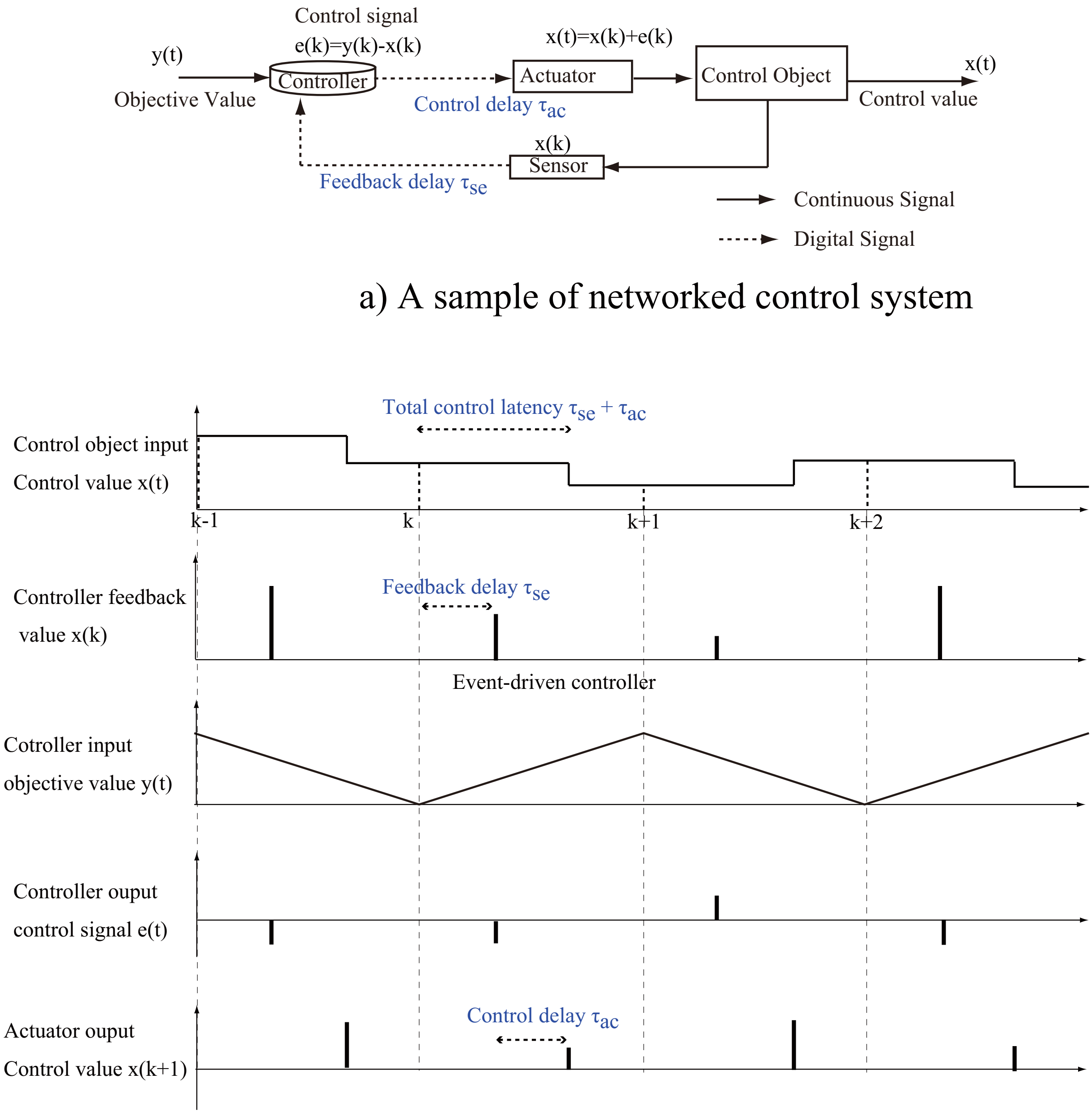
- *open-loop control system*: when no status information of control object is feedback to the controller, the output of control object only depends on the input value of controller. If there is any uncertain factor affecting the control object, it is difficult for the controller to keep the system under desirable control.

- *feedback loop control system*: when status information of control object is feedback to the controller through sensors. the output of control object depends on both the input value of controller and the last output value of control object. Since the knowledge of uncertain factor is included in the feedback, it is possible for the controller to keep the system under desirable control.

Because of uncertain factors such as noise, power spark, etc., the feedback loop control is quite necessary for real control systems.

2.1.3 Latency in Networked Control System

Thanks to the recent advance of communication technology, the control system can be implemented via networks, where controllers, sensors, actuators and objects are all connected to the network as nodes. This kind of control system is called networked control system. One example is the Smart Grid, which can be seen as a very large-scale networked control system. However, the network inherently induced time delay that occurs in the inter-communication between devices connected to the shared communicating medium. This inevitable network delay, called control time delay in common, can critically degrade the control performance and even unstabilize the control systems which are designed without consideration of it.



b) Timing of event-driven control

Figure 2.2 Control latency problem in network control system

To illustrate the effect of time delay on control performance, a simple network control system for linear position feedback loop control is introduced as in Fig, 2.2 (a).

The model consists of a object with continuous output $x(t)$ and a controller with varying objective value $y(t)$. At the control object side, there is a clock-driven sensor which sample the continuous output periodically at sampling instants k. The sampling value $x(k)$ is sent to event-driven controller to calculate control signal of $e(k) = y(k) - x(k)$ as soon as sampling value comes. An event-driven actuator change the control value of control object $x(t) = x(k) + e(k)$ as soon as the control signal comes. Two main network delays are considered in this case: the r_{se} sensor-controller delay r_se, the delay τ_ac between controller-actuator delay τ_{ac}. As illustrated in Fig, 2.2 (b) the controller cannot adjust the value $x(t)$ to the same as the varying $y(t)$ due to these network delays.

There are two main directions in approaching the control delay problem. One approach is to design the desirable control system without regarding any delay and then design an appropriate communication network that minimizes delay as much as possible. However, to set up a communication infrastructure with small delays, the cost is extremely high for large-scale systems. The other approach is to design better control strategies that minimize the effect of the delay induced from the existing control network. This approach is suitable for control system like Smart Grid where the existing communication infrastructure can be employed with a low cost of modification. In this approach, the typical distributed control strategy will be explained in the next section.

2.1.4 Distributed Control Algorithm

Distributed control strategy is a combination of algorithms designed to run on distributed systems where many processes cooperate by solving parts of a general objective in parallel. For this purpose, it is necessary to design a cooperative control algorithm for each distributed system in order to operate solely with minimal knowledge of other parts of the system. Thus, distributed control algorithms are suitable for the systems where the network architecture is complicated and the network resources are limited.

Distributed Cooperative Optimization can be used to address the time delays in networked control systems. For a group of multi-agents, the individual agent only uses the limited information exchanged from the local agent around to make decisions in order to satisfy the group's objective. It is also called multi-agent optimization problem.

The block diagram of distributed control compared to centralized single control is plotted

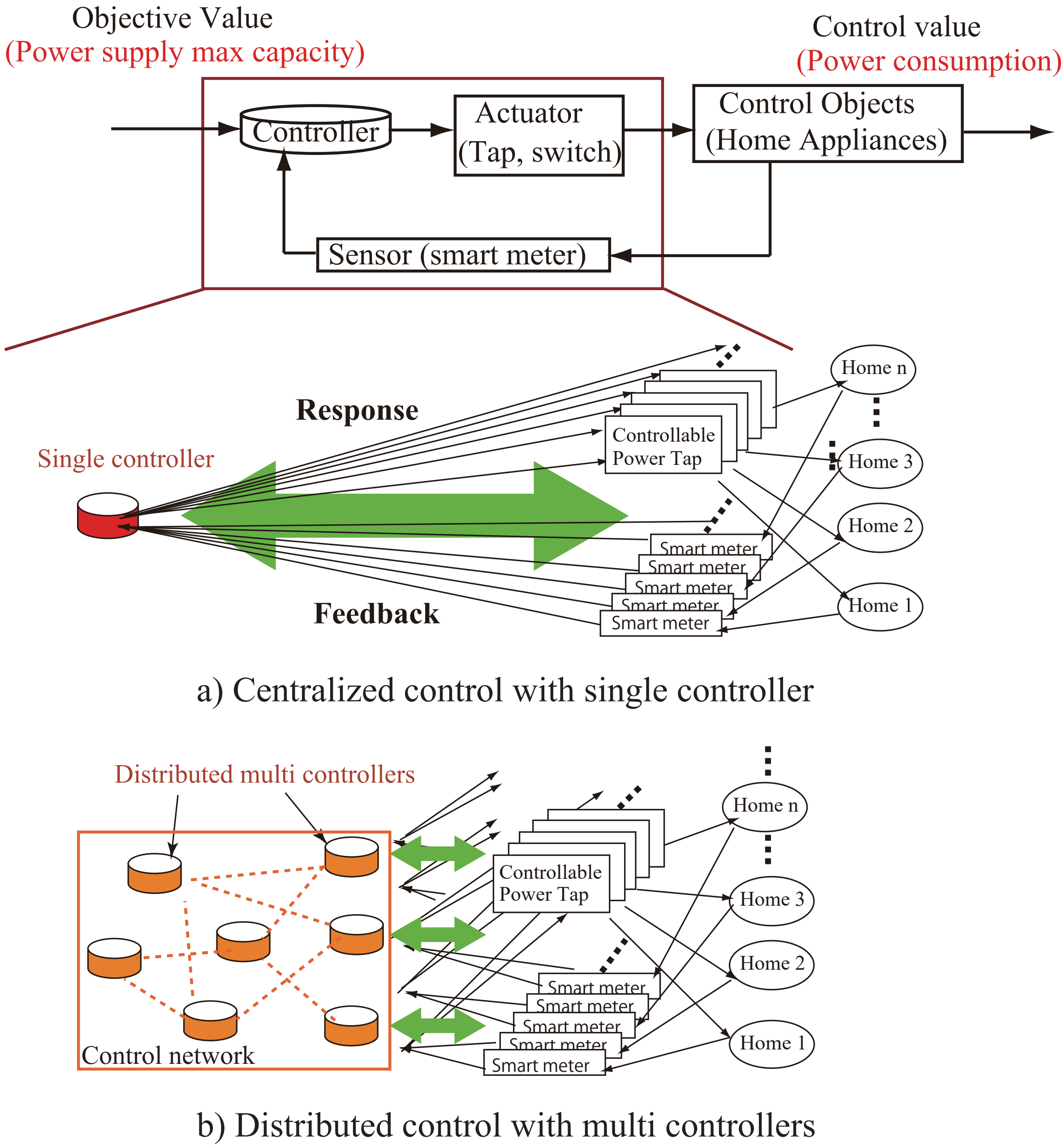


Figure 2.3 Block diagram of distributed control vs centralized control

in Fig. 2.3 below. Instead of a single controller, a combination of distributed multi-controllers forms big control network to control multi-objects cooperatively and in parallel.

In Chapter 3, we design a hierarchical distributed control network for Smart Grid, and it will be explained in details in the chapter.

2.2 Estimation by Distributed Sensors for Networked Control System

2.2.1 Basic Conception of Estimation over Networks

Accurate estimation and prediction of the state of control target are essential for a control system. Fundamentally, an estimator is a decision rule which takes as an argument a sequence of sensing data and whose action is to compute the state of the target. We obtain a lot of sensing data from a group of sensors and using this information we wish to find some estimate of the true state of the target.

In any estimation problem, there is a certain target process with the unknown state. It is always impossible to find a single source with perfect and complete knowledge about the target process. In most cases, such information must be obtained indirectly from sources which provide imperfect and incomplete knowledge.

The estimation problem studied in this thesis involve multiple sensors which can get sensing measurement or observations about the target, and transmit a pre-processed version of the observation to the controller where data aggregation and estimation are done. The objective of estimation by multiple sensors is to combine the received data in an optimal or sub-optimal form so that a reliable and informed estimation of the real state can be made. And based on such estimation, the controller will make the control decisions.

Consider a set of sensors physically distributed in a space. In a centralized estimator, the raw sensor data are transmitted to a central estimator which perform the estimation. Figure 2.4 shows the basic scheme for a centralized estimator.

In this scheme, the N sensors do not perform any significant data pre-processing. They send forward their raw sensing data to the central estimator, which then combines the incoming data to produce a global estimation. A distinct alternative is a distributed estimator, where each sensor has an associated local processor which can extract useful information from the raw sensor data before communication. The pre-processed local sensing data is then sent

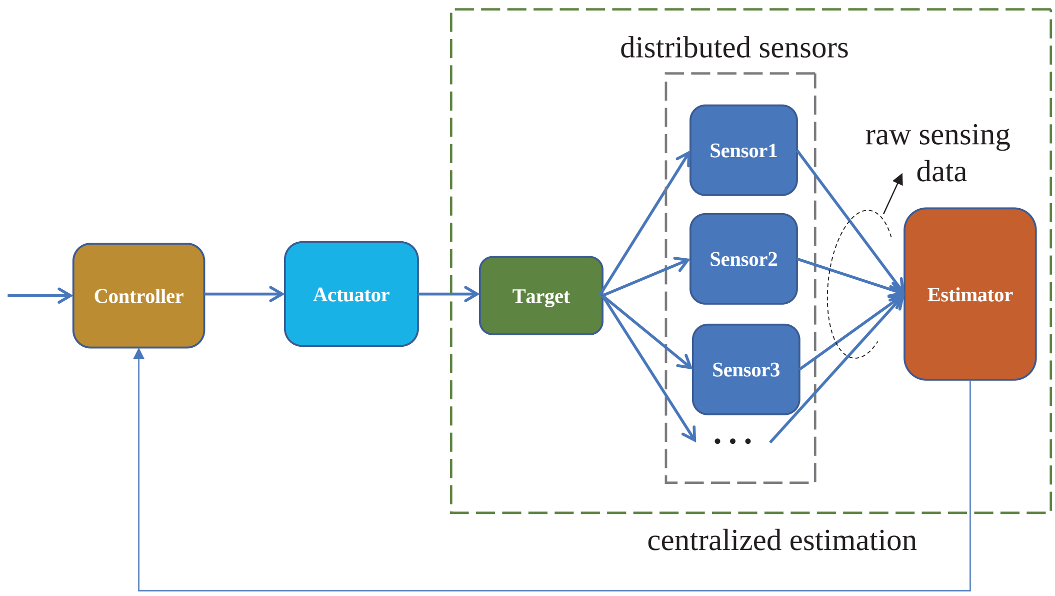


Figure 2.4 Centralized estimator for networked control system

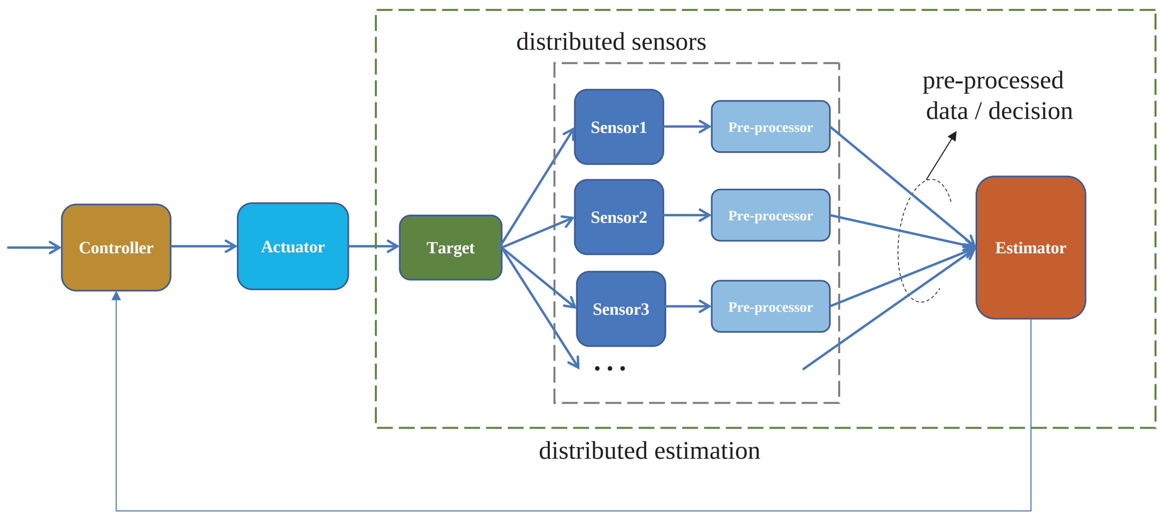


Figure 2.5 Distributed estimator for networked control system

to the estimator which then makes an estimation based on the received pre-processed sensing data.

The move to more distributed, autonomous, organizations is clear in many information processing systems. This is most often motivated by two main considerations:

- The desire to make the system more modular and flexible.

- A recognition that a centralized structure imposes unacceptable overheads on communication and central computation, especially for very large-scale systems, such as power control systems.

In a distributed estimation scheme by multiple sensors, as shown in Figure 2.5, the intermediate local pre-processors can make pre-process the sensing data or make some local estimations, and then transmit these results to the central estimator for information combination and estimation.

However, the intermediate sensing data pre-processing will lead to information loss. Hence even though the distributed scheme is modular, easier to implement and has much less communication bandwidth requirements, it almost always has suboptimal performance compared to a centralized architecture where the estimator works with all available information. We are facing a tradeoff between estimation performance and the required information storage, communication and processing required to achieve this performance.

For accurate estimation, sensor models are required to understand what information is provided, and target dynamical models are required to relate sensing observations to the parameters or states to be estimated. Some concept of information value is needed to judge the performance of the estimator. In other words, the estimation problem is central in linking the real world as observed by a sensor to the decisions we make about how to control or influence our target. In Chapter 5, a recurrent neural network is designed to obtain accurate dynamical models of the system. It will be explained in detail in the chapter.

2.2.2 Estimation by Distributed Sensors using Likelihood

Accurate estimation of target state based on the observations from the multiple distributed sensors is a challenging task. It is possible to relates the sensor observations to state hidden behind the really physical process, thanks to Bayesian statistics.

For the formulation of the estimation by distributed sensors, we assume the state-space in the following form:

$$
\begin{aligned}
\boldsymbol{u_t} &= h(\boldsymbol{u_{t-1}}, \boldsymbol{n_p}) \\
\boldsymbol{b_t} &= g(\boldsymbol{u_t}, \boldsymbol{n_s})
\end{aligned} \tag{2.1}
$$

where $\boldsymbol{u_t} = \boldsymbol{s_i} \in \boldsymbol{R^N}$ is the $N-D$ state at time t, $\boldsymbol{b_t} \in \boldsymbol{R^L}$ is the $L-D$ vector of all sensing data observed at time t, $h()$ is a the state transition model, $g()$ is the sensing model, $\boldsymbol{n_p}$ is state noise, and $\boldsymbol{n_s}$ is sensing noise. Thus, current sensing observations are only based on the current state of the system and sensing noise, and the current state of the system only depends on the previous state and state transition noise. It is assumed that the state transition model, sensing models and noises are known.

The state of target can be estimated by the Maximum Likelihood Estimation (MLE) by combining the sensor data and calculating the likelihood $f(\boldsymbol{b}|\boldsymbol{u})$ that target is in certain state. It fuses all the available sensing information about the target's state $\boldsymbol{u}$, based on the knowledge of sensing model and target state transition model.

The likelihood of a certain state $f(\boldsymbol{B_t}|\boldsymbol{u_t})$ is defined as the likelihood of all available sensing data from time 0 to time t given the state $\boldsymbol{u_t}$. And noise across time and sensors is assumed to be independent.

$$
f(\boldsymbol{B}_t|\boldsymbol{u}_t) = \prod_{i=1}^{t} f(\boldsymbol{b}_i|\boldsymbol{u}_t) \tag{2.2}
$$

where $\boldsymbol{B_t} = [\boldsymbol{b_0}, \boldsymbol{b_1}, ..., \boldsymbol{b_t}]$ is matrix including all the sensing vectors taken by sensors from time 0 to time t. The likelihood in Eq. 2.2 is proportional to $f(\boldsymbol{u_t}|\boldsymbol{B_t})$, with the assumption that the $f(\boldsymbol{u_t})$ is uniform .

Because all the sensor data is conditionally independent, the likelihood can be updated when new sensing observations are taken:

$$
\begin{aligned}
f(\boldsymbol{B}_t|\boldsymbol{u}_t) &= f(\boldsymbol{b}_t|\boldsymbol{u}_t) f(\boldsymbol{B}_{t-1}|\boldsymbol{u}_t) \\
&= f(\boldsymbol{b}_t|\boldsymbol{u}_t) \int_{-\infty}^{\infty} f(\boldsymbol{B}_{t-1}|\boldsymbol{u}_{t-1} f(\boldsymbol{u}_{t-1}|\boldsymbol{u}_t) \mathrm{d}\boldsymbol{u}_{t-1}
\end{aligned} \tag{2.3}
$$

Figure 2.6 illustrates the structure of the likelihood calculation in Eq. 2.3. In Chapter 4, we implement maximum likelihood estimation in user localization by multiple distributed human detection sensors.

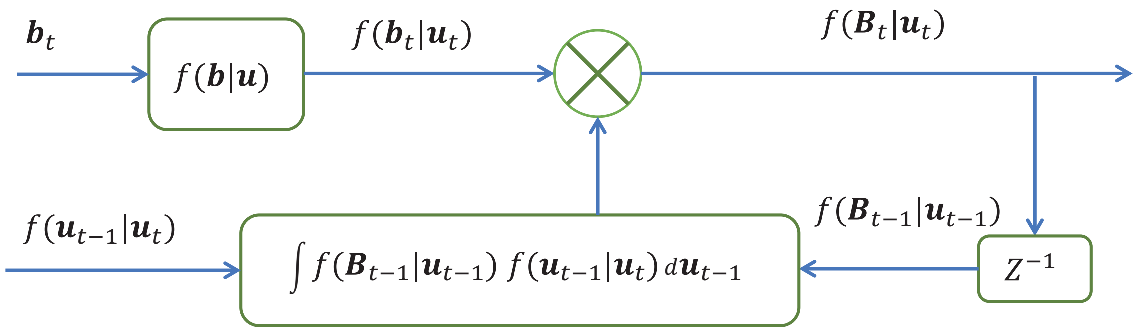


Figure 2.6 Update of likelihood.

2.2.3 Modeling Improvement by Machine Learning

In the last subsection, a maximum likelihood algorithm based state estimation strategy based on distributed sensors is introduced. It employs an explicit statistical model of how the target process of interest evolves over time and an explicit statistical model of how the observations that are made are related to this physical process. Such accurate statistical model is necessary, because the target dynamical models are required to relate sensing observations to the parameters or states to be estimated, and the sensing models are required to understand what information about the target process under surveillance by distributed sensors is provided. In other words, the statistical model of system dynamics is the bridges from what the target process is in the view of multiple sensors, to what the target process is in the real world, and to the control decisions controller makes about how to perform control or influence on the target.

In practice, it always depends on experiences and assumptions of the ideal and typical cases when selecting the models. It is effective to well model the process describing some effect of the average and overall behaviors. However, for the processes describing the individual behaviors rather than group actions, there are two drawbacks for the classical theoretical models:

- An explicit theoretical model, which well represents how the individual target's state evolves in the real world in time and space, is difficult to find.
- The accurate parameters of system dynamical model is difficult to obtain and adjust.

Recently, some efforts have been made to apply machine learning methods in some control systems, in which the system dynamics is difficult to be modeled by theoretical models and the control strategy is hard to design by convolutional methods.

2.3 Wireless Networks for Networked Control

When information exchange of a control system is transmitted over a wireless network, it is subject to a wide range of imperfections of the control network. They are due to variations in radio conditions, interference, etc. The imperfections in information exchange due to wireless communication can cause packets sent over the network to be delayed or even lost. In this section, two structures of wireless communication networks are introduced. They will be adopted in the application of designs in the following chapters of this thesis.

2.3.1 Distributed Sensor-Actuator Networks for Smart Grid

2.3.1.1 Concept of Smart Grid

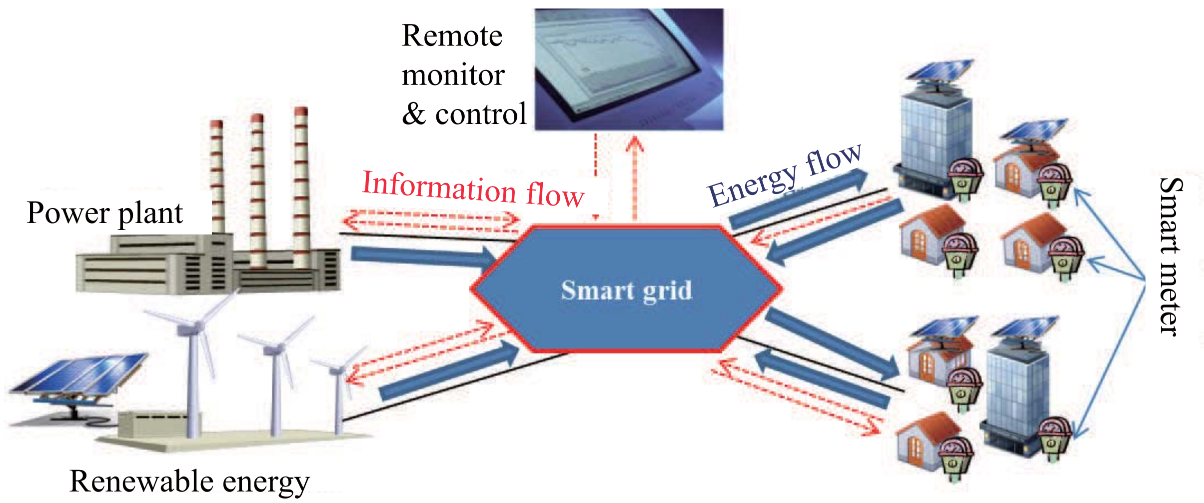


Figure 2.7 Smart Grid

Figure 2.7 shows the concept of Smart Grid. In Smart Grid[20], there are many entities including conventional centralized big-size power generators such as nuclear power plant, geographically distributed small-size power generators from solar and wind energy, distributed energy storage devices like heat transformer, end-user devices like industrial plant and home appliance, and in-the-middle distribution power line network like power transfers. Furthermore, besides the physical connection of power line, a communication network connecting all these entities is also a part of Smart Grid which can help to improve the operability of power systems. This communication network is made possible by two-way communication technology and computer processing that has been developed so fast in recent decades. Here, the "grid" implies a complex network of power lines that carry electricity from electric generators to consumers everywhere. The grid includes wires, substations, transformers, switches and all other physical parts of the power system. The "smart grid" means that the electric utility grid has been "computerizing" to become more reliable and more effective. Automation technology is the key feature which allows the utility grid to be self-adjusted and functional to guarantee the high performances of millions of devices, especially great improvements in energy efficiency. Therefore, Smart Grid is seen as the future of power system.

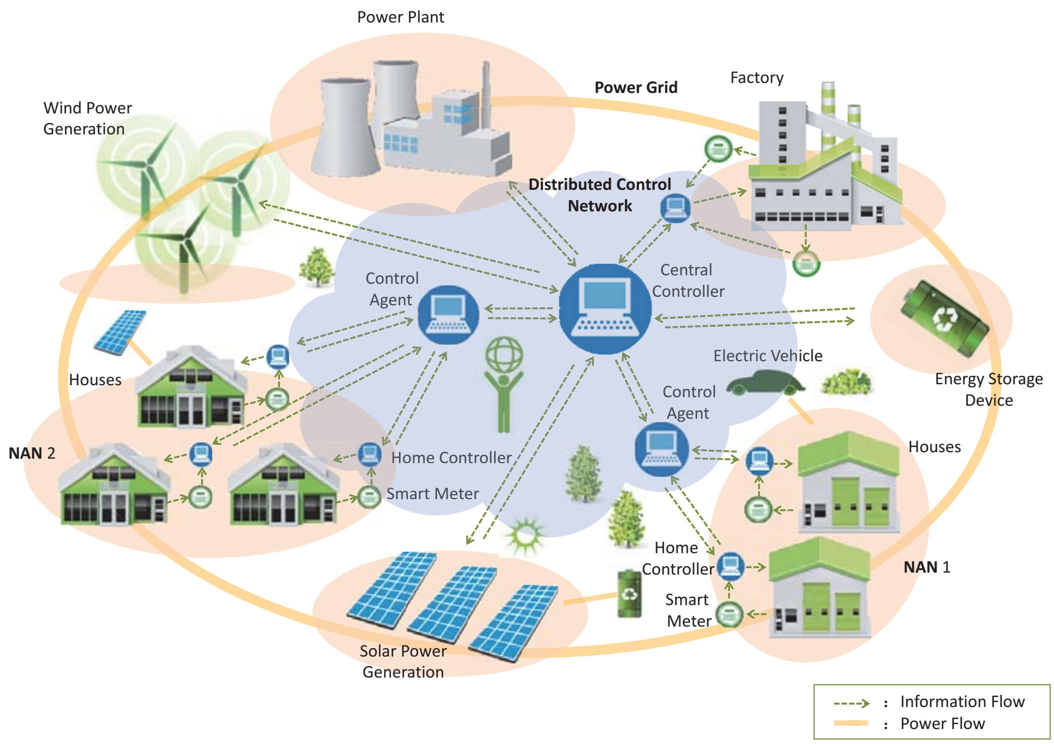
Once the communication technology is integrated into power grids, a large number of new functions can be applied. Here are the principal functions of Smart Grid in future.

- Self-healing from power disturbance events such as unexpected increase or drop in voltage.
- Enabling active participation by consumers in Demand Response service.
- Operating resiliently against physical and cyber attack.
- Accommodating all generation and storage options following the growth of the number of distributed renewable energy generators.
- Optimizing assets and operating efficiently with low-cost maintenance

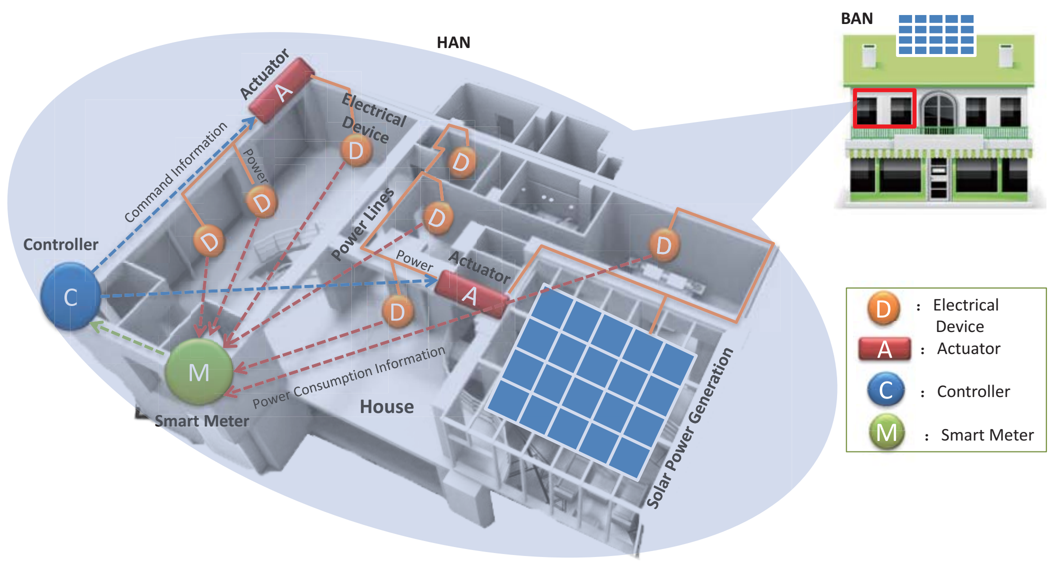
2.3.1.2 Wireless Communication Networks for Smart Grid

The Smart Grid communication network has been researched and developed by many academic organizations in both public and private sectors. Hence, a large number of ICT network frameworks have been proposed in recent years. For the sake of clarity, a simple Smart Grid communication network framework, which is commonly accepted by almost standardized alliances, is introduced in this section.

As described in [28] from the communication point of view, the Smart Grid topology is divided into a number of hierarchical networks. At the top, the distributed control centers



(a) Smart Grid.



(b) Green House.

Figure 2.8 ICT network framework for Smart Grid.

of the power utility side are located in the nodes of a meshed network. This mesh network is considered to be implemented over a core optical fiber technology for sustaining the high volume of Smart Grid data traffic with the least possible communication latency. Next, the communication framework for the customer side is a hierarchical network comprising neighborhood area network (NAN), building area network (BAN), and home area network (HAN) as illustrated in Fig. 2.8. Each network has a device called Network Gateway, which is assigned a routing interface to connect with the upper network with a different communication interface. In large-scale NAN, the high-speed and large-coverage WiMax wireless communication technology is commonly employed. Besides, Power Line Communication (PLC) is also another acceptable choice due to its characteristic of utilizing the existing power transmission line network. In the other hand, for the medium and small-size BAN and HAN, a low-power, low data rate and short-range communication protocol, such as ZigBee (IEEE802.15.4), is preferred. However, as an interface for home applications, ZigBee is not intended to support a large-coverage metering network with the capacity of hundreds of smart meters. Therefore, a new IEEE802.15.4g-based Smart Utility Network (SUN) supporting advanced telemetered and wireless meters are being developed to create a more reliable metering network. The details of SUN are given in the next section.

In Smart Grid, the power meter is not only equipped with the metering interface but also with a wireless communication interface, which helps to implement the automatic data metering network. This kind of power meter is called smart meter. The communication network connecting all the smart meters in an area is called Smart Utility Network.

2.3.2 Wireless Battery-less Human Detection Sensor Network

Office automation is an important application area of networked control systems, e.g., building energy control system and indoor navigation systems. A wireless battery-less human detection sensor network, which is designed for indoor localization and LED light control for power saving, is introduced in this section. The overview of the system if shown in Figure 2.9.

2.3.2.1 Human Detection Sensor Network

For office/home automation, a large number of sensors need to be deployed in the target space. There are two problems limiting the performance of normal wireless sensor networks:

- Sensing accuracy

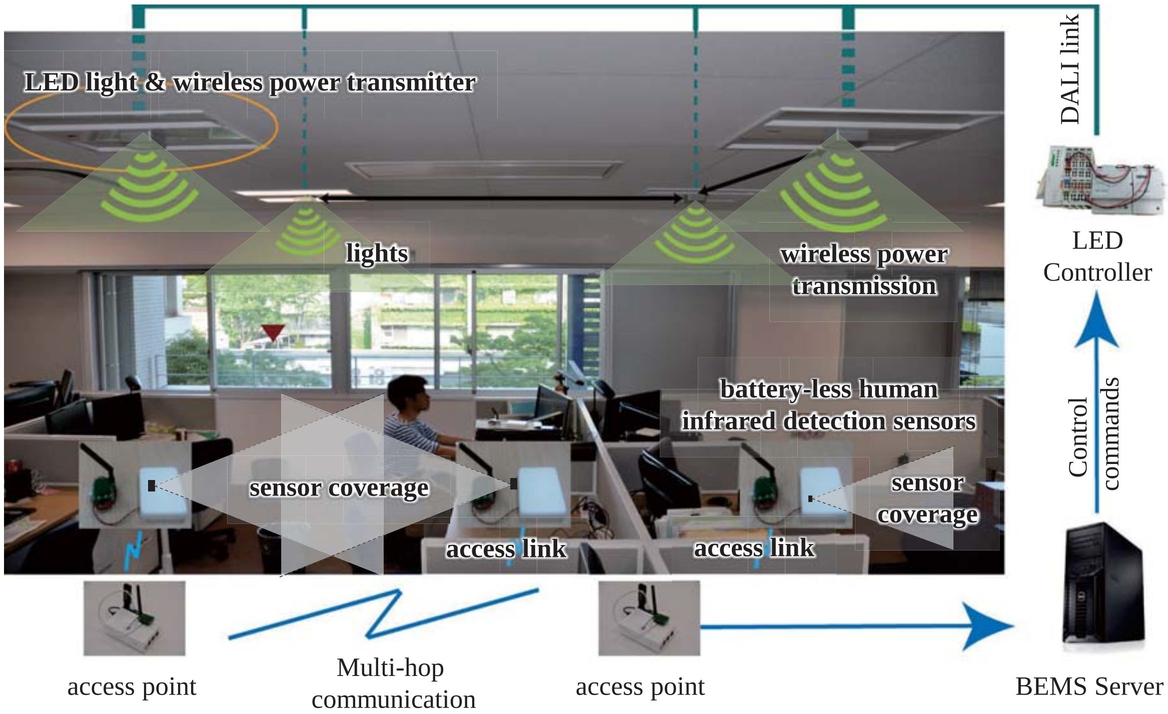


Figure 2.9 Overview of the wireless battery-less human detection sensor networks

- Energy supply for sensors

To address the problems, instead of placing the sensors in the ceiling or on the walls as did in many indoor wireless sensing system, we proposed to more flexibly locate sensors close to each user as much as possible to overcome the poor detection probability of sensors, by building a battery-less wireless sensor network in the target office. That is to say, in this work, all sensors are battery-less and activated by multiple wireless energy transmitters, which are embedded in the ceiling LED lights. Because of wireless power transmission and wireless sensing data communication, sensors can be put anywhere in the room rather than such fixed locations as walls and ceilings. More sensors can be deployed in hot areas and at user's side for more accurate detection. Moreover, there is almost no need for follow-up maintenance, such as recharging or changing the batteries.

On the transmitting side, the power of each energy transmitter is 1 W. Moreover, carrier shift diversity is employed [69][70], by which the interference among multiple energy transmitters can be effectively avoided, and hence the continuous and seamless coverage of energy supply can be achieved in the office. The energy efficiency of power transmitter can be further increased in the future by using intermittent energy transmission, high efficient rectennas, beaming control, energy harvesting sensors, etc. [73–75]

And to sense the environment illumination, illumination sensors are embedded along with each human detection sensor and also activated by wireless power transmission. Thus, the illumination sensors are much closer to user's working surface and can be placed more flexibly, compared with the conventional illumination sensors which are located in the ceiling.

And on the receiving side, with the consideration of power conversion efficiency of rectenna, the sensors in a battery-less sensor node needs 400 μW to be activated battery-lessly.

2.3.2.2 Multi-hop Communication Network

The communication system is one of the core parts of any intelligent lighting control system. Wired communications for sensors will result in not only costly remodeling and rewiring work, but also inflexible sensor placement. In this work, sensors and BEMS server form the networks wirelessly, so that sensors can be easily deployed and integrated into the existing rooms without much restriction of installation. It is an accessible and economical solution for light control systems. To note, the communication between controller and light is through a wired DALI link.

Each sensor node detects user's presence/absence status, measures the illumination, and then sends the sensing data to an access point through a wireless channel. The available power for a sensor is limited because it is activated by wireless power transmission. Therefore, to guarantee the converge of the wireless sensor network without significantly increasing the power consumption of the RF module in each sensor node, it is sensible and necessary to introduce multi-hop communication network. Thus, a hierarchical communication network is built, in which the access points have two wireless modules: sensing measurements collection, and multi-hop communication network among access points [76] to create a backhaul network.

Moreover, to reduce power consumption of sensors and extend the effective coverage of wireless power transmission, an intermittent data transmission scheme is employed. The sensor's sensing module, which is responsible for a very small amount of power compared to the RF module, is always active, but the RF module has two working modes (transmission mode/sleep mode), and intermittently transmits the output to the access points [70].

2.4 Summary

In this chapter, basic concepts and the theoretical background which are needed in later chapters are introduced and described. First, an introduction to feedback control systems with emphasis on distributed control system is given. Next, the concept of estimation by distributed sensors for networked control is introduced. In the last, specifically two communication network structures of wireless networks for networked control system are introduced.

Chapter 3

Distributed Networked Control System for Power Control

3.1 Introduction

As discussed in Chapter 2, the time delay is one of the most limiting factors for the performance of large-scale networked control systems, such as power control system in which there are great numbers of devices and huge amount communication traffic. To address such problems, in this chapter, motivated by the power control problem in smart grid, a hierarchical distributed networked control system is designed and applied in power control for Smart Grid in order to achieve control stability even in large-scale power networks.

In the proposed architecture, sub-controllers are introduced to partition the network into smaller clusters, in which corresponding local feedback loops are generated with shorter delays to achieve stable control. At the same time, the global objective can still be realized through vertically exchanging feedback information and control responses between sub-controllers in different layers. If the size of each local feedback loop is kept to satisfy stable control condition, the control network becomes scalable regardless of the number of houses or actuators by appropriately partitioning the network into stable control clusters and stacking them into layers in a hierarchical manner.

To evaluate its performance in power control, we set a up numerical simulation for in a scenario of 5000 houses to show the validity of the proposed hierarchical architecture in realizing peak load power reduction, while the performance of the centralized architecture becomes unstable. Moreover, a green building test-bed employing the proposed control scheme was developed and its power saving performance with respect to varying demand power is validated. Although the test-bed is a small-scale model, the results are still valuable for large-scale networks owing to the scalability of the proposed algorithm.

The rest of this chapter is organized as follows. At first, the background of power control and its challenge for stable networked control are introduced. Then, the architecture of the hierarchical control network and the distributed control strategy are explained in details. At last, in order to validate the proposed scheme, the performance of the system is evaluated by both numerical simulation and experiment using a green building test-bed employing the proposed distributed power control network.

3.2 Power Control in Smart Grid

After the nuclear accidents at Fukushima Daiichi nuclear power plant due to the terrible earthquake and tsunami which hit the Tohoku areas in Japan on 11th of March 2011, Japan has faced a serious shortage of power supply, especially in Tokyo area. Following efforts to prevent the same accidents, Japan has stopped almost all of its nuclear power plants so far. This leads to a serious shortage of power supply in all land of Japan now and in the near future. As a result, the load power consumed during peak hours should be reduced by 10% to 15% as stated by the government. To avoid tremendous power blackout over the whole area due to power overload, area-by-area planned blackouts were conducted in Tokyo in 2011 and are planned to be conducted again in Osaka and some areas of Japan in 2012. However, the cost of such planned blackouts on our daily life and business is prohibitive, and in a long term, more radical solutions on this power saving issue should be more considered. In this context, as the vision of future electric power system integrated with Information Communication Technology (ICT) to solve the energy problems, new power system called Smart Grid[31] has attracted much attentions recently.

Figure 3.1 shows the concept of Smart Grid. In Smart Grid, there are many entities such as conventional centralized big-size power generator including nuclear power plant, geographically distributed small-size power generators such as solar and wind energy, distributed energy storage devices including heat transformer, end-user devices like industrial plant and home appliance, and in-the-middle distribution power line network including power transfers. Furthermore, besides the physical connection of power line, a communication network connecting all these entities is also a part of Smart Grid which can help to improve the operability of

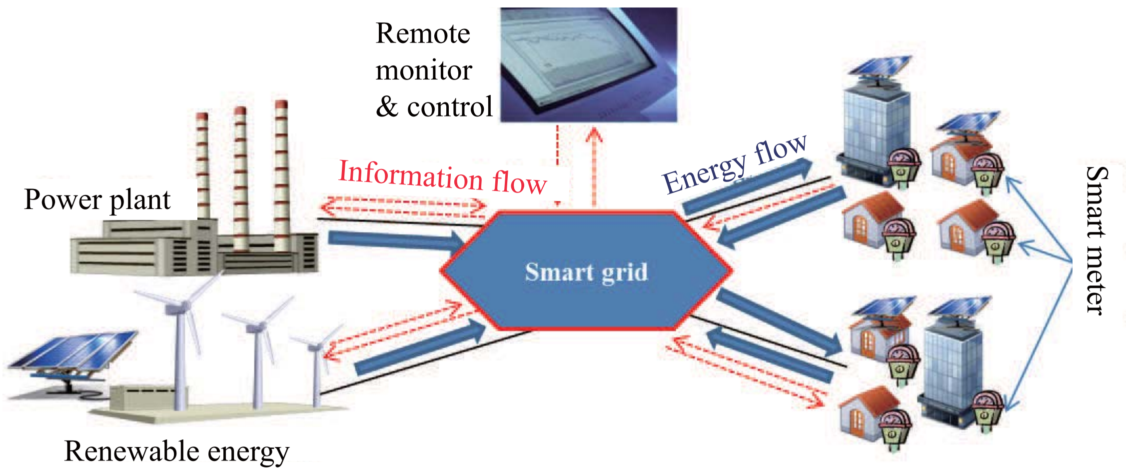


Figure 3.1 Concept of smart grid.

power systems. Especially, knowledge about power consumption at the consumer side can be collected by using such sensor like devices called smart meter. Under the described framework of Smart Grid, Demand Response (DR) which can efficiently control the power consumption of consumers regarding the available power supply is the key technology in the implementation of future Smart Grid.

In general, DR service is defined as a dynamic mechanism to manage the electricity power consumption of consumers in response to the supply condition in the whole system [32],[33] as illustrated in Fig. 3.2. As seen in Fig. 3.2(a), if the potential peak power demand is larger than the maximal power supply, the DR service should be applied to customers to decrease the power overload to be lower than the supply power. In addition, some kinds of time-varying renewable energy sources such as solar or wind can be utilized to increase the power supply capacity as in Fig. 3.2(b), but the gap between demand and supply power still exists, which degrades the quality of the power system. Hence, the DR needs to be applied to both the customers and the utilities such as energy storage devices for demand-and-supply power balancing. However, for both cases, the incentive metering information of customers are needed frequently and the control response should be sent back to the customers if there is a demand-supply gap, which can be seen as a feedback loop of power control network. However, the communication architecture of such kind of control network is still an open problem. The design of the network architecture obviously depends on the required response speed of the control. In the DR case, the response speed should be very high due to the rapidly changing power demand during peak hours, especially in the large power system such as metropolitan

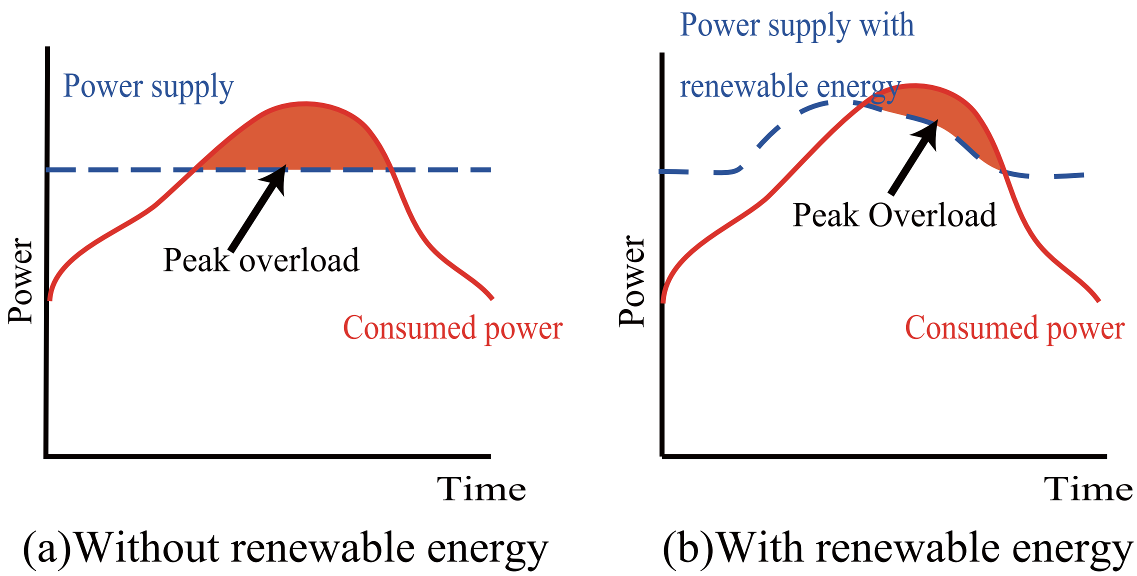


Figure 3.2 Demand and supply power balance.

electricity system. Hence, the design of network architecture for this control network is quite important to realize DR for peak load power shaping [34][35].

As reported in [36] ,[37], a theoretical bound of maximal allowable delay or minimum rate of communication was derived to guarantee stable control via a point to point communication network, but there was no discussion about designing of the point to multi-point networks which can be applied for large-scale system such as Smart Grid. Authors in [38] proposed how to design a smart message authentication system to reduce control delay time during peak hours, but the DR was not included. On the other hand, [32] evaluated the performance of DR restricted in a small-scale Home Energy Management System, or commercially called home gateway, with negligible delay. However, delay becomes the most critical parameter in realizing stable control in large-scale feedback systems like Smart Grid. Implementing a simple star-typed centralized architecture consisting of a central controller and multiple sensors and actuators, since feedback delay increases with respect to the size of the network, leads to an unstable control as reported in [39],[40]. In addition, coverage of the network becomes limited in the case of wireless access in the centralized architecture. Although multi-hop architecture [41] can solve the problem of restricted coverage, it worsens feedback performance due to packet relay. Therefore, instead of the centralized control architecture, a distributed architecture with multiple controllers is a reasonable solution for large-scale networks. However, to the best of our knowledge, its design criteria are not yet established. Some other recent related works are listed in Table 3.1.

The main differences between the related works and our proposed scheme reflect in the following aspects. First, we divided the whole system in a hierarchical structure with many layers, and put multiple agents in each layer and each root of branch. Second, all the agents do not only function as the power consumption information aggregator for its sub-system (cluster), but also work as sub-controllers aiming to maintain the local supply-demand balance. Third, by introducing the hierarchical and distributed topology, the proposed networked power control system is scalable and extendable regardless of the number of the electric appliances under control. Fourth, because the main application scenario of the proposed system is to avoid the overall blackout in peak hours, all sub-controllers in our control methodology try to cooperatively reach the global balance, whereas agents, such as in [48, 49], are greedy and try to optimize their own profit. Third, in our work, the design of hierarchical control and communication networks are combined, in order to reduce the time delays in each feedback control loop and achieve the stable control in it. Furthermore, a green building test-bed is practically built and implemented to validate the effectiveness of the proposed networked power control system.

3.3 Hierarchical Distributed Power Control Network

In DR service, the knowledge of power consumption of the whole system is required in making control decision. Generally, there are two measures of calculating the consumed power in the centralized control system. The conventional measure is to monitor the output power from electric power generators or distribution lines, however, this scheme cannot identify the electric appliances being used by customers. As the result, the DR cannot apply the control to the customer side. The other measure is to calculate the summation of all consumed power by monitoring all the consumed power of electric appliances. By this measure, the knowledge of electric appliances being used can be known, however, the time spent for gathering data is prohibitive since it is almost proportional to the number of appliances. This means that the control performance based on this measure becomes unstable especially in the power systems with a large number of houses and appliances. To solve the problem of unstable control in such large systems, we propose a hierarchical distributed power control network shown in Fig. 3.3. The control network consists of bottom layer sub-controllers, middle layer sub-controllers and top layer central controller corresponding to specific control functions. The role of the

Table 3.1 Summary of power consumption control in Smart Grid

Author	Type of Control	Method
Hamidi et al. [42]	Centralize	To study the effect of different tariffs on level of responsiveness
Babar et al. [43]	Centralize	To minimize inconvenience of the consumers by using a demand reduction bidding incentive DR programs.
Wang et al. [44]	Hierarchical	To build a load management system of hierarchical multi-agent control system using PSO to optimize the energy and the user comfort problems.
Gomes et at. [45]	Distributed	To make load management control system using multi-objective optimization model.
Alam et al. [46]	Distributed	To optimize energy cost by using multi-model to break up the dependencies between grid system components
Bhatarai et al. [47]	Hierarchical	To make load management system using hierarchical control architecture (HCA) for different DR schemes.

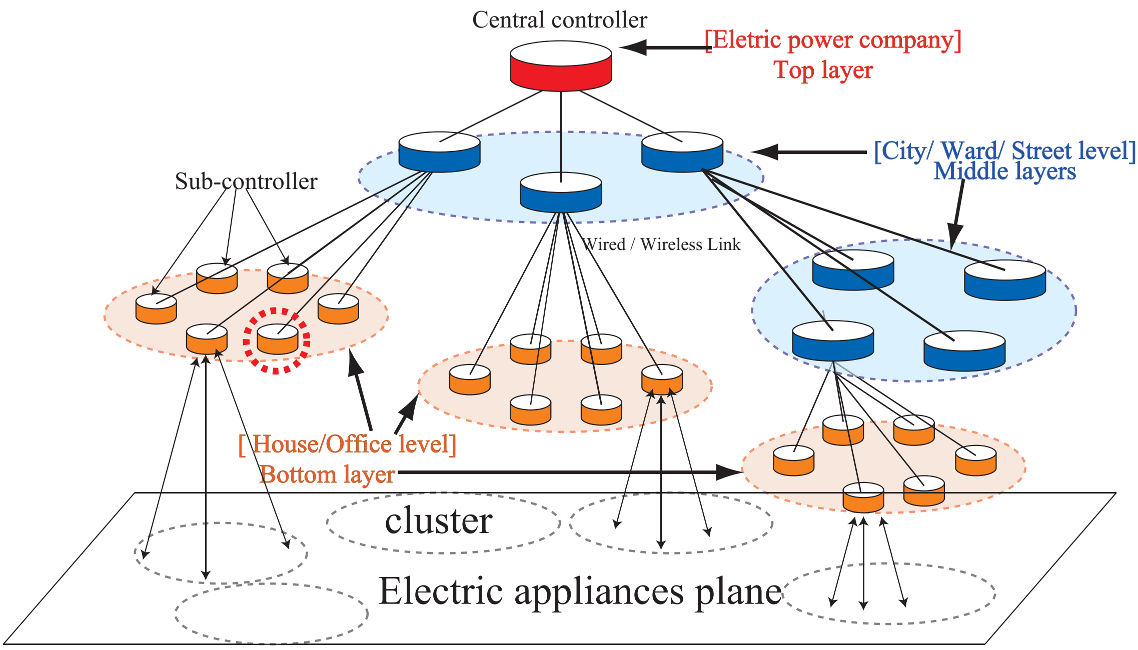


Figure 3.3 Hierarchical distributed control network.

sub-controller in each layer is explained as follows.

- Sub-controllers at bottom layer: partition the large system into many small-size clusters with local feedback loops. Here, each sub-controller can directly change the power consumed by electric appliances adapting to its assigned power consumption limit. The control in the cluster becomes stable if the cluster size is small enough to keep the control latency below a maximal allowable duration.

- Sub-controllers at middle layers: feedback information of power consumption from the lower layer to upper layer and determine the power consumption limits of the sub-controllers at their subsequent lower layer, by which the power consumption of the clusters at the bottom layer can be adjusted indirectly.

- Central controller at top layer: keeps demand-and-supply power balancing by comparing the overall power consumption and the maximal supply power from energy generators to assign appropriate power consumption limits to its sub-controllers at the lower layer.

It is obvious that the global objective of DR control is realized through assigning power consumption limits of sub-controllers turn by turn. The power consumption limits are periodically sent to the sub-controllers at the bottom layer. During this interval, the local sub-controllers at bottom layer can simultaneously adjust the power consumption of their cluster to fulfill the assigned limit without wasting the time in waiting for responses from other clusters. In the next sub-section, the control algorithm for sub-controllers at each layer will be explained.

3.4 Control Strategy

First of all, we explain the notations used in this section of the chapter. For a specific sub-controller i of layer l ($l = 1$ for the top layer and $l = L$ for the bottom layer), $P^{\mathrm{c}}_{l,i}$ denotes the total consumption power of all electric appliances under the control of this sub-controller. $P^{\mathrm{s}}_{l,i}$ denotes the power consumption limit assigned to this sub-controller. Since there is only one sub-controller at the top layer, $P^{\mathrm{c}}_{1,1} = P^{\mathrm{c}}$ represents the total consumption power of the system and $P^{\mathrm{s}}_{1,1} = P^{\mathrm{s}}$ is the power consumption limit of the whole system, which equals the total power supply in this chapter. On the other hand, the power consumption of the electric appliance k is denoted as $P^{\mathrm{c}}_{\mathrm{e},k}$.

Since this chapter focuses on power saving during peak hours and discrete time control is assumed, the global objective can be described as a function of discrete time inequality below,

$$P^{\mathrm{c}}(kt_0) \lesssim P^{\mathrm{s}}(kt_0), \tag{3.1}$$

where $\lesssim$ denotes the control operator of suppressing power below an assigned value and t_0 is the time interval of making decisions on power control.

Let us assume a power control system consisting of a total of N electric appliances. In the case of centralized control, all the power consumption data are required to be collected prior to the decision making of control response. Therefore, t_o turns into $2 \times N \times T_{\mathrm{slot}}$ assuming a simple Round Robin fashion as described in Fig. 3.4(b), where T_{slot} is the length of the time slot assigned for each uplink (feedback) and downlink (response) transmission. For such a long interval, the consumed power might be increased above the limit with high probability, which leads to unstable DR performance.

In contrast, the distributed control with multiple sub-controllers can keep the consumption power under the limit by partitioning the system into small clusters to reduce the control time.

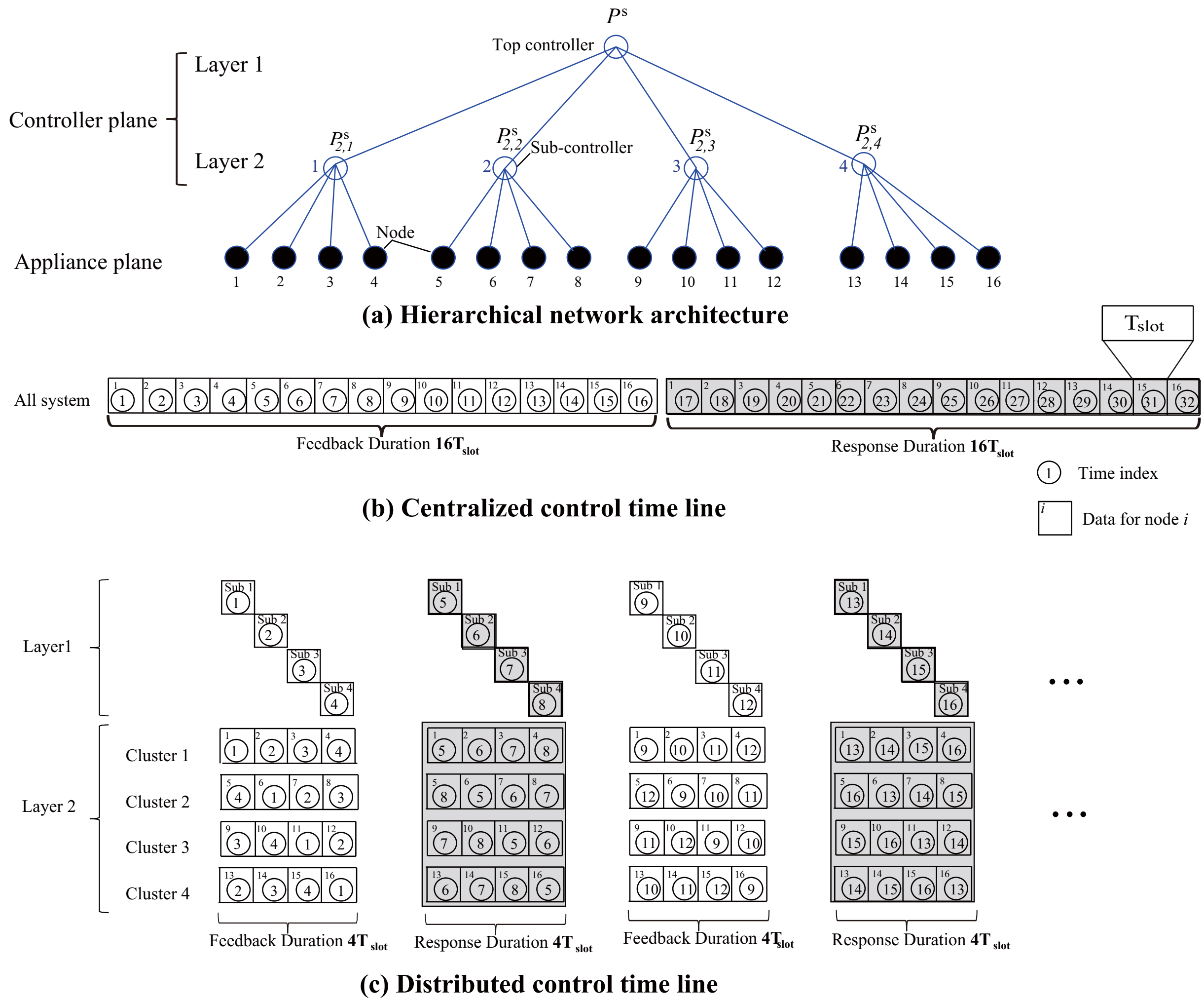


Figure 3.4 An example proposed network and communication framework.

3.4.1 Simple scenario of distributed control algorithm

In order to explain the distributed control algorithm, a simple example with $N = 16$ electric appliances is illustrated in details before describing the general scheme. Figure 3.4 shows the structure of the control network in this simple scenario.

3.4.1.1 Distributed Control Algorithm

In Fig. 3.4(a), the control network forms a 4-ary tree topology where each parent node has four children nodes. The terminal vertices (black circles) of the tree correspond to electric appliances, which form a so-called electric appliance plane in this chapter. All the other vertices denote sub-controllers and they form a controller plane. The degree of each sub-controller is defined by the number of children nodes connected to the sub-controller. Especially, the degree of a sub-controller at the bottom layer of the controller plane or the number of electrical appliances grouped by that sub-controller is called as cluster size N_{cs} and is the most important parameter in this chapter. For simple illustration, the degrees of all sub-controllers are the same as $N_{\mathrm{cs}} = 4$. Within the controller plane, the tree is separated into L layers where the root is called the top layer or layer 1 and the layer L is the bottom layer. The number of layers in this case are determined by $L = \log_{N_{\mathrm{cs}}} N = \log_4 16 = 2$. On the other hand, the electric appliances are grouped into four clusters, each of which is controlled by a sub-controller at layer 2 (or called home-gateways in commercial). These four sub-controllers at layer 2 are then again controlled by a central controller at layer 1 (top layer). In this chapter, a sub-controller which is controlled by another sub-controller at its upper layer is called the children sub-controller of the upper layered one. Inversely, a sub-controller which supervises another sub-controller at its lower layer is called the parent sub-controller of the lower layered one.

As electric appliances are partitioned into four different clusters, the time period of the control loop can be reduced into $t_0 = 2 \times N_{\mathrm{cs}} \times T_{\mathrm{slot}}$ as shown in Fig. 3.4(c) owing to parallel processing of each cluster and layer. For example, at the time index of 1, four appliances numbered $\{1, 6, 11, 16\}$ and the sub-controller 1 at layer 2 simultaneously communicate with their corresponding parent sub-controllers. It is noted that there is only one appliance can communicate every time slot in the case of centralized control.

In the initial phase, the power consumption limit is set equally as $P^{\mathrm{s}}_{2,i} = P^s/4$. After that, the control algorithm is repeated every interval of t_0 at each layer of the control system as follows.

At the bottom layer (layer 2):

At the bottom layer, each sub-controller has a list of electric appliances and their corresponding power usage priority. Without loss of generality, we assume electric appliance with the lower priority has lower device index. The function of these sub-controllers at bottom layer is to appropriately turn off low priority electric appliances such that the power consumption of the cluster after control satisfies the power consumption limit assigned by the parent sub-controller at layer 1. The algorithm is summarized using mathematical formulas for a specific bottom layer sub-controller with index i as follows.

$$\begin{cases} N_{\text{off}} = \arg\min_{N_{\text{off}} \geq 0} \left(P^{\text{s}}_{2,i} - \sum_{ch(i)=N_{\text{off}}+1}^{N_{\text{cs}}} P^{\text{c}}_{\text{e},ch(i)} \right)^2 \\ \qquad \text{s.t.} \\ \sum_{ch(i)=N_{\text{off}}+1}^{N_{\text{cs}}} P^{\text{c}}_{\text{e},ch(i)} \leq P^{\text{s}}_{2,i} \\ P^{\text{s}}_{\text{e},ch(i)} := 0 \quad \forall ch(i) \leq N_{\text{off}} \quad \text{(power turn off)} \\ P^{\text{s}}_{\text{e},ch(i)} := P^{\text{c}}_{\text{e},ch(i)} \quad \forall ch(i) > N_{\text{off}} \quad \text{(power maintain)} \end{cases} \tag{3.2}$$

where $ch(i)$ denotes the children of node i and $P^{\text{c}}_{\text{e},ch(i)}$ denotes the consumed power of a child electric appliance controlled by sub-controller i. Here, $P^{\text{c}}_{\text{e},ch(i)}$ is measured at the electric appliance $ch(i)$ and fed back to its parent sub-controller i using the assigned feedback time slot as depicted in Fig. 3.4(c). After collecting all feedback information about the power consumption of its children electric appliances, the sub-controller calculates the total power consumption of the cluster $P^{\text{c}}_{2,i} = \sum_{ch(i)} P^{\text{c}}_{\text{e},ch(i)}$ and confirms if the value does not exceed its pre-assigned power consumption limit $P^{\text{s}}_{2,i}$. Otherwise, the sub-controller finds the smallest number of low priority electric appliances to turn off such that the power consumption condition holds. Then, it responses a turn-off command $\{P^{\text{s}}_{\text{e},ch(i)}\}$ to the corresponding selected low priority electric appliances. During normal hours of a day when there is no power overload, the downlink traffic from sub-controller to its electric appliances is rather light. Thus, these communication resources can be saved for other purposes. During peak hours, the sub-controller needs to select a positive number $0 < N_{\text{off}} < N_{\text{cs}}$ of devices to turn off.

At the top layer (layer 1):

The sub-controller at top layer (central controller) determines the power consumption limits $P^{\text{s}}_{2,i}$ of the sub-controllers at bottom layer using the following algorithm,

$$\begin{cases} \{P^{\text{s}}_{2,1}, \ldots, P^{\text{s}}_{2,N_{\text{cs}}}\} = \arg\min_{\{P^{\text{s}}_{2,i}\}} \sum_{i=1}^{N_{\text{cs}}} \left(P^{\text{s}}_{2,i} - P^{\text{c}}_{2,i} \right)^2 \\ \qquad \text{s.t.} \\ \sum_{i=1}^{N_{\text{cs}}} P^{\text{s}}_{2,i} = P^{\text{s}}. \end{cases} \tag{3.3}$$

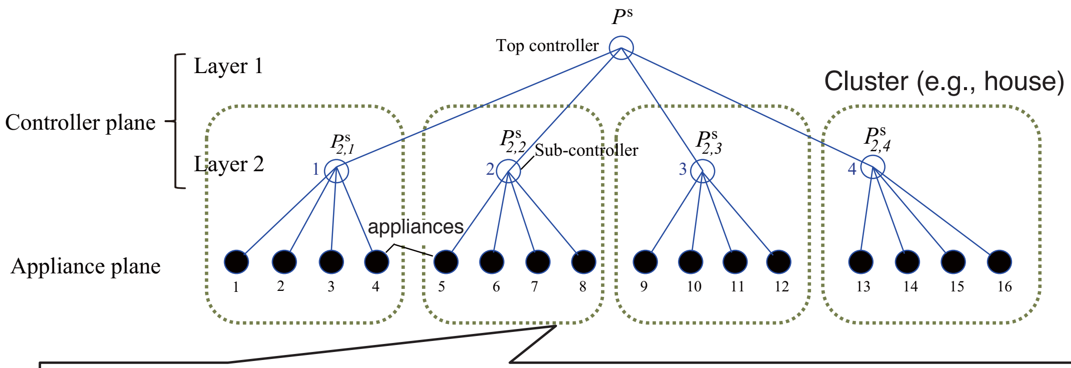
In this algorithm, based on the feedback information about power consumption $P^{\text{c}}_{2,i}$ from its children sub-controller at layer 2, the central controller calculates the corresponding power consumption limits $P^{\rm s}_{2,i}$ to achieve demand-and-supply power balancing by finding their minimum mean square distance under the constraint of the available power supply $P^{\rm s}$. After the optimized power consumption limits $P^{\rm s}_{2,i}$ are determined, these values are sent back to the sub-controllers at layer 2. The sub-controllers then use these power consumption limits for decision making in the next iteration of the control process. During peak hours with power excess, if the electric power consumption of different clusters is uniformly distributed, i.e. $P^{\rm c}_{2,i} = P^{\rm c}_{2,i'}\ \forall i \neq i'$, the optimized power consumption limits are then $P^{\rm s}_{2,i} = P^{\rm s}/N_{\rm cs}$. In other words, the central controller attempts to distribute its available power to its uniform clusters equally. On the contrary, when the power distribution between different clusters is non-uniform, this algorithm still guarantees that the cluster consuming more power is assigned with a higher value of power consumption limit under the sum power consumption constraint. Therefore, the power allocation introduced in this chapter is spontaneously strict in terms of power suppression and equal in terms of power allocation over clusters.

Owing to the above algorithm, the power system can be controlled with a shorter control period, which leads to better performance. There might be different methods to determine such power consumption limit values, however, the proposed algorithm is selected since it gives the unique solution of limit values by finding the minimum mean square distance between demand and supply power.

3.4.1.2 Priority of Appliances

In this chapter, as the nature of the distributed algorithm, we consider only 'local priority', where 'priority metric' is defined locally and independently at each cluster. In other words, the priority tables are registered by the end-users of each cluster based on their own preferences. Because only local priority is considered in this chapter, our algorithm does not guarantee 'priority fairness' among clusters.

An example is given in Fig. 3.5. At a certain house, the home gateway classifies the home appliances into two groups of high and low priorities. High priority appliances are the prerequisite for normal life and cannot be turned off, while low priority appliances can be turned off in a predefined order to save power during peak hours. Several typical electric appliances including air-conditioner (831W/unit) and refrigerator (268W/unit) with high priority, lamp (60W/unit) and television (141W/unit) with low priority.



Appliances	Air-Conditioner	Refrigerator	TV	Lamp
Power	831W	268W	141W	60W
Priority	prerequisite	prerequisite	2	1

Figure 3.5 An example priorities of appliances in a cluster.

3.4.2 General algorithm

In the last subsection, the distributed networked power control system is explained by a simple example with 16 electric appliances. If the number of appliances in the system is quite large, it is necessary to extend the system into more layers and more clusters to maintain the stable control. For example, in the system shown in Fig. 3.3, there are three layers and it can be used for the electric power company of city level for demand and supply control in peak hours.

In this subsection, we generalize the algorithm for an arbitrary number of N. For general purpose, we consider the scenario that N electric appliances are grouped into N_{g} clusters with size $N_{\mathrm{cs}} = \lceil N/N_{\mathrm{g}} \rceil$. As explained previously, the controller plane of the distributed control network is then formed as a tree topology with $L = \lceil \log_D N_{\mathrm{g}} \rceil + 1$ layers of sub-controllers where D denotes the degree of each sub-controllers at middle and top layers. The algorithms explained in the previous subsection can be extended for an arbitrary number of layers as follows.

At the bottom layer (layer L):

At the bottom layer, each sub-controller has a list of electric appliances and their corresponding power usage priority. The function of these sub-controllers at bottom layer is to

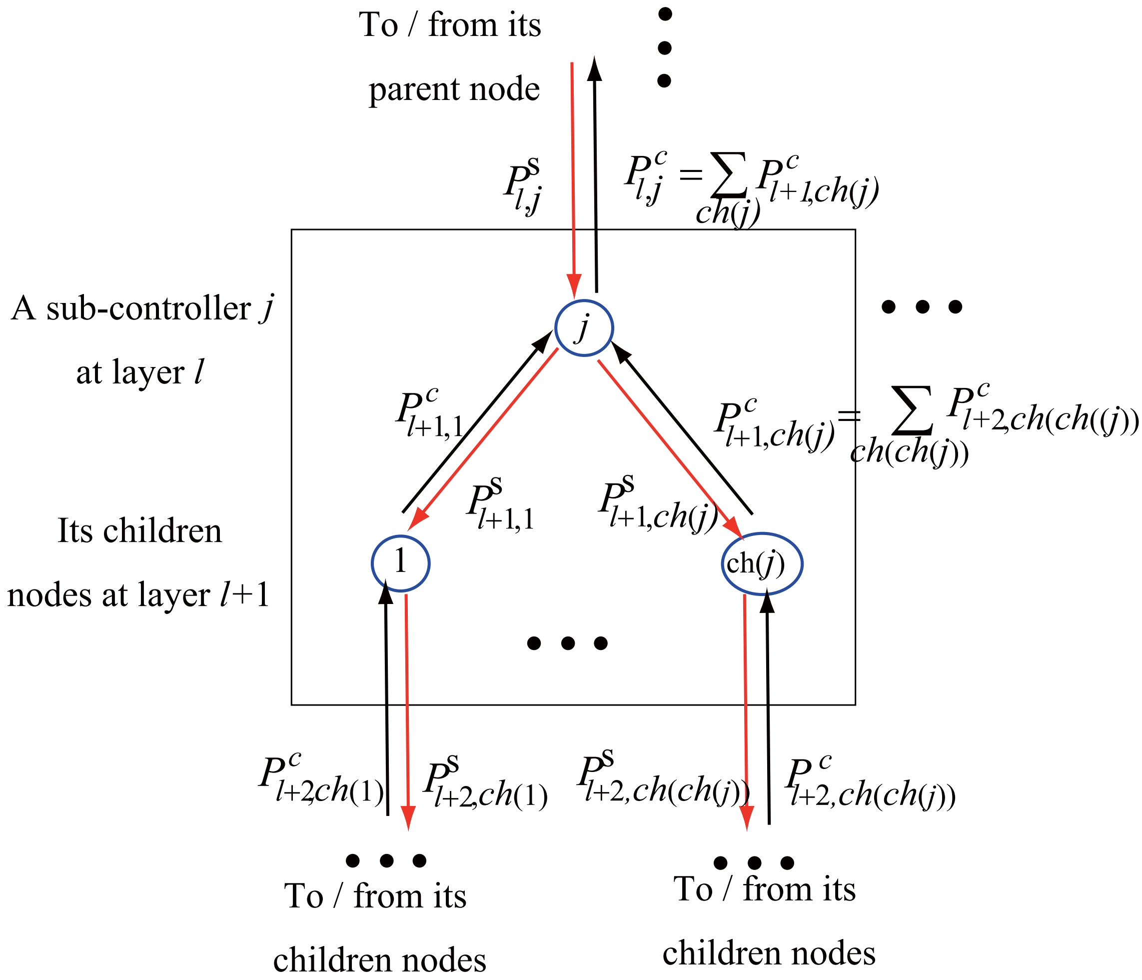


Figure 3.6 Distributed feedback and response mechanism.

appropriately turn off low priority electric appliances such that the power consumption of the cluster after control satisfies the power consumption limits assigned by the parent sub-controller at layer $L-1$. The control algorithm of a sub-controller at bottom layer is similar as that in the simple example, so detailed explanation is omitted for brevity. However, different from the simple example with the cluster size of four, it should be noted that N_{cs} in real scenario has the order of hundreds or thousands of electric appliances.

At the middle layer and the top layer:

As depicted in Fig. 3.6, a sub-controller j at a layer $l \neq L$ determines the power consumption limits $P^{\mathrm{s}}_{l+1,ch(j)}$ of its children sub-controller at the lower layer $l+1$ using the following algorithm.

$$\begin{cases} \{P^{\mathrm{s}}_{l+1,ch(j)}\} = \arg\min_{P^{\mathrm{s}}_{l+1,ch(j)}} \sum_{ch(j)=1}^{D} \left(P^{\mathrm{s}}_{l+1,ch(j)} - P^{\mathrm{c}}_{l+1,ch(j)}\right)^2 \\ \qquad \text{s.t.} \\ \sum_{ch(j)=1}^{D} P^{\mathrm{s}}_{l+1,ch(j)} = P^{\mathrm{s}}_{l,j} \end{cases} \tag{3.4}$$

Here, similarly as the simple example, based on the feedback information about power consumption $P^{\mathrm{c}}_{l+1,ch(j)}$ from its children sub-controllers $ch(j)$ at layer $l+1$, the sub-controller j calculates the corresponding power consumption limits $P^{\mathrm{s}}_{l+1,ch(j)}$ to balance the demand and supply of power under its assigned constraint of consumption power $P^{\mathrm{s}}_{l,j}$. It is noted that $P^{\mathrm{c}}_{l+1,ch(j)} = \sum_{ch(ch(j))} P^{\mathrm{c}}_{l+2,ch(ch(j))}$ is calculated at the sub-controller $ch(j)$ at layer $l+1$ by summing the power consumption information sent from its children sub-controllers $ch(ch(j))$ at layer $l+2$. After the optimized power consumption limits $P^{\mathrm{s}}_{l+1,ch(j)}$ are determined, these values are sent back to the children sub-controllers of j at layer $l+1$. The children sub-controllers then use these power consumption limits for decision making in the next iteration of the control process.[1]

It is remarkable that the above algorithm is general at any middle and top layers of the distributed control network. At each corresponding sub-controller, as mentioned in the simple case, the algorithm guarantees that the power constraint is satisfied while available power is distributed proportionally to the demands of the children sub-groups. Therefore, the algorithm is scalable regardless of the number of electric appliances in terms of guaranteeing peak power suppression, even for the real scenario with the number of electric appliances up to the order of million nodes. However, to realize such large-scale distributed control networks,

[1] This algorithm can be extended even for the case with small-scale renewable energy resources. Let us denote $P^{\mathrm{r}}_{L,i}$ as the amount of power generated from distributed renewable energy resources in cluster i at the bottom layer. As small-size power generator is concerned, it is reasonable to assume that $P^{\mathrm{r}}_{L,i} \leq P^{\mathrm{c}}_{L,i}$. In this case, the effective consumed power of cluster i at the bottom layer can be defined as $\tilde{P}^{\mathrm{c}}_{L,i} = P^{\mathrm{c}}_{L,i} - P^{\mathrm{r}}_{L,i}$. By substituting this effective consumed power $\tilde{P}^{\mathrm{c}}_{L,i}$ instead of $P^{\mathrm{c}}_{L,i}$ in the above distributed optimization problem at the bottom layer, the proposed power control algorithm is still effective to control power of a system integrated with distributed small-size generators. In contrast, when the generated renewable power becomes larger than the consumed power, i.e. $P^{\mathrm{r}}_{L,i} > P^{\mathrm{c}}_{L,i}$, it is necessary to introduce distributed energy storage devices as well as power trading strategy among customers and suppliers,which is out of the scope of this chapter and remains as our potential future works.

it is important to design the cluster size N_{cs} and the sub-controller degree D in accordance to the communication link capacity. As this chapter assumes a perfect backbone network for communication between sub-controllers, it only focuses on the design of N_{cs}.

3.4.3 Iterative control algorithm and home-gateway

The distributed algorithm explained in Sec. 3.4.2 is baseline, and there are many ways to improve control performance by introducing some approximation and a priori knowledge of electric appliances. As such schemes, we introduce an iterative control algorithm and the concept of home-gateway in this chapter.

3.4.3.1 Iterative control algorithm

In the baseline algorithm, a sub-controller receives all feedback and sends back response afterward to all its children sub-controllers or appliances. In the iterative control algorithm, this order of feedback and response is changed as child sub-controller by child sub-controller or appliance by appliance. So that the waiting time per child node can be reduced to t_o while the control period per cluster remains the same. It is noted that the consumed power at the mother sub-controller should be calculated iteratively in this algorithm. Since the response is sent before waiting for all the feedback, this algorithm is considered as an approximation of the baseline algorithm.

3.4.3.2 Home-gateway

As mentioned in Sec.1, there are varieties of entities and electric appliances in Smart Grid. Thus it is quite complex to monitor and control the whole large-scale power systems. However, it is necessary to monitor all the electric appliances to identify which appliances being used and calculate the total consumption power. It is clearly that monitoring all the appliances one by one makes the control time become long. To reduce the time spent on monitoring the appliances, smart metering devices called home gateway can be introduced. Home-gateway can calculate the total power consumption in the house by directly measuring the output power from power line, and it can further analyze the shapes of electric current and voltage to identify which appliances are being used as reported in [50]. By using the home gateway, the consumed power at several appliances can be calculated with quite small latency.

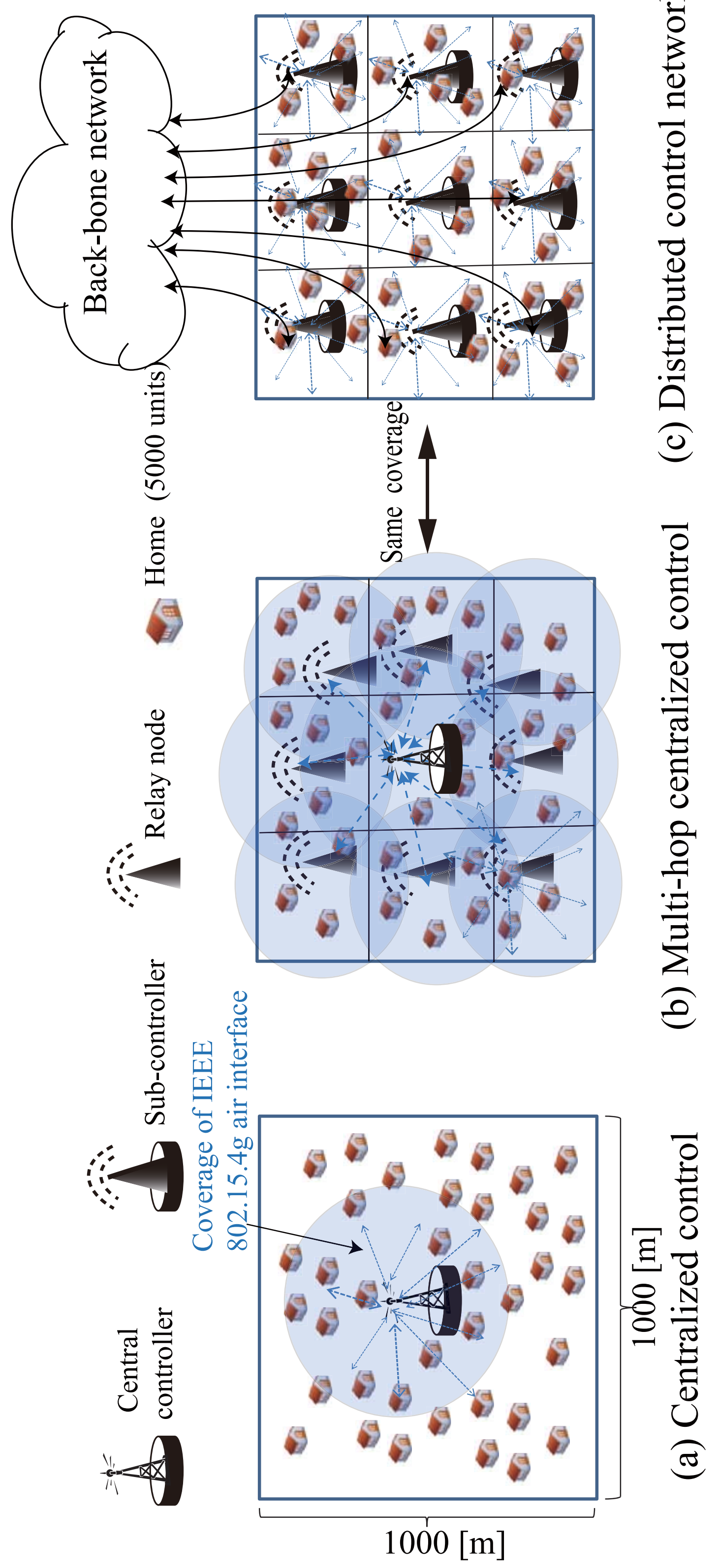


Figure 3.7 Target scenario for simulation.

3.5 Performance Evaluation

In this section, in order to both evaluate the performance of the proposed control network and explain how to specify the parameters to design the control network, numerical simulations in a realistic scenario are conducted and taken into discussion. And then, a building for the Department of Electrical & Electronic Engineering in Tokyo Institute of Technology is used for the test-bed implementation. This small-scale testbed is sufficient to check the feasibility of the proposed algorithm since it is scalable against the number of nodes in the network as explained in the previous section.

The performance can be evaluated by power saving rate, namely, how many power is suppressed compared to the power consumption without control. In the simulation, it is easy to get such power consumption information and use it as a good indicator to show the theoretical performance of the system. But in the real implementation, it is difficult to get the accurate value about how many power is saved, because the pattern of power usage by is quite complicated. For example, in real case, if a lamp is turned off by the controller, it is hard to accurately give the suppressed power consumption, because we do not know how long time the user was going to use the lamp. History information and statistical information can be used to give a statically significant result.

Since the global objective of the proposed system is to maintain the power consumption to be equal or smaller than the limited value to avoid the blackout, it is better to show the system performance by checking whether the power consumption under control is equal or smaller than the limited value in peak hours. In the latter sections of this chapter, the performance of the proposed distributed networked power control system is mainly evaluated in this manner.

3.5.1 Numerical Simulation

In this section, in order to both evaluate the performance of the proposed control network and explain how to specify the parameters to design the control network, numerical simulations in a realistic scenario are conducted and taken into discussion.

3.5.1.1 Target Scenario

The target scenario is illustrated in Fig. 3.7. There is an area of 1 km^2 with up to 5000 houses sharing the same electric power line. As reported in [51], an average peak load power per house of 1200W is assumed in this scenario as the representative value in the case of Japan, so that in total 6MW is usually consumed during peak hours. If the local power generator only supplies the maximum power lower than 6MW, the blackout will occur in this area during peak hours. To prevent the blackout, a smart grid with centralized cluster controller and home-gateways at every house are introduced to reduce the peak power consumption 10% lower than the maximum supply power. At each house, the home gateway classifies the home appliances into two groups of high and low priorities. High priority appliances are prerequisite for normal life and cannot be turned off, while low priority appliances can be turned off in a predefined order to save power during peak hours. Several typical electric appliances including air-conditioner (831W/unit) and refrigerator (268W/unit) with high priority, lamp (60W/unit) and television (141W/unit) with low priority, in each house are emulated to produce an average peak load power of 1200W in a duration of one hour. Besides, the On/Off switches of all appliances are generated based on a random Poisson process to imitate variable load power. The details of simulation parameters are shown in Table I.

As illustrated in Fig. 3.7, there are three control network topologies used in this scenario: a star-typed centralized control topology (Fig. 3.7a), a star-typed centralized control topology with multi-hop (Fig. 3.7b) and a proposed distributed control topology (Fig. 3.7c). In all cases, the standard wireless protocol of IEEE802.15.4g for smart meter is used in wireless link between home-gateway and the cluster controller, where the time slots are allocated equally for the downlink and uplink. Moreover, to ensure fairness of control among different houses in the clusters, guaranteed time slot of IEEE802.15.4g is assigned for each home-gateway using simple Round Robin scheduling. In the star-typed centralized control case, it is obvious that the coverage of wireless link is limited to the houses near the central controller. By using multi-hop transmission with relay devices for smart meter, the wireless coverage can be extended but transmission time also becomes larger, which leads to longer control delay. In the distributed control network, it is assumed that sub-controllers are connected to the upper layer controller via a backbone network such as Power Line Communication (PLC) with a moderate rate up to 1Mbps. Each cluster is assumed to be assigned with an orthogonal channel not interfered by other clusters.

3.5.1.2 Simulation Results

Figure 3.8 shows the average throughputs at controller versus the distance between a house and the controller in the case of star-typed network with and without multi-hop transmis-

Table 3.2 Simulation parameters.

Parameter	Value
Target area	1000m^2
Number of houses/consumers	$500 \sim 5000$
Average peak power per house	1200W
Average limit power per house	1080W
Air interface	IEEE802.15.4g 50kbps
Transmit power	250mW
Channe model	Rayleigh fading
Path-loss exponential	3.2
Shadowing variance	8dB
Modulation scheme	Binary FSK
Coding rate	1/2
Packet length	32bytes
Time slot length	960 symbols

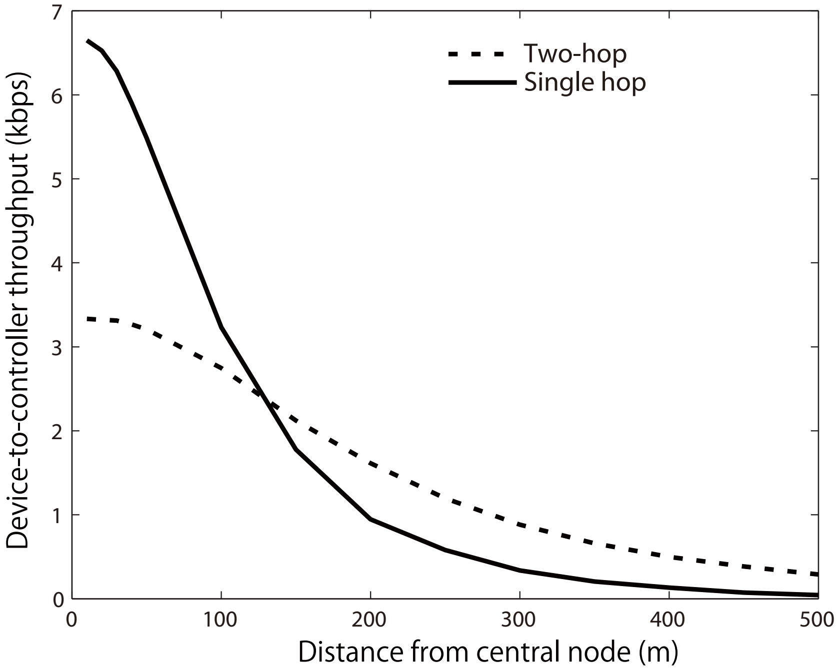


Figure 3.8 Average throughput vs. distance.

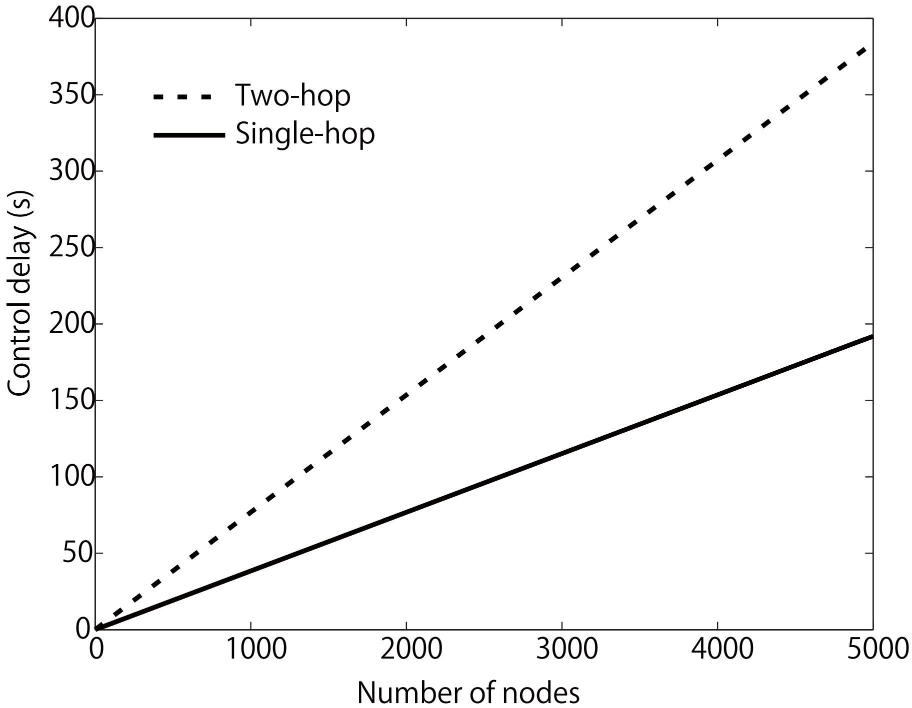


Figure 3.9 Average control delay vs. number of nodes.

sion, which uses one relay device ideally placed between the house and the controller. The throughput is calculated by counting the number of correctly received packets at the controller when the houses transmit packets in the TDD fashion with IEEE802.15.4g air interface. The maximum throughput is approximately 50kbps $\times \frac{32\times8}{960\times2} \approx$ 7kbps. Figure 3.8 shows that the throughput decreases with the distance in both cases, but using multi-hop transmission the coverage can be extended to the farthest houses at 500m distance. On the other hand, Fig. 3.9 shows the period required for control of each home-gateway with respect to the number of houses in the same network topologies. It is obvious that the time spent for multi-hop transmission is much longer than that of the direct transmission, which is not preferable to control system.

Figure 3.10 shows the simulation results on the control performance in the case of using star-typed centralized control network with and without multi-hop transmission. It reveals that the centralized control scheme can only fulfill the objective limit of power consumption when the number of houses is less than 500 and the control performance degrades dramatically as the number of houses increases. Because the time required for gathering feedback data from all the home-gateways in the area increases with the number of houses, the larger number of houses results in the larger control latency, that yields a larger amount of power overloaded. One more reason is that the number of home-gateways at the edge of transmission coverage also increases. By using 2-hop relay transmission, the number of uncontrollable home-gateways decreases owing to a larger area of coverage. However, the longer control period spent for multi-hop transmission leads to an even degraded control performance in terms of suppressing the power consumption.

The results on control performance of the distributed power control network with two layers are shown in Figs. 3.11 and 3.12. As seen in Fig. 3.11, the distributed control scheme works well even when there are 5000 houses in the area. The main reason is that multiple power control loops are conducted simultaneously at all clusters in the system, which equivalently leads to the reduction of the total time required for controlling the whole system. However, the performance of the distributed control scheme varies with the cluster size. As seen in Fig. 3.12, the distributed control with 9 clusters (approx. 555 houses/ cluster) can perfectly avoid the consumed power overload while that with 4 clusters (approx. 1250 houses/cluster) has a slight power excess over the target limit of 1080W. It is obvious that the larger cluster size has worse performance, or equivalently leads to inferior control performance of the overall system. On the other hand, a distributed control system with many tiny-size clusters is

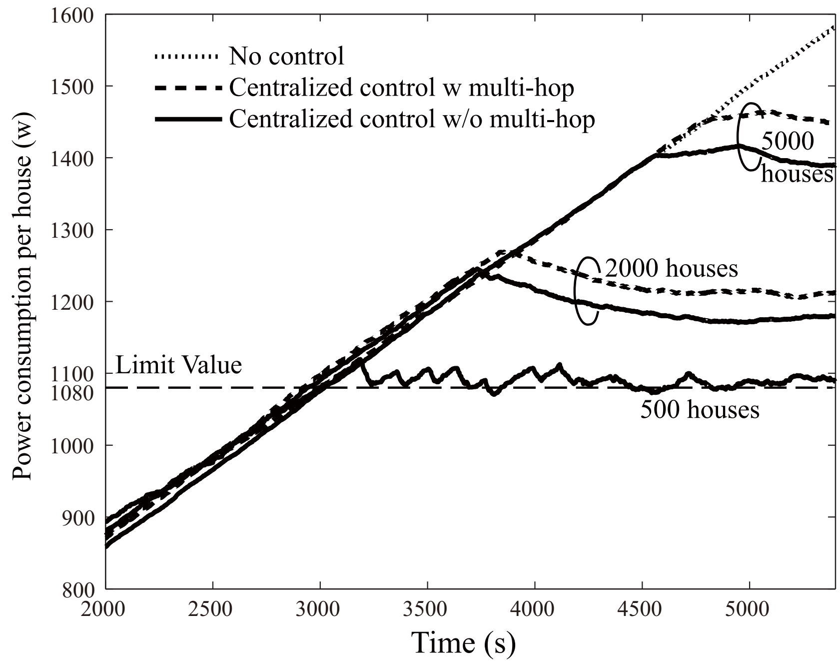


Figure 3.10 Power control performance of centralized scheme.

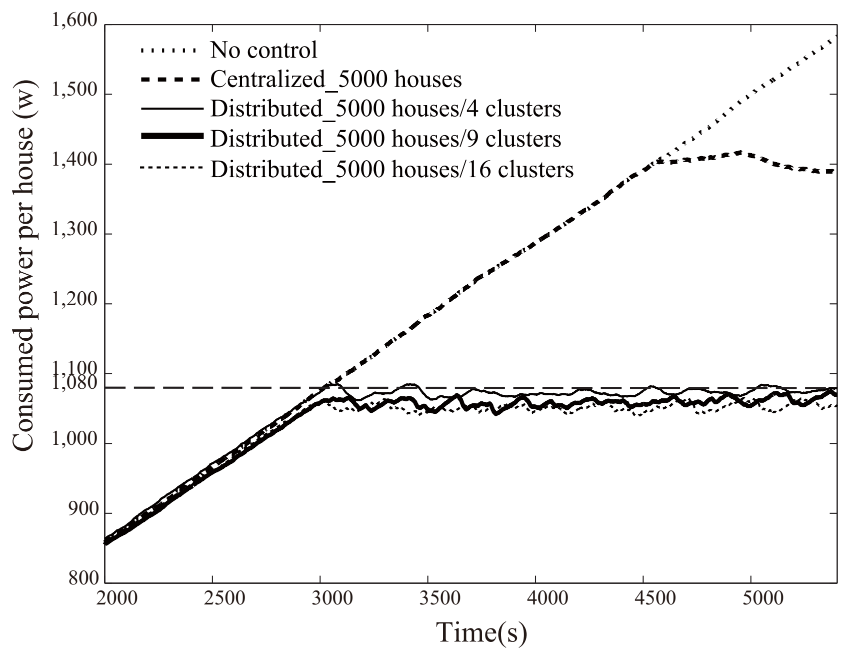


Figure 3.11 Power control performance of distributed scheme.

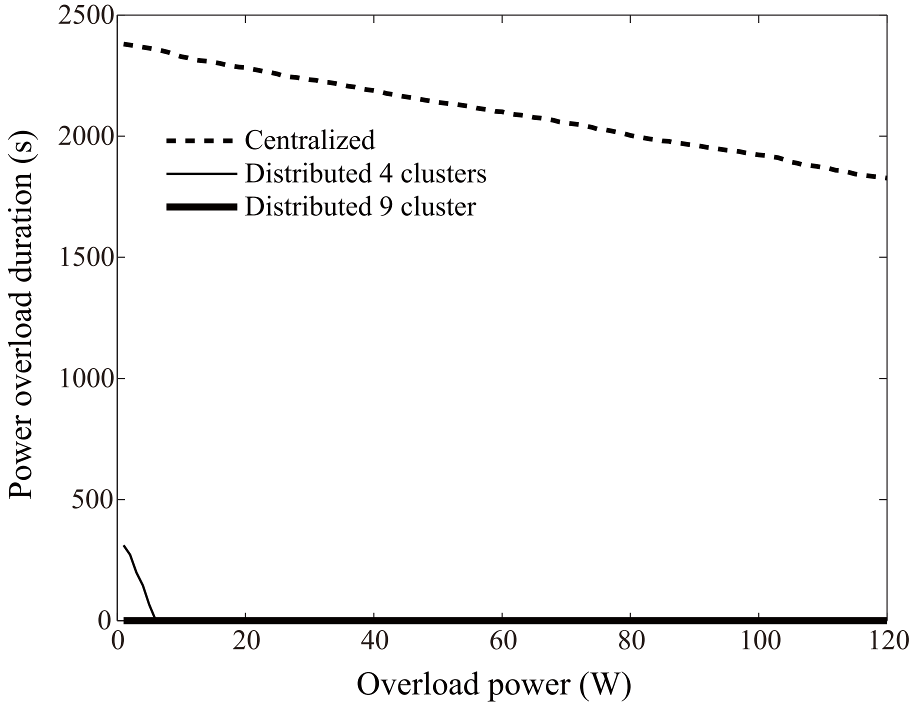


Figure 3.12 Overload power performance.

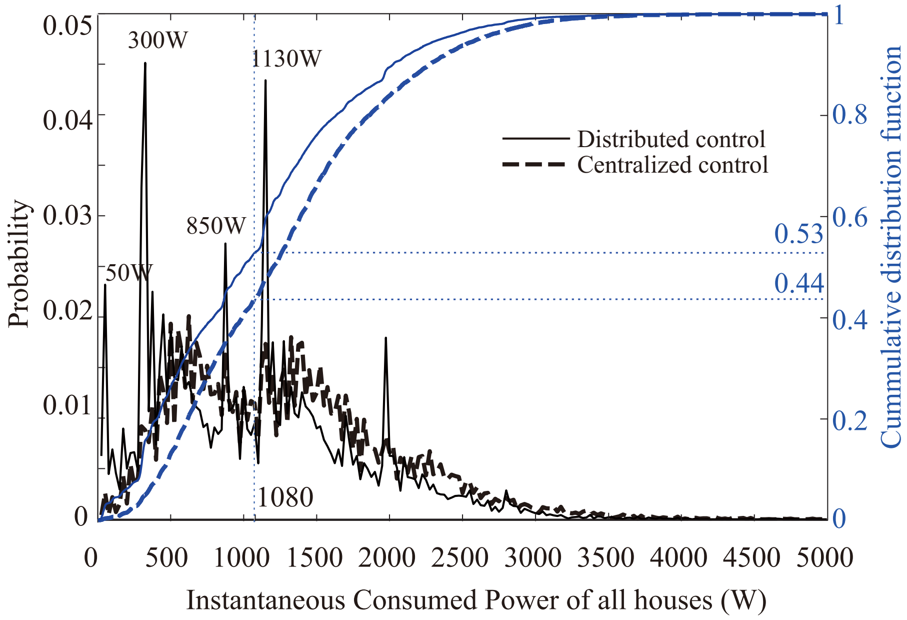


Figure 3.13 Probability distribution of instantaneous consumed power.

not reasonable due to the following two reasons. Firstly, each sub-controller of the tiny-size cluster has only very few knowledge of the overall system, which makes the control of each cluster become diversified, so the cooperative control of all clusters becomes loose. As seen in Fig. 3.11, the consumed powers of both 5000 houses/16 clusters and 5000 houses/9 clusters cases are kept below the power limit. However, the consumed power of the former case is over-suppressed more pessimistically than that of the latter case. If the cluster size $N_{\rm cs}$ is too small as compared to 500, the time variation of the average consumed power per house becomes significantly large. In this case, the performance of distributed control becomes pessimistic, or over-suppressed. It implies that the performance of power suppression in this chapter is convex against the cluster size, and thus there should be an optimal cluster size, which is approximately 500 in this scenario. Secondly, data traffic burden on the backbone network will increase with the number of clusters, which is not desirable because of the limited capacity of the backbone networks for Smart Grid. Based on the above discussion, we could confirm the validity of proposed distributed control system and recommend approximately 500 houses per cluster in this design.

Furthermore, Fig. 3.13 shows probability distribution as well as the cumulative distribution of instantaneous power consumption over the total 5000 houses during the simulation time. It can be observed from Fig. 3.13 that the events that instantaneous power consumption exceed 1080W have been reduced by about 9 percent as the benefit of the distributed control. In the centralized control case, there is a higher probability that some home-gateways could not control properly due to limited coverage and longer delay. In the distributed control case, most of the home-gateways succeed to control the load demand and to reduce their power usage of low priority appliances to avoid overload. As the result, the power consumption during peak hours converges to some specific values, e.g. 300W, 1130W etc., which corresponds to the consumed power of appliances with high priority.

3.5.2 Experiment by Green Building Test-Bed System

A building for the Department of Electrical & Electronic Engineering in Tokyo Institute of Technology is used for the test-bed implementation. This small-scale testbed is sufficient to check the feasibility of the proposed algorithm since it is scalable against the number of nodes in the network as explained in Sec. 2. Figure 3.14 shows the whole system structure, in which each laboratory-scale power system consists of a sub-controller installed in a PC server in charge of laboratory power management, a smart meter network, and a load power

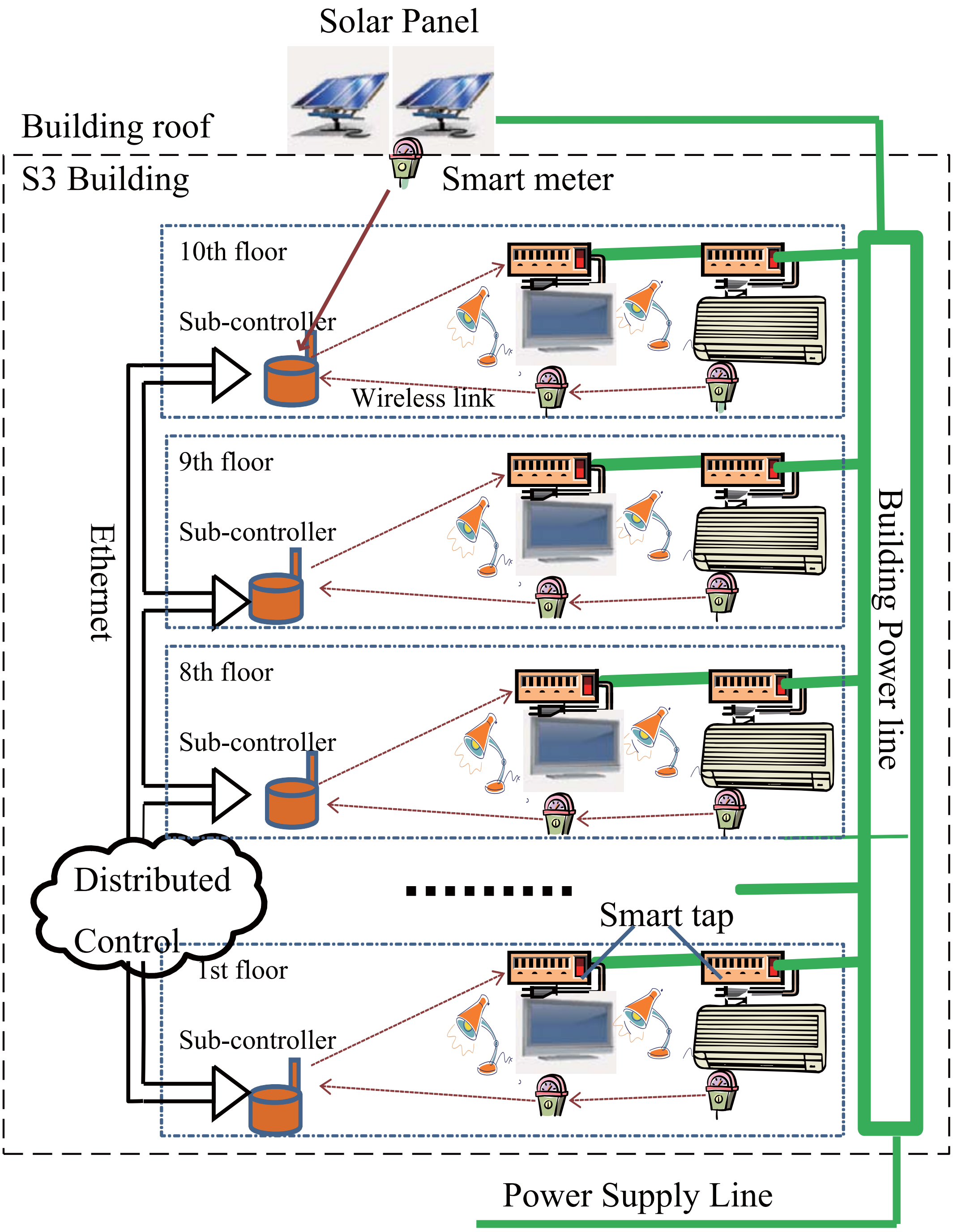


Figure 3.14 Green building test-bed system.

control network. Figure 3.15 shows the installed smart meter network based on IEEE 802.15.4 standard in our laboratory at 10th floor. The smart meter is located at a circuit breaker box in each room to measure the consumed power every 5s with a resolution of 10W. The smart meter sends the measured data to the server via the wireless link of IEEE 802.15.4 using multi-hop topology. Figure 3.16 shows the installed load power control network using IEEE 802.11b WLAN in our laboratory. All electric appliances in each room are connected to power switches which are remotely controllable via IEEE 802.11b standard.

The smart meter network measures the power consumption of all electric appliances in each laboratory. If the total load power becomes larger than a power threshold, each sub-controller locally turns off the power switch connected to each appliance via the load power control network. In the power switch, there are four ports with different priorities. In the case of power saving, the server starts to turn off the switch connecting to the appliance with the lowest priority. The power threshold in the central controller is determined based on the average power consumption data in the previous year, power saving ratio, and current supply power from the solar power generator.

Figure 3.17 shows an example of the variation of consumption power in the room 1020 over a week. Nominally, six students are in the room. The figure reveals that the students come around noon and leave the room around 22 o'clock. There is no one in the room on Sunday, and the power consumption of 100W on this day corresponds to standby power of devices.

Finally, Fig. 3.18 shows the performance of power saving with and without the proposed power control applying to the four laboratories in the building. In this setup, a total power threshold of 14kW is artificially employed during the peak hour around 14 o'clock. The distributed control algorithm is implemented in all four laboratory sub-controllers to fulfill the total power threshold. The total power consumptions of four laboratories with and without control, the power consumption and the assigned power limit in our laboratory are illustrated in the Fig. 3.18. The total power consumption increases from normal power usage of 10kW to 14kW in approximately five minutes. After that, the control is applied to suppress the excess consumption power. At the same time, the power consumption limit corresponding to our laboratory is calculated by the proposed algorithm and reassigned every 10s. As seen in the figure, the controller of our laboratory starts to reduce the consumption power as soon as the total consumption power exceeds the threshold value, which contributes to avoiding power overload in peak hours. In conclusion, these results indicate the effectiveness of the

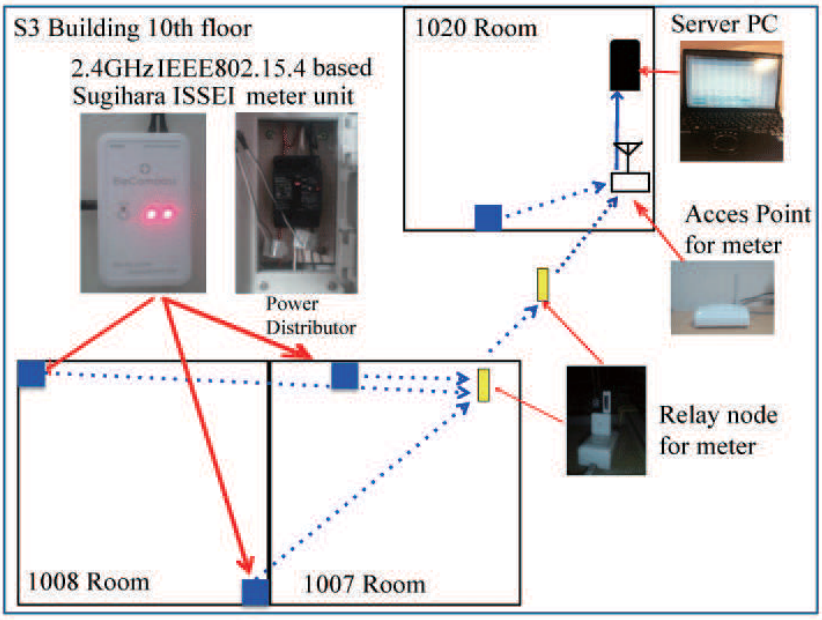


Figure 3.15 Smart meter network for green building test-bed.

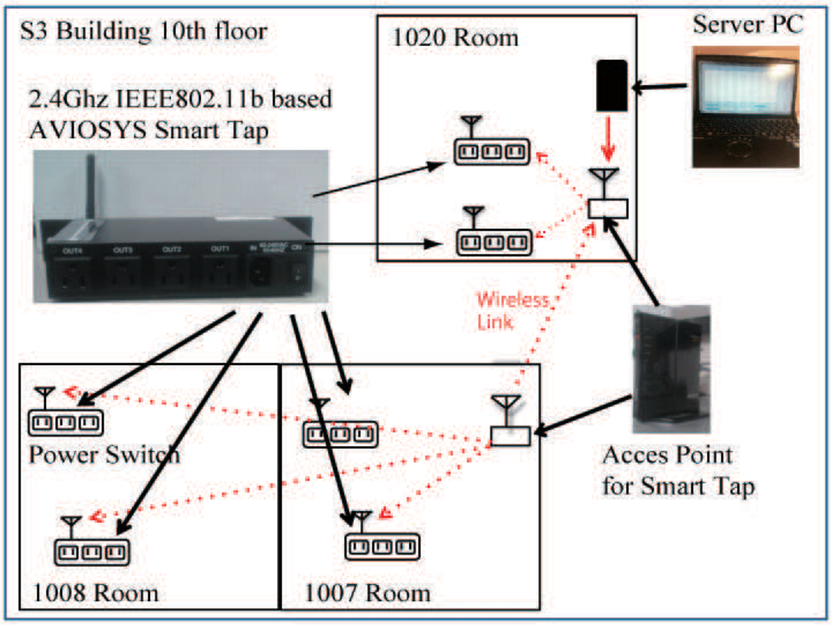


Figure 3.16 Actuator network for green building test-bed.

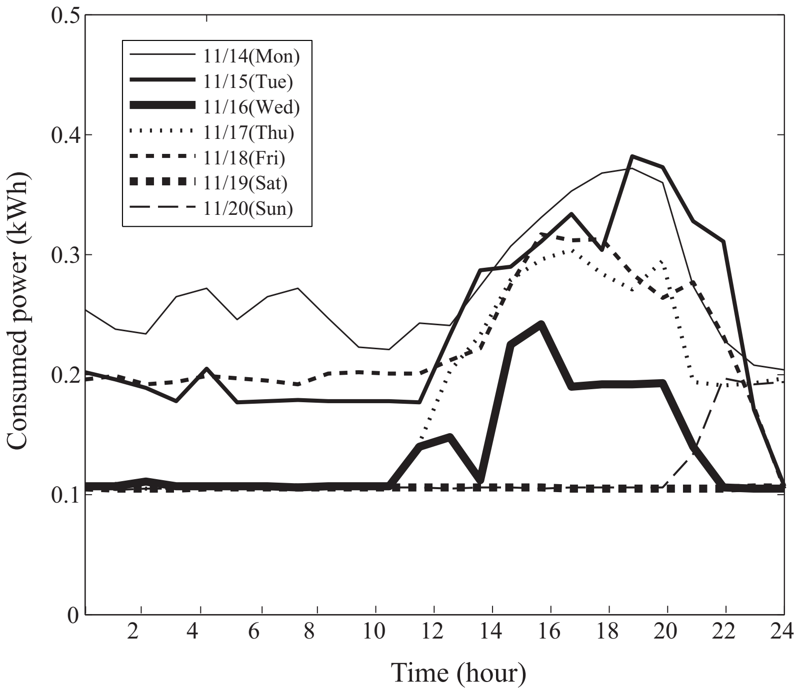


Figure 3.17 Power consumed in student room during a week.

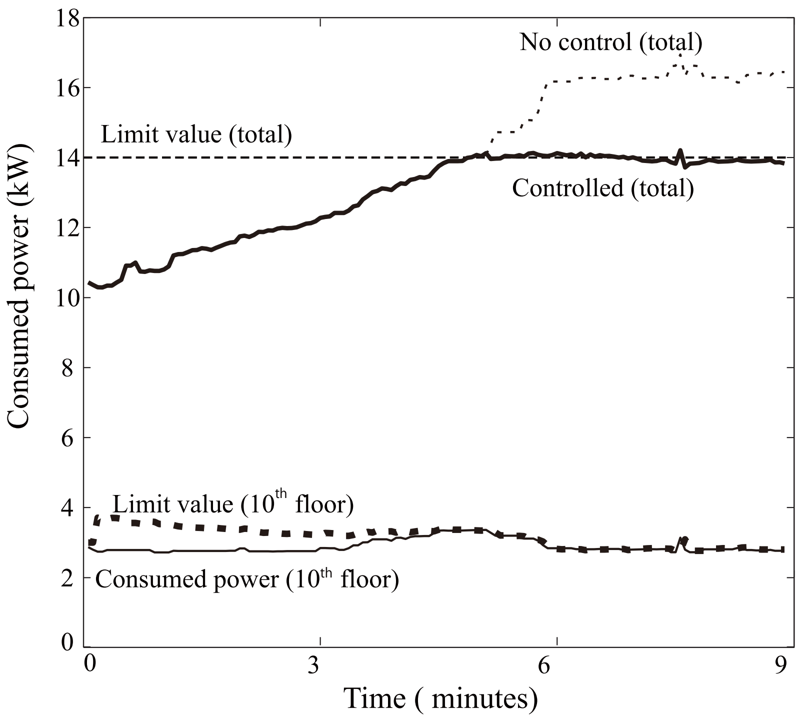


Figure 3.18 Results on performance of testbed system.

developed control system in real applications.

3.6 Summary

To address the problem of time delay in networked control systems, this chapter designs a hierarchical distributed networked control system and applied in power control. It takes the first step toward establishing hierarchical distributed architecture for large-scale power control system to realize demand and response during peak hours. In the proposed architecture, there are many sub-controllers in charge of managing the power consumption in their own clusters of approximately 500 houses. The sub-controllers are subject to local power consumption limits assigned from the upper layer, which forms a local control loop which is small enough to guarantee stable control. In addition, we proposed a distributed control algorithm where sub-controllers at higher layers determine appropriate local power consumption limits, which contributes to realizing the global objective of power reduction during peak hours. We showed that the proposed control network is scalable regardless of the size of the power system through numerical simulations with realistic parameters. Furthermore, a building-scale test-bed for power control system was implemented to show the effectiveness of the proposed scheme contributing to daily life power saving instead of high-cost planned blackouts. Our future work will focus on the impact of integrating a large number of electric vehicles, distributed batteries and other renewable energy sources to the system for improvement of demand response performance. Besides, as the chapter only considers local priority at each cluster, it is impossible to evaluate the fairness in terms of power consumption across clusters. In the future works, the authors will consider a global priority metric, e.g. proportional fair priority, in the power control algorithm, to realize 'priority fairness' among clusters.

Chapter 4

Networked Luminance Control System Based on User State Estimation

4.1 Introduction

In a networked control system, there are always a series of distributed sensors deployed in the space. A large amount of data must be combined and fused to obtain the estimation, based on which the controller makes the control command. Therefore, accurate estimation of target's state based on the measurement from distributed sensors is one of the determining factors on the performance of a networked control system. The reason for incorporating multiple information sources to collect information is that the aggregated sensing data could be more reliable and less noisy. Therefore, it can give the controller a better understanding of the target under surveillance. When the estimation's objective is to compute numeric estimates of certain quantities, e.g., such physical attributes as position and speed, from the noisy sensing observations, one of the most versatile estimation and fusion algorithms is the maximum likelihood estimation. It is a recursive linear estimator which successively calculates an estimate for a continuous-valued state, that evolves over time, on the basis of periodic observations that of this state. It employs an explicit statistical model of how the parameter of interest evolves over time and an explicit statistical model of how the observations that are made are related to this parameter.

This chapter aims to address the challenge of state estimation based on distributed sensors. It is motivated by the problem of indoor localized lighting control for power saving, in which a series of distributed human detection sensors are distributed in the target space to detect and estimated user's state for intelligent lighting control. Accurate user state estimation is essential for the performance of localized lighting control. A wireless battery-less human detection sensor network for networked control and the target state estimation strategy based on distributed sensors are designed in this chapter. Because each sensor's sensing capability is quite limited, the controller must well combine and fuse the sensing observations from all sensors in order to accurately estimate user's state and make correct decisions. And it is applied in an LED lighting networked control system which bases on user's position and environment illumination level. It mainly focuses on the power consumption of the lighting system and the satisfaction of user's illumination requirement. It is suitable for office/home automation and can be easily installed in almost any environment without restriction. And a verification experiment is also conducted. In the experiment, the power consumption is logged by a power logger in office's electricity box, and the test user measures the practical illumination in his positions while walking around in the office. The experimental results show that the LED light control system can reduce power consumption by 57% without any loss of user satisfaction.

The rest of this chapter is organized as follows. At first, the background of lighting control and it challenges in control are introduced. Then, the configuration and deployment of proposed networked control system using a battery-less wireless human detection sensor networks are described. After that, the lighting control algorithm and the estimation strategy of user state are explained in details. Last, an experiment is conducted to evaluate the performance of the proposed networked control system.

4.2 Lighting Control based on Estimation of User State

It has become a crucial issue to make more efforts on the optimization of energy usage, because of the limited resources and the consequent increase in energy cost. A better energy usage results in fewer energy bills, less grid loads and less environmental impact. Energy consumed by artificial lighting system constitutes a big portion of total energy consumption. In Japan, annual energy consumption of lighting amounts to 150.6 TWh, accounting for 16% of national energy consumption [52]. Therefore, it will make a notable positive impact for energy conservation to make lighting energy usage more efficient and to reduce energy consumption.

User occupancy is one of the key factors of an energy-efficient lighting control system [53].

In conventional occupancy-based batch lighting control systems, when the presence of any user is detected in an area, a controller switches all or several corresponding lights on, and when the absence is detected for a given delay period, it switches off the lights. Experimental study shows that in such system 20-26% energy can be saved compared with manual switching [54].

Occupancy sensors have been used for detecting user's presence or absence. In [55–57], user occupancy or position is detected using infrared sensors by dividing the space into partitions according to sensor coverages and then differentiating the single triggered sensor or the set of triggered sensors. In [58], multiple infrared sensors are integrated as a sensor node to increase the detection capacities. Ultrasonic sensors [59, 60], RFID [61] and surveillance cameras [62] are also employed to obtain more accurate information of user's occupancy.

Past studies are inadequate for the application of intelligent lighting controls in three main aspects. First, in long-term uninterruptible surveillance, to avoid the frequent battery changes, sensors have to be located in the ceiling or on the wall near the power source. The placements are limited and far from users, which greatly weaken the detection accuracy. Second, for infrared-sensor-based schemes, there is a lack of consideration of its large inevitable detection errors especially for a static object, but in an indoor environment user quite probably stays somewhere. Thus, the systems would suffer from the possible incorrect light switching operations when detection error happens, or user is out of the coverage. Third, for schemes using ultrasonic sensors, RFID and surveillance cameras, although more accurate information of user's occupancy can be obtained for lighting controls, their consumed power and price are relatively high, and they are more invasive and difficult to install in existing rooms, compared with infrared sensors. Therefore, to address the challenges, we design a localization scheme for lighting control by using multiple battery-less infrared sensors to detect user's occupancy and positions with low energy consumption and easy installation.

Since the goal of the lighting control is to change the ON/OFF status or dimmer level of LED lights to create an area with convenient and productive illumination with minimum power consumption, the artificial lighting and environment illumination cannot be separately considered. Adaptively making the best use of environment illumination, such as daylight and reflected light, can highly decrease the requirement of artificial lighting. Therefore, combining both of them when designing a lighting project would efficiently increase the energy efficiency [57, 63–67]. Moreover, all research to date has detailed only simulations or small-scale testbeds. Our system has been implemented and applicated in a practical indoor office environment in E3-315, Osaka University, Japan [68]. The image of the system is illustrated in Fig. 4.1.

4.3 Wireless Battery-less Human Detection Sensor Networks for Networked Control

The overall image and structure of the LED light control system are illustrated in Fig. 4.1. It has been deployed in a practical indoor office environment in E3-315 of Osaka University. As shown in this figure, all LED lights are controlled by an LED light controller through a DALI (Digital Addressable Lighting Interface) link [71][72], in accordance with the commands generated by the BEMS server. And to capture user's location and to perform position-based light control, a battery-less wireless human detection sensor network is also implemented in the office [69][70]. Multiple battery-less infrared human detection sensors are placed on the desks with overlapped sensing coverages. The sensing measurements from sensors are transmitted to the BEMS server through multi-hop communication. The details of the system configuration and deployment will be described in this section.

4.3.1 LED Lights and Controller

LED lights are suitable for energy-efficient lighting control systems because compared to the fluorescent and incandescent light sources, LED lights have many merits including faster-switching response time, lower energy consumption, higher physical robustness and longer lifespan.

In the target office of this work, shown in Fig. 4.2, the LED lighting system consists of a plenty of LED light blocks which are spatially distributed on the ceiling of illuminated space. By adjusting the emitting illumination of the spatially distributed LED lights, it can offer more flexible illumination distribution and light rendering than conventional light sources. This adjustable illumination distribution can also save the energy spent on the illumination into areas where illumination is not actually required.

All of the LED lights are connected to an LED light controller. The controller receives control commands from the BEMS server and then sends the commands to LED lights through a wired DALI link, which is a global industry standard protocol specifically designed for artificial lighting systems. The adoption of industrial standards simplifies the development

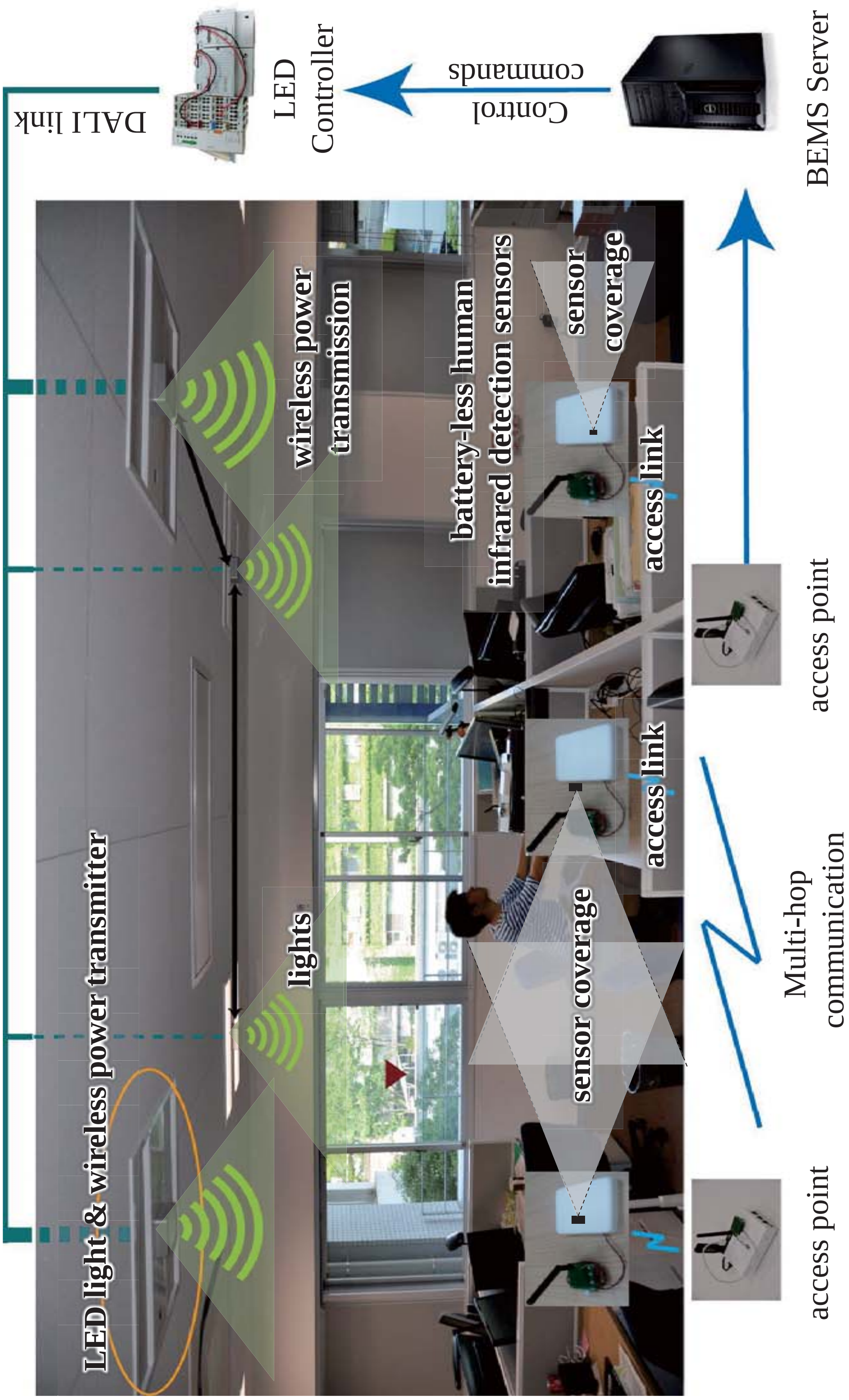


Figure 4.1 Illustration of LED control system using battery-less sensor network.

and setup of such complex systems. Each DALI loop can control up to 64 devices each of which is fully addressable. The BEMS server can collect the sensing information from human detection sensors networks and create the LED control commands.

4.3.2 Human Detection Sensor Network

As is in most current conventional lighting control systems, binary infrared human detection sensor, which relies on detecting changes in the temperature pattern in the sensor's detection zone, is employed in this work, because its energy consumption and price are much lower than other types of human detection sensors (e.g., ultrasonic sensor and microwave sensor). The sensor of this work consumes only 150 μW in intermittent data transmission mode. The chief drawback of currently available infrared sensors is their low efficiency in detecting a static object and tiny movements. This makes it difficult to realize comfortable and effective lighting control.

To address the poor detection probability, instead of placing the sensors in the ceiling or on the walls, we proposed to more flexibly locate sensors close to each user as much as possible, by building a battery-less wireless sensor network in the target office, as shown in Fig. 4.1. That is to say, in this work, all sensors are battery-less and activated by multiple wireless

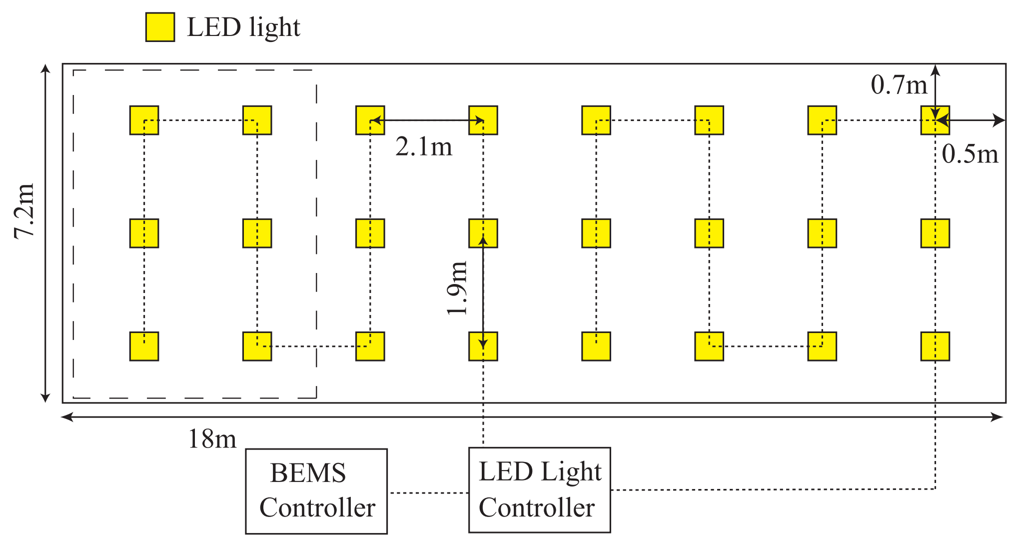


Figure 4.2 LED light and controller.

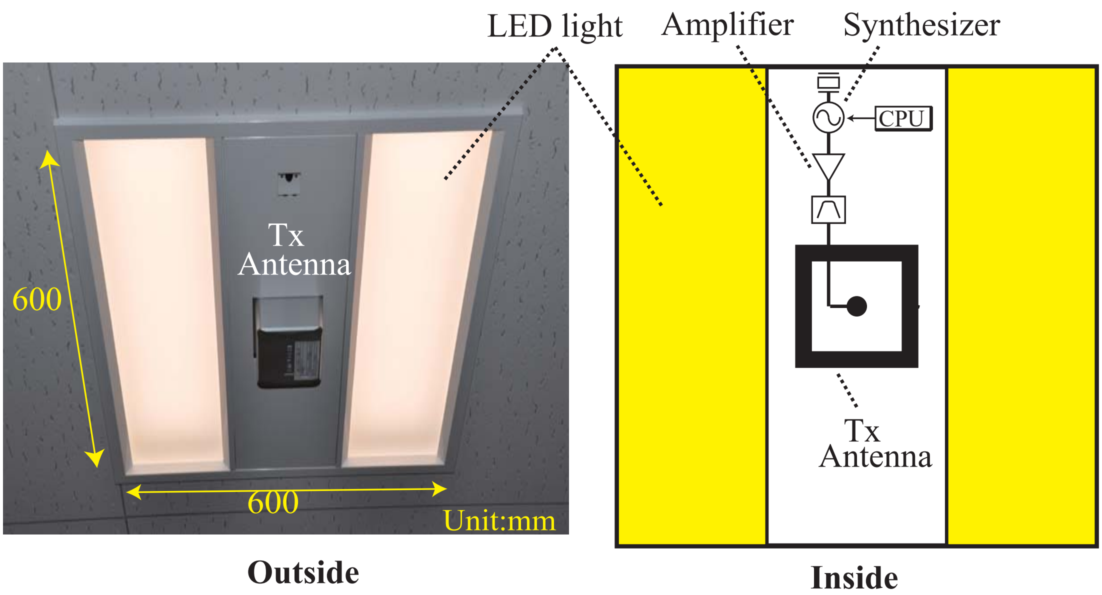


Figure 4.3 LED light and energy transmitter.

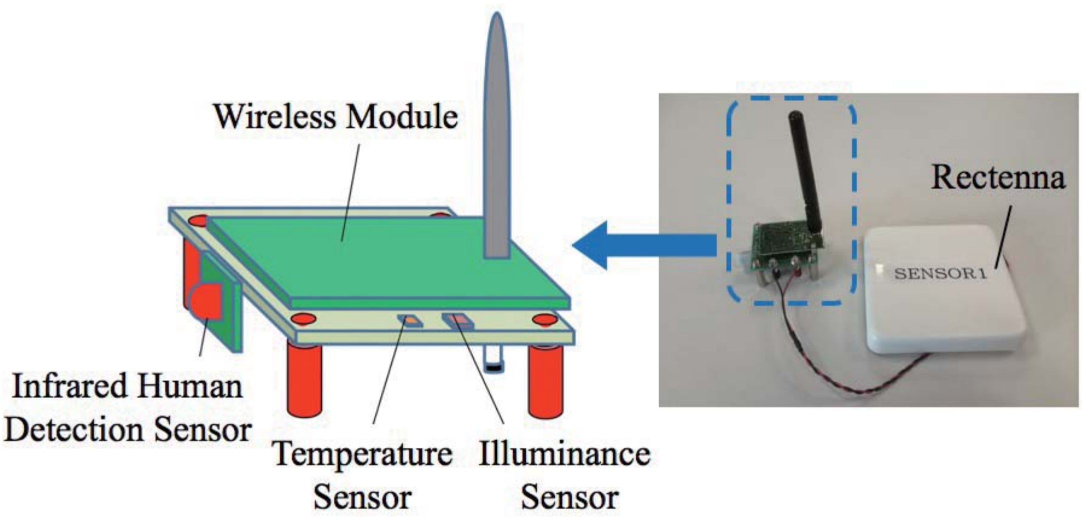


Figure 4.4 Battery-less sensors.

energy transmitters, which are embedded in the ceiling LED lights, as shown in Fig. 4.3 and Fig. 4.4. Because of wireless power transmission and wireless sensing data communication, sensors can be put anywhere in the room rather than such fixed locations as walls and ceilings. More sensors can be deployed in hot areas and at user's side for more accurate detection. Moreover, there is almost no need for follow-up maintenance, such as recharging or changing the batteries.

On the transmitting side, the power of each energy transmitter is 1 W. Moreover, carrier shift diversity is employed [69][70], by which the interference among multiple energy transmitters can be effectively avoided, and hence the continuous and seamless coverage of energy supply can be achieved in the office. The energy efficiency of power transmitter can be further increased in the future by using intermittent energy transmission, high efficient rectennas, beaming control, energy harvesting sensors, etc. [73–75]

On the other hand, the sensor's function is simple. The binary infrared human detection sensor cannot directly give the information of user's location and movement. In each transmission process, it can only output 1-bit sensing information, which represents an estimation whether the user is present (1) or absent (0) in its coverage. To solve this problem, we proposed to deploy a distributed set of sensors with overlapping coverages in the human detection sensor network, instead of a single sensor for one LED light and one area.

And to sense the environment illumination, illumination sensors are embedded alone with each human detection sensor and also activated by wireless power transmission, as shown in Fig. 4.4. Thus, the illumination sensors are much closer to user's working surface and can be placed more flexibly, compared with the conventional illumination sensors which are located in the ceiling.

And on the receiving side, with the consideration of power conversion efficiency of rectenna, the sensors in a battery-less sensor node needs 400 μW to be activated battery-lessly.

4.3.3 Multi-hop Communication Network

The communication system is one of the core parts of any intelligent lighting control system. Wired communications for sensors will result in not only costly remodeling and rewiring work, but also inflexible sensor placement. In this work, sensors and BEMS server from the networks wirelessly, so that sensors can be easily deployed and integrated into the existing rooms without much restriction of installation. It is an accessible and economical solution for light control systems. To note, the communication between controller and light is through a wired DALI link.

Each sensor node detects user's presence/absence status, measures the illumination, and then sends the sensing data to an access point through a wireless channel. The available power for a sensor is limited because it is activated by wireless power transmission. Therefore, to guarantee the converge of the wireless sensor network without significantly increasing the power consumption of the RF module in each sensor node, it is sensible and necessary to introduce multi-hop communication network. Thus, a hierarchical communication network is built, in which the access points have two wireless modules: sensing measurements collection, and multi-hop communication network among access points [76] to create a backhaul network.

Moreover, to reduce power consumption of sensors and extend the effective coverage of wireless power transmission, an intermittent data transmission scheme is employed. The sensor's sensing module, which is responsible for a very small amount of power compared to the RF module, is always active, but the RF module has two working modes (transmission mode/sleep mode), and intermittently transmits the output to the access points [70].

4.3.4 Implementation Cost

The LED lights and light controller (DALI) are all common retail productions and have no difference from those used in our daily life or in any other LED lighting control systems. The wireless power transmission system is also a general-purpose system and can continuously supply energy wirelessly to variety kinds of sensors and devices. We expect that in the future it would be located at ceilings or integrated into lights as a standard feature in every room [70]. Therefore, the only specialized part in this work is the wireless sensor network. It includes sensors, wireless modules, development board, USB interface, APs for sensing data transmission and APs for multi-hop communication. They totally cost around 60,000JPY in this work, and they could be much cheaper if mass produced.

4.4 Illumination Control Strategy

The illumination control in this work mainly focuses on minimizing the lighting power consumption while satisfying user's illumination requirements, based on the user's position and illumination preference.

4.4.1 Consumed Power of LED Lights

The power efficiency of LED lights, i.e., the ratio of consumed power to emitting illumination, is a function of many factors, which includes temperature, optical loss, working time, electrical and spectral efficiency, etc. [84][85] If the LED light is not overheated, its power efficiency can be controlled to be a constant level in stable environments, such as indoor facilities. Thus, the relationship between emitting illumination and power consumption of LED lights can be considered as:

$$C^l = r^l \, F^l \tag{4.1}$$

where C^l is the consumed power of LED light l, r^l denotes the power efficiency factor of LED light l, and F^l is the LED light's emitting illumination.

Therefore, the overall power consumption C_{All} of the LED light control system is given by the summation of the power consumed by all LED lights and the other devices as:

$$C_{\mathrm{All}} = C_{\mathrm{S}} + \sum_{l}^{I} C^l = C_{\mathrm{S}} + \sum_{l}^{I} r^l \, F^l \tag{4.2}$$

where I denotes the number of LED lights, and C_{S} is the system's overhead power consumption which includes the power consumed by the wireless power transmitter, wireless access point, BEMS server and LED light controller, etc. Note that compared to LED lights' power (maximum 100 W per LED light in this work), C_{S} is relatively small (around tens of watts). Therefore, it is treated as constant standby power here. Moreover, this part of energy consumption could be further decreased, e.g., by using lower energy cost devices and more efficient wireless energy transmission.

4.4.2 Lighting Model

Figure 4.5 illustrates the geometry of LED lights in the ceiling and illuminated positions in working surface, which is a flat plane at desk height in the space. The illumination distribution of each position can be denoted by:

$$F^l_{x,y} = F^l \, h^l_{x,y} = sw_l \, F^l_{\mathrm{full}} \, h^l_{x,y} \tag{4.3}$$

where $F^l_{x,y}$ is the received illumination in position (x, y) contributed by LED light l. $F^l = sw_l F^l_{\mathrm{full}}$ denotes luminous power of the LED light l, which is related to its maximum emitting illumination F_{full} and current switch status sw_l of working dimmer level. $h^l_{x,y}$ is lth LED light's attenuation factor, which indicates the path loss in light's propagation from an LED light to an illuminated position. Obviously, the attenuation factor depends on the specification of LED lights (e.g. the physical shape and beaming angle of LED lights), the system geometry (e.g. the spatial relationship between LED lights and illuminated positions) and the target environment (e.g. building materials which result in light reflection). In most practical cases, such parameters will be nearly constant after setting up the system, so the factor $h^l_{x,y}$ can also be consequently considered as time-invariant.

Theoretically, the LOS (Line of Sight) propagation of lights from LED can be conveniently approximated by the generalized Lambertian source model, and $h^l_{x,y}$ can be accordingly defined by Lambertian functions following Lambert's cosine law [77]. However, practically various common furnishing and building materials, such as walls and furniture surfaces, are efficient diffuse reflectors of visible light. In comparison with LOS propagation, it is much more complicated and cumbersome to analytically model the effect of multiple diffuse reflections by reflectors of different materials in the complex circumstance of a practical room. The illumination contributions from reflections are unneglectable and necessary to be taken into

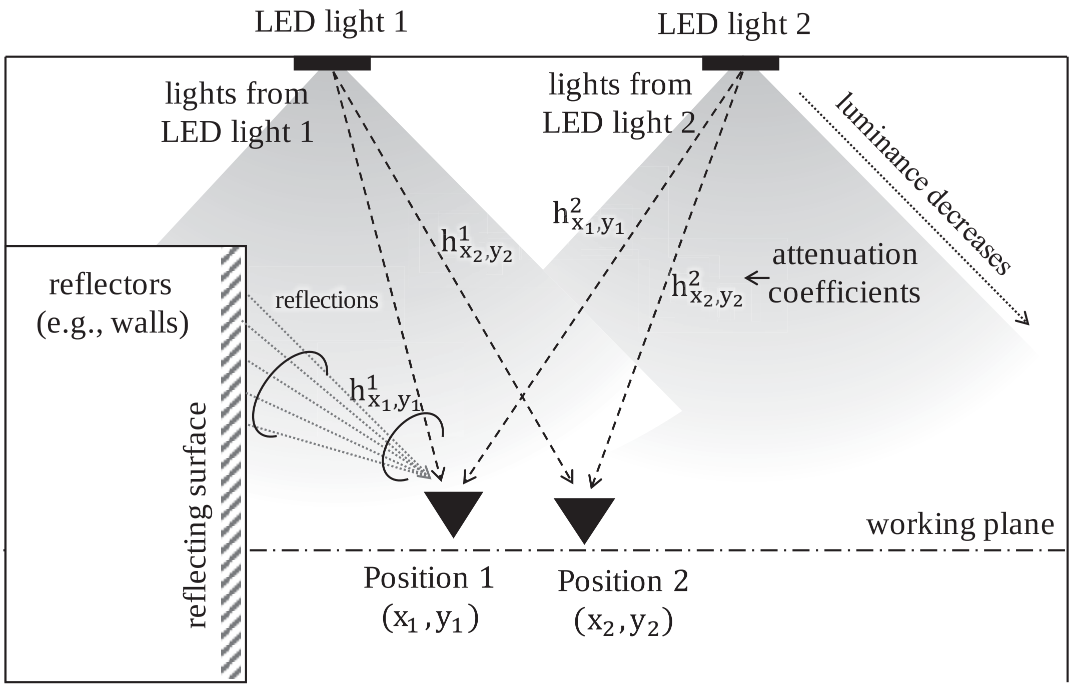


Figure 4.5 Lighting model.

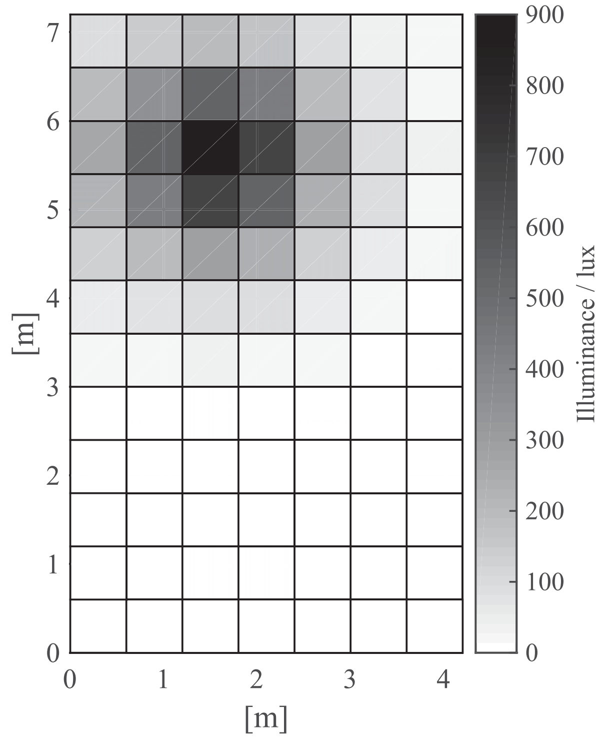


Figure 4.6 Measured illumination.

consideration for the total illumination of each illuminated position. For example, the typical indoor smooth white wall can reflect almost 90% of light. If there is a lack of such consideration of reflection, the system has to cost extra energy to satisfy the illumination requirement near reflectors, and this will consequently decrease the systems energy saving performance.

In the most cases, the dominated indoor reflectors, such as white walls and large smooth surfaces of furniture, are fixed after the construction of the room. Therefore, alternatively in this work, rather than model-based calculation, we practically obtain $h^l_{x,y}$ by respectively measuring F'^l (the measured emitting illumination from LED light l) and $F'_{x,y}$ (the measured received illumination at illuminated position), while other LED lights are off, using illumination sensors:

$$h^l_{x,y} = F'_{x,y} \ / \ F'^l \tag{4.4}$$

Figure 4.6 gives an example of the measured received illumination from a full-on LED light in the left quarter of the office, which is shown in the dashed box in Fig. 4.2. Dividing it by the LED light's maximum emitting illumination, the attenuation factor can be derived.

The benefits of such method are that both of direct illumination and the multiple diffuse reflections of lights in the practical room are well involved in total illumination without complicated environment and lighting model.

In an illuminated position, its total illumination is contributed by the direct and reflected illumination from all LED lights. It is denoted as:

$$F_{x,y} = \sum_{l=1}^{I} F_{x,y}^{l} = \sum_{l=1}^{I} sw_l F_{\text{full}}^{l} h_{x,y}^{l} \tag{4.5}$$

The environment illumination in each position is approximated by that of the closest illumination sensor, which is co-located beside the infrared human detection sensor and spatially distributed in the office.

$$F_{x,y}^{\text{en}} \approx F_{N(x,y)}^{\text{en}} \tag{4.6}$$

where $F_{x,y}^{\text{en}}$ denotes the environment illumination in position (x, y). $N(x, y)$ is the position of nearest illumination sensor to (x, y).

$$\begin{aligned} F_{N(x,y)}^{\text{en}} &= F^s - F_{N(x,y)} \\ &= F^s - \sum_{l=1}^{I} sw_l F_{\text{full}}^{l} h_{N(x,y)}^{l} \end{aligned} \tag{4.7}$$

where F^s is the illumination measurements from illumination sensors. $F_{N(x,y)}$ is the illumination contributed by LED lights.

4.4.3 LED Light Control Strategy

In an office, only the illuminations on and around occupants or some specified objects which need to be illuminated (e.g., a notice board) are necessary. And only when the necessary illuminations are higher than a satisfaction level, they are productive and can increase the efficiency at work and the health of people. Therefore, we consider a localized illumination control scheme.

From the analysis above, given the location of user and the satisfaction illumination level, the optimization problem of illumination control can be derived:

$$\begin{cases} \min\limits_{sw_1, sw_2 \ldots} C_{\text{All}} = \sum\limits_{l} r^l sw_l F_{\text{full}}^{l} + C_{\text{S}} \\ \qquad s.t. \\ F_{x,y} > F_{u;x,y}^{\min} - F_{x,y}^{\text{en}} \quad (x, y) \in G_u \quad u = 1, 2 \ldots U \\ 0 \le sw_l \le 1 \quad l = 1, 2 \ldots L \end{cases} \tag{4.8}$$

where $F^{\text{en}}_{x,y}$ denotes the environment illumination on position (x, y), which is obtained from illumination sensors. $F^{\min}_{u;x,y}$ is the minimum satisfaction illumination of user u, which can vary in different positions. U is the number of users. Switch status $sw_l \in [0, 1]$ indicates a certain dimmer level of LED light l.

The satisfaction of the user is only evaluated by the luminance in user's position. If it is larger than the pre-set required luminance value, the user's luminance requirement is 'satisfied' which means a successful control, otherwise, 'unsatisfied' which means a failed control. Note that there are some other luminance metrics of illumination distribution (e.g., fluctuation in user's path, contrast ratio of illumination in an area [82]) are not implemented, because currently in the verification experiments only ON/OFF control is conducted, i.e., $sw_l = 1$ *or* 0. The more flexible and convenient dimmer control scheme will be conducted soon.

4.5 User Localization Strategy

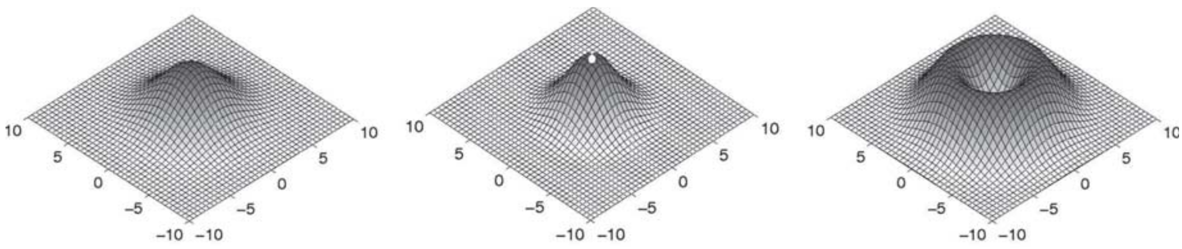
To realize the localized illumination control presented in Sec. 4.4, a battery-less wireless human detection sensor network is implemented to detect user's position and moving status. As described in Sec. 4.3, a series of battery-less infrared human detection sensors are distributed in the target room. The binary sensing measurements are used to estimate user's moving states.

4.5.1 State transition model

In this paper we consider a 4-D state space $\boldsymbol{\mathcal{S}} \subset \boldsymbol{\mathcal{R}}^4$, with the state vector $\boldsymbol{s} = [x,\ y,\ v_x\ , v_y]^T$, $\boldsymbol{s} \in \boldsymbol{\mathcal{S}}$, where x, y and v_x, v_y represent user's position and velocity in x-axis and y-axis respectively.

The state transition model takes into account that in the target indoor environment, user's motion typically has two modes with different characteristics. *Static Mode*: user stays in some location for a period. *Moving Mode*: user walks following certain moving-pattern. Therefore, we use a switching-mode approach to model it based on the consideration above.

User's state transition rules in the two modes are different. In the moving mode, as shown in Fig. 4.8, it is a one-order Markov process [78, 79], and the states transition follows a variable acceleration motion. Normal distribution is adopted here as the model for the variable accelerations [80]. According to the characteristic of target's motion, Beta distribution and



Gaussian distribution Beta distribution Gaussian ring

Figure 4.7 PDF of different transition probabilities.

Gaussian ring [81] are also usually used to model the state transition for indoor movement. The probability density distributions of different transition probabilities are shown Fig. [**?**].

Additionally, to model the non-uniform acceleration or non-rectilinear motion within a time interval, two normally distributed deviations are added to user's position in both x- and y-axis respectively. Note that if we only focus on the positions of the target, the Markov model is actually a two-order Markov model with 2-D state space $\boldsymbol{\mathcal{S}'} \subset \boldsymbol{\mathcal{R}}^2$, with the state vector $\boldsymbol{s} = [x,\ y]^T$, $\boldsymbol{s} \in \boldsymbol{\mathcal{S}'}$.

On the other hand, in the static mode, user's current state should either be the same as last state with probability $Pr^{\mathrm{S}}()$, or turn into moving mode with probability $1 - Pr^{\mathrm{S}}()$. Naturally this mode should only contain the states with zero velocity. The self-transition probability $Pr^{\mathrm{S}}()$ is a predefined function of user's last state. For example, in an office environment, in the area near the desk, user is more likely to maintain the static mode with higher $Pr^{\mathrm{S}}()$. The transitions of other states will follow the moving model.

Therefore, the state transition model can be written as:

$$\boldsymbol{u_t} = \boldsymbol{u_{t-1}} + (\boldsymbol{A}\boldsymbol{u_{t-1}} + \boldsymbol{r_t} + \boldsymbol{n_t})\ I(\boldsymbol{u_{t-1}}) \tag{4.9}$$

with

$$\boldsymbol{A} = \begin{bmatrix} 0 & 0 & \Delta t & 0 \\ 0 & 0 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},\ \boldsymbol{r_t} = \begin{bmatrix} a_{t,x}\Delta t^2/2 \\ a_{t,y}\Delta t^2/2 \\ a_{t,x}\Delta t \\ a_{t,y}\Delta t \end{bmatrix},\ \boldsymbol{n_t} = \begin{bmatrix} n_{t,x} \\ n_{t,y} \\ 0 \\ 0 \end{bmatrix},$$

where, $\boldsymbol{u_t} = \boldsymbol{s} \in \boldsymbol{S}$ is user's state in time t. $\boldsymbol{A}$ is the state transition matrix for linear motion in moving mode. Δt is the time interval. $a_{t,x}, a_{t,y} \sim \mathcal{N}\left(0, \sigma_a^2\right)$ are the independent normal accelerations in x-axis and y-axis. As described above, the deviation movement is modeled by normal velocities following $\mathcal{N}(0, \sigma_v^2)$. Therefore, the deviations $n_{t,x}, n_{t,y} \sim \mathcal{N}(0, \sigma_n^2)$ with $\sigma_n = \sigma_v \Delta t$.

$I(\boldsymbol{u_{t-1}})$ is an indicator function for user's moving mode, which is related to user's last state $\boldsymbol{u_{t-1}}$. It is given by:

$$I(\boldsymbol{u_{t-1}}) = \begin{cases} \mathbf{0} & \text{with Prob. } Pr^{\mathrm{S}}(\boldsymbol{u_{t-1}}) \\ \mathbf{1} & \text{with Prob. } 1 - Pr^{\mathrm{S}}(\boldsymbol{u_{t-1}}) \end{cases} \tag{4.10}$$

Therefore, the transition probabilities that user is in state m in time $t-1$ and in state j in time t can be written as:

$$T_{ij} = \begin{cases} Pr^{\mathrm{S}}(\boldsymbol{s_i}) & \text{when } i = j \\ [1 - Pr^{\mathrm{S}}(\boldsymbol{s_i})] Pr^{\mathrm{M}}(\boldsymbol{u_t} = \boldsymbol{s_j} | \boldsymbol{u_{t-1}} = \boldsymbol{s_i}) & \\ & \text{when } i \neq j \end{cases} \tag{4.11}$$

with

$$Pr^{\mathrm{M}}(\boldsymbol{u_t} = \boldsymbol{s_j} | \boldsymbol{u_{t-1}} = \boldsymbol{s_i},\ \boldsymbol{\xi_t},\ \boldsymbol{\Sigma_s}) \sim \mathcal{N}(\boldsymbol{\xi_t}, \boldsymbol{\Sigma_s})$$

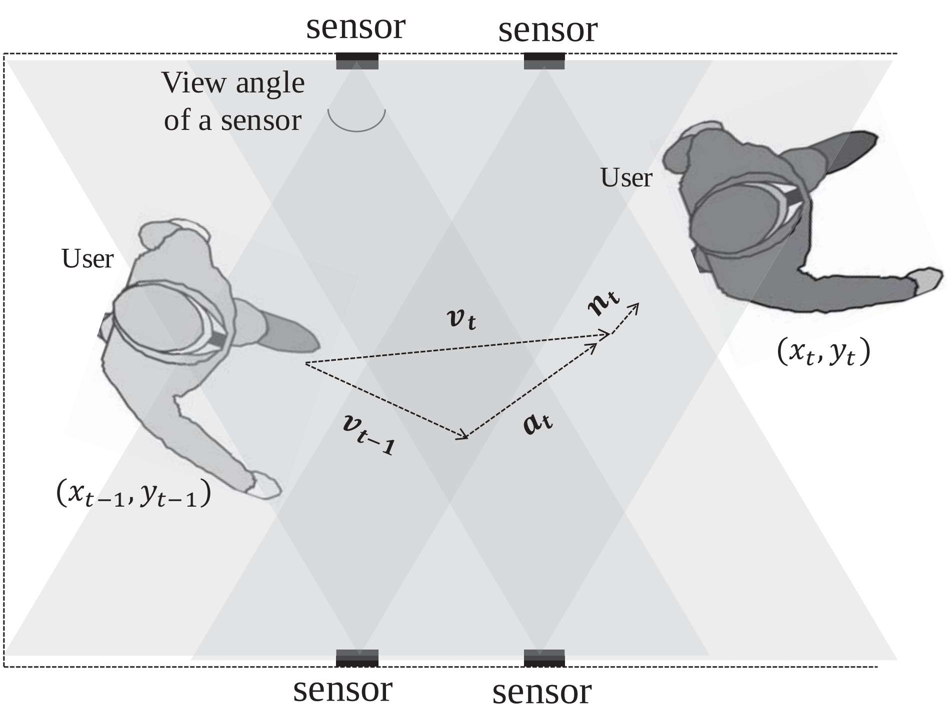


Figure 4.8 User moving model.

where $\boldsymbol{\xi_t}$ and $\boldsymbol{\Sigma_s}$ are mean vector and covariance matrix respectively:

$$\boldsymbol{\xi_t} = [x_{t-1} + v_{t-1,x}\Delta t,\ y_{t-1} + v_{t-1,y}\Delta t,\ v_{t-1,x},\ v_{t-1,y}]^T,$$

$$\boldsymbol{\Sigma_s} = \begin{bmatrix} \sigma_v^2\Delta t^2 + \frac{\sigma_a^2\Delta t^4}{4} & 0 & \frac{\sigma_a^2\Delta t^3}{2} & 0 \\ 0 & \sigma_v^2\Delta t^2 + \frac{\sigma_a^2\Delta t^4}{4} & 0 & \frac{\sigma_a^2\Delta t^3}{2} \\ \frac{\sigma_v^2\Delta t^3}{2} & 0 & \sigma_a^2\Delta t^2 & 0 \\ 0 & \frac{\sigma_v^2\Delta t^3}{2} & 0 & \sigma_a^2\Delta t^2 \end{bmatrix}$$

For convenience, $\boldsymbol{\xi_t}$ and $\boldsymbol{\Sigma_s}$ are left out in the following content from the probability equation.

In the practical case, the moving model should be modified according to the real environment. The transition probabilities from or to invalid positions, e.g., positions in the invalid area, such as furniture's location, or out of the edges of the target area, should set to be 0. When the state transition model is non-linear, generally there is no analytic expression of the result of the Maximum Likelihood estimation, so that the transition process should be converted into a discrete form to search all possible states.

4.5.2 Sensing model

Because all sensors in this work are activated by wireless power transmission, the power consumption becomes one of the most important determining factors in choosing the sensor. Therefore, the sensors employed in this work are infrared directional binary human detection sensors. The sensors cannot directly give the information of user's location or moving status. The sensing outputs are binary only. The output 1 represents that the sensor detects the user in its coverage. And the output 0 represents that sensor does not detect any user in its coverage. Moreover, the infrared sensor is the cheapest solution among all types of sensors which can be used in localization, such as ultrasonic sensors and microwave sensors.

The employed sensors are directional sensors with fan-shaped sensing coverage, comparing with the disk-shaped coverage of omni-directional sensors. Considering the working mechanism of infrared sensors, distinct sensing-boundary in the fan-shape's two edges of radii are assumed. And we also assume that the detection probability is uniform within the effective coverage radius R, and when outside of effective coverage, it decreases exponentially with the distance. Fig. 4.9 illustrates the directional coverage model. Therefore, the likelihood function of sensor detection is given by:

$$Pr(b_k|x_i, y_i) = \begin{cases} P_{\mathrm{D}}c_{ik} & \text{when } b_k = 1 \\ 1 - P_{\mathrm{D}}c_{ik} & \text{when } b_k = 0 \end{cases} \tag{4.12}$$

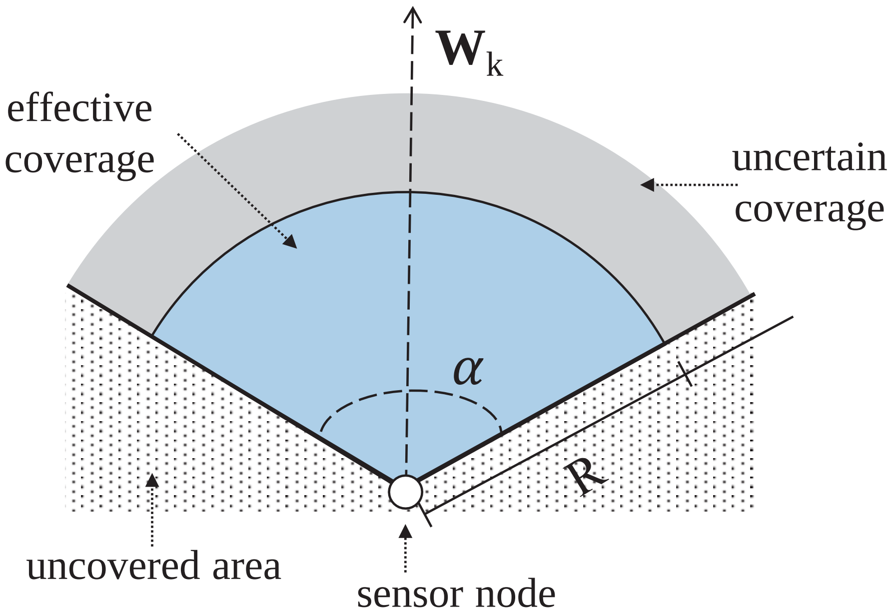


Figure 4.9 Directional sensing coverage model.

where

$$c_{ik} = \begin{cases} 0 & \text{when } a_{ik} > \frac{\alpha}{2} \\ e^{-\lambda \eta^{\beta}} & \text{when } R < d_{ik} \text{ and } a_{ik} < \frac{\alpha}{2} \\ 1 & \text{when } R \geq d_{ik} \text{ and } a_{ik} < \frac{\alpha}{2} \end{cases} \tag{4.13}$$

where b_k is the output sensing measurement of sensor k. (x_i, y_i) denotes the position of object. P_{D} is the detection probability within the sensor's effective coverage radius R. d_{ik} is the distance between sensor k and position (x_i, y_i). a_{ik} is the angle between sensor's working direction $\boldsymbol{W}_k$ and the vector from sensor k to position (x_i, y_i). α is the view angle of the sensor. c_{ik} is the attenuation factor of detection probability according to distance. $\eta = d_{ik} - R$. λ, β are parameters shaping the attenuation of detection probability.

Due to the mechanism that typically infrared sensor detects the fluctuation of infrared radiation impinging upon it from the objects in front of the sensor, the detection probabilities are different from the static and moving objects. By detecting the infrared radiation changes from the background and the moving object in its field of view, the sensor is sensitive to moving object, such as a walking human. While it is quite insensitive to static objects or small movements, because the tiny temperature changes may be treated as environment noises. This poses difficulties for the current infrared sensor based lighting control systems, because the user may stay somewhere even for a long time in an office.

And according to our test, the false alarm probability of the employed infrared sensors is negligible and can be assumed to be 0.

4.5.3 User localization algorithm

To estimate user's state, multi-sensor is deployed with overlapped coverage. Therefore, by combining the sensing measurements from multi-sensors, the large detection error of infrared human detection sensor can be overcome. In this section, a maximum likelihood estimation algorithm and a non-uniform resolution approximation algorithm are presented. The result will be used for LED light control in the next section.

User's state is estimated by maximizing the accumulated likelihood function that user is currently in certain state given the sensor outputs, which is given by:

$$\arg\max_{\boldsymbol{u_t}} L\left(\boldsymbol{u_t}|\boldsymbol{\mathcal{B}_t}\right) = \arg\max_{\boldsymbol{u_t}} Pr\left(\boldsymbol{\mathcal{B}_t}|\boldsymbol{u_t}\right) \tag{4.14}$$

where $\boldsymbol{\mathcal{B}_t} = [\boldsymbol{b_1},\ \boldsymbol{b_2}, ..., \boldsymbol{b_t}]$, and $\boldsymbol{b_t} = [b_{t,1},\ b_{t,2}, ..., b_{t,N}]$ is the sensing vector of all sensors at time t, and N is the number of sensors. All the sensing measurements are temporally and spatially conditionally independent. Therefore, for convenience of calculation, the accumulated likelihood can be separated into two parts: current likelihood and historical likelihood:

$$\begin{aligned} L\left(\boldsymbol{u_t} = \boldsymbol{s}_i|\boldsymbol{\mathcal{B}_t}\right) &= Pr\left(\boldsymbol{\mathcal{B}_t}|\boldsymbol{u_t} = \boldsymbol{s_i}\right) \\ &= Pr\left(\boldsymbol{b_t}|\boldsymbol{u_t} = \boldsymbol{s_i}\right) Pr\left(\boldsymbol{\mathcal{B}_{t-1}}|\boldsymbol{u_t} = \boldsymbol{s_i}\right) \end{aligned} \tag{4.15}$$

In our cases, the detection probability of employed sensor varies when the user is static (namely, $\boldsymbol{u_{t-1}} = \boldsymbol{s_i},\ \boldsymbol{u_t} = \boldsymbol{s_i}$) and moving (namely, $\boldsymbol{u_{t-1}} = \boldsymbol{s_i},\ \boldsymbol{u_t} = \boldsymbol{s_j},\ j \neq i$). Therefore, current likelihood is further separated into these two cases and calculated as:

$$\begin{aligned} & Pr\left(\boldsymbol{b_t}|\boldsymbol{u_t} = \boldsymbol{s_i}\right) \\ = & \sum_{j=1}^{M} Pr\left(\boldsymbol{b_t}|\boldsymbol{u_{t-1}} = \boldsymbol{s_j}, \boldsymbol{u_t} = \boldsymbol{s_i}\right) T_{ij} \\ = & Pr\left(\boldsymbol{b_t}|\boldsymbol{u_{t-1}} = \boldsymbol{s_i}, \boldsymbol{u_t} = \boldsymbol{s_i}\right) T_{ii} \\ + & \sum_{j=1, j\neq i}^{M} Pr\left(\boldsymbol{b_t}|\boldsymbol{u_{t-1}} = \boldsymbol{s_j}, \boldsymbol{u_t} = \boldsymbol{s_i}\right) T_{ij} \end{aligned} \tag{4.16}$$

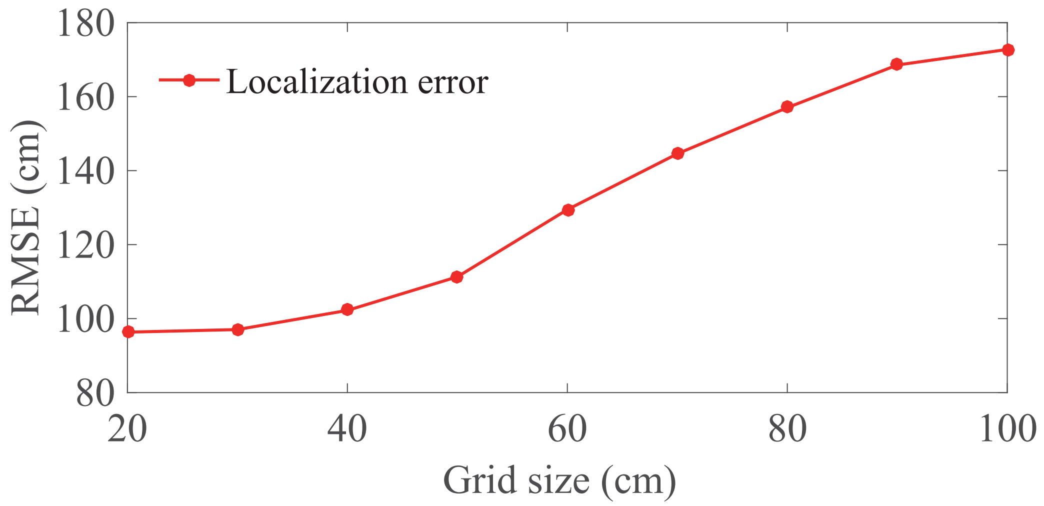


Figure 4.10 Localization error.

where $M = |\boldsymbol{\mathcal{S}}|$ denotes the number of states in state space. T_{ii} and T_{ij} are the transition probability between two successive states for a static and moving status correspondingly. They are defined by the movement model and can be derived from Eq. (4.11).

The historical likelihood can be calculated as:

$$
\begin{aligned}
& Pr\left(\boldsymbol{\mathcal{B}_{t-1}} | \boldsymbol{u_t} = \boldsymbol{s_i}\right) \\
= & \sum_{j=1}^{M} Pr\left(\boldsymbol{\mathcal{B}_{t-1}} | \boldsymbol{u_{t-1}} = \boldsymbol{s_j}\right) T_{ij} \\
= & \sum_{j=1}^{M} L\left(\boldsymbol{u_{t-1}} = \boldsymbol{s_j} | \boldsymbol{\mathcal{B}_{t-1}}\right) T_{ij} \qquad (4.17)
\end{aligned}
$$

where $L(\boldsymbol{u_{t-1}} = \boldsymbol{s_j} | \boldsymbol{\mathcal{B}_{t-1}})$ is the accumulated likelihood in the previous time step $t-1$.

Generally, it is difficult to obtain the closed form of result for Eq. (4.14). The numerical calculation should be done on discrete states in the state space. The estimation error is inevitable because of the grid search and the sensing capability of the employed directional infrared binary human detection sensors. Figure 4.10 shows the relationship between grid size and the localization error.

Therefore, to compensate the estimation error and avoid loss of user satisfaction, not only the position with maximum likelihood, but the illumination requirement in all the positions in a set G_{T} should be satisfied. The set of location candidates G_{T} contains positions whose current total likelihood is larger than threshold $\mathrm{Th_c}$.

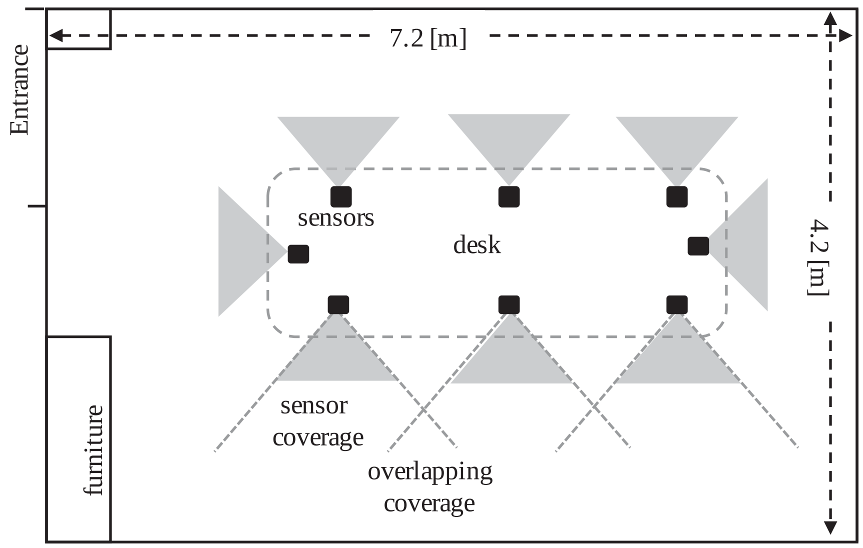
$$G_{\mathrm{T}} = \{(x_i, y_i)|L(\boldsymbol{u_t} = \boldsymbol{s_i}|\boldsymbol{\mathcal{B}_t}) > \mathrm{Th_c}, \boldsymbol{s_i} \in \boldsymbol{S}\} \tag{4.18}$$

Apparently the setting of $\mathrm{Th_c}$ affects the performance of LED lights control and should balance the power consumption and user's satisfaction. Currently in the verification experiments, $\mathrm{Th_c}$ is set empirically. The optimized threshold should depend on locations, because of the location-invariant estimation accuracy, which is caused by the non-uniform deployment of directional sensors and user's nonuniform moving patterns in a restricted indoor space. And the illumination distribution resulted from LED lights' spatial distribution should also be taken into consideration. The theoretical analyses of optimized thresholds will be included in the future work.

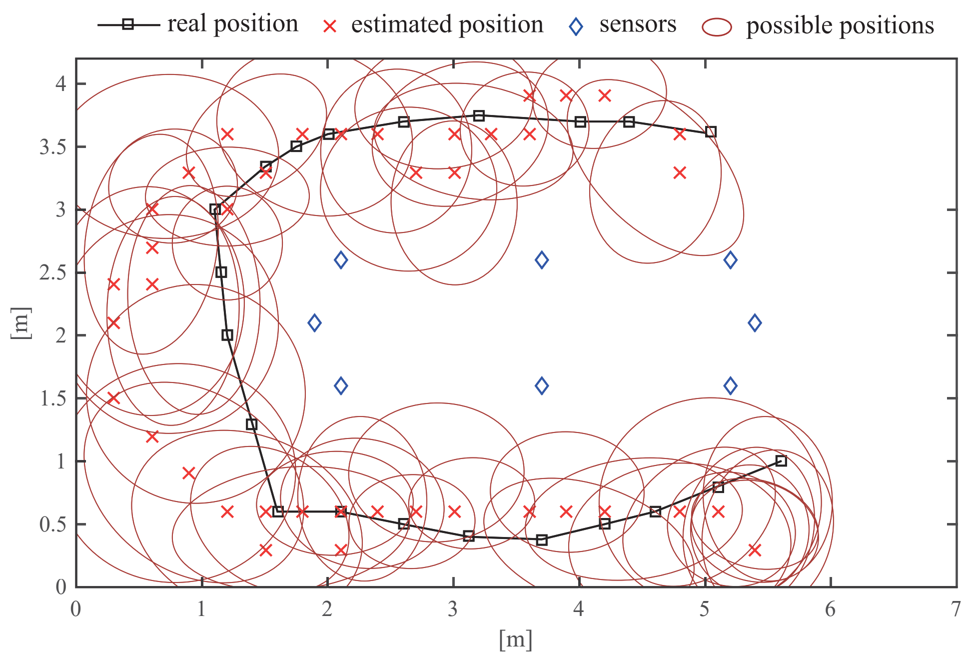
4.5.4 User localization experiment

An experiment is conducted to verify the performance of the battery-less human detection sensor network. Because the proposed lighting control system is mainly designed for such indoor environments as office, the target space is a typical indoor office environment. It includes desks and pathways, and the size is 7.2 m × 4.2 m, as shown in Fig. 4.11(a). Human detection sensors are placed on the desks. In the experiment, a user walks around in the space, from top right corner to down right corner.

The real positions and experimental results are shown in 4.11(b). The black line denotes user's real routes, and the red x denotes the position with maximum likelihood. The ellipses indicate the area of all possible positions, which are positions with probabilities higher than a threshold, as described in Sec 4.5. Although the sensing capacity of a single binary infrared sensor is very coarse and cannot directly give the information of user's position, but by deploying a series of distributed sensors, the estimated positions are close to real routes. The performance is also related to user's moving status, the number and placement of sensors. Additionally, although it is a single user experiment, it is easy to extend to multi-user cases if the number of users is known. With the consideration of calculation amount and to ensure the accuracy of LED control, the space is divided into grids whose size is $30cm \times 30cm$. And it results in the localization error of 91 cm. Note that the real positions of the user are derived from the video of the experiment, so there could exist difference between the localization error in experiment and theoretically in Fig. 4.10.



(a) Top view diagram of target space.



(b) Experiments results.

Figure 4.11 Results of user localization experiments.

4.6 Performance Evaluation by Experiment

The LED light control system is implemented in an indoor office environment. To evaluate the performance, an experiment is conducted. The test user walks in the office. Meanwhile the user measures and records the illumination by a handheld illumination meter at working surface height. And at the same time, the real-time lighting power consumption of the office is recorded by a power logger, which is installed in the cable box and clipped on the electricity cable. The illumination meter and power logger are shown in Fig. 4.12.

4.6.1 Experiment environment

The experiment area is a part of the office. Seven LED lights are under the ON/OFF control by the controller. Wireless power transmitters are embedded in all LED lights. Eight battery-less human detection sensors are put on the desk to detect user's location and track user's motion. By our measurements, practical false alarm probability of the employed sensor is approximately 0, and for moving user detection probability is about 0.8, while for a static user it is only 0.1 which is quite low and makes it almost impossible to effectively detect the user. The reason is discussed in Sec. 4.5.2. And the minimum required illumination is set to be 400 lux according to the standard of indoor lighting levels of Japan [86].

The full-on working power consumption of an LED light is 100 W. Each wireless power transmitter transmits power of 1 W, which is quite small compared to the power consumption of LED light and can be further decreased by optimization of energy transmission.

The walking path is as shown in Fig. 4.13. To simulate the real office user, the test user also switches between moving mode and static mode. If the system works well, only the lights near user's location and path will be turned on, while others will be turned off to save the power.

The setup of the experiment tries to simulate the practical case in real daily life as well as possible. For example, the system is implemented in a real office, and the experiment is also conducted there, where the layouts remains as they are under practical usage. And the test user also tries to simulate the common indoor behaviors such as walking around the desks and staying at the desk.

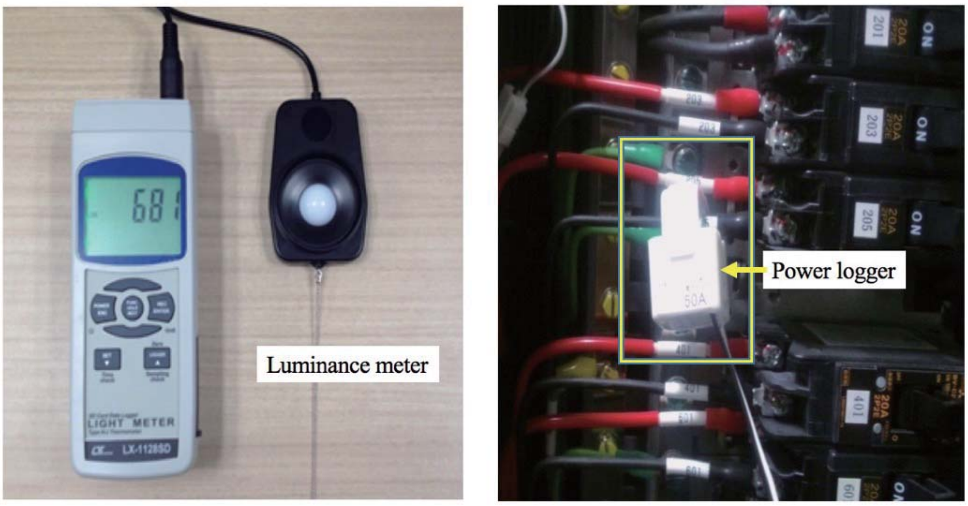


Figure 4.12 Experiment devices.

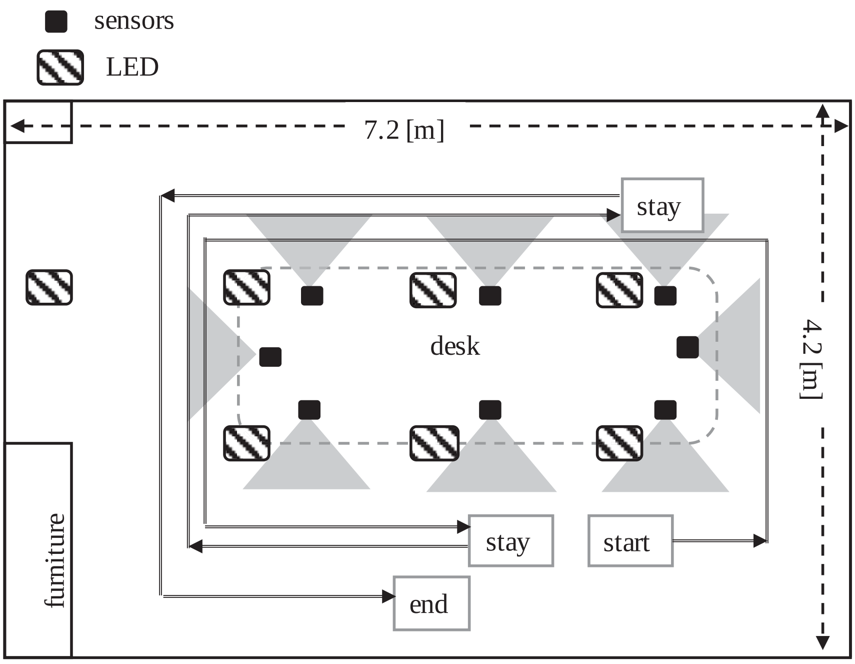


Figure 4.13 Experiment environment and walking path.

4.6.2 Experimental Result

The performance of proposed scheme is compared with the individual control, batch control and the ideal case of perfect user localization. In individual control, each LED light is individually triggered by a single sensor which is embedded beside LED light on the ceiling and can cover the area below the LED light. In the batch control, which is currently the most widely used sensor-based lighting control scheme, if any of the sensors detects user's presence, the controller switches on all LED lights simultaneously, and if all sensors detect absence for a given delay period, it switches off all the LED lights.

Experimental results of power consumption are given in Fig. 4.14. The red curve is the measured results using the proposed scheme. The green curve is the simulation results of individual control. The blue curve is the simulation results of the case of perfect user localization. And the black dot line drawn at the power of 0.7 kW is the power consumption for the batch control case.

In our proposed LED control scheme, in most cases, only 2 or 3 working LED lights are enough to satisfy user's illumination requirement, compared to that in the batch control scheme all 7 LED lights are on. Therefore, the power consumption of our LED light control system is always lower than that of batch control. In the experiment, its power consumption is 57% less than the batch control. The power consumed by the LED control system is almost negligible compared to the working power of LED light and saved power. However, the practical power consumption is still about 1.7 times of ideal case. This is caused by the inaccurate estimation of user's location. As discussed in Sec. 4.3, in this case, the controller has to satisfy the illumination requirement not only in the estimated position, which is the position with maximum possibility, but also the potential positions, which is the positions with possibilities larger than a threshold. Thus, obviously, the energy saving performance of proposed lighting control scheme highly depends on the information of user's position. Figure 4.15 shows the effect of localization error on the energy saving performance from simulation and experiment. Therefore, the performance could be improved by more accurate indoor localization technique. And in the case of individual control, although the power consumption is the lowest, it sacrifices the user satisfaction because it fails to switch the corresponding LED lights on correctly sometimes due to sensors' miss detection.

Figure 4.16 gives the experimental results of illumination. The red, green and blue curves correspond to the power consumption curves with the same color in Fig. 4.14. The red curve is the measured illumination results using the proposed scheme. And the green curve is the

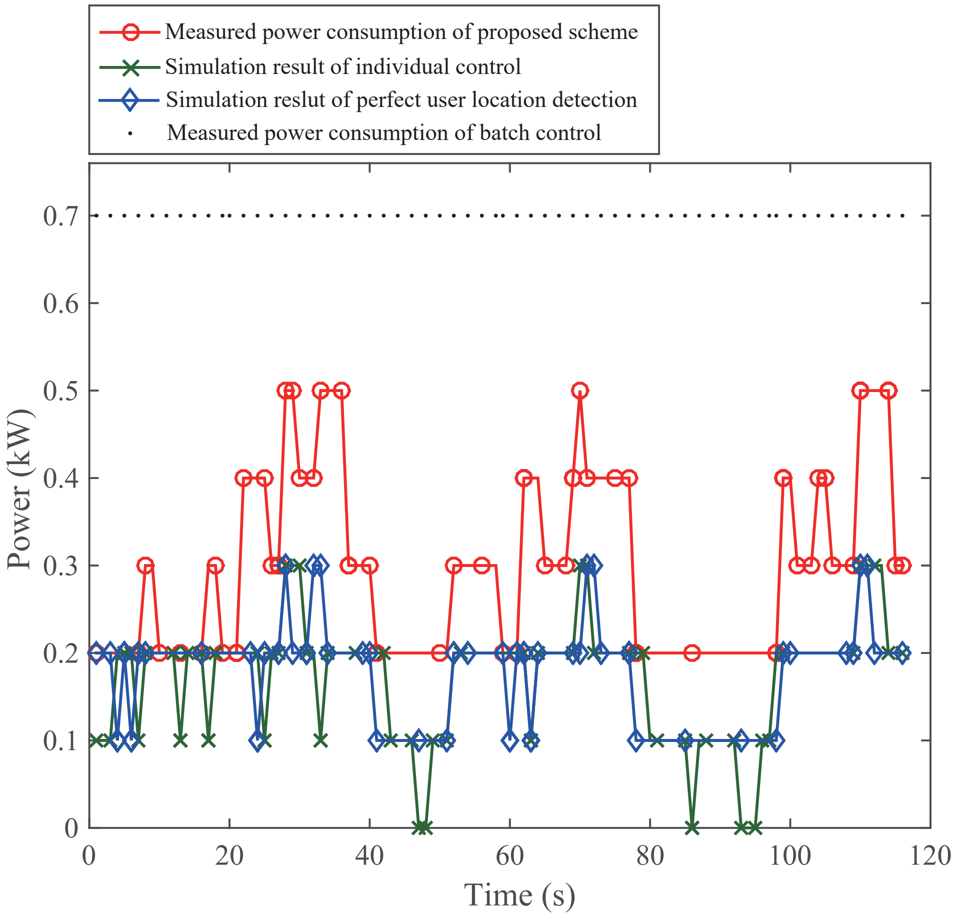


Figure 4.14 Experimental result of power consumption.

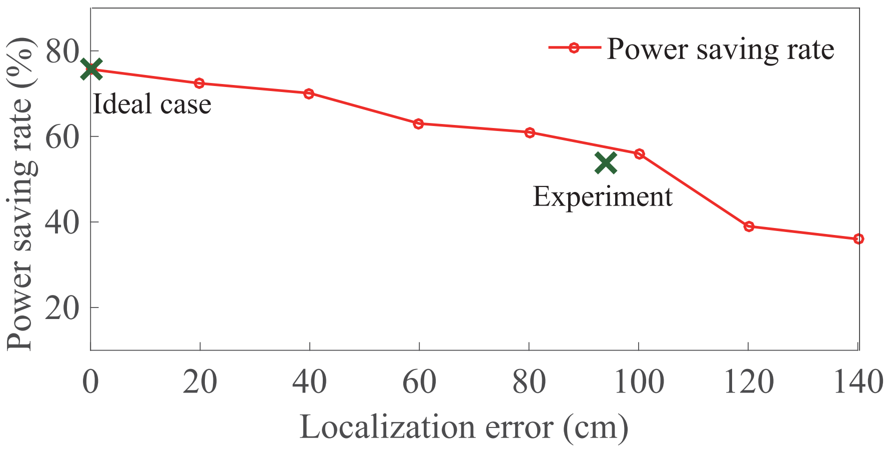


Figure 4.15 Power saving rate.

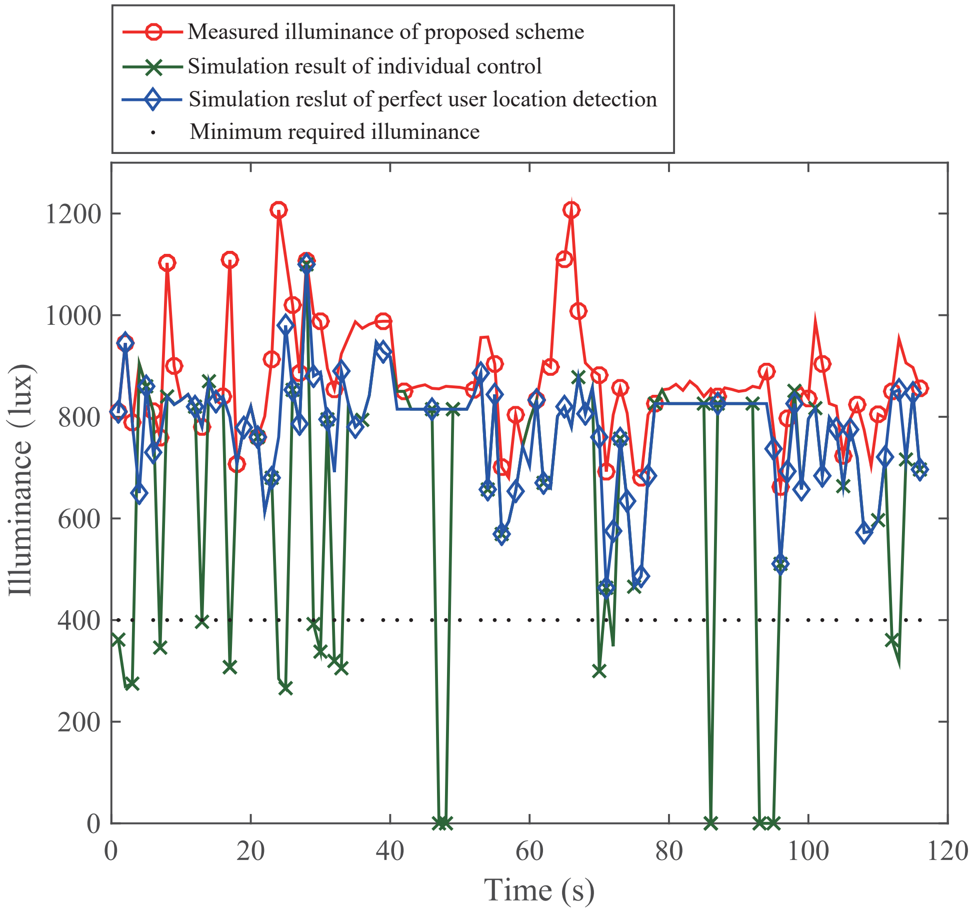


Figure 4.16 Experimental result of illumination.

illumination results of the simulation, in which each LED light is individually triggered by a single sensor. The blue curve is the simulation results, in which user localization is perfectly detected. And the black dot line drawn at the illumination of 400 lux is the minimum required illumination level.

During the experiment, the practically measured illumination is always higher than 400 lux with 100% probability, i.e., the user's illumination requirement can always be satisfied. The average illumination is 867 lux, the maximum illumination intensity is 1207 lux and the minimum illumination intensity is 662 lux. However, Fig. 4.16 shows that even the minimum practical illumination is larger than the required illumination, which is pre-set to be 400 according to the standard of indoor lighting levels of Japan. This is because in the current stage only ON/OFF LED light control is conducted. In the case of dimmer control, the results should be improved. The illumination of individual control sometimes drops lower than 400 lux and even to 0 lux, due to the miss detection of infrared sensors, especially for a static user.

Additionally, the measured illumination curve in Fig. 4.16 seems to be fluctuating severely when the test user is moving, but in practice, such fluctuation is generally imperceptible for users with the naked eyes, especially when walking. On the other hand, in the case that the testing user is staying somewhere in the room to simulate daily working status, the number of working LED lights does not change and hence the illumination is quite stable.

Note that there are still some imperfections and limitations in the experiment, because the accurate position of user in the experiment is difficult to get and the current system is still in a preliminary version. For example, mechanism to avoid the interference on luminance sensing caused by temporal and unintentional blocking by human behavior needs to be developed. As shown in Fig. 4.17, the luminance sensor, which senses the environment luminance level, is easily blocked unintentionally by user, and this may leads to wrong operations of turning on or dimming up the lights. Moreover, in the experiment, the readings from luminance measurer also may be affected by test user's pose and direction. In order to obtain the correct and statistically significant results about the power saving performances and luminance performances of the system from the experiment, in long term, e.g., hours, experiment should be done by automation such as using a robot, as shown in Fig. 4.17.

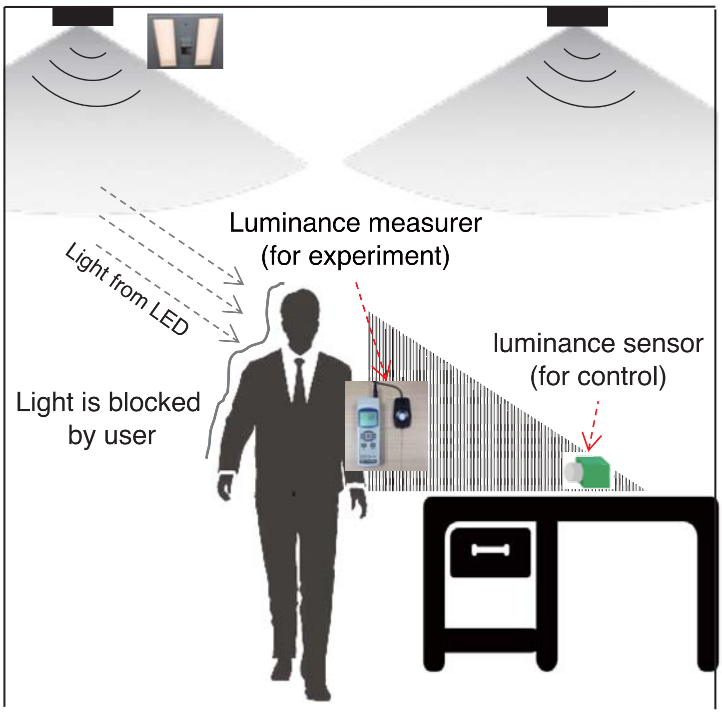


Figure 4.17 Interference of human behavior on luminance sensing.

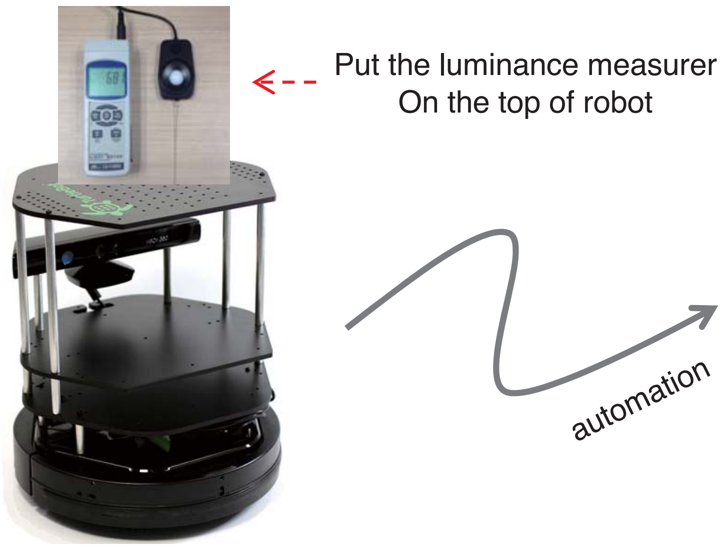


Figure 4.18 Automation in experiment by robot.

4.7 Summary

A wireless battery-less human detection sensor network for networked control and the target state estimation strategy based on distributed sensors are designed in this chapter. And it is applied in an LED lighting networked control system which bases on user's position and environment illumination level. It mainly focuses on the power consumption of the lighting system and the satisfaction of the user's illumination requirement. It is suitable for office/home automation and can be easily installed in almost any environment without restriction. And a verification experiment is also conducted for performance evaluation, whose results show that by using the estimation of the user state based on distributed sensors, the LED light control system can reduce power consumption by 57% without any loss of the user satisfaction.

Chapter 5

Improvement of System Dynamical Model for Networked Control

5.1 Introduction

In Chapter 4, a maximum likelihood algorithm based state estimation strategy based on distributed sensors is designed and applied in indoor lighting networked control system for power saving. It employs an explicit statistical model of how the target process of interest evolves over time and an explicit statistical model of how the observations that are made are related to this physical process, as shown in Fig. 5.1. Such accurate statistical model is necessary, because the target dynamical models are required to relate sensing observations to the parameters or states to be estimated, and the sensing models are required to understand what information about the target process under surveillance by distributed sensors is provided. In other words, the statistical model of system dynamics is the bridges from what the target process is in the view of multiple sensors, to what the target process is in the real world, and to the control decisions controller makes about how to perform control or influence on the target.

It always depends on experiences and assumptions of the ideal and typical cases when selecting the models. This is effective to well model the process describing some effect of the average and overall behaviors. However, for the processes describing the individual behaviors rather than group actions, there are two drawbacks for the classical theoretical models:

- An explicit theoretical model, which well represents how the individual target's state evolves in the real world in time and space, is difficult to find.

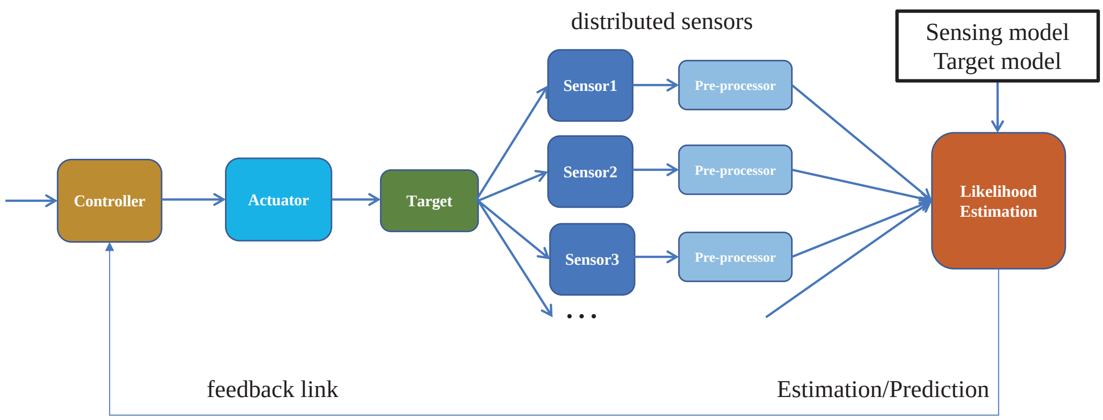


Figure 5.1 Estimation by using maximum likelihood algorithm.

- The accurate parameters of system dynamical model is difficult to obtain and adjust.

To address the challenge to get the model which accurately describe the system dynamics for target state estimation for networked control system, in this chapter, a recurrent neural network is designed to represent how target process and sensing processes evolve and produce interaction effects on each other.

The rest of this chapter is organized as follows. At first the background of machine learning for control problem. Then, the design of the architecture of the recurrent neural network and the training process is explained in details. At last, training and test process are discussed.

5.2 Machine Learning for Control

The networked control system is expected to be adopted in the tasks in which the interactions among the target, sensor and controller are complicated, non-linear and hard to model because of the spatial distribution of the system, the networked control structure and communication structure. Hand-designing networked control systems for some of the tasks is very challenging and difficult to achieve high control performance because the estimation and prediction of target state cannot be accurately performed due to the lake of system dynamical models and consequently the controller cannot make control commands performing best influence on the control target. However, these issues may be addressed by viewing the problem from the machine learning perspective.

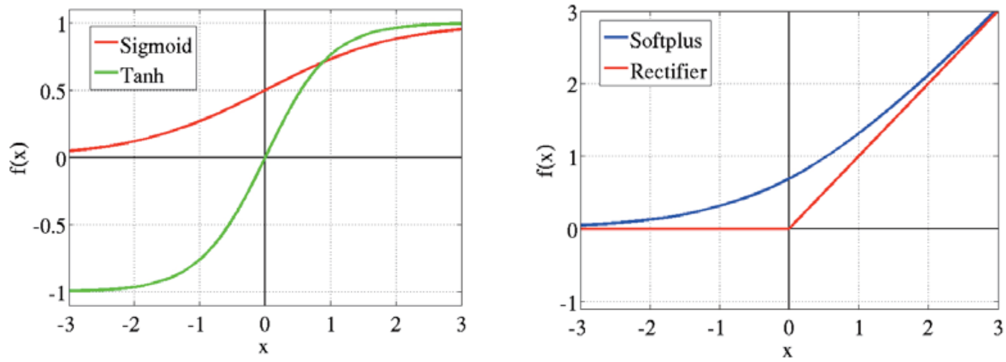


Figure 5.2 Activation functions in neural network.

We choose to use a deep learning algorithm to model the system dynamics for several reasons.

- Universal model approximators for the non-linear process.

One of the biggest advantages of neural networks is that they have been proved to be powerful learners and universal model approximators for the non-linear process. The non-linearity in neural networks mainly from the non-linear activation functions in neurons in hidden layers. The shape of commonly used activation functions, including sigmoid, thanh, ReLU and softplus, are shown in Fig. 5.2.

For example, let us consider a simple neural network with two inputs, two hidden neurons and one output, as shown in Fig. 5.3. The mathematics in the model can be expressed by the following equations:

$$\begin{aligned} h_1 &= f_{ac}(x_1 w_{x_1,h_1} + x_2 w_{x_2,h_1}) \\ h_2 &= f_{ac}(x_1 w_{x_1,h_2} + x_2 w_{x_2,h_2}) \\ y &= f_{ac}(b w_{b,y} + h_1 w_{h_1,y} + h_2 w_{h_2,y}) \end{aligned} \tag{5.1}$$

The non-linearity is introduced into the relation between the inputs x_1, x_2 and output y by the non-linear activation function f_{ac}.

Other reasons include:

- Deep learning networks are able to extract features by themselves rather than hand-designing features

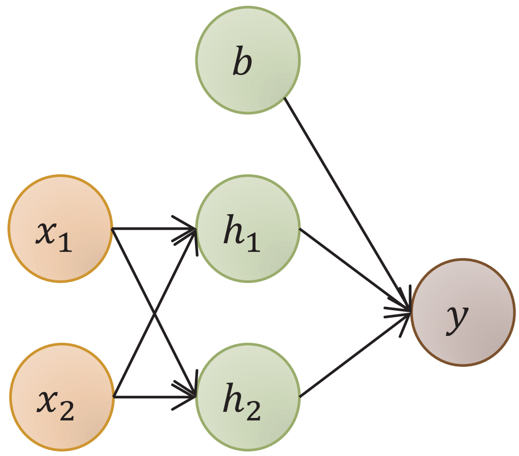


Figure 5.3 An example of a simple neural network.

- They can be efficiently trained by back-propagation algorithms, and there exists well-developed machine learning frameworks for implementation.
- Recurrent neural network can effectively take uses of historical information.
- If the calculation capability of the controller is limited, the numbers of hidden layers and features can be scaled down in the cost of estimation and cost performance.

To put it simply, machine learning could be considered as a powerful universal approximator and be trained to approximate complicated mathematical and even human behaviors. The deep learning such as convolutional networks have gained lots of great successes in numbers of recognition and classification tasks, such as object recognition in computer science and nature language processing.[88, 90] It has much larger numbers of hidden layers, neurons and features than those of the conventional neural networks. By using these features, it can solve large and complex problems, which could be impossible to complete by conventional neural networks in the past. Recently, some efforts have been made to apply machine learning in some control systems, in which the system dynamics is difficult to be modeled by a theoretical model and the control strategy is hard to design by convolutional methods.

Some usages of multilayer perceptrons in control are explored, e.g., in [89], however, such methods is always used small controllers and only for simple tasks. Early experiments with neural network control represented both the system dynamics and policy as neural networks, so that the gradient of the policy could be propagated backward in time [89, 90]. However, this direct optimization approach may generate very unstable gradients, and is always unsuitable for learning the complex and detailed behaviors. More recent reinforcement learning methods instead attempt to improve the policy by using sample rollouts on the actual system, which avoids the need to propagate gradients through time [91] .However, such methods are still susceptible to local optima, and only work simple and linear policies with good performance.

Hence, rather than learning the whole control system, currently it is a good choice that the machine learning algorithm is only used to model the system dynamics and the controller still follow conventional mathematical way. In essence, system dynamics, including the targets dynamics and sensing model, are spatio-temporal sequences, which can be considered as a black-box with the sequence of past states and observations as input and the sequence of future states as output.

The development in deep learning, especially recurrent neural network (RNN), give some useful insights on how to tackle this problem. In [89], RNN is used to predict next frame in the video and gives good results. Let's recall the indoor localization and lighting control problem. Obviously, except for the temporal relation, the spatial correlation also must be taken into consideration. Hence convolutional layer should also be introduced to model the system dynamics.

5.3 Recurrent Neural Networks

One of the most attractive advantages of neural networks is that they are able to flexibly model the nonlinearity. Neural networks are model-less and can adaptively learn the model from the training data, which is manipulated by the system dynamic model from behind the scenes. They are especially useful when large amounts of real historical data exist but it is difficult or even impossible to represent the system dynamics by theoretical model or hand-designed rules.

In this chapter, we still take the indoor lighting networked control by distributed sensors as an example. This problem is a good testbed for our algorithms because of the varieties of dynamics involved the user behavior and sensing observation process. We consider the more practical but more complex user behavior in indoor environment and the interaction between user and the human detection sensors. Practically, when such a control system is implemented, the system designer always has no prior knowledge if the dynamics is linear or nonlinear, and if the theoretical model fits the dynamics behind scenes or not. Traditionally, the designer would empirically try numbers of models and check which model and parameters match the real case best. However, the final chosen model may mismatch the future dynamics because of many potential influencing factors such as sampling variation, model uncertainty, and structure change. By using neural networks, such problem of model selection can be solved, on the other hand, in the cost of computation amount in the training phase. Moreover, the practical problem in the real world is often complex in nature and any single model may not be able to capture different patterns equally well. Therefore it is difficult to use single model to model all dynamical patterns for a real physical process.

5.3.1 Recurrent Neural Networks

Although deep networks are able to learn any non-linear dynamics, care must still be taken when designing a task-appropriate model. Thus, the recurrent neural network is adopted for modeling dynamics of our target problem.

Recurrent neural networks (RNN)[92] have recently become a popular tool for modeling sequences systems which have large temporal dependence. RNNs have been successfully used for various task such as language modeling [93–95], learning word embeddings [96], online handwritten recognition [97] and speech recognition [98].

A recurrent neural network is a neural network which is always used to simulate a system with discrete-time dynamical model due to the feedback connection among itself in time, as

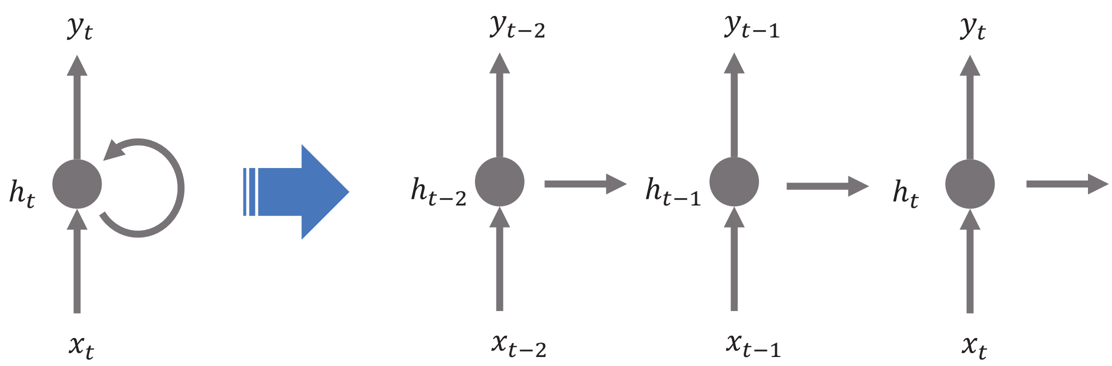


Figure 5.4 Recurrent neural networks.

shown in Fig. 5.4. The system has an input $\boldsymbol{x_t}$, an output $\boldsymbol{y_t}$ and hidden layer vector $\boldsymbol{h_t}$. The dynamical system is represented by:

$$\boldsymbol{h}_t = f_{hidden}(\boldsymbol{x_t}, \boldsymbol{h}_{t-1}) \tag{5.2}$$

$$\boldsymbol{y}_t = f_{output}(\boldsymbol{y_{t-1}}, \boldsymbol{b}_t) \tag{5.3}$$

where f_{hidden} is the model describing how the dynamical system evolves, and f_{output} represents the mapping relation between system state and the output.Each of them is defined by a set of parameters $\boldsymbol{\theta}_{hidden}$ and $\boldsymbol{\theta}_{output}$, whose number is always very large.

A recurrent neural network is always contracted by defining the transition function of hidden layer and the output function as follows:

$$\boldsymbol{h}_t \quad = \quad f_{hidden}(\boldsymbol{x}_t, \boldsymbol{h}_t) = \phi_{hidden}(\boldsymbol{W}_{rec}\boldsymbol{h}_{t-1} + \boldsymbol{W}_{in} + \boldsymbol{b}) \tag{5.4}$$

$$\boldsymbol{y}_t \quad = \quad f_{output}(\boldsymbol{h}_t, \boldsymbol{x}_t) = \phi_{output}(\boldsymbol{W}_{out}\boldsymbol{h}_t) \tag{5.5}$$

where the parameters are given by the recurrent matrix $\boldsymbol{W}_{rec}$, the input matrix $\boldsymbol{W}_{in}$, the output matrix $\boldsymbol{W}_{out}$ and the bias $\boldsymbol{b}$. All parameters are collected in $\boldsymbol{\theta}_{hidden}$ and $\boldsymbol{\theta}_{output}$ respectively for clearness. ϕ_{hidden} and ϕ_{output} are the element-wise nonlinear functions, e.g., saturating nonlinear function such as a logistic sigmoid function or a hyperbolic tangent function.

Given a set of N training sequences:

$$\boldsymbol{D}_{train} = \left\{ \left(\left(\boldsymbol{x}_1^{(i)}, \boldsymbol{y}_1^{(i)}\right), \left(\boldsymbol{x}_2^{(i)}, \boldsymbol{y}_2^{(i)}\right), ..., \left(\boldsymbol{x}_{T_n}^{(i)}, \boldsymbol{y}_{T_n}^{(i)}\right) \right) \right\}_{i=1}^{N} \tag{5.6}$$

where $\left(x_{T_n}^{(i)}, y_{T_n}^{(i)}\right)$ is the training pair, T_n is the length of the training sequences, and N is the size of training set. The parameters of the recurrent neural network, $\boldsymbol{\theta}_{hidden}$ and $\boldsymbol{\theta}_{output}$, can be derived by minimizing the following loss function:

$$J(\boldsymbol{\theta}_{hidden}, \boldsymbol{\theta}_{output}) = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T_n} d\Big(\boldsymbol{y_t}, f_{output}(\boldsymbol{h}_t^{(i)})\Big) \tag{5.7}$$

with

$$\boldsymbol{h}_t^{(i)} = f_{hidden}(\boldsymbol{x}_t^{(i)}, \boldsymbol{h}_{t-1}^{(i)})$$

where $d()$ is a predefined cost function, such as cross-entropy, which measures the performance of the network on some given task.

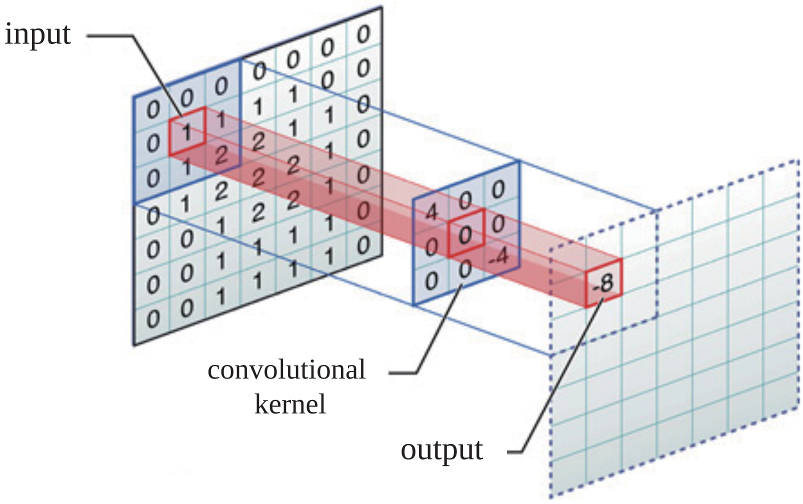


Figure 5.5 Convolutional layers.

All the parameters in the model can be estimated by, e.g., gradient descent. One common approach for computing the necessary gradients is back-propagation through time (BPTT), where the recurrent model is represented as a multi-layer one (with an unbounded number of layers) and back-propagation is applied on the unrolled model.

5.3.2 Convolutional Layers

The major drawback of the fully connected recurrent neural network is that the full connections in the input-to-state and state-to-state transitions do not take spatial information into account. However, in this chapter, the localized lighting networked control system is also used as an example application, in which can be considered as an estimation and prediction problem in both time and space. Hence, the spatial information is as essential as the temporal information for the model. Hence, to overcome this problem, the sensing observations is transfer into a sensing maps which are 2-D spatial grids. Each cell in the grid corresponds to a position in the real world and contains the sensing information of this position. This can be achieved conveniently by using convolution layers in the hidden layers in the recurrent neural networks. Convolutional layers are good at learning and extracting features from the spatial information in the input multi-dimensional data, as shown in Fig. 5.5. Hence, the neural networks is able to estimate and predict the state of a certain cell in the grid by taking the input sensing observations and historic information of this cell and its neighbors into account. It can be considered as pre-process that analyzes the raw sensing map and exact features for the recurrent layer for likelihoods.

5.4 Modeling System Dynamics by Recurrent Neural Network

Let's briefly recall the maximum likelihood estimation by distributed sensor. Given all the sensing observations, the likelihood of user in a certain state, can be calculated iteratively as follows:

$$\begin{aligned} & L\left(\boldsymbol{u_t} = \boldsymbol{s}_i | \boldsymbol{\mathcal{B}_t}\right) \\ = \quad & Pr\left(\boldsymbol{b}_t | \boldsymbol{u_t} = \boldsymbol{s}_i\right) P \sum_{j=1}^{M} L\left(\boldsymbol{u_{t-1}} = \boldsymbol{s}_j | \boldsymbol{\mathcal{B}_{t-1}}\right) Pr\left(\boldsymbol{u_{t-1}} = \boldsymbol{s}_j | \boldsymbol{u_t} = \boldsymbol{s}_i\right) \end{aligned} \tag{5.8}$$

where, $\boldsymbol{b_1}$ is the sensing observation vector, $\boldsymbol{\mathcal{B}_t} = [\boldsymbol{b_0}, \boldsymbol{b_1}, ..., \boldsymbol{b}_t]$ is the all sensing observations up to time t, $\boldsymbol{u_t}$ is user's state in time t, $\boldsymbol{s_j} \in \boldsymbol{\mathcal{S}}$ is the state in state space, $L\left(\boldsymbol{u_t} = \boldsymbol{s_i} | \boldsymbol{\mathcal{B}_t}\right)$ is the likelihood of user in state $\boldsymbol{s_i}$ given all sensing observations up to time t.

And then, a set of possible states of the target is estimated:

$$\boldsymbol{S}_t^E = E\Big(L\left(\boldsymbol{u_t} = \boldsymbol{s_0} | \boldsymbol{\mathcal{B}}_t\right), L\left(\boldsymbol{u_t} = \boldsymbol{s_1} | \boldsymbol{\mathcal{B}}_t\right), ..., L\left(\boldsymbol{u_t} = \boldsymbol{s}_M | \boldsymbol{\mathcal{B}}_t\right)\Big) \tag{5.9}$$

where $\boldsymbol{S}_t^E$ is a set of possible states of the target. It can be, e.g., a function that finds all states with likelihood which is larger than a threshold, or a $\arg\max$ function and in this case obviously $||\boldsymbol{S}_t^E|| = 1$.

Given the observations up to current time, the likelihood of user in a certain state in future time step can also be derived:

$$\begin{aligned} & L\left(\boldsymbol{u_{t+1}} = \boldsymbol{s}_i | \boldsymbol{\mathcal{B}}_t\right) \\ = \quad & \sum_{j=1}^{M} L\left(\boldsymbol{u_t} = \boldsymbol{s}_j | \boldsymbol{\mathcal{B}}_t\right) Pr\left(\boldsymbol{u_{t+1}} = \boldsymbol{s}_j | \boldsymbol{u_t} = \boldsymbol{s}_i\right) \end{aligned} \tag{5.10}$$

$$\boldsymbol{S}_{t+1}^{E+} = E^{+}\Big(L\left(\boldsymbol{u_t} = \boldsymbol{s_0} | \boldsymbol{\mathcal{B}}_t\right), L\left(\boldsymbol{u_t} = \boldsymbol{s_1} | \boldsymbol{\mathcal{B}}_t\right), ..., L\left(\boldsymbol{u_{t+1}} = \boldsymbol{s}_M | \boldsymbol{\mathcal{B}_{t+1}}\right)\Big) \tag{5.11}$$

In Eq. 5.8, $Pr\left(\boldsymbol{b_t}|\boldsymbol{u_t}=\boldsymbol{s_i}\right)$ represents the sensing model, which related the sensing observations to the user's current state. And $Pr\left(\boldsymbol{u_{t-1}}=\boldsymbol{s_j}|\boldsymbol{u_t}=\boldsymbol{s_i}\right)$ is the target model, which describe the target's state transition model. These two models are essential for the estimation and consequently also very important for the networked control system.

In Chapter 4, both of the model of target process and sensing observation process are based on assumptions. The detection probabilities of sensors are assumed to be constant in effective coverage and exponential decreasing in uncertain coverage. Its parameters, such as effective coverage range, angle of view and detection probability are measured from the real sensors. And the target transition model is assumed to be switching between static and moving mode following a two-state Markov process, and in the moving mode, Gaussian random walk model is adopted, which is always adopted to describe the motion model of a normal moving object. Its parameters, such as static/moving switching probability, mean and variance of velocity, are set experientially. The simulation and experiments in Chapter 4 have shown that by such assumptions acceptable estimation accuracy can be achieved for the lighting networked control system. However, theoretical and experimental assumptions of the system model still have drawbacks. The assumed models are too general and in many cases do not agree with the real target process in the real world.

The trajectory of a target is not totally random and must follow more specific patterns. For example, the activity of a human user in an indoor environment always has clear goals. The trajectories are always between some explicit positions, such as the door, his seat, printer and so on. They should be able to be estimated and predicted in higher accuracies than those by Gaussian models.

And the sensing model also contains many mismatchings with the real sensors. First, the parameters of each sensor may have large differences and uncertainties due to the production tolerance. Such individual differences are ignored in the previous sensing observation model, and could decrease the estimation accuracy. Second, some assumptions in the model are for simplicity and may probably not fit the real case. For example, the assumption of uniform distribution of detection probability could be not correct in the center and edge of sensor's view of angle.

5.4.1 Model by A Recurrent Neural Network

In the Eq. 5.8, the likelihood in current time step is a function of sensing model, target model and the likelihood in previous time step. By further observation, a fact can be found that

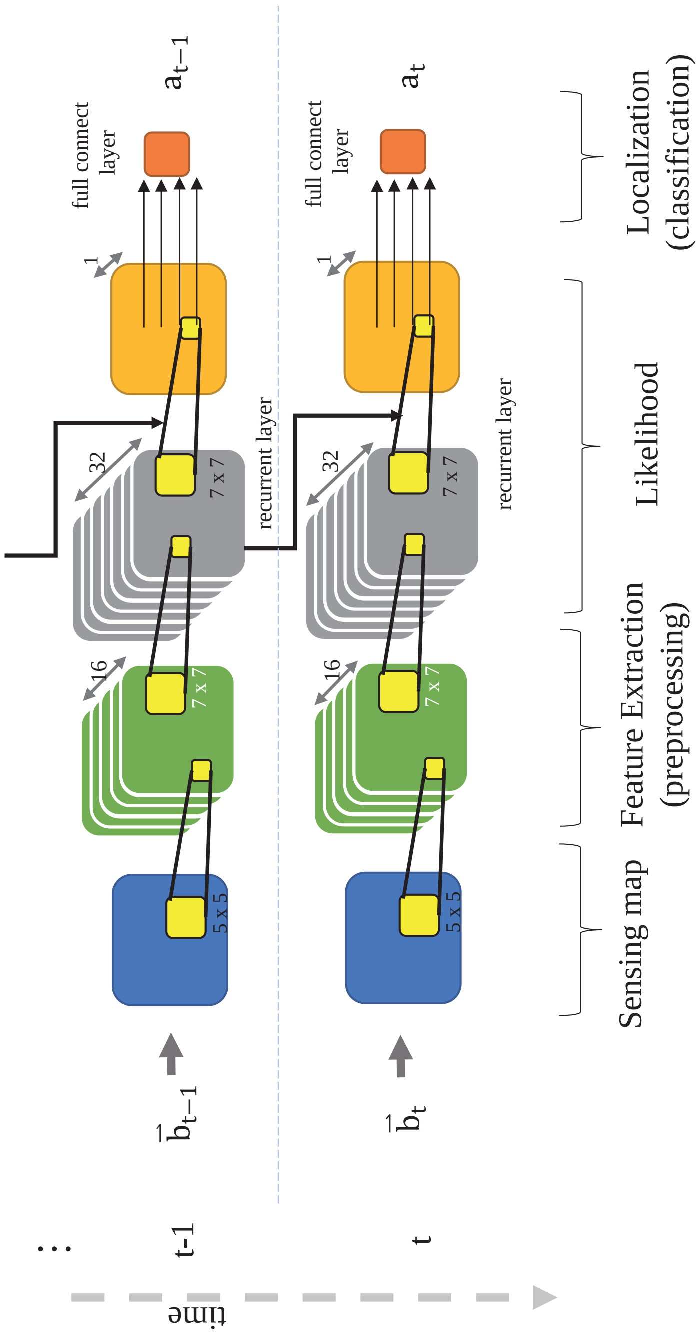


Figure 5.6 Structure of the designed recurrent neural network for modeling system dynamics.

the current likelihood can be considered as a function of only previous likelihood and sensing observations in the current time step, and the output estimated states is a function of current likelihoods:

$$\boldsymbol{L_t} = f_L(\boldsymbol{L_{t-1}}, \boldsymbol{b_t}) \tag{5.12}$$

$$\boldsymbol{S}_t^E = f_E(\boldsymbol{L_t}) \tag{5.13}$$

where $\boldsymbol{L_t} = [L(\boldsymbol{u_t} = \boldsymbol{s_0}|\boldsymbol{\mathcal{B}_t}), L(\boldsymbol{u_t} = \boldsymbol{s_1}|\boldsymbol{\mathcal{B}_t}), ..., L(\boldsymbol{u_t} = \boldsymbol{s}_M|\boldsymbol{\mathcal{B}_t})$ denotes the vector of likelihood of all states.

The function $f(\boldsymbol{L_{t-1}}, \boldsymbol{b_t})$ in fact integrated both of target model and sensing model together. If we try to obtain the explicit expression of it, the problem discussed above will come again. One big advantage of the scheme in this chapter is to skip the explicit system dynamical model. A neural network is designed to model the function of likelihood vector $f()$. The neural network represents the system dynamical model which connects the sensing observations $\boldsymbol{b_t}$ to the sensing model and target model, and then maps it into likelihoods for the following state estimation and the control process. It learns the relation directly from the training data. Since in the function $f()$ the historical information $\boldsymbol{L_{t-1}}$ is necessary, specifically the feed-forward recurrent neural network is adopted here, because the feedback connections among itself can work as the internal memory of previous likelihood $\boldsymbol{L_{t-1}}$ to process sequences of inputting sensing observations.

Equation 5.12 and 5.13 has the same shapes with Eq. 5.2 and 5.3, which implies that the system dynamics could be well models by the recurrent neural networks.

In fact, the likelihood of future state given the observations up to current time has the similar shape.

5.4.2 Neural Controller

The structure of the designed recurrent neural network is as shown in Fig. 5.7. The input is the sensing map which is mapped from the sensing observations from distributed sensors. The following is the convolutional layers for pre-processing. It analyzes the raw sensing map and extracts spatial features for the likelihood modeling. The recurrent layer represents how the likelihoods evolve in time. It has the link from previous time step which provides the historical likelihood information about the system dynamics. The output layer is full connection layer for the estimation or prediction process based on the likelihoods from the previous layer.

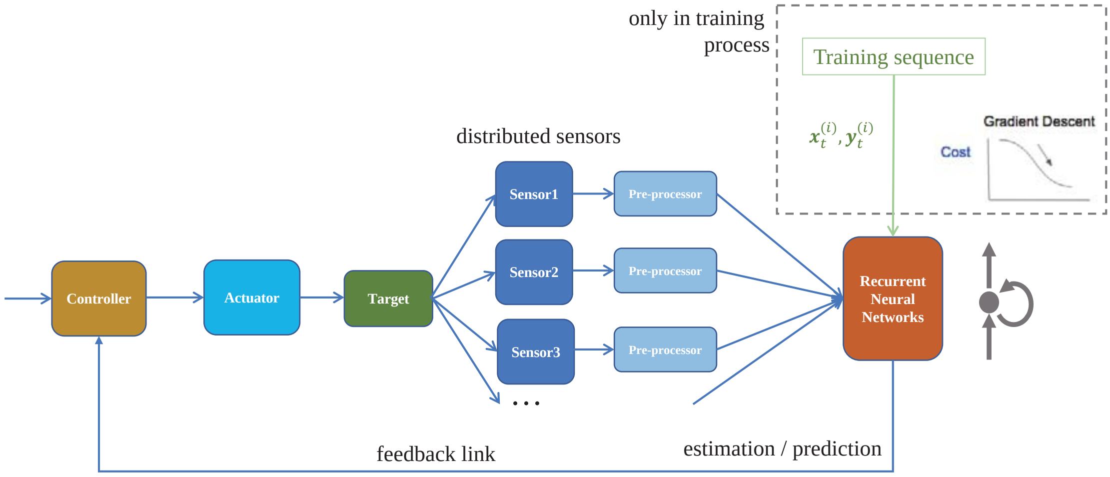


Figure 5.7 Estimation by using the proposed neural network based model.

And then the estimated state will be sent to the networked controller to make control decisions. In the estimation process, the only inputs are the sensing observations in the current time step, and no other prior information and assumptions are needed. All the knowledge about the system dynamics is learned from the training data. The underlying relation between the sensing observations and target behavior, and the relation between target's current and past behaviors will be represented by the designed recurrent neural network and the huge amount of parameters in $\boldsymbol{\theta}_{hidden}$ and $\boldsymbol{\theta}_{output}$. The block diagram of the networked control system is shown in Fig. 5.7.

5.5 Performance Evaluation

In this section, the performance of the designed recurrent neural network, which aims to give a more accurate representation of the real system dynamical models, will be evaluated. In the simulation, the scene is similar to the experiment environment in Chapter 4, and the control scheme is the same except that the maximum likelihood estimator is replaced by the designed recurrent neural network, which is expected provide more accurate estimation for the controller.

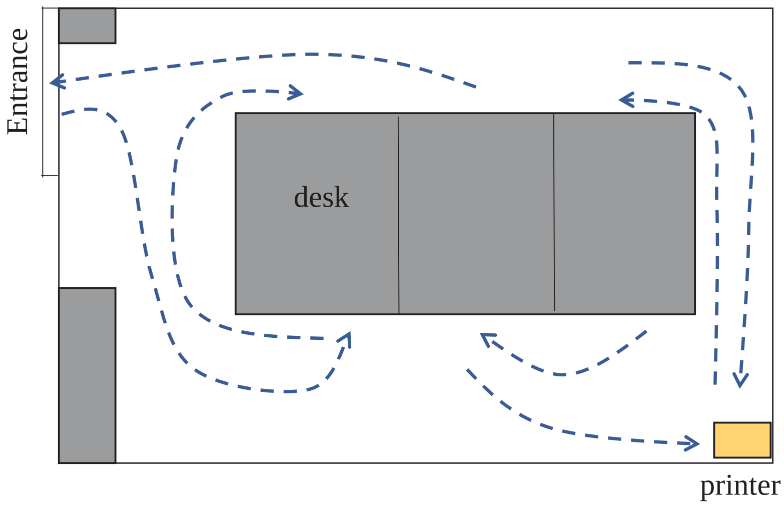


Figure 5.8 Non-random walk.

5.5.1 Training

The performance is evaluated by simulation. In future work, it can be tested by real data, e.g., by capturing and recording the user motion as training data using such devices as Kinect. The generated training sequences may not totally simulate the real cases, but it tries to generate target trajectories with complex patterns to evaluate the designed recurrent neural network's capability to model the dynamics.

In the simulated scene, multiple binary human detection sensors are placed in the space. The simulated user trajectories are not random as described by the Gaussian motion model, but follows a pattern that any user must have some destination when walking. Obviously, this is practical. In such indoor space as an office, a user's walking trajectories are always between some hot position, such as the door, seat, printer and so on. Some examples of trajectories are shown in Fig. 5.8.

The training state sequences are generated in such way: when a user is static in a certain 'hot position', e.g., seat, it follows a probability to remain the static mode, and a probability to switch to moving mode. In moving mode, the user has a destination. The program at first searches a route from the original position to the destination, and then generate a motion towards the first turning point according to a predefined velocity with a random noise in both x- and y-axis, which represents the randomness in real motion. And then at next time

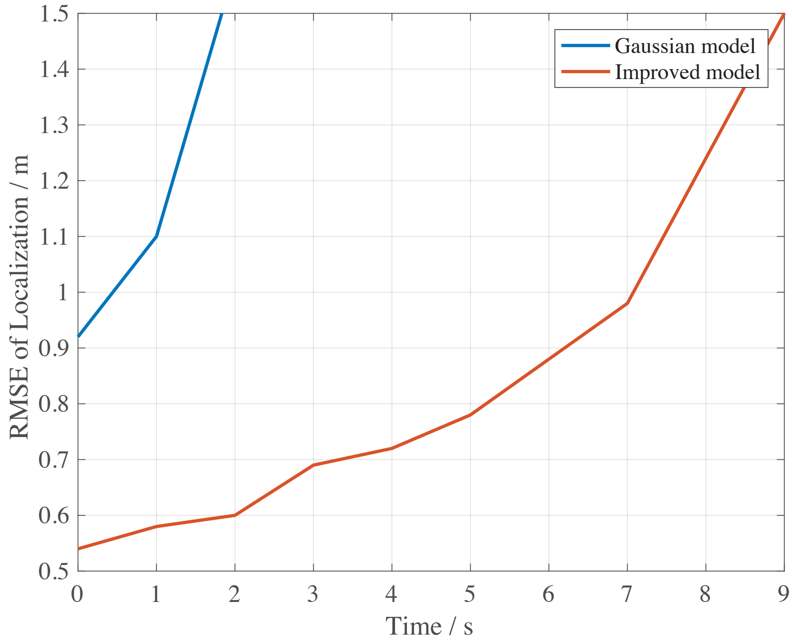


Figure 5.9 Performance of previous model and improved model.

step, the user will stay in the moving mode and from its new position repeat the path route search and motion generation. This process does not step until reaching the destination. And inaccuracies are also introduced into the placements and sensing capabilities of sensors.

The parameters of the recurrent neural network, $\boldsymbol{\theta}_{hidden}$ and $\boldsymbol{\theta}_{output}$, are optimized by training with the training data set using an ADAM optimizer. The size of the training dataset is 10000 sequences, each of which contains 100 motions with an 1s time interval. The batch size is 16. The network is trained by 1000 iterations.

5.5.2 Results

The Euclidean norm from the estimated and predicted positions to the ground-truth trajectory from 0s (current time) to 9s in the future are used as the metric to evaluate the models. The RMSE of state estimation and prediction are shown in Fig. 5.9. The explicit model based method's is highly limited by the model, since it cannot provide detailed knowledge about the system. And when it mismatches with the real system dynamical model, error becomes even larger. And because the assumed Gaussian motion model can be considered as a Markov process of one order, it can only provide quite rough prediction about target's future state, which is basically meaningless for a control system.

The accuracy of the estimation and prediction by recurrent neural network based model gained large increase compared with the Gaussian model based method because the designed recurrent network learned the system dynamics including the real motion patterns and sensing patterns from the training data set, where lots of detailed information exists. The accurate knowledge of the system dynamics also makes the system predictable. The prediction accuracy in future in 6 seconds is even comparable with the estimation accuracy using the previous model.

Main reasons of the errors of estimation and prediction using the recurrent neural networked based model are:

- The randomness of the system, which gives an upper bound of accuracy
- The lack of target identification
- Sensing capability of sensors
- Limitation of the structure of the designed recurrent neural network

And the performance of the designed recurrent network is also compared with that of a convolutional neural network, which has the similar structure with the designed machine learning networked except that the recurrent layer is removed by a convolutional layer. Thus, the temporal information is lost in the this model. As shown in Fig. 5.10, the recurrent neural network with convolutional layers models the system much better than a convolutional network which is only good at capturing the spatial features.

Let us also take the localized lighting networked control as an example for test. As shown in Fig. 5.11, the curve of the power saving rates to the localization accuracies, with the same control scheme the performance of the lighting networked control system is increased by using the improved model. This improvement of system dynamical model can also bring performance improvement to the networked control system by more accurate knowledge from the training data rather than experience and theoretical assumptions.

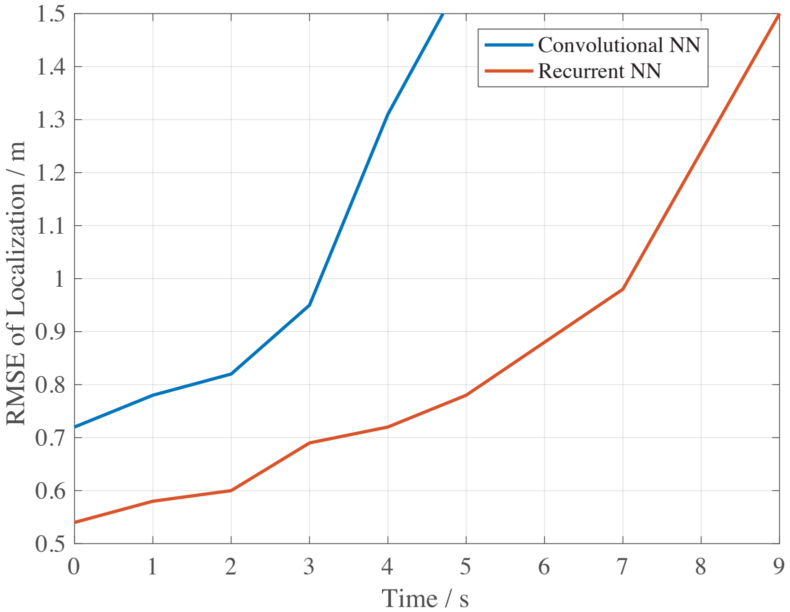


Figure 5.10 Performance of a convolutional NN and the designed recurrent NN.

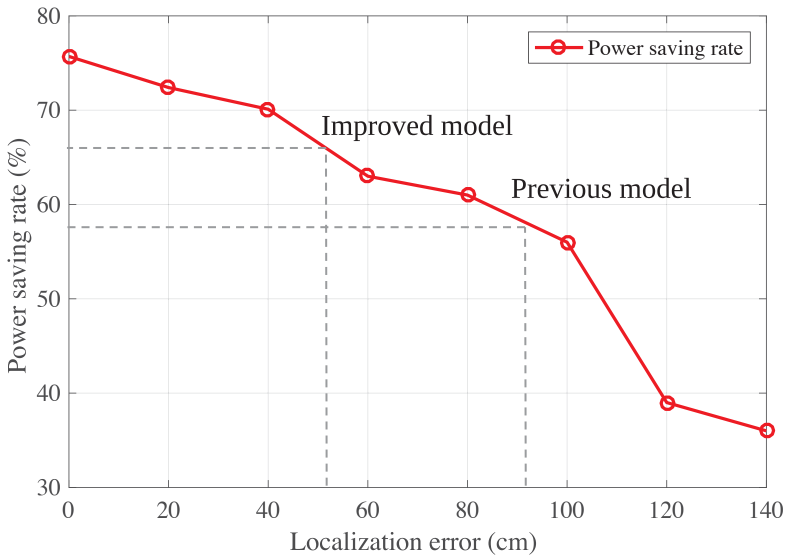


Figure 5.11 Power saving performance.

5.6 Summary

To address the challenge to get the model which accurately describe the system dynamics for target state estimation for networked control system, in this chapter, a recurrent neural network with convolutional layers is designed to represent how the target process and sensing processes evolve and interact with each other. The performance is evaluated by simulation to validate the effectiveness. The results show that the proposed modeling method can give better representation of the target-sensor dynamical system than the explicit mathematical model and pure convolutional model.

Chapter 6

Conclusion

6.1 Summary of the Thesis

In a networked control system, the sensors, actuators and controllers work in a separate manner in networks. By using wireless networks in control loops, the systems can achieve benefits such as flexibility, extended range and easier implementation. However, it also creates new problems. This thesis aims to provide designs of networked control systems using distributed wireless sensors and their applications in building energy control. It focuses on the challenges for effective control through networked control systems mainly in three aspects: time delay of the large-scale system, state estimation based on distributed sensors and improvement of system dynamics models. And the applications of networked control systems in energy control are also studied. The outline and contributions of this thesis is described as follows.

In Chapter 2, the conception of networked control systems and estimation by distributed sensors over wireless networks, which is the theoretical background of this thesis, are given. And specifically, two wireless communication network structures for the implementation of networked control systems are introduced. They will be employed in the application of the design in Chapter 3 and Chapter 4.

To address the problem of time delay in networked control system, this chapter design a hierarchical distributed networked control system and applied in power control. It takes the first step toward establishing hierarchical distributed architecture for large-scale power control system to realize demand and response during peak hours. In the proposed architecture, there are many sub-controllers in charge of managing the power consumption in their own clusters of approximately 500 houses. The sub-controllers are subject to local power consumption limits assigned from upper layer, which forms a local control loops small enough to guarantee stable control. In addition, we proposed a distributed control algorithm where sub-controllers at higher layers determine appropriate local power consumption limits, which contributes to realizing the global objective of power reduction during peak hours. We showed that the proposed control network is scalable regardless of the size of the power system through numerical simulations with realistic parameters. Furthermore, a building-scale test-bed for power control system was implemented to show the effectiveness of the proposed scheme contributing to daily life power saving instead of high-cost planned blackouts. Our future work will focus on the impact of integrating a large number of electric vehicles, distributed batteries and other renewable energy sources to the system for improvement of demand response performance. Besides, as the chapter only considers local priority at each cluster, it is impossible to evaluate the fairness in terms of power consumption across clusters. In the future works, the authors will consider a global priority metric, e.g. proportional fair priority, in the power control algorithm, to realize 'priority fairness' among clusters.

Chapter 3 aims to address the challenge of state estimation based on distributed sensors. It is motivated by the problem of indoor localized lighting control for power saving, in which a series of distributed human detection sensors are distributed in the target space to detect and estimated user's state for intelligent lighting control. Accurate user state estimation is essential for the performance of localized lighting control. A wireless battery-less human detection sensor network for networked control and the target state estimation strategy based on distributed sensors are designed in this chapter. Because each sensor's sensing capability is quite limited, the controller must well combine and fuse the sensing observations from all sensors in order to accurately estimate user's state and make correct decisions. And it is applied in an LED lighting networked control system which bases on user's position and environment illumination level. It mainly focuses on the power consumption of the lighting system and the satisfaction of user's illumination requirement. It is suitable for office/home automation and can be easily installed in almost any environment without restriction. And a verification experiment is also conducted. In the experiment, the power consumption is logged by a power logger in office's electricity box, and the test user measures the practical illumination in his positions while walking around in the office. The experimental results show that the LED light control system can reduce power consumption by 57% without any loss of user satisfaction.

Proper models of systems, such as sensing process and target dynamics, are also key factors for accurate state estimation and stable networked control. In Chapter 5, a recurrent neural network is designed to accurately capture system dynamics from training data instead of theoretical assumptions. Performance analysis shows that both the performance of location estimation and lighting control gain a further increase compare to using experiential models.

6.2 Suggestion for future works

There are still several remaining challenges. Several directions for future research could be taken as I summarize below:

- Evaluation of the impact of integrating of a large number of electric vehicles, distributed battery and renewable energy sources should be made in future. They may make the power supply system unstable if there is no consideration of them when designing the power control system. However, large benefits may also be gain from them for peak shifting. And an analyze of the designed distributed control network under communication constraints should be done theoretically besides numerical simulation and experiments.

- In the current lighting control system, the centralized control scheme is implemented to solve the problem of localized indoor illumination control. Its performance in the target office in the experiment is very good, but when the application scene is a very large-scale, system performance may decrease due to the same problem discussed in the power control system. The distributed control algorithm should be implemented in the lighting control system.

- The power of human detection sensors is quite limited because all of them are activated by wireless power transmission. Low power consumption always also results in low sensing capabilities. Involving more advanced sensors, which could get extra energy, e.g., by energy harvesting from ambient energy, may sufficiently increase the accuracy of detection network, and create more interesting applications.

Appendix I

List of Publications

I.1 Journal Papers

- K. Sakaguchi, V.K. Nguyen, T. Yu, G.K. Tran, K. Araki, Distributed Power Control Network and Green Building Test-Bed for Demand Response in Smart Grid, IEICE Trans. Fund., Vol.E96-A, No.5, May. 2013.

- T. Yu, Y. Kuki, G. Matsushita, D. Maehara, S. Sampei, K. Sakaguchi, Design and implementation of lighting control system using battery-less wireless human detectionăsensor networks, IEICE Trans. Comm., Vol.E100-B, No.6, Jun. 2017.

I.2 International Conference

- T. Yu, Y. Kuki, G. Matsushita, D. Maehara, S. Sampei, K. Sakaguchi, Deployment of LED Light Control System Using Battery-less Wireless Human Detection Sensor Networks, RFID-TA 2015, IEEE, 2015.

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