การประยุกต์การควบคุมแบบเหมาะที่สุดกับกระบวนการผลิตน้ำแข็งซอง
โดยใช้การสร้างโปรแกรมพลวัต

นายฮาย มิง ลี

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรมหาบัณฑิต
สาขาวิชาวิศวกรรมไฟฟ้า ภาควิชาวิศวกรรมไฟฟ้า
คณะวิศวกรรมศาสตร์ จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2552

OPTIMAL CONTROL APPLICATION TO BLOCK-ICE
PRODUCTION PROCESS USING DYNAMIC PROGRAMMING

Mr. Hai Minh Le

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Engineering Program in Electrical Engineering
Department of Electrical Engineering
Faculty of Engineering
Chulalongkorn University
Academic Year 2009

Thesis Title	OPTIMAL CONTROL APPLICATION TO BLOCK-ICE PRODUCTION PROCESS USING DYNAMIC PROGRAMMING
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Field of Study	Electrical Engineering
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ฮาย มิง ลี: การประยุกต์การควบคุมแบบเหมาะที่สุดกับกระบวนการผลิตน้ำแข็งซองโดยใช้การสร้างโปรแกรมพลวัต (OPTIMAL CONTROL APPLICATION TO BLOCK-ICE PRODUCTION PROCESS USING DYNAMIC PROGRAMMING), อาจารย์ที่ปรึกษาวิทยานิพนธ์หลัก: รศ.ดร. เดวิด บรรเจิดพงศ์ชัย, 50 หน้า.

วิทยานิพนธ์ฉบับนี้นำเสนอการประยุกต์การออกแบบตัวควบคุมแบบเหมาะที่สุดกับกระบวนการผลิตน้ำแข็งซองโดยใช้การสร้างโปรแกรมพลวัต เริ่มต้น เราพัฒนาแบบจำลองคณิตศาสตร์สำหรับกระบวนการผลิตน้ำแข็งซองโดยใช้เทคนิคการระบุเอกลักษณ์ระบบ โดยเฉพาะอย่างยิ่ง เราสร้างแบบจำลองเชิงพารามิเตอร์ 2 แบบ แบบจำลองแรกเป็นแบบจำลองเชิงเส้นถดถอยตัวเองที่มีสัญญาณจากภายนอก หรือเรียกสั้น ๆ ว่า แบบจำลองเชิงเส้น ARX แบบจำลองที่สองเป็นแบบจำลองโครงข่ายประสาทการป้อนไปข้างหน้าที่มีโครงสร้างคล้ายกับแบบจำลองเชิงเส้น ARX จึงเรียกแบบจำลองแบบที่สองว่าแบบจำลอง NNARX นอกจากนี้ เราใช้วิธีศัลยแพทย์สมองแบบเหมาะที่สุดเพื่อตัดลดแบบจำลองโครงข่ายประสาท เมื่อเปรียบเทียบผลการทดลองของแบบจำลองทั้งสอง ปรากฏว่า แบบจำลองเชิงเส้น ARX ให้สมรรถนะที่ดีในแง่ของความพอเหมาะของแบบจำลอง ต่อจากนั้น เรานำแบบจำลองที่ได้เพื่อสืบค้นการใช้พลังงานไฟฟ้าและค่าใช้จ่ายในการดำเนินการของโรงงานผลิตน้ำแข็งเมื่อใช้อัตราค่าไฟฟ้าแบบเวลาของการใช้ (TOU) และแบบเวลาของวัน (TOD) เราพัฒนาการออกแบบตัวควบคุมแบบเหมาะที่สุดสำหรับกระบวนการผลิตน้ำแข็งซอง กลยุทธ์แบบเหมาะที่สุดมีเป้าหมายเพื่อทำให้ค่าไฟฟ้าในช่วงเวลาจำกัดมีค่าต่ำสุดและสอดคล้องกับเงื่อนไขบังคับเกี่ยวกับสัญญาณควบคุมของเครื่องคอมเพรสเซอร์ อุณหภูมิน้ำเกลือและจำนวนน้ำแข็งซองพร้อมขาย นอกจากนี้ เราวิเคราะห์ปัจจัยต่างๆ ในเกณฑ์การออกแบบที่มีผลต่อการใช้พลังงานและค่าใช้จ่าย พร้อมทั้งเปรียบเทียบสมรรถนะระหว่างตัวควบคุมแบบเหมาะที่สุดกับตัวควบคุมแบบสัญนิยม ผลการจำลองด้วยคอมพิวเตอร์แสดงว่าตัวควบคุมแบบเหมาะที่สุดมีสมรรถนะดีกว่าตัวควบคุมแบบสัญนิยม นอกจากนี้ การประยุกต์การควบคุมแบบเหมาะที่สุดอิงกับอัตราค่าไฟฟ้าแบบ TOU สามารถลดค่าใช้จ่ายได้มากกว่าเมื่อเปรียบเทียบกับการควบคุมที่อิงกับอัตราค่าไฟฟ้าแบบ TOD

ภาควิชา	วิศวกรรมไฟฟ้า	ลายมือชื่อนิสิต	[signature]
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ปีการศึกษา	2552		

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KEY WORD: ARX MODELS / NEURAL NETWORKS / NONLINEAR SYSTEMS / BLOCK-ICE PROCESS / OPTIMAL CONTROL STRATEGY / DYNAMIC PROGRAMMING / TIME OF USE TARIFF / TIME OF DAY TARIFF

HAI MINH LE: OPTIMAL CONTROL APPLICATION TO BLOCK-ICE PRODUCTION PROCESS USING DYNAMIC PROGRAMMING. THESIS ADVISOR: ASSOC. PROF. DAVID BANJERDPONGCHAI, Ph.D., 50 pp.

This thesis presents an application of optimal controller design to a block-ice production process using dynamic programming. First, we develop mathematical models for such a process by employing system identification techniques. In particular, we build two parametric models, namely, linear model and neural network model. Linear models are built with Auto-Regressive model with exogenous inputs (linear ARX model). Feedforward neural networks (NNARX model) are constructed using the information provided by the linear ARX models. In addition, the Optimal Brain Surgeon (OBS) method is employed to prune the neural network models. Comparing the experimental results obtained from these models, it indicates that linear ARX models yield reasonably good performance in terms of the model fit. Then, using the obtained models, we investigate the energy consumption and operation cost of an ice factory when using time of use (TOU) tariff and time of day (TOD) tariff. Specifically, we develop an optimal control design for block-ice production process. The optimal strategy aims to minimize the electricity cost over a finite-time horizon and is subjected to constraints involving the control input of compressors, the brine temperature, and the number of block-ices ready for sales. Moreover, various factors in the design criteria have been analyzed with respect to the energy consumption and the operation cost. We compare the performance of the optimal controllers and the conventional control strategy. The simulation reveals that the proposed optimal control design has better performance than that of the conventional control. Furthermore, the optimal control using TOU tariff can reduce the operation cost when comparing to the one using TOD tariff.

Department: Electrical Engineering Student's signature: minh
Field of study: Electrical Engineering Advisor's signature: David Banjerdpongchai
Academic year: 2009

Acknowledgments

In the first place I would like to express my deepest gratitude and respect to my advisor, Associate Professor David Banjerdpongchai, for his supervision, advice, and guidance from the very early stage of my study at Chulalongkorn University. This thesis would not have been possible without his persistent encouragement and support in various ways. He is always willing to use his precious time for discussions, giving useful comments and suggestions along the way. I am indebted to him more than he knows.

I gratefully thank Doctor Naebboon Hoonchareon for his many helpful comments, suggestions. In particular, he suggested to change the demand and energy rates from the values for customers purchase electricity at 69 kV and above to the values for those purchase at 22-33 kV which are more practical for block-ice factories. My special thanks also go to many other Professors in the Department of Electrical Engineering, Faculty of Engineering, Chulalongkorn University. Among them, I am very thankful to Associate Professor David Banjerdpongchai, Assistant Professor Manop Wongsaisuwan, Assistant Professor Suchin Arunsawatwong, Associate Professor Watcharapong Khovidhungij for providing me the fundamental background on Control Systems field. In addition, I gratefully acknowledge to all the members of my committess, Doctor Naebboon Hoonchareon, Associate Professor David Banjerdpongchai, Assistant Professor Manop Wongsaisuwan, Associate Professor Waree Kongprawechnon, for their willingness in examining the thesis and their constructive advices.

Furthermore, I would like to thank all my graduate friends, especially all members of the control systems research laboratory at Chulalongkorn University, for their friendship and creating a pleasant working atmosphere. I would also greatly acknowledge the financial support from the Electricity Generating Authority of Thailand (EGAT) and JICA project for AUN/SEED-Net for my higher education.

Finally, my family deserves special mention for their love, support, and faith in me. I would like to express my heartfelt gratitude to them, especially to my parents, for all of their love and support throughout my life.

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Symbols

θ	Vector used to parametrize models
$\hat{y}(t\|\theta)$	Predicted output at time t using parameters θ
$\varphi(t)$	Regression vector at time t
$V_N(\theta, Z^N)$	Criterion function to be minimized
$\\| \cdot \\|$	Norm of a vector
J	Cost function
$E\{x\}$	Mathematical expectation of the random vector x

Acronyms

MPC	Model Predictive Control
ARX	Auto-Regressive Exogenous
AR	Auto-Regressive
NNARX	Neural Network ARX
NNAR	Neural Network AR
OBS	Optimal Brain Surgeon
LSM	Least Squares Method
TOU	Time of Use
TOD	Time of Day

CHAPTER I

INTRODUCTION

1.1 Introduction

Ice factories produce block-ices for commercial using in different industrial applications. Such an ice factory usually consumes a huge amount of electricity in the manufacturing process. Thus, there has been a need to seek an efficient control strategy to save energy and electricity cost. In this thesis, we present an application of optimal control design to block-ice production process by using dynamic programming. Figure 1.1 provides a schematic diagram of the components of a typical ice factory [1].

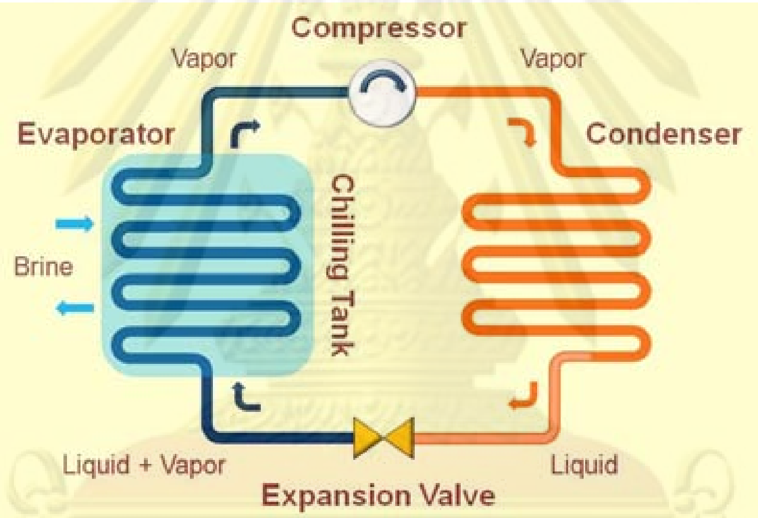

Figure 1.1: Block-ice production process.

The main components of an ice factory are as follows.

- Compressor.
- Condenser is a heat transfer surface which employs air or water as the condensing medium.
- Expansion valve controls the supply and demand relation between the condenser and evaporator.
- Evaporator is used as heat transfer surface in which a volatile liquid is vaporized for the purpose of removing heat from refrigerated space.
- Chilling tank contains the coils of evaporator which are equally distributed throughout the tank and are submerged in brine. The brine in the tank acts as a medium of contact only, the

refrigerant evaporating in the coils absorbs the heat from the brine, which again absorbs the heat of the water in the moulds.

In this cycle, a circulating refrigerant such as Ammonia or Freon enters the compressor as a vapor. The vapor is compressed. This raises the vapor's pressure and temperature. Then, the vapor travels through the condenser in which it dissipates its heat and condensed into liquid. When liquid refrigerant flows through the expansion valve, it moves from a high-pressure zone to a low-pressure zone, so it expands and evaporates. That results in a mixture of liquid and vapor at a lower temperature and pressure. The cold liquid-vapor mixture then travels through the evaporator coils and is completely vaporized by cooling the brine (which again extracts the heat of the water in the moulds). The resulting refrigerant vapor returns to the compressor. The cycle then repeats.

1.2 Literature review

1.2.1 System identification

Constructing models from observed data is a fundamental element in science. Several methodologies and nomenclatures have been developed in different applications areas. In the control area, the techniques are known under the term *System Identification*. System identification is the art and science of building mathematical models of dynamic systems from observed input-output data [2–4]. This term has been coined by Zadeh in 1956 [5] for the model estimation problem of dynamic systems in the control community. There were two main avenues for the development of the theory and methodology [4]. The first one is the *realization avenue* that starts from the theory how to realize linear state space models from impulse responses, Ho and Kalman [6] followed by Akaike [7], leading to so-called subspace methods. The other avenue is the *prediction-error approach*, more in line with statistical time-series analysis and econometrics. This approach and all its basic themes were outlined in the pioneering paper Aström and Bohlin [8]. It is also the main perspective in [3].

Three types of models are common in the field of system identification, which have been color-coded as follows [9]:

1. White Box models: This is the case when a model is perfectly known and it has been possible to construct it entirely from prior knowledge and physical insight.

2. Grey Box models: This is the case when some physical insight is available, but several parameters remain to be determined from observed data. It is useful to consider two sub-cases:

   - Physical Modeling: A model structure can be built on physical grounds, which has a certain number of parameters to be estimated from data. This could, e.g., be a state space model of given order and structure.

   - Semi-physical modeling: Physical insight is used to suggest certain nonlinear combinations of measured data signal. These new signals are then subjected to model structures of black box character.

3. Black Box models: No physical insight is available or used, but the chosen model structure belongs to families that are known to have good flexibility and have been “successful in the past”.

One could build a white box model, e.g. a model for a physical process from the Newton equations, but in many cases such models will be overly complex and possibly even impossible to obtain in reasonable time due to the complex nature of many systems and processes [10]. Therefore, a much more common approach, black box models are used in most system identification algorithms. In this work, we use both linear and nonlinear black-box identification techniques to construct mathematical models for block-ice production process.

1.2.2 Dynamic programming

In mathematics and computer science, dynamic programming is a method of solving complex problems by breaking them down into simpler steps. It refers to simplifying a complicated problem by breaking it down into simpler subproblems in a recursive manner. The term was originally used in the 1940s by the mathematician Richard Bellman to describe the process of solving problems where one needs to find the best decisions one after another [11, 12]. The first paper on dynamic programming was published in 1952 [12].

The principle of optimality is the basis of dynamic programming. An optimal sequence of decisions in a multistage decision process problem has the property that whatever the initial stage, state, and decision, the remaining decisions must constitute an optimal sequence of decisions for the remaining problem, with the stage and state resulting from the first decision considered as initial conditions [13].

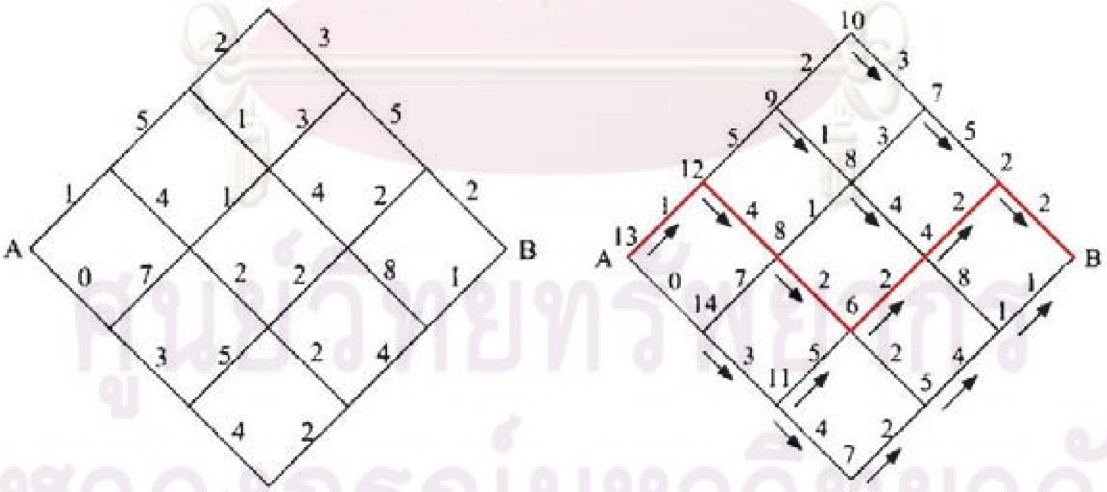

Figure 1.2: Dynamic programming concepts are illustrated by a simple example (left diagram) and its solution (right diagram).

A typical application of dynamic programming is the problem of traveling from point A to point B in Figure 1.2 (left diagram) [14]. Movement is only allowed from left to right and the cost of traveling from one point on the grid to the another is given by the number at the edge connecting the two points. The goal is to find the path from A to B that minimizes the total cost.

The number by each point in the grid in Figure 1.2 (right diagram) is the cost of the lowest-cost path from that point to B. These numbers are obtained recursively by moving backward from B to A and applying the principle of optimality. The arrows in Figure 1.2 (right diagram) indicate the direction to be taken from each point to minimize the total cost of getting to B. The best path from A to B is seen to have a cost of 13. The path moves *udduud*, where *u* denotes up to the right and *d* denotes down to the right.

1.2.3 Model predictive control

Model Predictive Control, or MPC, is an advanced method of process control that has been in use in the process industries such as chemical plants and oil refineries since the late seventies. MPC is a form of control in which the current control action is obtained by solving on-line, at each sampling instant, a finite horizon open-loop optimal control problem, using the current state of the plant as the initial state; the optimization yields an optimal control sequence and the first control in this sequence is applied to the plant [15, 16].

Although the ideas of receding horizon control and model predictive control can be traced back to the 1960s [17], interests in this field started to surge only in the 1980s after publication of the first paper on Dynamic Matrix Control and the first comprehensive exposition of Generalized Predictive Control. The MPC scheme is nowadays very popular in the oil refining and petrochemical process industry and has adequately proved its usefulness in practice [18].

1.3 Objectives

The purposes of this thesis are fourfold.

1. To obtain suitable mathematical models for block-ice production process. There are two kinds of models: linear and nonlinear models. In the system identification literature there is a number of methods to deal with each kind of models. This work examines the models for block-ice process in which we pay attention to using the black-box identification techniques. At first, the linear ARX models are constructed. Then the nonlinear models based on feedforward neural networks are constructed using the same regressors with the best linear models. Afterward, these neural network models are pruned with Optimal Brain Surgeon (OBS) method [19].

2. To construct a demand predictor of number of block-ices for an ice factory. The predictor is constructed by using time series models. In this work, we consider the weekly-based and daily-based models for the demand prediction.

3. To develop an optimal control design for block-ice production process by using dynamic programming. The main objective is to minimize the electricity cost which incurs from the usage of electrical energy of compressors. The optimal control strategy is obtained by employing

dynamic programming in solving the optimization problem. In addition, numerous factors in the design procedure will be analyzed with respect to the electricity cost.

4. To develop a MPC strategy for block-ice production process in which the set of future control signals is calculated by minimizing the electricity cost at every time step over a finite look-ahead time. The first actions of this set are executed and the process is repeated at the following time step.

1.4 Scope of thesis

The scope of this thesis is specified as follows.

1. To construct mathematical models including linear models and neural network models for block-ice production process.
2. To build a demand predictor of number of block-ices which is a time series model for an ice factory.
3. To design an optimal controller for block-ice production process by using dynamic programming. Moreover, numerous factors in the design procedure will be analyzed with respect to the electricity cost.
4. To develop a MPC strategy for block-ice production process.

1.5 Organization of the thesis

The thesis is organized as follows. The application of system identification techniques for block-ice production process is shown in Section II. Section III is devoted to the optimal control design for block-ice production process. Then in Section IV, we deal with the model predictive control for such an ice factory. Finally, concluding remarks and future work are shown in Section V.

CHAPTER II

SYSTEM IDENTIFICATION

2.1 The black-box parametric identification

The black-box identification consists of inferring a relationship between inputs and outputs of a system based on experimental data. It represents an alternative to the analytical modeling when no physical insight is available or used or when the model based on physical insight contains a number of unknown parameters. There are two main types of model structures that can be used in the black-box identification: non-parametric and parametric models. Some examples of non-parametric models are step response, impulse response and frequency response [2]. In this work only parametric models have been considered.

Let u and y be the input and output of the system, respectively. The black-box identification through parametric methods is to find a mapping from past data to the space of the output. This mapping has the general structure [3]

$$\hat{y}(t|\theta) = g(Z^{t-1}, \theta) \tag{2.1}$$

where θ is the parameter vector and Z^{t-1} are input-output measurements of the system available at time $t-1$

$$Z^{t-1} = (u^{t-1}, y^{t-1}) = (u(1), y(1), ..., u(t-1), y(t-1)). \tag{2.2}$$

The function g in (1) could be considered as a combination of two mappings: one that takes the past observations Z^t and maps them into a vector $\varphi(t)$ of fixed dimension, and one that takes this vector to the space of the outputs

$$g(Z^{t-1}, \theta) = g(\varphi t, \theta) \tag{2.3}$$

where

$$\varphi(t) = \varphi(Z^{t-1}). \tag{2.4}$$

The measured outputs and components of vector $\varphi(t)$ (regressors) form a set of regressor-output pairs Z^N called estimation data set

$$Z^N = \{(y(t), \varphi(t))|t = 1, ..., N\}. \tag{2.5}$$

The goal of the identification is then to determine a mapping from the estimation data set Z^N to the set of possible parameters θ so that the model will produce output $\hat{y}(t)$ which in some sense are close to the true values $y(t)$. A leading guideline for estimating θ will be to minimize the error between the output of the model and the measured output [9]

$$V_N(\theta, Z^N) = \frac{1}{N}\sum_{t=1}^{N} \|y(t) - \hat{y}(t)\|^2 . \tag{2.6}$$

The parameters are found as

$$\hat{\theta} = \arg\min_{\theta} V_N(\theta, Z^N). \tag{2.7}$$

Finally, the derived model is validated on a fresh set of data called validation data set. To know how well the result is, the fit is introduced

$$f(\%) = 100 \times (1 - \frac{\|y - \hat{y}\|}{\|y - \bar{y}\|}) \tag{2.8}$$

where

$$\bar{y} = \frac{1}{N}\sum_{t=1}^{N} y(t). \tag{2.9}$$

2.2 Linear identification

In this work linear ARX model is used. An ARX model is described by the following equation [20]

$$A(q^{-1})y(t) = B(q^{-1})u(t - n_k) + e(t) \tag{2.10}$$

where y is the output of the dynamic model, u is the input, e is the disturbance or noise, q^{-1} is the shift operator, n_k is the dead time of the system and

$$\begin{aligned} A(q^{-1}) &= 1 + a_1 q^{-1} + ... + a_{n_a} q^{-n_a} \\ B(q^{-1}) &= b_1 + b_2 q^{-1} + ... + b_{n_b} q^{-n_b} + 1 \end{aligned} \tag{2.11}$$

where n_a is equal to the number of poles, $n_b - 1$ is the number of zeros.

In this case, the Least Squares Method (LSM) is employed to estimate the parameters. The estimation of the parameters using LSM is straightforward but the problem is how to choose the optimal structure of the model. A simple approach is to consider various structures, use the estimation data set to estimate the parameters, and choose the model that produces the best fit when it is applied to the validation data set.

2.3 Neural network identification

The results with the simpler model give some guidelines how the structural parameters should be chosen in a more complex model. It is common to start with a linear ARX model. The delay and number of delayed inputs and outputs give a good initial guess how the structure should be chosen for the more complex NNARX model. In addition, many nonlinear systems can be described fairly well by linear models. Therefore, it is a good idea to use insight from the best linear model to select the regressors for the neural network models [21].

The NNARX models are built using a Multi-Layer Perceptron network with a single hidden layer. The choice of this network is based on the previous experience [22] for its ability to model simple and complex functional relationships. Moreover, only hidden neurons with hyperbolic tangent function have been considered.

The weights in 2.7 are found by an iterative scheme of the following kind [21]

$$\hat{\theta}^{(i+1)} = \hat{\theta}^{(i)} - \mu_i R_i^{-1} \nabla \hat{f}_i \tag{2.12}$$

where $\hat{\theta}^{(i)}$ is the parameter estimate after i iterations, μ_i is step size, $\nabla \hat{f}_i$ is an estimate of the gradient $V_N'(\hat{\theta}^{(i)})$, R_i is a matrix that modifies the search direction. A large number of training algorithms exist. In this work, the Levenberg-Marquardt algorithm is used because of its rapid convergence properties and robustness [23]. The performance function used in this algorithm is chosen as the mean squared error.

The minimization of $V_N(\theta, Z^N)$ in 2.6 has to be done by numerical search procedure because there is no analytic solution to this problem. However, $V_N(\theta, Z^N)$ may have several local minima where local search algorithms may get caught. Since the initialization of the parameters is taken randomly, it is necessary to process the identification several times in order to obtain acceptable results.

In the scheme 2.12, the iterations can be run until there is no further improvement in the performance function. It is noted that if the model is evaluated on validation data, the validation error first decreases with the number of iterations, but then starts to increase with increasing number of iterations (although the estimation error continues to decrease). This phenomenon is called *overtraining* [9]. To deal with this phenomenon the *early stopping* method [23] is employed. When the overtraining happens, the validation error typically begins to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned.

The NNARX model obtained from training process is then pruned using OBS method. The network pruning is used to remove unimportant weights from a trained network. Its goals are to improve generalization, simplify networks, and increase the speed of further training [19]. Let E and w be the error and weights corresponding to this trained network. The functional Taylor series of the error with respect to weights is

$$\delta E = \left(\frac{\partial E}{\partial w}\right)^T \partial w + \frac{1}{2} \partial w^T H \partial w + O(\|\partial w\|^3) \tag{2.13}$$

where $H = \partial^2 E / \partial w^2$ is the Hessian matrix. The main idea of OBS method is to set one of the weights to zero (called w_q) but the increase in error in 2.13 is smallest. For a network trained to a local minimum in error, the first term in 2.13 vanishes, and we can ignore the third and all higher order terms. The task now becomes to solve

$$\min_q \{ \min_{\partial w} (\frac{1}{2} \partial w^T H \partial w) | e_q^T \delta w + w_q = 0 \} \tag{2.14}$$

where e_q is the unit vector in weight space corresponding to weight w_q. The optimal weight change and resulting change in error are as follows [19]

$$\partial w = -\frac{w_q}{[H^{-1}]_{qq}} H^{-1} e_q \;\text{ and }\; L_q = \frac{1}{2} \frac{w_q^2}{[H^{-1}]_{qq}} \tag{2.15}$$

Also in [19] the OBS procedure is given

1. Train a "reasonably large" network to minimum error.

2. Compute H^{-1}.

3. Find the q that gives the smallest $L_q = w_q^2/(2[H^{-1}]_{qq})$. If this candidate error increase is much smaller than E , then the q^{th} weight should be deleted, and we proceed to step 4; otherwise go to step 5.

4. Use the q from step 3 to update all weights $\delta w = -w_q H^{-1} e_q/[H^{-1}]_{qq}$. Go to step 2.

5. No more weights can be deleted without large increase in E.

In our study, the NNARX models are pruned using OBS method: compute the inverse Hessian matrix, find the weight that gives the smallest $L_q = w_q^2/(2[H^{-1}]_{qq})$ and delete this weight, update all weights, and retrain the network; This process is repeated until there are two weights left (the minimum of weights).
In this work, our approach to construct the neural network models is as follows.

- Construct the linear ARX models.

- Use the regressors from best linear ARX models for the construction of NNARX models based on feedforward neural networks.

- The NNARX models are then pruned using OBS method.

- Validate the best NNARX models.

2.4 Numerical results

The case study is to find models for block-ice process of a local ice factory. From the block-ice process in Section I, the whole system consists of two parts as illustrated in Figure 2.1.

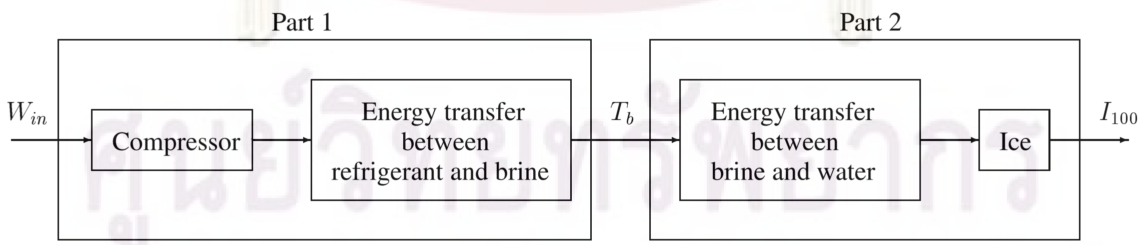

Figure 2.1: Block diagram of the block-ice system.

The available data taken from [24] include:

- The electric energy consumption (kWh) of the compressors.

- The average brine temperature (degree Celsius).

- The number of block-ice are ready for sales (unit).

The electric energy consumption and the average brine temperature are acquired by measurement while the number of block-ice ready for sales is achieved by simulation [24].

We divide the data into two sets, namely, data set 1 and data set 2. The data are shown in Figure 2.2 and 2.3. In each data set, there are 336 values for each variable. We divide the data into two subsets:

- A training (or estimation) set starts from the 1^{st} to the 168^{th} value.
- A test (or validation) set consists of the 169^{th} to the 336^{th} value.

In the linear ARX identification, we vary n_a and n_b from 1 to 10, fix $n_k = 1$ and use LSM for estimation parameters. As a result, we obtain the linear models, some of the models that yield high fit are shown in Table 2.1.

Table 2.1: Performances of the linear ARX models.

Part	Data set 1				Data set 2			
	n_a	n_b	n_k	*Fit*(%)	n_a	n_b	n_k	*Fit*(%)
1	1	5	1	85.35	4	3	1	82.63
	1	4	1	85.19	4	2	1	82.63
	2	2	1	84.94	2	2	1	81
2	1	3	1	84.74	1	7	1	70.69
	3	3	1	84.25	1	6	1	70.38
	2	2	1	84.14	2	2	1	68.8

From results in Table 2.1, we choose the linear ARX models for part 1 and 2 with $n_a = 2$, $n_b = 2$, $n_k = 1$ because of their simple structure and high fit.

The NNARX models are then constructed using the same regressors with the linear ARX models, i.e., the regression vector is $\varphi(t) = (u(t-1), u(t-2), y(t-1), y(t-2))$. First, we use 10 neurons in the hidden layer, after that the number of hidden neurons is decreased. Each model has been processed several times, the best results obtained with NNARX models are shown in Table 2.2.

The NNARX models with the highest fit are chosen to prune with OBS method. In part 1 with data set 1 and 2 are the models containing 9 hidden neurons (labeled model 1 and 2, respectively), in part 2 with data set 1 is the model containing 6 hidden neurons (labeled model 3), in part 2 with data set 2 is the model containing 8 hidden neurons (labeled model 4). Using OBS method some weights are eliminated. After each weight elimination, the network is retrained. During the pruning process, the test error is also calculated so that it can be subsequently used for pointing out the optimal network. We will select the network with the smallest test error as the final one. The pruning process for model 1, 2, 3 and 4 are illustrated in Figure 2.4, 2.5, 2.6 and 2.7, respectively.

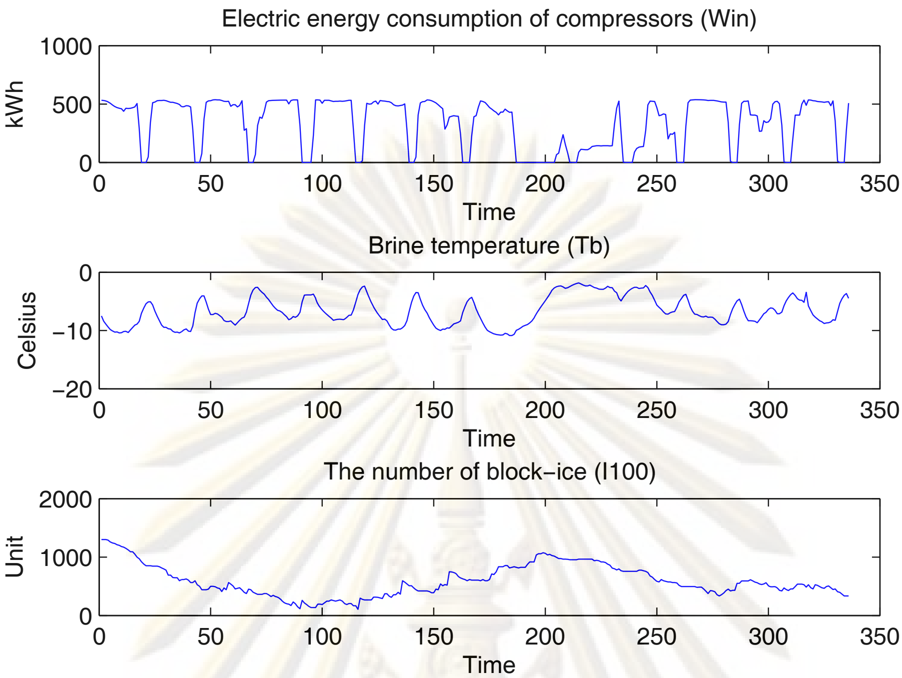

Figure 2.2: Data set 1 including electric energy consumption of compressors, brine temperature, and number of block-ice.

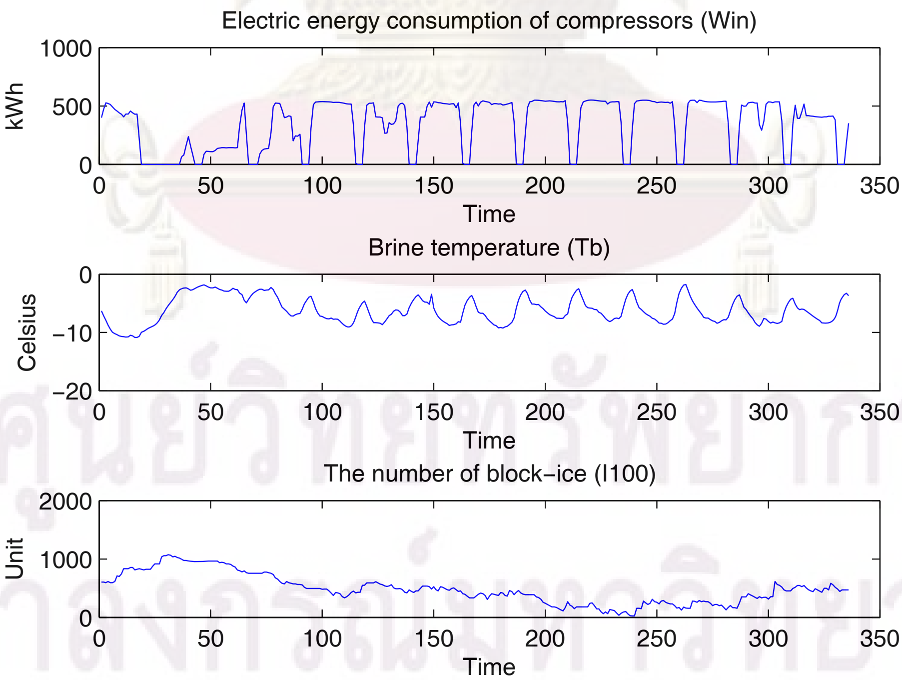

Figure 2.3: Data set 2 including electric energy consumption of compressors, brine temperature, and number of block-ice.

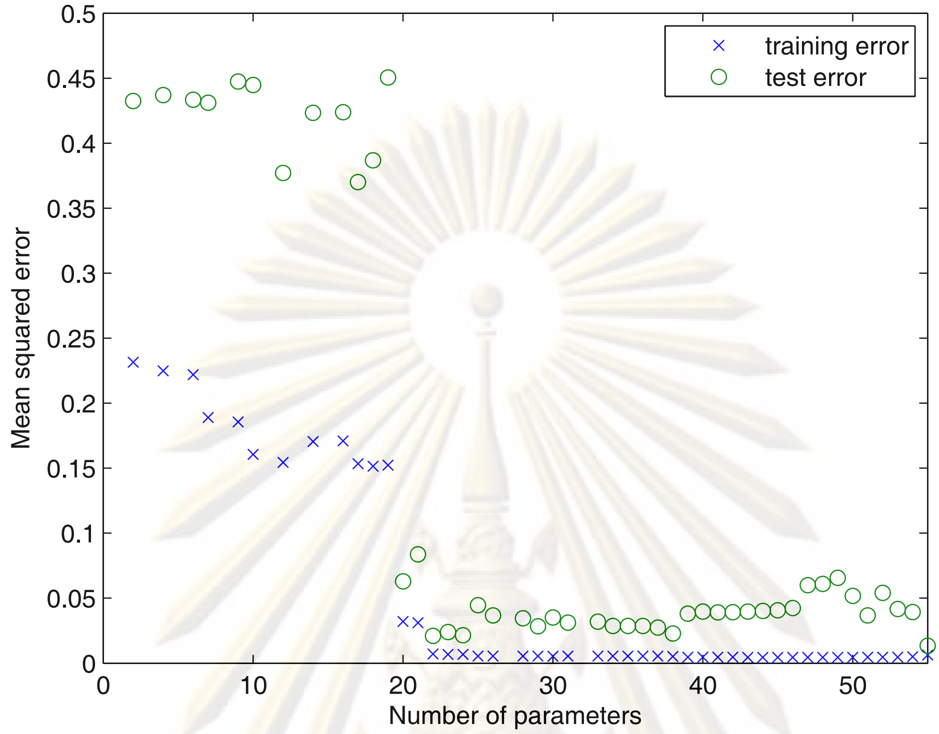

Figure 2.4: The error during pruning process of model 1.

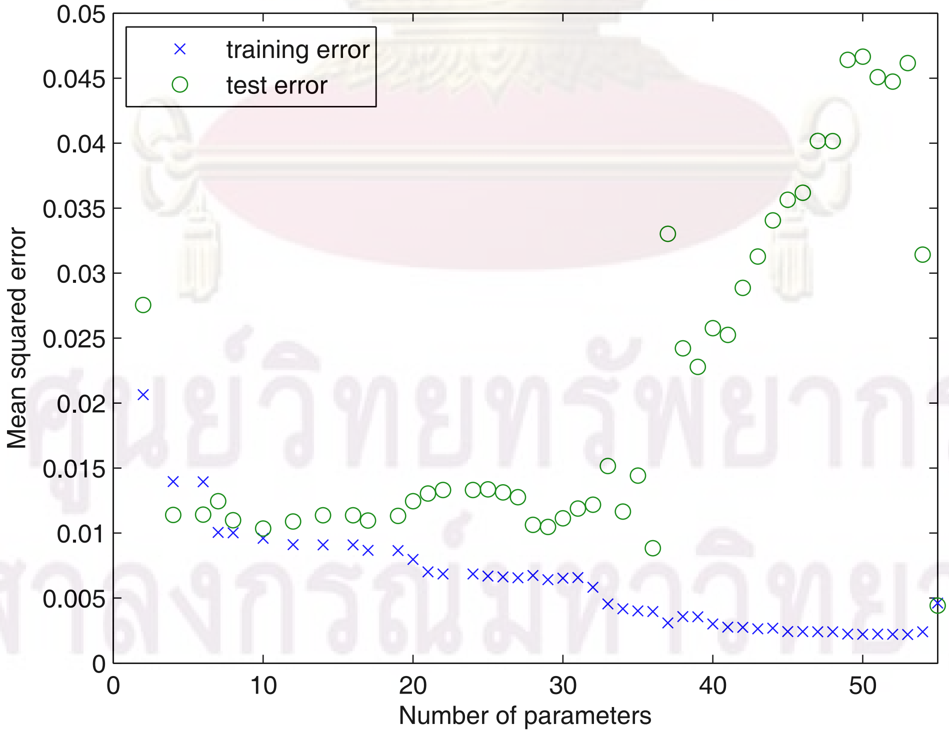

Figure 2.5: The error during pruning process of model 2.

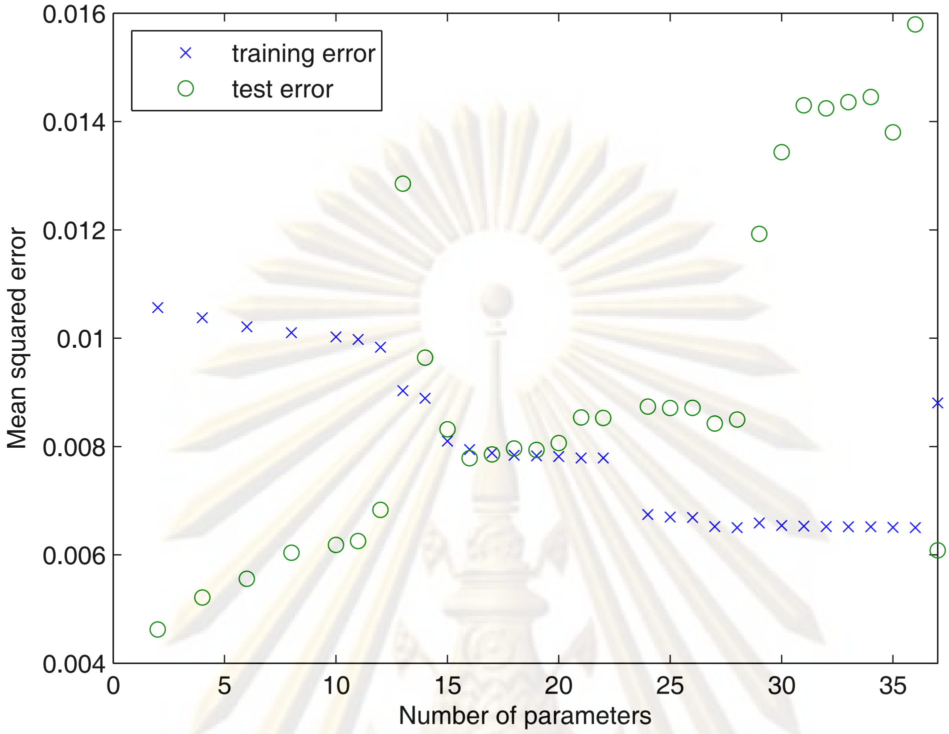

Figure 2.6: The error during pruning process of model 3.

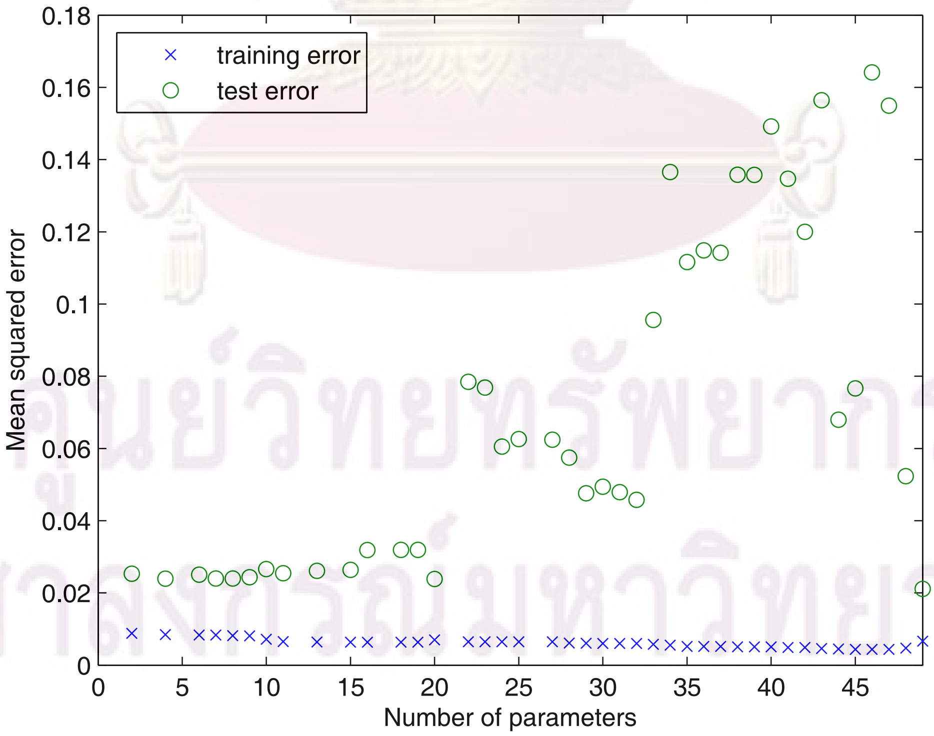

Figure 2.7: The error during pruning process of model 4.

Table 2.2: Performances of the NNARX models.

Part	Data set 1		Data set 2	
	Hidden neurons	*Fit(%)*	*Hidden neurons*	*Fit(%)*
1	10	82.89	10	85.68
	9	86.32	9	86.65
	8	85.64	8	85.45
	7	85.66	7	86.40
	6	85.35	6	84.68
2	10	81.77	10	68.02
	9	83.85	9	68.03
	8	83.23	8	69.63
	7	83.27	7	66.59
	6	84.47	6	63.81

Figure 2.4, 2.5, 2.6 and 2.7 should be read from right to left. The training error and test error of each of intermediate networks are displayed in these figures. These figures reveal that the minimum of the test error of the model 1, 2, 3 and 4 occurs when there are 55, 55, 2, and 49 weights left in the network, respectively. Comparing to the number of original weights of the model 1, 2, 3 and 4, it is seen that after pruning the model 1, 2 and 4 do not change, and the number of weights of model 3 decreases from 37 to 2. The results (i.e, the fit) obtained with pruned NNARX models, original NNARX models and linear ARX models are summarized in Table 2.3.

Table 2.3: Comparison between ARX and NNARX models.

Part	Data set 1					Data set 2				
	ARX	*Original NNARX*		*Pruned NNARX*		*ARX*	*Original NNARX*		*Pruned NNARX*	
		Fit(%)	*Weights*	*Fit(%)*	*Weights*		*Fit(%)*	*Weights*	*Fit(%)*	*Weights*
1	84.94	86.32	55	86.32	55	81	86.65	55	86.65	55
2	84.14	84.47	37	86.46	2	68.8	69.63	49	69.63	49

The results in Table 2.3 show that the performance of both linear and neural network models are very good. In particular, the NNARX models give better results in terms of the fit compared to the corresponding linear ARX models. The measured and one-step ahead predicted model output for NNARX model 1, 2, 3 and 4 (after pruning) are shown in Figure 2.8, 2.9, 2.10 and 2.11, respectively.

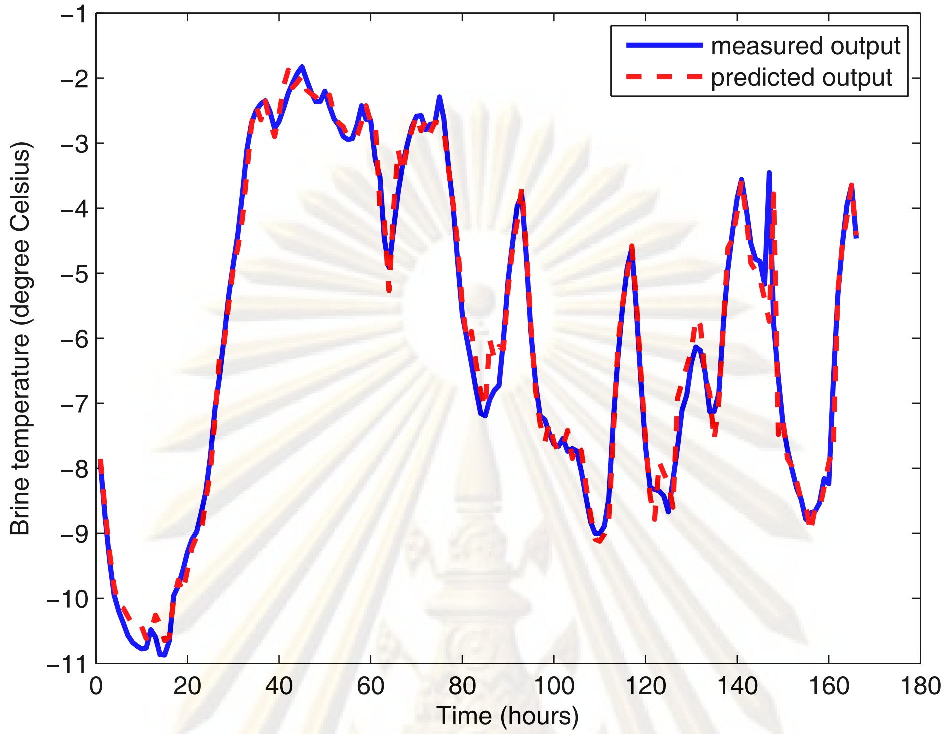

Figure 2.8: The measured and predicted output of NNARX model 1.

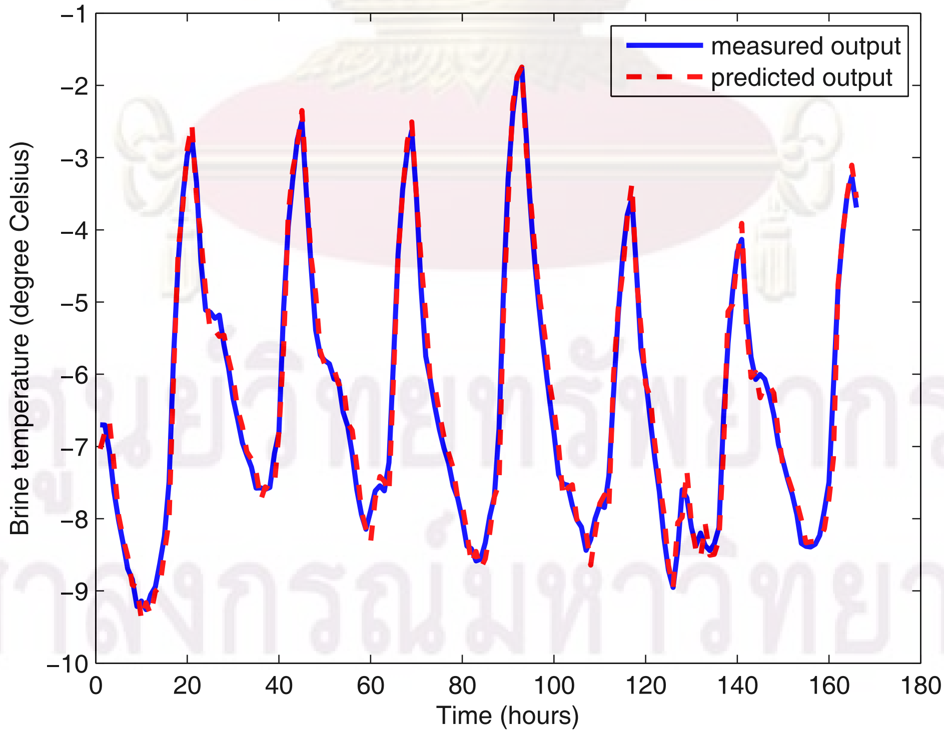

Figure 2.9: The measured and predicted output of NNARX model 2.

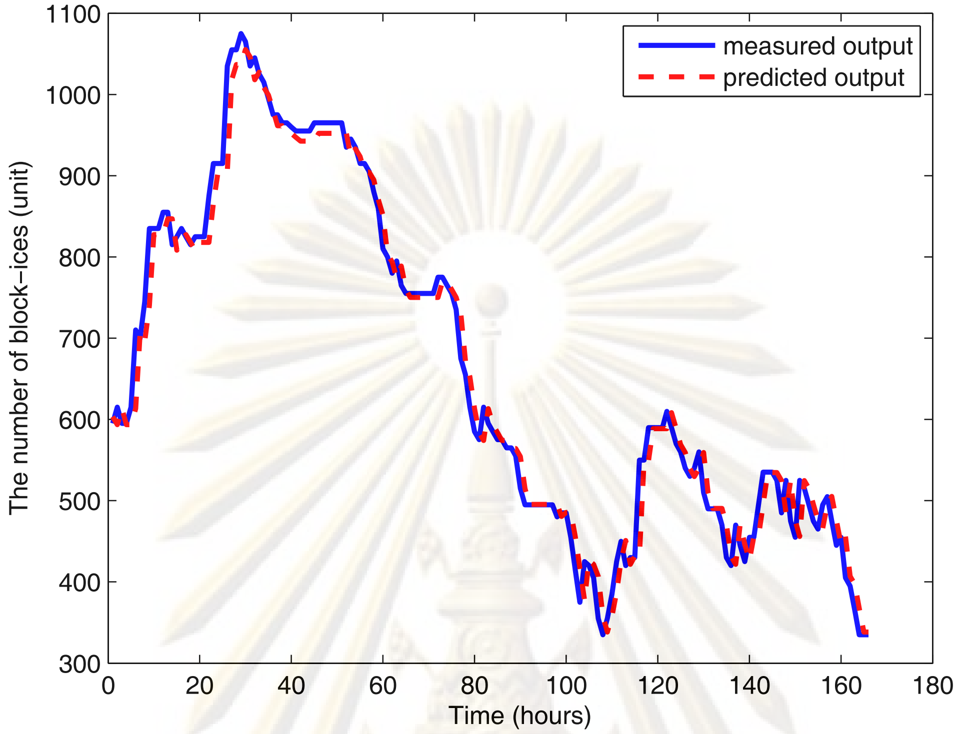

Figure 2.10: The measured and predicted output of NNARX model 3.

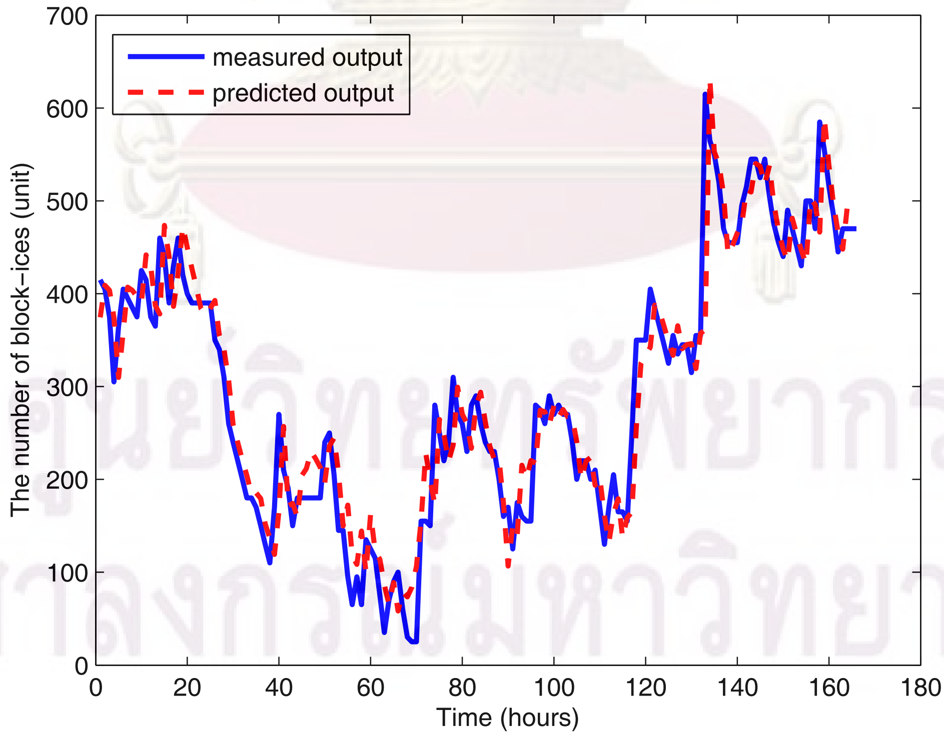

Figure 2.11: The measured and predicted output of NNARX model 4.

2.5 Ice demand predictor

We build an ice demand predictor for an ice factory based on time series models. A time series is one or more measured output channels with no measured input [20]. In this work, linear AR model is used. The AR model is given by the following equation [20].

$$A(q^{-1})y(t) = e(t) \tag{2.16}$$

where y is the output of the dynamic model, e is the disturbance or noise, q^{-1} is the shift operator, and

$$A(q^{-1}) = 1 + a_1 q^{-1} + ... + a_{n_a} q^{-n_a}. \tag{2.17}$$

Similar to ARX models, the Least Squares Method (LSM) is used to estimate the parameters for AR models and the fit is used as prediction performance measurement. The data used for building the predictor is shown as Figure 2.12 [24].

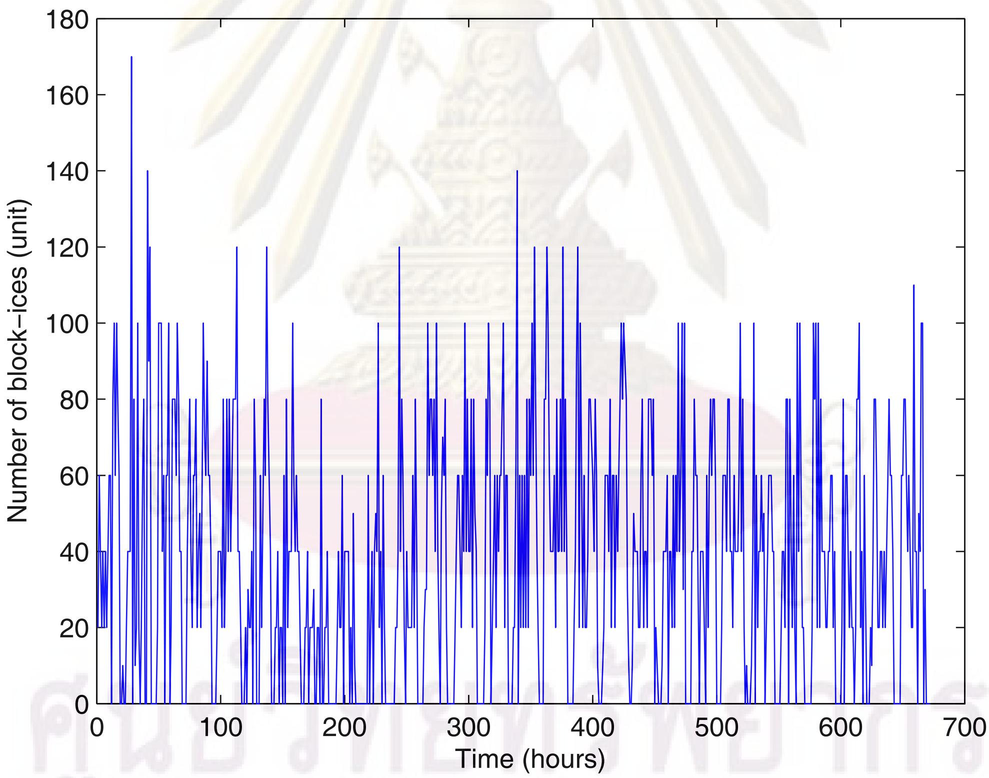

Figure 2.12: The demand of block-ices in one month.

2.5.1 Weekly-based models

The data are divided into four weeks, namely, week 1, 2, 3 and 4 starting from the 1^{st} to the 168^{th} value, from the 169^{th} to the 336^{th} value, from the 337^{th} to the 504^{th} value, and from 505^{th} to the 672^{th} value, respectively.

At first, we build the linear AR model then the nonlinear NNAR models are constructed based on the regression of the best AR model. Using different sets of estimation and validation data, we have results as shown in Table 2.4. The results indicate that the performance of NNAR models are much better than the performance of linear AR models in terms of the model fit.

Table 2.4: Performances of weekly-based models.

Estimation data	Validation data	Linear AR		NNAR	
		Models	*Fit(%)*	*Hidden neurons*	*Fit(%)*
Week 1	Week 2	ar2	10.31	10	27.04
Week 2	Week 3	ar2	9.21	10	26.10
Week 3	Week 4	ar2	1.58	9	19.17
Week 1 + 2	Week 3 + 4	ar2	5.18	10	19.38

Let NNAR1_2, NNAR2_3, NNAR3_4 and NNAR12_34 be the names of NNAR models in which the estimation data are week 1, week 2, week 3, week 1 + 2 and validation data are week 2, week 3, week 4, week 3 + 4, respectively. Figures 2.13, 2.14, 2.15, and 2.16 show the measured and predicted output for these NNAR models.

In Chapter 3 and 4, we will use the NNAR1_2 model where week 1 is estimation data and week 2 is validation data for optimal control design. The weights of this model are shown in Equation (2.18) and (2.19).

$$W_1 = \begin{bmatrix} -1.7017 & 2.4325 & 4.9286 \\ 1.6411 & 4.5144 & 4.1262 \\ 0.4418 & 1.3004 & -4.5317 \\ 0.9607 & 0.1566 & -2.9541 \\ -3.1151 & -4.3163 & 9.5470 \\ -2.9498 & 3.1280 & -4.8573 \\ -2.3587 & 1.0888 & -2.4374 \\ -2.8505 & 1.8948 & -3.3966 \\ 1.8025 & 2.1829 & -5.1091 \\ -2.9821 & -6.8949 & -6.4593 \end{bmatrix} \tag{2.18}$$

$$W_2 = [-1.4951 \quad 3.8219 \quad 3.1573 \quad -3.2864 \quad 3.2135 \quad -1.2799 \quad -2.9785 \quad 3.5907 \quad 3.6313 \quad 3.5788 \quad 1.1387] \tag{2.19}$$

2.5.2 Daily-based models

The data are divided into 28 days, each day contains 24 hour of data. Some of the daily-based models with high fit are shown in Table 2.5. The results show that the NNAR models are far better than linear AR models.

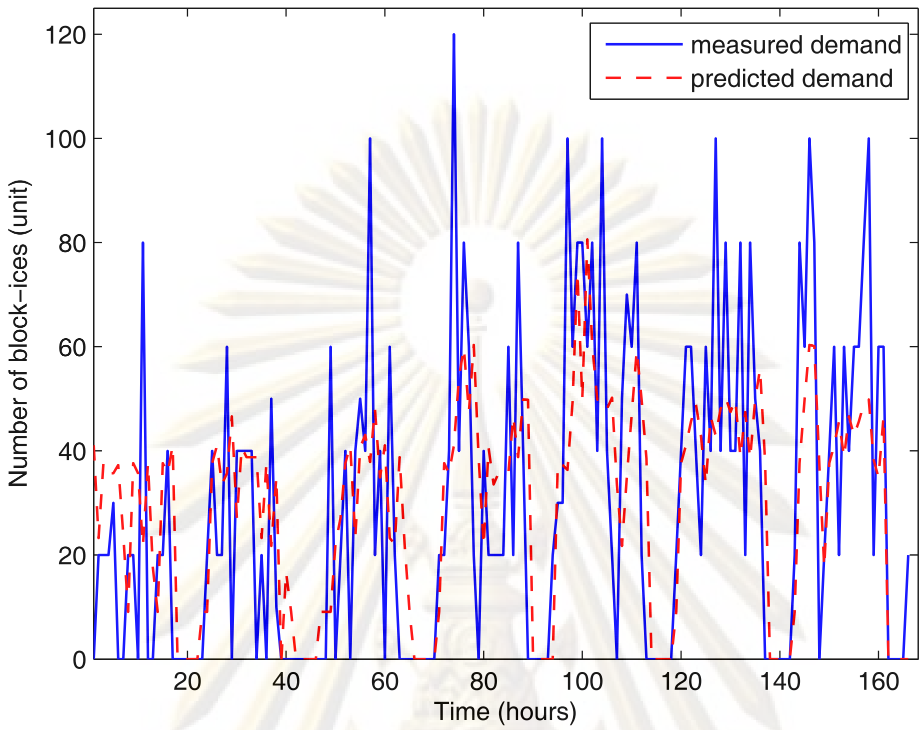

Figure 2.13: The measured and predicted output of NNAR1_2.

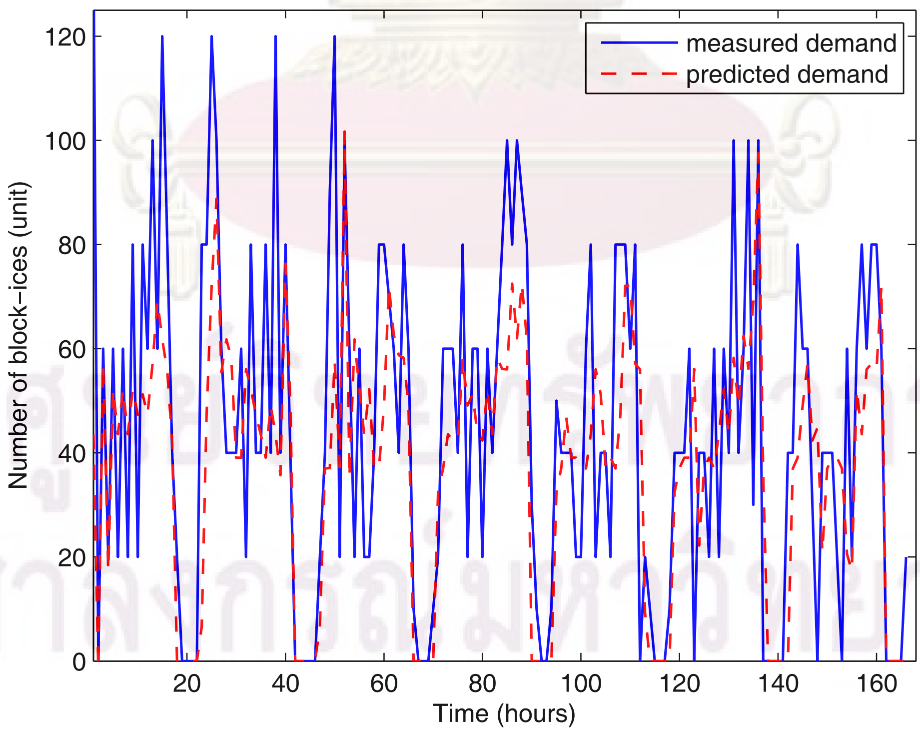

Figure 2.14: The measured and predicted output of NNAR2_3.

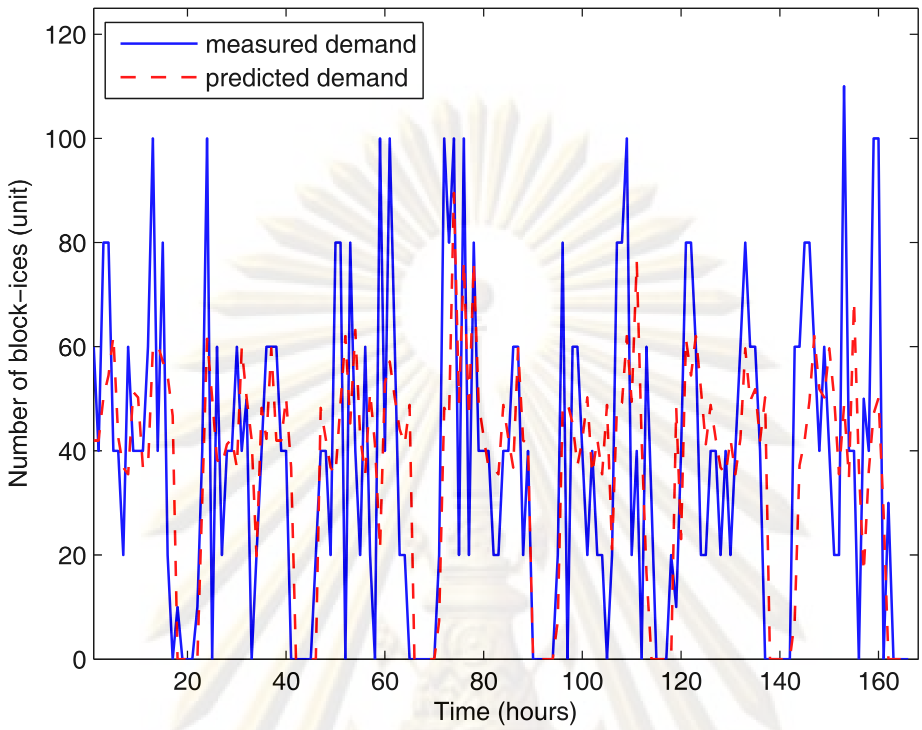

Figure 2.15: The measured and predicted output of NNAR3_4.

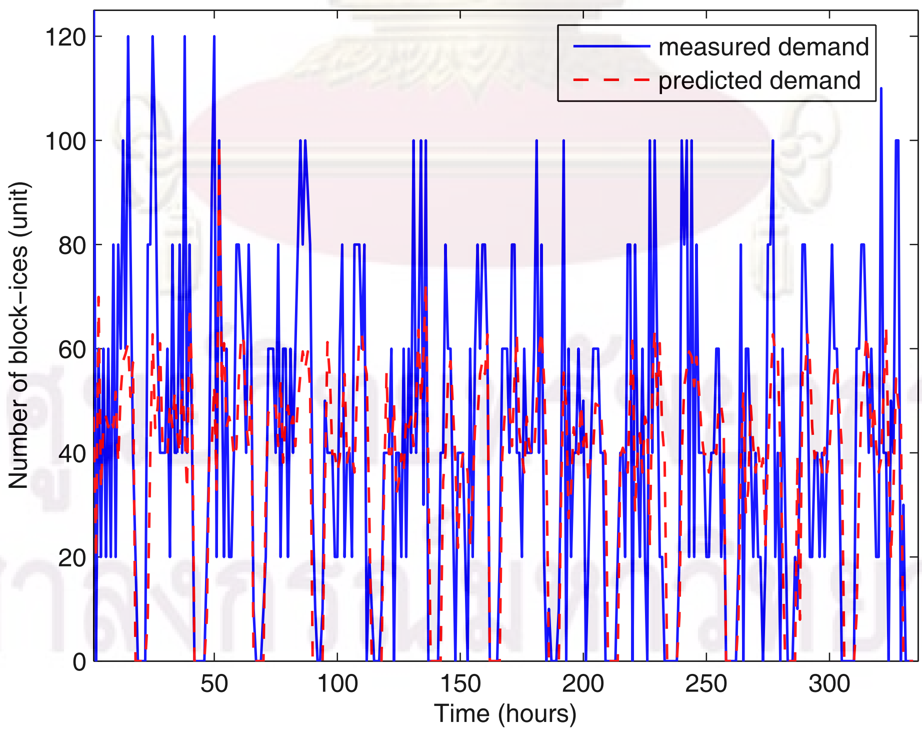

Figure 2.16: The measured and predicted output of NNAR12_34.

Table 2.5: Performances of daily-based models.

Estimation data	Validation data	Linear AR		NNAR	
		Models	*Fit(%)*	*Hidden neurons*	*Fit(%)*
Day 17	Day 18	ar2	22.3	10	60.43
Day 24	Day 25	ar2	28.88	9	50.41
Day 16 + 17	Day 18 + 19	ar2	15.86	6	38.49
Day 22 + 23 + 24	Day 25 + 26 + 27	ar2	10.23	8	32.74

2.6 Conclusion

In this chapter, we have applied the system identification technique for block-ice production process. We construct two parametric models which are linear and neural networks models. Linear models are built with Auto-Regressive model with exogenous inputs structure. Nonlinear models based on feedforward neural networks are constructed using the regressors provided by the best linear ARX models. Then the OBS method is used to prune the neural network models. Numerical results show that the performance of both linear ARX and NNARX models are very good, however, the NNARX models yield slightly better results in terms of the model fit than linear ARX models. In addition to constructing models for block-ice production process, we also build the ice demand predictors based on time series models.

CHAPTER III

OPTIMAL CONTROL DESIGN

3.1 Problem formulation

A previous section has examined different models of block-ice production process. Experiments with real data indicate that linear models yield reasonably good results in terms of the model fit. In this section, we use a linear mathematical model to describe the dynamical behavior of block-ice production process. This model consists of two parts with a series connection and has a high fit in both parts, namely, 81.59% and 85.03%, respectively. Figure 3.1 and 3.2 show the measured and predicted model output for this model.

The discrete-time model of block-ice process is given as follows.

$$\begin{cases} x_1(k+1) = 0.84x_1(k) - 0.002869u(k) \\ x_2(k+1) = 0.9588x_2(k) - 2.375x_1(k) \end{cases} \tag{3.1}$$

where $u(k)$ is the electric energy consumption of the compressors (kWh), $x_1(k)$ is the average brine temperature (Celsius), $x_2(k)$ is the number of block-ices ready for sales (unit), and k is time index.

The control objective is to minimize the monthly electricity cost which consists of the cost of peak electrical demand (kW) and the cost of electrical energy (kWh).

Thus, the cost function using TOU tariff is defined as

$$J = \sum_{\nu=0}^{1} r_{d,\nu} u_{\max,\nu} + \frac{672}{N} \sum_{\nu=0}^{1} \sum_{k=1}^{N} r_{e,\nu}(k) u(k) \tag{3.2}$$

and the cost function using TOD tariff is defined as

$$\begin{aligned} J = \; & r_{d,1} u_{\max,1} + r_{d,2} \max\{u_{\max,2} - u_{\max,1}, 0\} \\ & + \frac{672}{N} \sum_{\nu=0}^{2} \sum_{k=1}^{N} r_{e,\nu}(k) u(k) \end{aligned} \tag{3.3}$$

where ν is equal to 0 for off-peak, 1 for on-peak, and 2 for partial-peak period, $r_{d,\nu}$ is the demand charge in period ν, $u_{\max,\nu}$ is peak demand in period ν, N is the time duration, and $r_{e,\nu}$ is the energy charge in period ν.

The system is subjected to a number of the constraints on the control input and state variables. First, the brine temperature is kept within an appropriate bound in order to maintain the operating point and store block-ices in the tank. Second, the number of block-ices in the tank is limited by the maximum capacity and there should be enough for sale according to the predicted demand. In this thesis, we build a block-ice demand predictor based on time series models. The measured and predicted demand of number of block-ices used in the thesis are shown as Figure 2.13, the model fit is

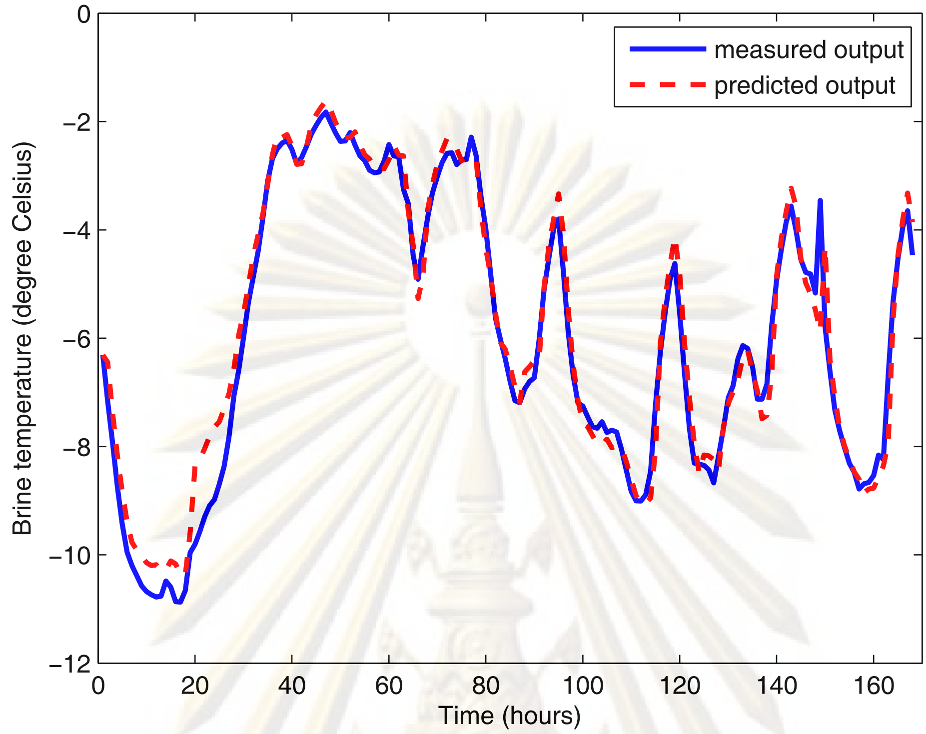

Figure 3.1: The measured and predicted model output for part 1.

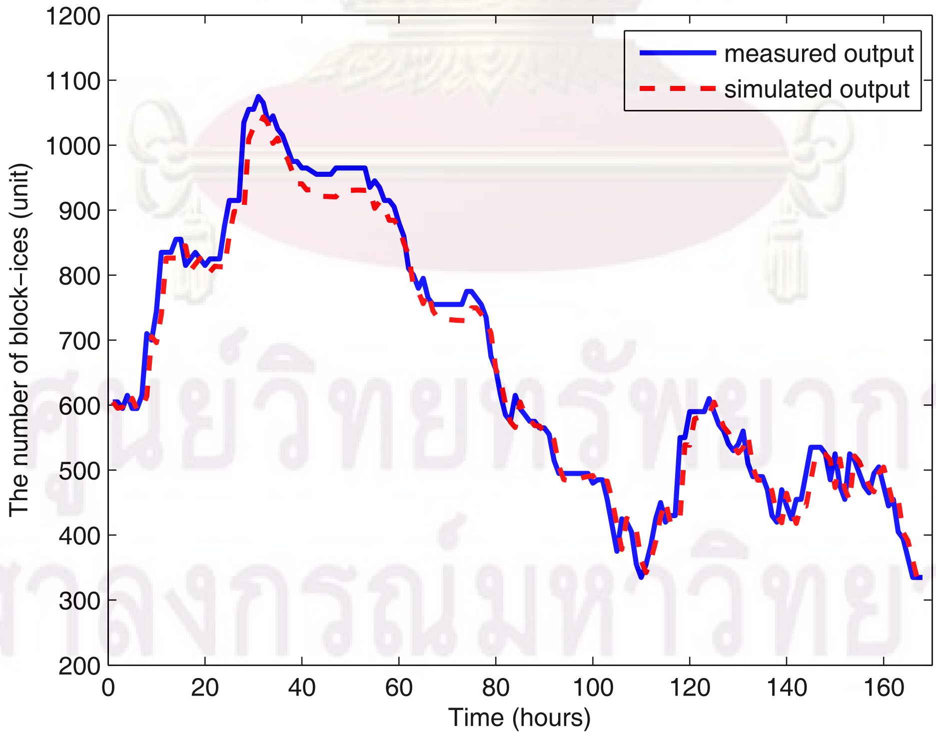

Figure 3.2: The measured and predicted model output for part 2.

$f = 27.04\%$. Third, the control input is limited by the electrical rated power of compressors. Lastly, compressors are kept working continuously within a period of time. In view of a previous study of local block-ice factory [24], the constraints are specified as follows.

$$\begin{cases} -11°\text{C} \leq x_1(k) \leq -2°\text{C} \\ \hat{d}(k) \text{ units} \leq x_2(k) \leq 2600 \text{ units} \\ 0 \text{ kWh} \leq u(k) \leq 520 \text{ kWh} \\ u(k) \text{ is unchanged over a time interval } \Delta t \end{cases} \tag{3.4}$$

where $\hat{d}(k)$ is the predicted demand of number of block-ice at time k.

3.2 Dynamic programming

The optimal control strategy in our work is the sequence of control inputs that minimizes the cost function (energy cost) of the block-ice process over a finite-time horizon.

$$J_e = J_e(u(1), \ldots, u(N)) = \sum_{\nu=0}^{1} \sum_{k=1}^{N} r_{e,\nu}(k)u(k). \tag{3.5}$$

The task of minimizing energy cost J_e is framed as a sequential decision-making process of decision variables $u(1), \ldots, u(N)$. The optimization technique called dynamic programming is commonly used for this type of problems.

Consider a discrete-time dynamic system

$$x_{k+1} = f_k(x_k, u_k, w_k), \qquad k = 0, 1, ..., N-1, \tag{3.6}$$

where the state x_k is an element of a space S_k, the control u_k is an element of a space C_k, the disturbance w_k is an element of a space D_k.

The constraint is $u_k \in U_k(x_k) \subset C_k$ for all $x_k \in S_k$ and k.

We consider the class of policies (also called control laws)

$$\pi = \{\mu_0, ..., \mu_{N-1}\},$$

where $u_k = \mu_k(x_k) \in U_k(x_k)$ for all $x_k \in S_k$. Such policies are called *admissible*.

Given an initial state x_0 and an admissible policy $\pi = \{\mu_0, ..., \mu_{N-1}\}$, the state x_k and disturbance w_k are random variables defined through the system equation

$$x_{k+1} = f_k(x_k, \mu_k(x_k), w_k), \qquad k = 0, 1, ..., N-1. \tag{3.7}$$

Denote $g_k(x_k, u_k, w_k)$ is the cost incurred at time k, so the expected cost of π starting at x_0 is

$$J_\pi(x_0) = E\left\{g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, \mu_k(x_k), w_k)\right\} \tag{3.8}$$

where the expectation is taken over the random variables w_k and x_k.

An optimal policy π^* is one that minimizes this cost

$$J_{\pi^*}(x_0) = \min_{\pi \in \Pi} J_\pi(x_0),$$

where Π is the set of all admissible policies.

The optimal cost depends on x_0 and is denoted by $J^*(x_0)$, that is

$$J^*(x_0) = \min_{\pi \in \Pi} J_\pi(x_0).$$

The most important concept of dynamic programming, the Principle of Optimality [13], is stated as: Let $\pi^* = \{\mu_0^*, ..., \mu_{N-1}^*\}$ be an optimal policy for the basic problem. Consider the subproblem whereby we are at x_i at time i and wish to minimize the "cost-to-go" from time i to time N

$$E\left\{ g_N(x_N) + \sum_{k=i}^{N-1} g_k(x_k, \mu_k(x_k), w_k) \right\}. \tag{3.9}$$

Then the truncated policy $\{\mu_i^*, \mu_{i+1}^*, ..., \mu_{N-1}^*\}$ is optimal for this subproblem.

In other words, an optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision.

Also in [13] the dynamic programming algorithm is given: For initial state x_0, the optimal cost $J^*(x_0)$ of the basic problem is equal to $J_0(x_0)$ which proceeds backward in time from period $N-1$ to period 0

$$J_N(x_N) = g_N(x_N), \tag{3.10}$$

$$J_k(x_k) = \min_{u_k \in U_k(x_k)} E_{w_k} \{g_k(x_k, u_k, w_k) + J_{k+1}(f_k(x_k, u_k, w_k))\} \qquad k = 0, 1, ..., N-1. \tag{3.11}$$

Applying dynamic programming [25], the iterative procedure for calculating optimal control inputs is as follows.

1. Set the *stopping* or *final conditions* $J_N(x_N)$ for all states. Thereby, the importance of one particular state over another at the end of the process at N can be reflected.

2. Consider a quantized state x_{N-1} at $N-1$: Apply each of the admissible control inputs u_{N-1}^m and determine the cost of the applied control over next stage

$$G_1^m = g_{N-1}(x_{N-1}, u_{N-1}^m) \tag{3.12}$$

for all $m = 1, ..., M$ where M is the number of quantized controls. The next state at stage N becomes

$$x_N^m = f_{N-1}(x_{N-1}, u_{N-1}^m) \tag{3.13}$$

for all $m = 1, ..., M$.

3. If x_N^m does not assume one of the quantized states, values of minimal cost at state x_N^m are interpolated by values of minimal cost at quantized states x_N

$$J_N(x_N^m) = \mathcal{P}^i(x_N^m, J_N(x_N)) \tag{3.14}$$

where $\mathcal{P}^i$ is the interpolation of order i. For the given problem, linear interpolation $\mathcal{P}^1$ between values of $J_N(x_N)$ is considered sufficient.

4. Calculate the total cost of applying u_{N-1}^m at state x_{N-1} from

$$J_{N-1}^m(x_{N-1}) = G_1^m + J_N(x_N^m). \tag{3.15}$$

Compare this cost for all M controls to find

$$J_{N-1}(x_{N-1}) = \min_{u_{N-1}^m \in U_{N-1}(x_{N-1})} \{g_{N-1}(x_{N-1}, u_{N-1}^m) + J_N(x_N^m)\} \tag{3.16}$$

The control input that makes this cost minimal is the optimal control input in that state-stage pair.

5. Repeat *steps 2-4* for each of the quantized states at stage $N-1$. Set $N = N-1$ and go to *step 2*.

This procedure is illustrated as in Figure 3.3. In practice, the optimal control inputs are determined when starting from one of the quantized state-stage pairs.

3.3 Simulation results

Due to large energy consumption, many ice factories in Thailand use the Schedule 4: Large General Service [26]. And normally such an ice factory purchases the electricity at 22-33 kV. This research employs the demand charge and energy charge based on both TOU tariff and TOD tariff. Table 3.1 and 3.2 show the monthly tariff and the applicable time for Schedule 4, respectively. State x_1, state x_2 and control signal u are quantized by $40, 200$, and 8, respectively.

Table 3.1: Monthly tariff of Schedule 4.

Tariffs	Demand charge (Baht/kW)			Energy charge (Baht/kWh)		
	Off-peak	On-peak	Partial-peak	Off-peak	On-peak	Partial-peak
TOD	0	285.05	58.88	1.7034	1.7034	1.7034
TOU	0	132.93		1.1914	2.6950	

The feasible regions for the final condition are as follows.

$$\begin{cases} \text{Case 1:} & -11\ ^\circ\text{C} \le x_1 \le -5.6\ ^\circ\text{C}, & 650 \text{ units} \le x_2 \le 2600 \text{ units} \\ \text{Case 2:} & -11\ ^\circ\text{C} \le x_1 \le -3.8\ ^\circ\text{C}, & 325 \text{ units} \le x_2 \le 2600 \text{ units} \\ \text{Case 3:} & -11\ ^\circ\text{C} \le x_1 \le -2\ ^\circ\text{C}, & 0 \text{ units} \le x_2 \le 2600 \text{ units} \end{cases} \tag{3.17}$$

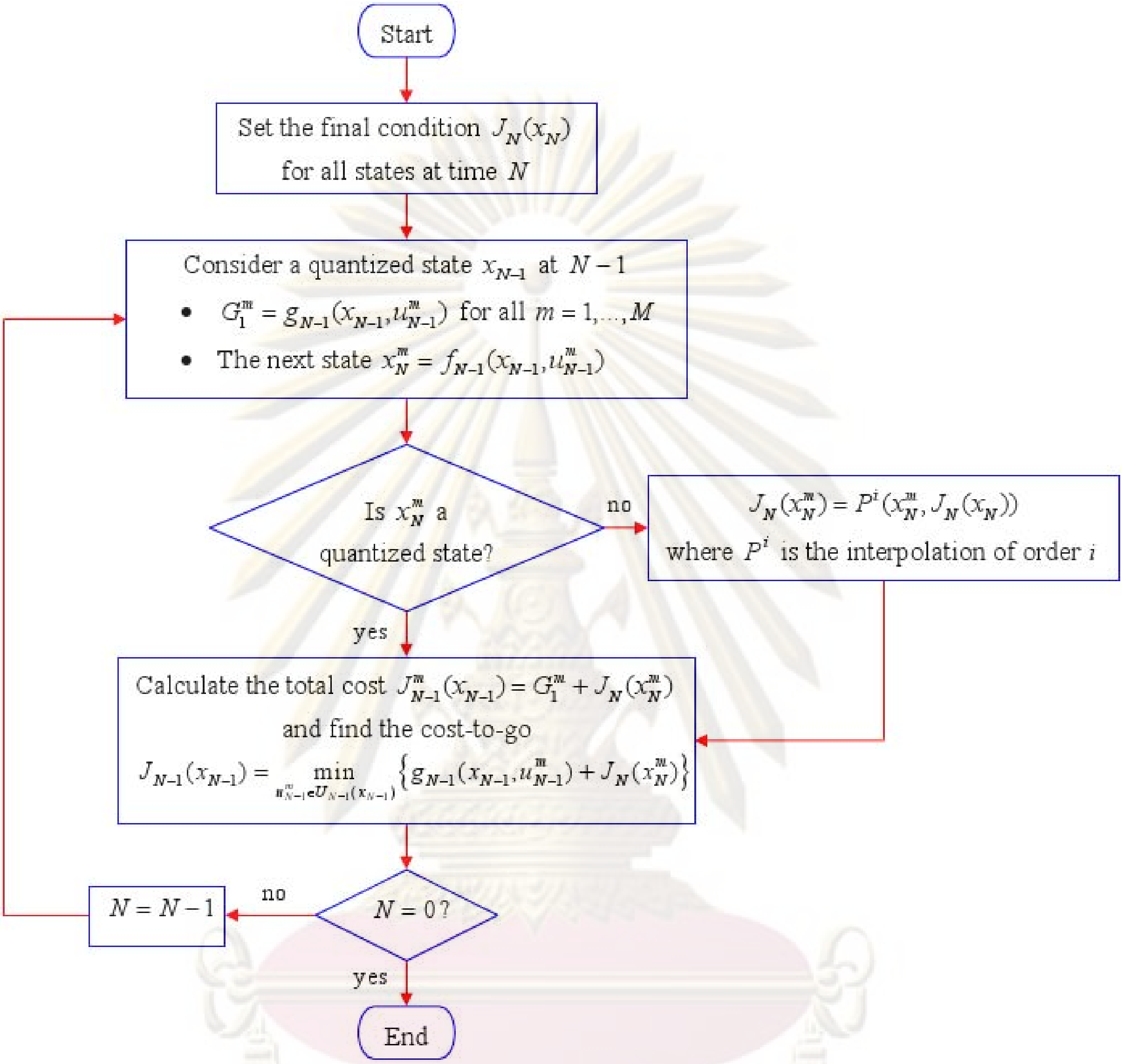

Figure 3.3: The iterative procedure for calculating optimal control inputs.

Table 3.2: Applicable time of Schedule 4.

Tariffs	Off-peak	On-peak	Partial-peak
TOD	09.30 p.m.–08.00 a.m. everyday	06.30 p.m.–09.30 p.m. everyday	08.00 a.m.–06.30 p.m. everyday
TOU	the rest of time	9 a.m.–10 p.m. Monday-Friday	

Figures 3.4, 3.5, 3.6 show the optimal control and corresponding state variables for block-ice production process over a period of two days when the final condition is set to Case 1, 2 and 3, respectively. The simulation results based on the assumptions that the initial condition is $x_1 = -11$ °C, $x_2 = 2600$ units, and the time interval is $\Delta t = 2$.

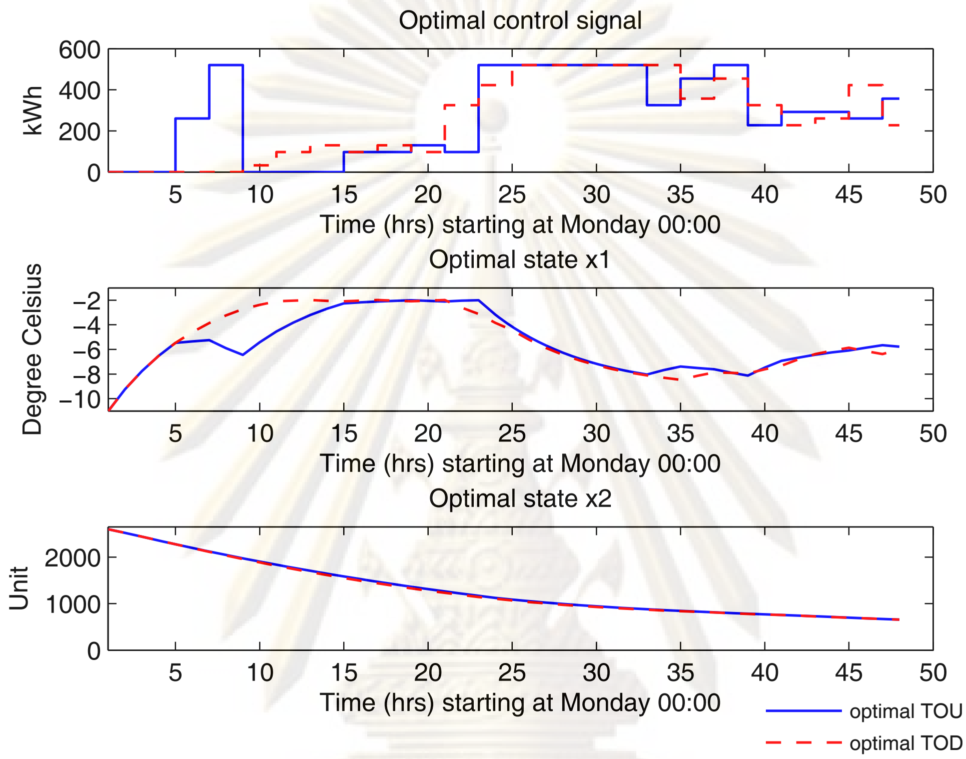

Figure 3.4: Optimal control and state variables for block-ice process (Case 1).

3.3.1 Effect of final condition

The effect of final condition is summarized in Table 3.3. In all cases, we fix the initial condition $x_1 = -11$ °C, $x_2 = 2600$ units, time interval $\Delta t = 2$ and the cost is assigned zero in the feasible region and a very high value otherwise. The results show that the cost is minimum if the whole region is feasible (Case 3) and the cost is increased if the feasible region is more restricted.

3.3.2 Effect of initial condition

Figure 3.7 depicts the effect of the initial condition to the electricity cost, when using TOU tariff, with the assumptions that the final condition is Case 1 and $\Delta t = 2$. It is clearly seen that the cost will be minimum if we start from the smallest value of brine temperature and the largest value of block-ices in the storage. When using TOD tariff, the obtained result also possesses the same property.

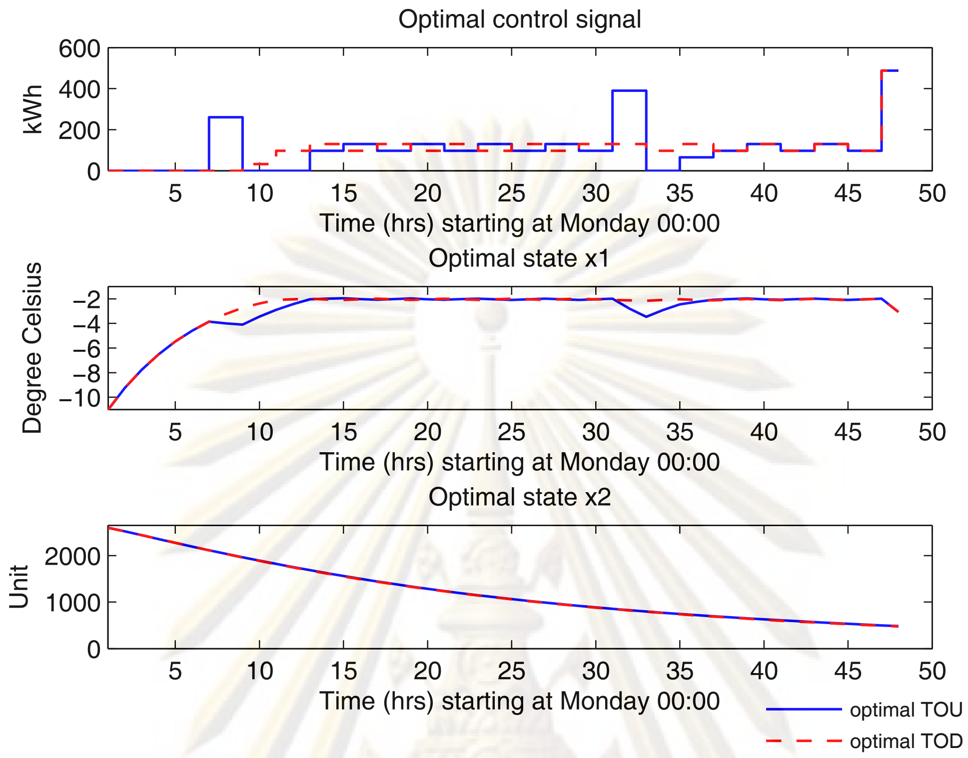

Figure 3.5: Optimal control and state variables for block-ice process (Case 2).

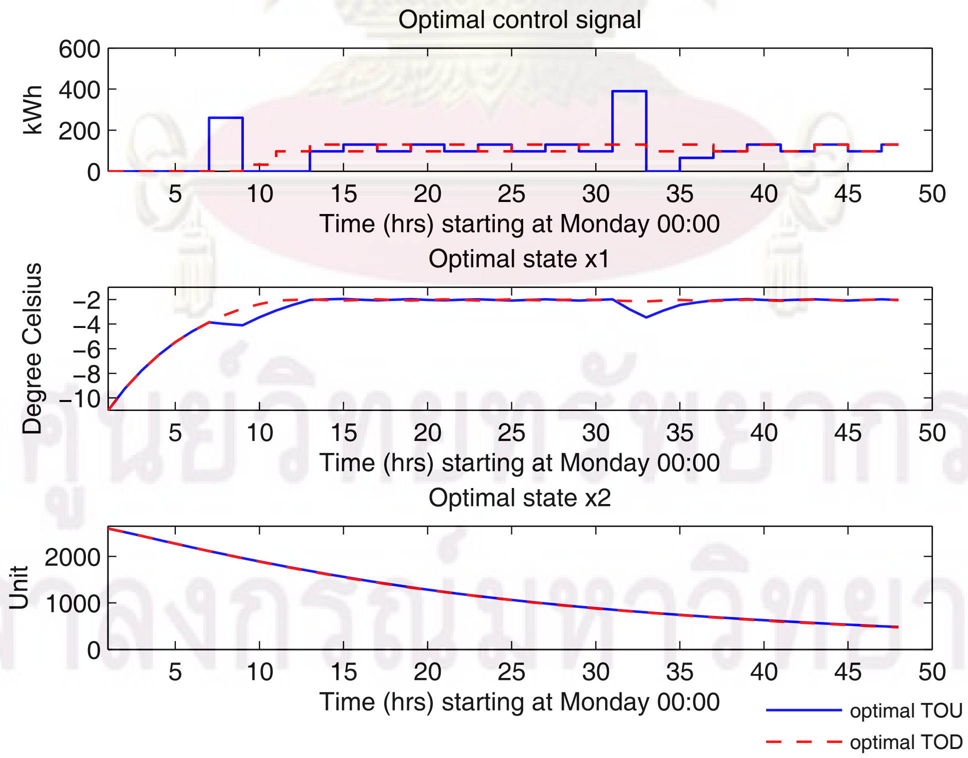

Figure 3.6: Optimal control and state variables for block-ice process (Case 3).

Table 3.3: Effect of final condition to electrical energy and electricity cost using optimal control design.

Final conditions		**Electrical energy (kWh)**				**Electricity cost (Baht)**		
		Off-peak	On-peak	Partial-peak	Total	Demand	Energy	Total
TOU	Case 1	104,650	78,260		182,910	69,124	335,591	404,715
	Case 2	44,590	32,760		77,350	17,281	141,413	158,694
	Case 3	34,580	32,760		67,340	17,281	129,487	146,768
TOD	Case 1	79,625	20,475	73,710	173,810	126,174	296,068	422,242
	Case 2	31,395	9,555	30,940	71,890	37,057	122,457	159,514
	Case 3	21,385	9,555	30,940	61,880	37,057	105,406	142,463

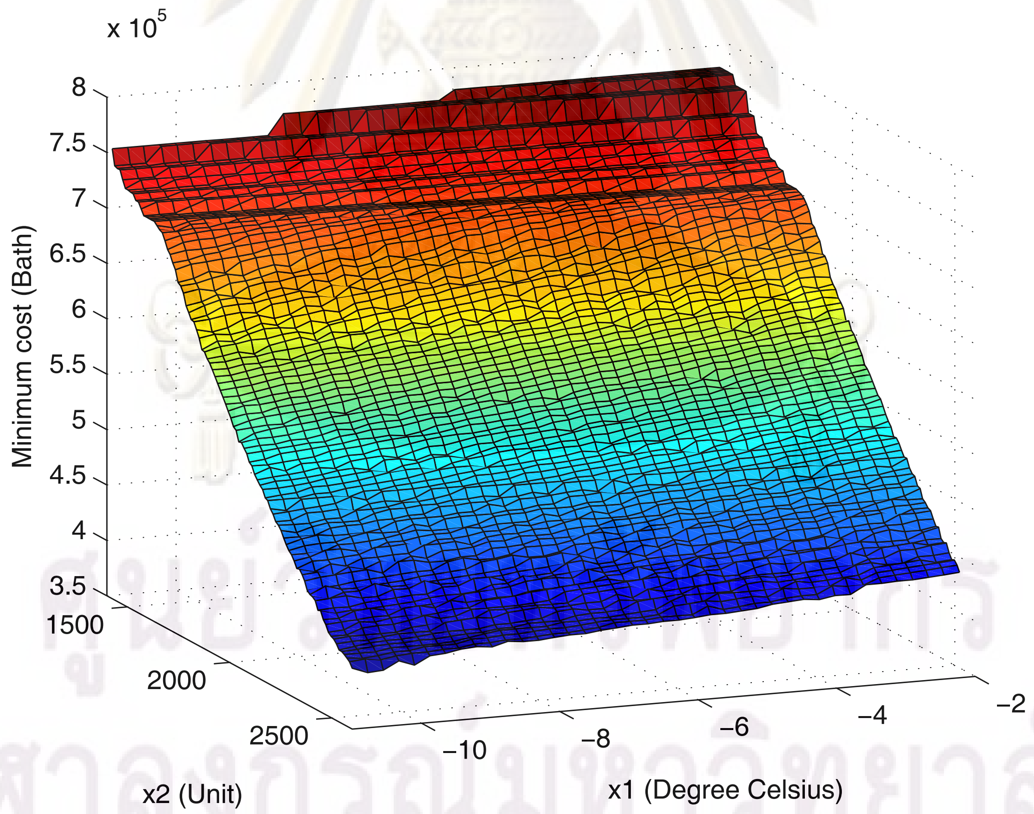

Figure 3.7: Effect of initial condition to electrical energy and electricity cost using optimal control design.

3.3.3 Effect of Δt

Table 3.4 shows the effect of time interval Δt. The results are obtained with final condition Case 1 and initial condition $x_1 = -11$ °C, $x_2 = 2600$ units. First, the backward process in dynamic programming is executed with time interval $\Delta t = 1$. The control signal is then calculated from the initial condition using the forward process. In the cases $\Delta t = 2,\ 3$, the control signals are calculated by taking the average values of the optimal control signals with $\Delta t = 1$ in the consecutive 2 and 3 hours, respectively. Using the obtained control signal and the initial condition, the state variables of the system are simulated using the model of block-ice production process. It is observed that the total energy of all cases in Table 3.4 is unchanged but there is a slight difference in the off-peak and on-peak energy. The results suggest that, when using TOU tariff, the cost is increased if the time interval is increased. And when using TOD tariff, the cost is decreased if the time interval is increased. Figures 3.8, 3.9 show the control signal and state variables for block-ice production process when time interval $\Delta t = 1$, and 3, respectively. When $\Delta t = 2$ the control signal and state variables are shown in Figure 3.4.

Table 3.4: Effect of Δt to electrical energy and electricity cost using optimal control design.

Δt		**Electrical energy (kWh)**				**Electricity cost (Baht)**		
		Off-peak	On-peak	Partial-peak	Total	Demand	Energy	Total
TOU	1	104,650	78,260		182,910	69,124	335,591	404,715
	2	104,650	78,260		182,910	69,124	335,591	404,715
	3	91,000	91,910		182,910	60,483	356,115	416,598
TOD	1	80,990	19,110	73,710	173,810	148,226	296,068	444,294
	2	79,625	20,475	73,710	173,810	126,174	296,068	422,242
	3	80,990	19,110	73,710	173,810	109,023	296,068	405,091

3.3.4 Effect of brine temperature

The brine temperature is varied in the way that either the upper bound or the lower bound is changed each time. Varying the bounds of the brine temperature appeared in the first constraint in Equation (3.4) affects the energy consumption and the electricity cost. The results in Table 3.5 are obtained using the final condition Case 1 and initial condition $x_1 = -11$ °C, $x_2 = 2600$ units. It is clearly observed that the cost is decreased if the brine temperature is restricted in a wider range. In addition, the cost is increased if the bounds of brine temperature are pushed lower.

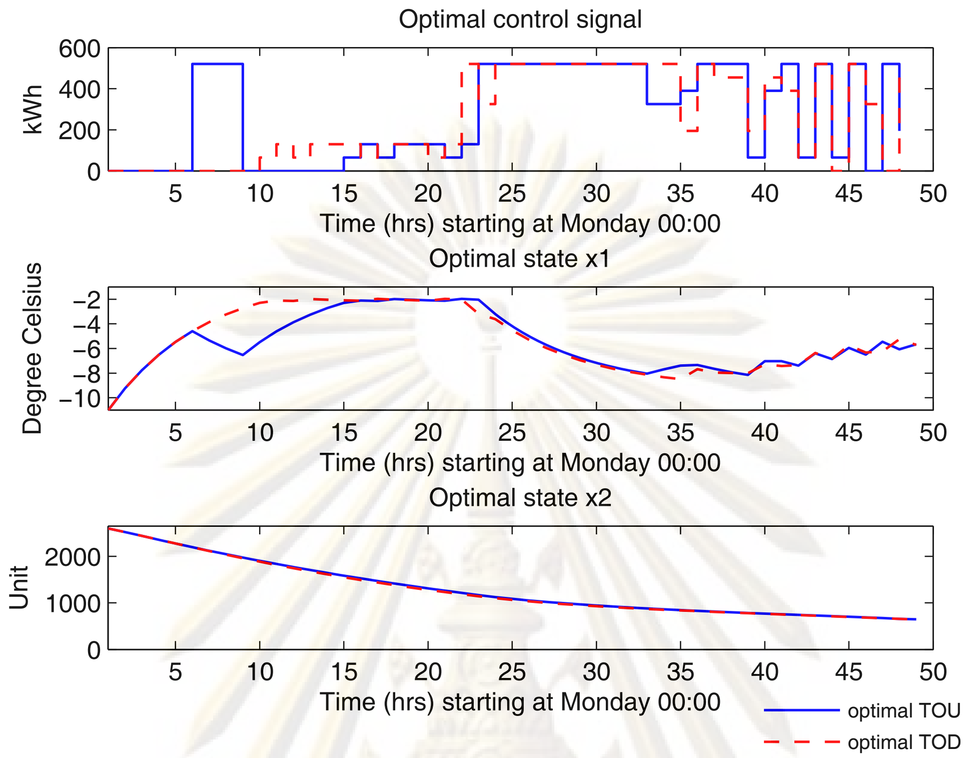

Figure 3.8: Control signal and state variables for block-ice process: $\Delta t = 1$.

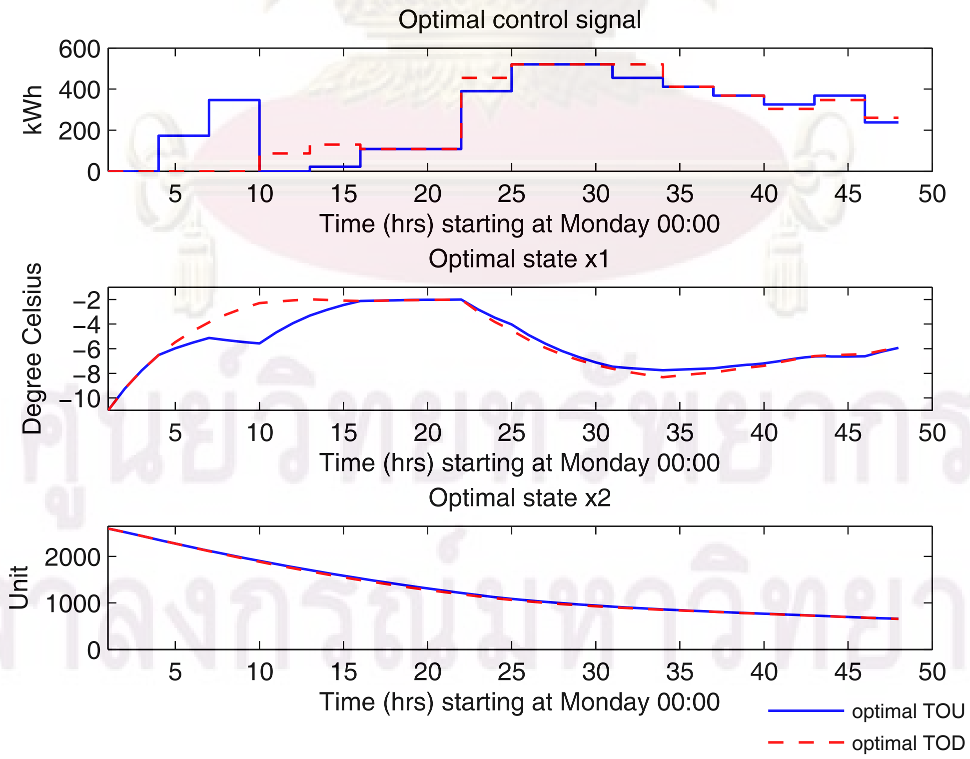

Figure 3.9: Control signal and state variables for block-ice process: $\Delta t = 3$.

Table 3.5: Effect of brine temperature to electrical energy and electricity cost using optimal control design.

	T_b (Celsius)		Electrical energy (kWh)				Electricity cost (Baht)		
	Lower	Upper	Off-peak	On-peak	Partial-peak	Total	Demand	Energy	Total
TOU	-11	-4	116,480	91,910		208,390	60,483	386,472	446,955
	-11	-2	104,650	78,260		182,910	69,124	335,591	404,715
	-11	0	111,020	70,980		182,000	69,124	323,560	392,684
	-9	-2	110,110	78,260		188,370	69,124	342,096	411,220
	-13	-2	104,650	78,260		182,910	69,124	335,591	404,715
TOD	-11	-4	73,255	20,475	99,190	192,920	118,824	328,620	447,444
	-11	-2	79,625	20,475	73,710	173,810	126,174	296,068	422,242
	-11	0	75,530	29,120	61,880	166,530	148,226	283,667	431,893
	-9	-2	76,440	20,930	79,170	176,540	133,525	300,718	434,243
	-13	-2	78,715	19,110	75,985	173,810	104,123	296,068	400,191

3.4 Conclusion

We have presented an optimal control design for block-ice production process in this chapter. First, the problem is formulated in which the system is subjected a number of the constraints on the control input and state variables such as brine temperature, the number of block-ices in the tank; and the control objective is to minimize the monthly electricity cost of an ice factory. The procedure based on dynamic programming for calculating optimal control inputs is then proposed. Furthermore, a number of factors are analyzed with respect to the energy consumption and the electricity cost. It is seen that the final condition and initial condition have the most significant effect on the electricity cost.

CHAPTER IV

MODEL PREDICTIVE CONTROL DESIGN

4.1 Model Predictive Control

In this section basic knowledge on Model Predictive Control, or MPC, is briefly reviewed.

4.1.1 MPC strategy

The term Model Predictive Control does not designate a specific control strategy but a very ample range of control methods which make an explicit use of a model of the process to obtain the control signal by minimizing an objective function.

The various MPC algorithms are based on the same idea only differ amongst themselves in the model used to represent the process and the cost function to be minimized. The methodology of all the controllers belonging to the MPC family is characterized by the following strategy, represented in Figure 4.1 [15]:

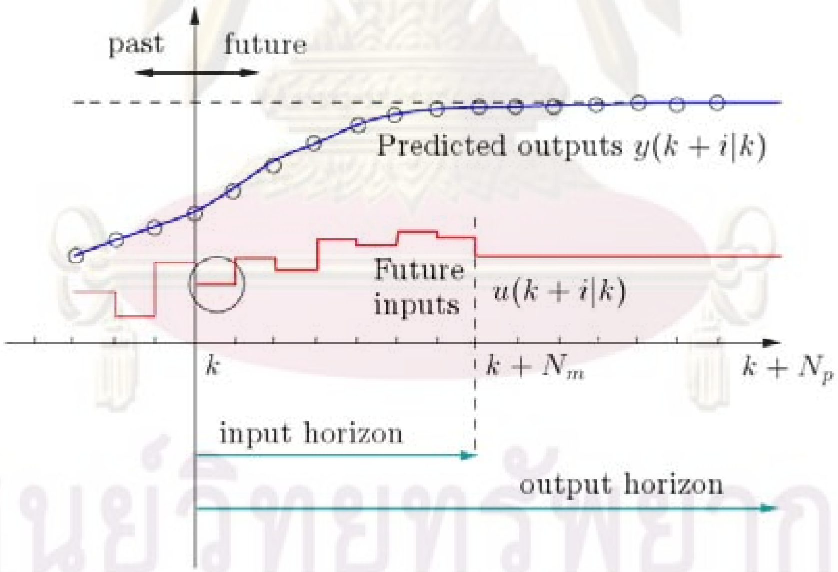

Figure 4.1: MPC Strategy.

1. The future outputs for a determined horizon N_p, called the prediction horizon or output horizon, are predicted at each instant k using the process model. These predicted outputs $\hat{y}(k+i|k)$ for $k = 1, 2, ..., N_p$ depend on the known values up to instant k (past inputs and outputs) and on the future control signals $u(k+i|k)$, $k = 0, ..., N_p - 1$, which are those to be sent to the system and to be calculated.

2. The set of future control signals is calculated by optimizing the objective function. This objective function usually takes the form of a quadratic function of the errors between the predicted output signal and the reference trajectory. The control effort is also included in the objective function in most cases.

3. The control signal $u(k|k)$ is sent to the process while the next control signals calculated are rejected.

In order to implement this strategy, the basic structure is used as shown in Figure 4.2. A model is used to predict the future plant outputs, based on past and current values and on the proposed optimal future control actions. These actions are calculated by the optimizer taking into account the cost function as well as the constraints.

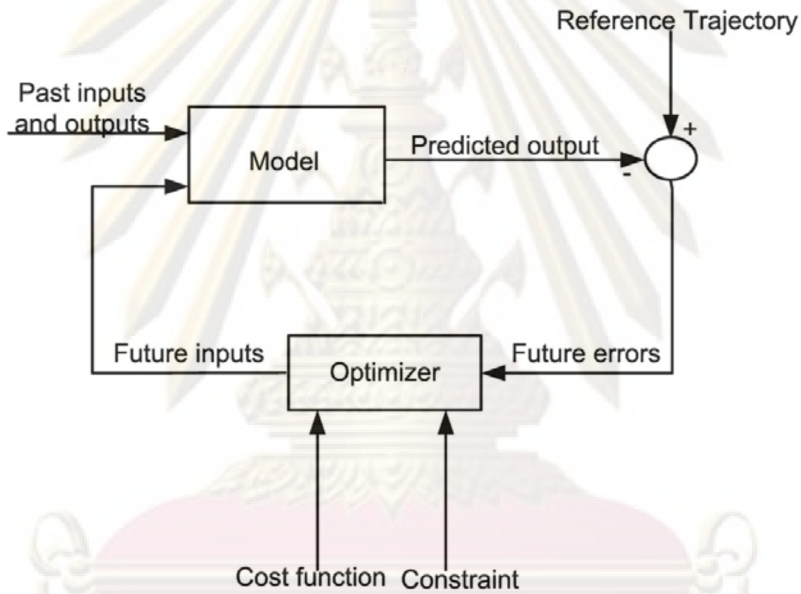

Figure 4.2: Basic structure of MPC.

4.1.2 MPC elements

All the MPC algorithms possess common elements which are:

- Prediction model
- Objective function
- Obtaining the control law

1. Prediction model
   Practically every possible form of modeling a process appears in MPC. It can be impulse response, step response, transfer function, state space, nonlinear models.

2. Objective function
   The general aim is that the future output on the considered horizon should follow a determined reference signal and, at the same time, the control effort necessary for doing so should be penalized.

3. Obtaining the control law
   An analytical solution can be obtained for the quadratic objective function if the model is linear and there are no constraints, otherwise an iterative method of optimization should be used.

4.2 Problem formulation

In this section, we use the linear discrete-time model of block-ice process as given in Equation (3.1).

The objective function is the electricity cost over the prediction horizon N_p. We want to minimize this cost which consists of the cost of peak electrical demand (kW) and the cost of electrical energy (kWh).

Thus, the cost function using TOU tariff is defined as

$$J = \sum_{\nu=0}^{1} r_{d,\nu} u_{\max,\nu} + \sum_{\nu=0}^{1} \sum_{k=1}^{N_p} r_{e,\nu}(k) u(k) \tag{4.1}$$

and the cost function using TOD tariff is defined as

$$J = r_{d,1} u_{\max,1} + r_{d,2} \max\left\{u_{\max,2} - u_{\max,1}, 0\right\} + \sum_{\nu=0}^{2} \sum_{k=1}^{N_p} r_{e,\nu}(k) u(k) \tag{4.2}$$

where ν is equal to 0 for off-peak, 1 for on-peak, and 2 for partial-peak period, $r_{d,\nu}$ is the demand charge in period ν, $u_{\max,\nu}$ is peak demand in period ν over the prediction horizon, N_p is the prediction horizon, and $r_{e,\nu}$ is the energy charge in period ν.

The monthly electricity cost when using MPC strategy is calculated similarly as in Equations (3.2) and (3.3).

In addition, the system is subjected to constraints on the control input and state variables stated as in Equation (3.4).

4.3 MPC using dynamic programming

The cost function in Equations 4.1 and 4.2 is different to the cost function of a typical MPC which usually takes the form of a quadratic function. As a result, we use dynamic programming for solving the optimization problem as we do in the previous chapter. Applying dynamic programming, the procedure for calculating control inputs in MPC is as Figure 4.3.

4.4 Simulation results

Similarly to Chapter 3, both TOU tariff and TOD tariff are used in this simulation. State x_1, state x_2 and control signal u are still quantized by $40, 200$, and 8, respectively. Figures 4.4, 4.5 and 4.6 show

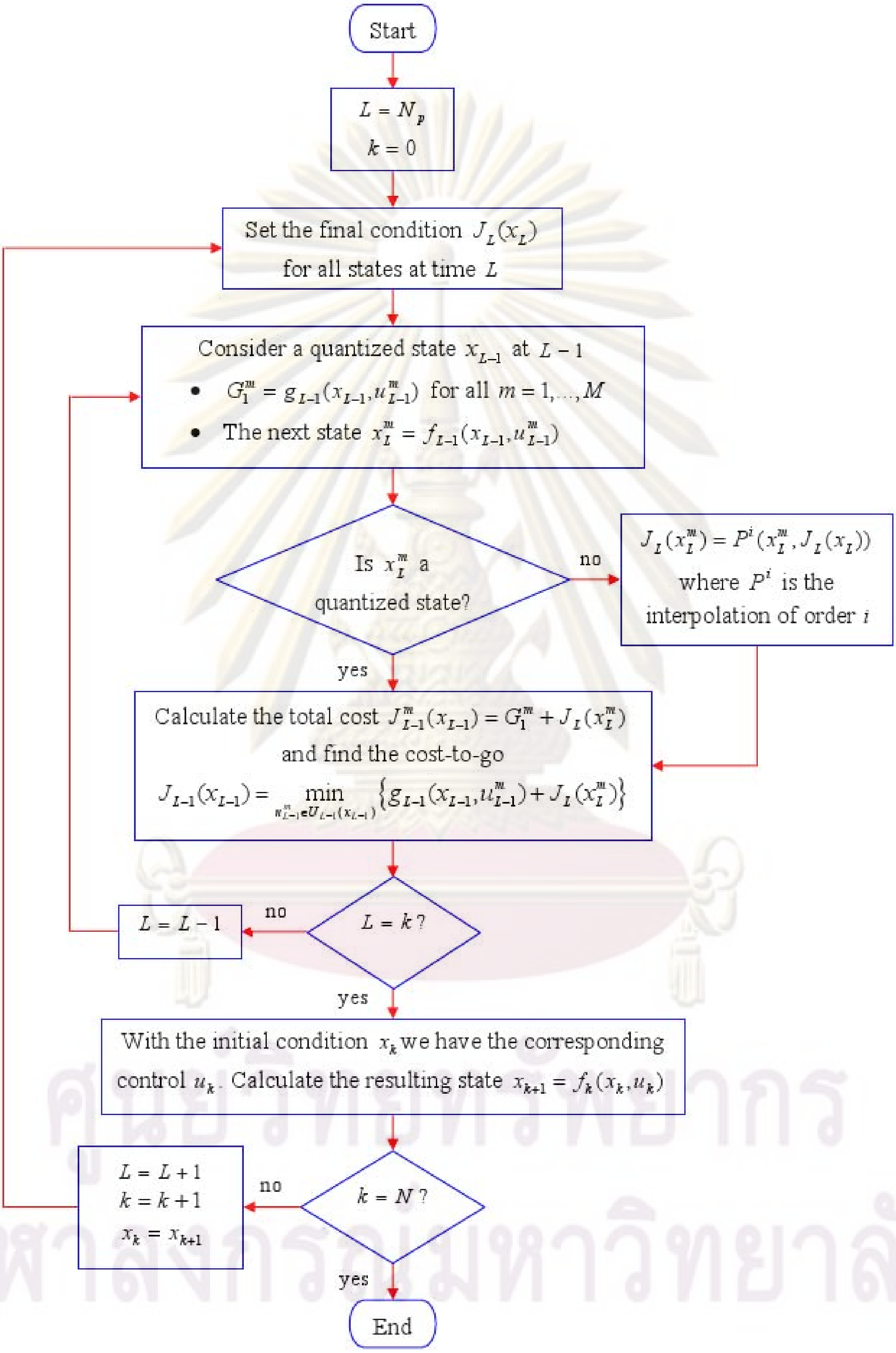

Figure 4.3: The procedure for calculating control inputs in MPC strategy.

the control signal and corresponding states obtained by MPC for block-ice production process over a period of 84 hours. Case 1, 2 and 3 represent the MPC at which we update the control signal every one hour, two hours and three hours, respectively. The simulation results based on the assumptions that the initial condition is $x_1 = -7.4$ °C, $x_2 = 2600$ units, the final condition is -11 °C $\leq x_1 \leq -6.8$ °C, 416 units $\leq x_2 \leq 2600$ units and the prediction horizon is $N_p = 10$. The monthly electricity cost using MPC strategy is summarized in Table 4.1. It can be seen that the MPC strategy using TOU tariff is more effective than that using TOD tariff in terms of cost reduction.

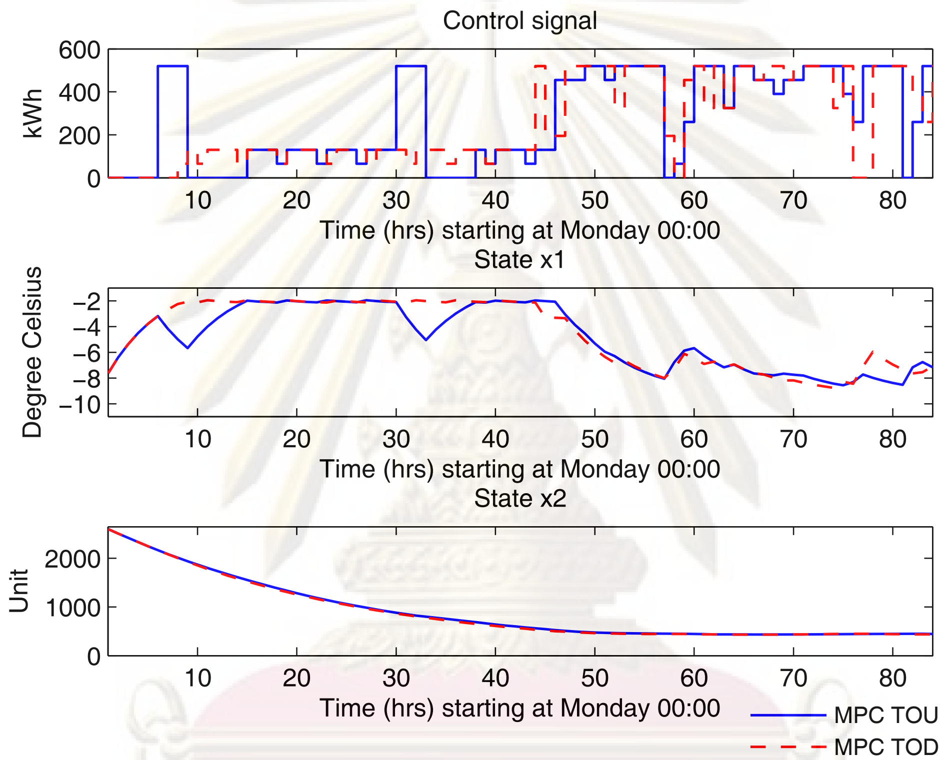

Figure 4.4: Control signal and state variables by MPC for block-ice process (Case 1).

4.4.1 Effect of prediction horizon

Table 4.2 represents the effect of the prediction horizon. The results are obtained by using MPC Case 2 with the initial condition $x_1 = -7.4$ °C, $x_2 = 2600$ units and the final condition -11 °C $\leq x_1 \leq -6.8$ °C, 416 units $\leq x_2 \leq 2600$ units. It is seen that, when using both TOU tariff and TOD tariff, we can reduce the cost by using longer prediction horizon.

4.4.2 Effect of Δt

The effect of time interval Δt is summarized in Table 4.3. In all cases, we fix the initial condition $x_1 = -7.4$ °C, $x_2 = 2600$ units, the final condition -11 °C $\leq x_1 \leq -6.8$ °C, 416 units $\leq x_2 \leq 2600$ units and the prediction horizon $N_p = 10$. When the time interval $\Delta t = 1, 2,$ and 3, the control

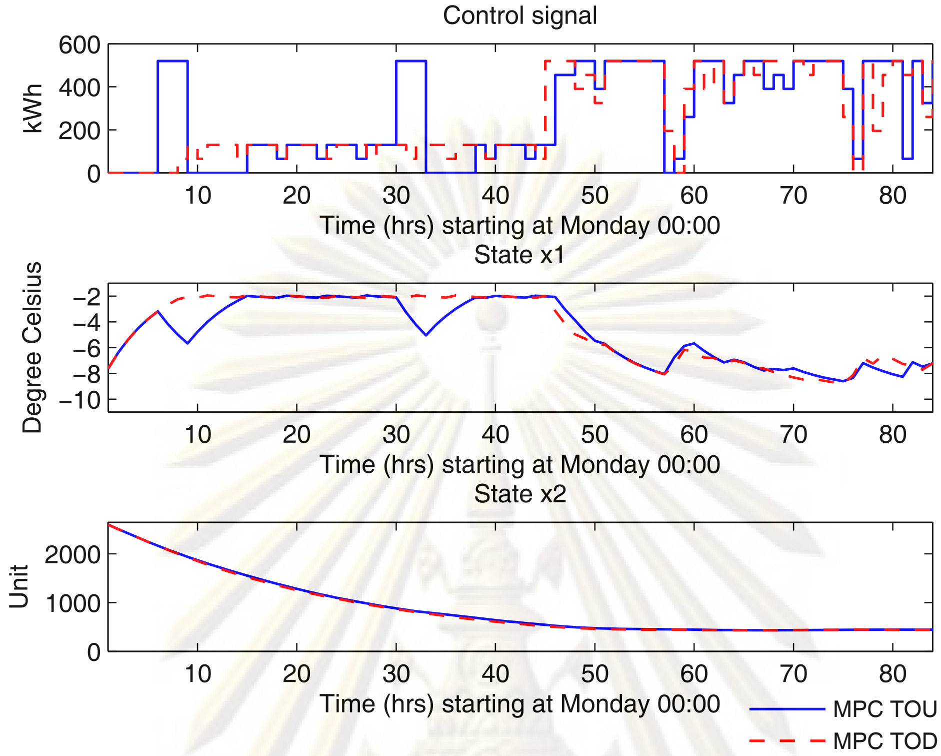

Figure 4.5: Control signal and state variables by MPC for block-ice process (Case 2).

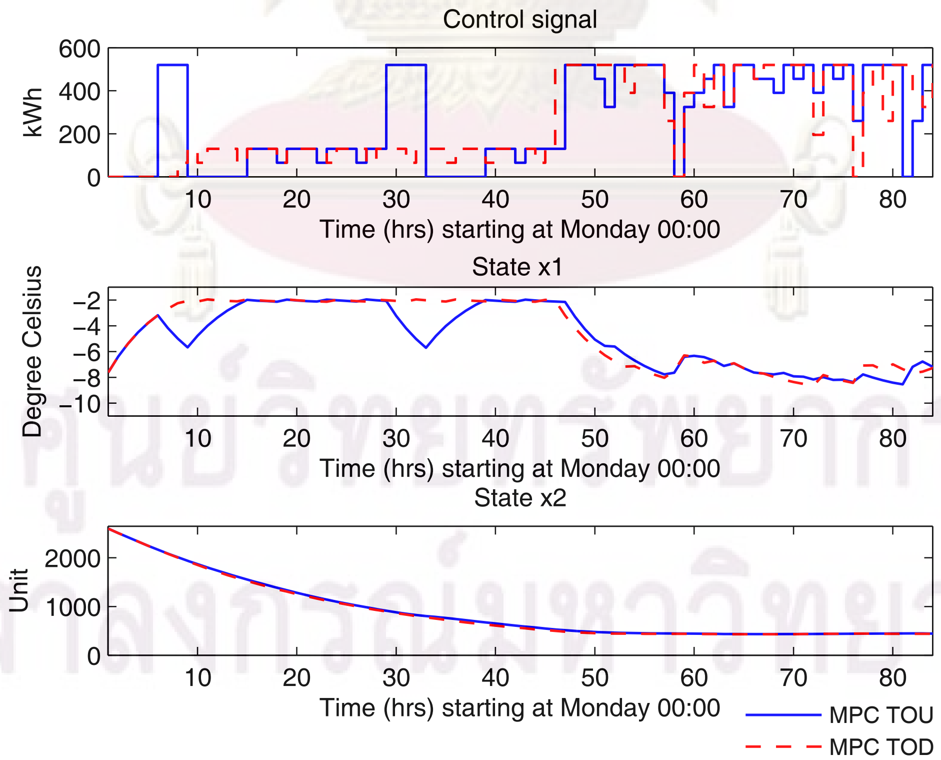

Figure 4.6: Control signal and state variables by MPC for block-ice process (Case 3).

Table 4.1: Electrical energy and electricity cost using model predictive control design.

MPC		Electrical energy (kWh)				Electricity cost (Baht)		
		Off-peak	On-peak	Partial-peak	Total	Demand	Energy	Total
TOU	Case 1	110,240	72,280		182,520	69,123	326,135	395,258
	Case 2	108,680	73,320		182,000	69,124	327,079	396,203
	Case 3	112,320	71,240		183,560	69,124	325,810	394,934
TOD	Case 1	78,000	21,840	72,280	172,120	148,226	293,189	441,415
	Case 2	79,040	21,320	72,280	172,640	148,226	294,075	442,301
	Case 3	81,120	18,200	72,800	172,120	148,226	293,189	441,415

Table 4.2: Effect of prediction horizon (Case 2) to electrical energy and electricity cost using model predictive control design.

MPC		Electrical energy (kWh)				Electricity cost (Baht)		
		Off-peak	On-peak	Partial-peak	Total	Demand	Energy	Total
TOU	$N_p = 6$	114,400	95,160		209,560	69,124	392,752	461,876
	$N_p = 10$	108,680	73,320		182,000	69,124	327,079	396,203
	$N_p = 14$	98,800	76,440		175,240	69,124	323,716	392,840
TOD	$N_p = 6$	79,560	18,720	101,920	200,200	148,226	341,021	489,247
	$N_p = 10$	79,040	21,320	72,280	172,640	148,226	294,075	442,301
	$N_p = 14$	79,040	20,800	72,280	172,120	148,226	293,189	441,415

Table 4.3: Effect of Δt to electrical energy and electricity cost using model predictive control design.

Δt		Electrical energy (kWh)				Electricity cost (Baht)		
		Off-peak	On-peak	Partial-peak	Total	Demand	Energy	Total
TOU	1	110,240	72,280		182,520	69,123	326,135	395,258
	2	110,760	75,920		186,680	64,803	336,564	401,367
	3	100,187	81,293		181,480	66,243	338,448	404,691
TOD	1	78,000	21,840	72,280	172,120	148,226	293,189	441,415
	2	84,240	21,060	72,020	177,320	148,226	302,047	450,273
	3	79,387	20,280	74,013	173,680	148,226	295,847	444,073

signals at each step are calculated by using the optimal control design with the corresponding time interval (see Section 3.3.3) and we update the control signal every 1, 2, and 3 hours, respectively. The results suggest that, when using TOU tariff, the cost is increased when the time interval increases. Figures 4.7, 4.8 show the control signal and state variables for block-ice production process when time interval $\Delta t = 2$, and 3, respectively ($\Delta t = 1$ see Figure 4.4).

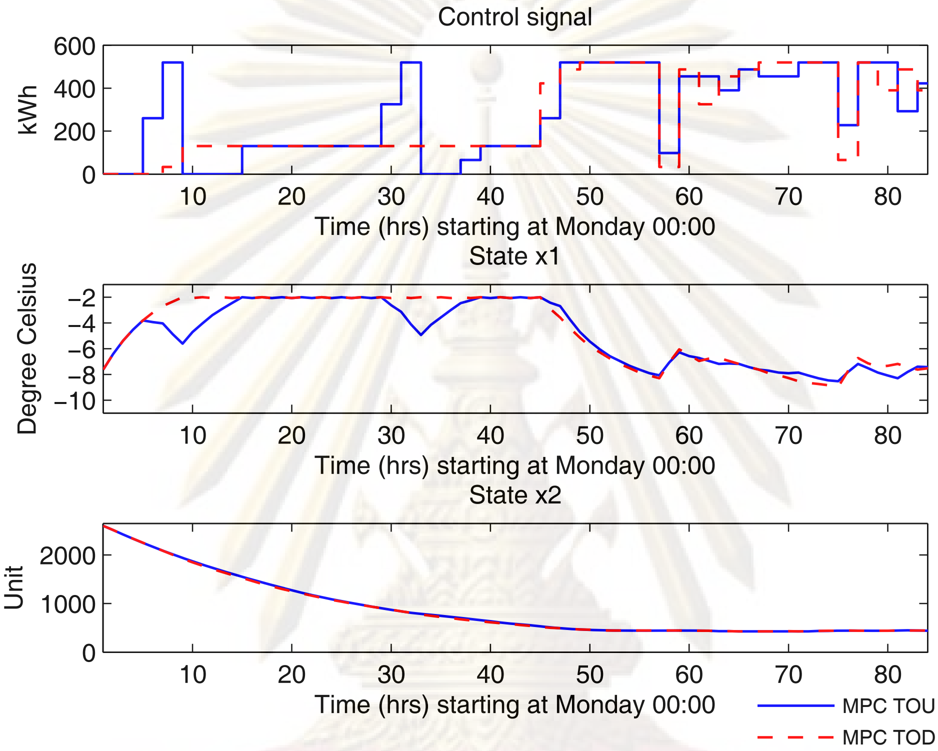

Figure 4.7: Control signal and state variables by MPC for block-ice process: $\Delta t = 2$.

4.5 Comparison of control strategies

In this section, we compare three control strategies, namely, MPC, optimal control and conventional control. In the conventional control strategy, the compressors are simply run at the maximum capacity all days except for three hours off at the end of each day. Figure 4.9 shows the conventional control strategy of the local block-ice factory in one week [24]. The electric energy consumption of compressors and the average brine temperature are acquired by measurement whereas the number of ready for sales block-ices is achieved by simulation.

In Figures 4.10 and 4.11, the optimal control strategy and MPC strategy calculated in the first 84 hours using both TOU and TOD tariffs are compared to the conventional control strategy. All strategies start with the same initial condition $x_1 = -7.4$ °C, $x_2 = 2600$ units, and end with nearby final conditions as in Table 4.4.

From Figures 4.10 and 4.11 it is easily seen that the compressors using the optimal control

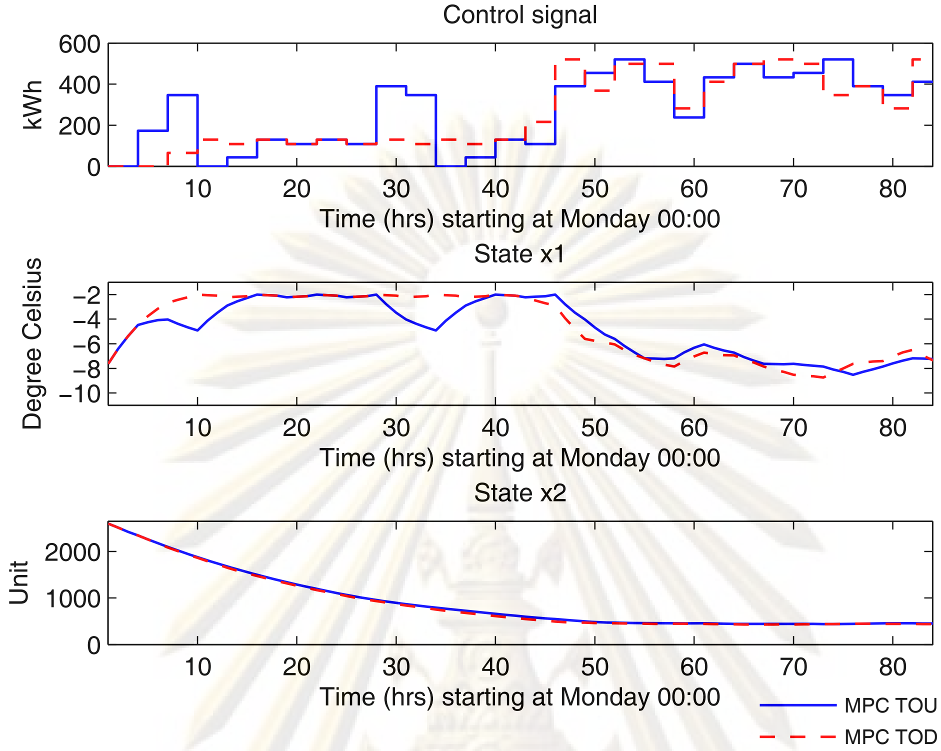

Figure 4.8: Control signal and state variables by MPC for block-ice process: $\Delta t = 3$.

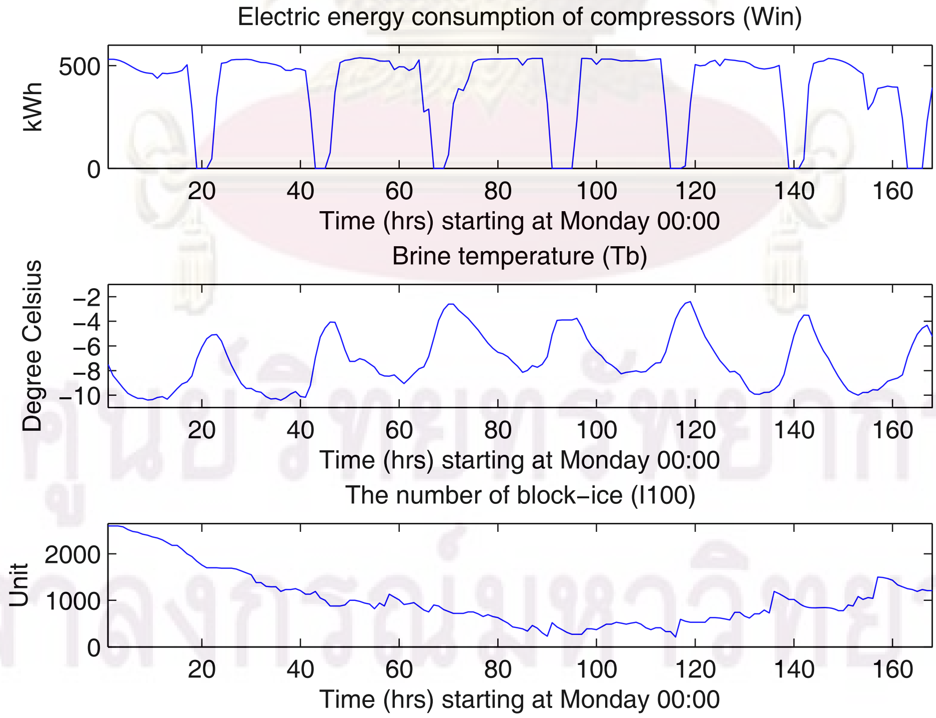

Figure 4.9: Conventional control strategy.

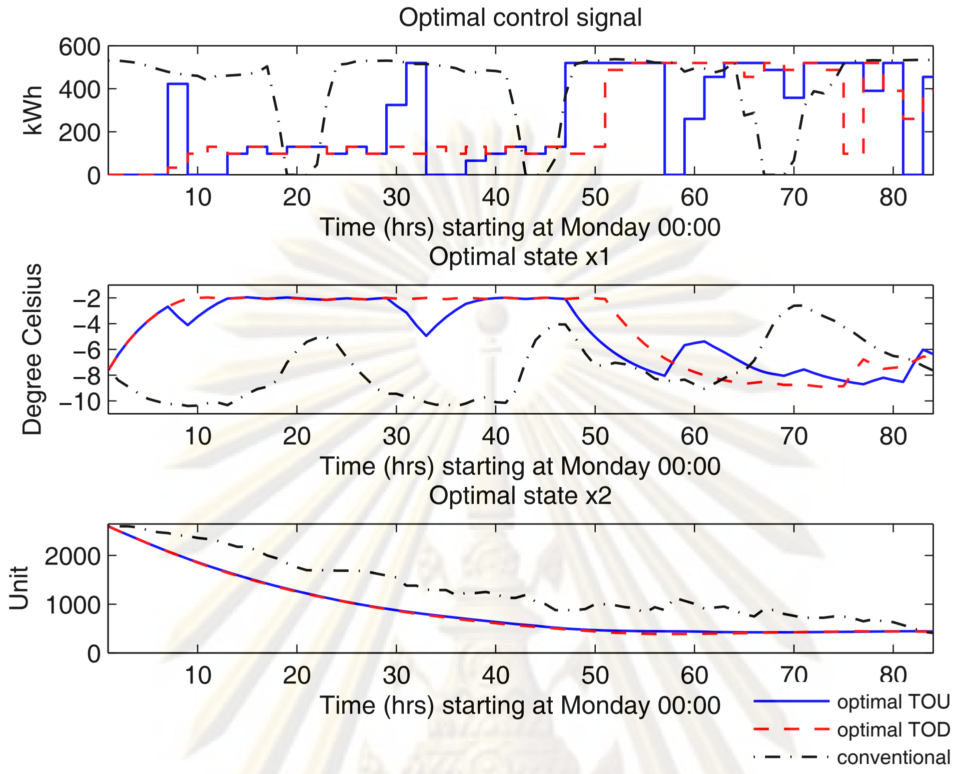

Figure 4.10: Comparison between optimal and conventional control strategies.

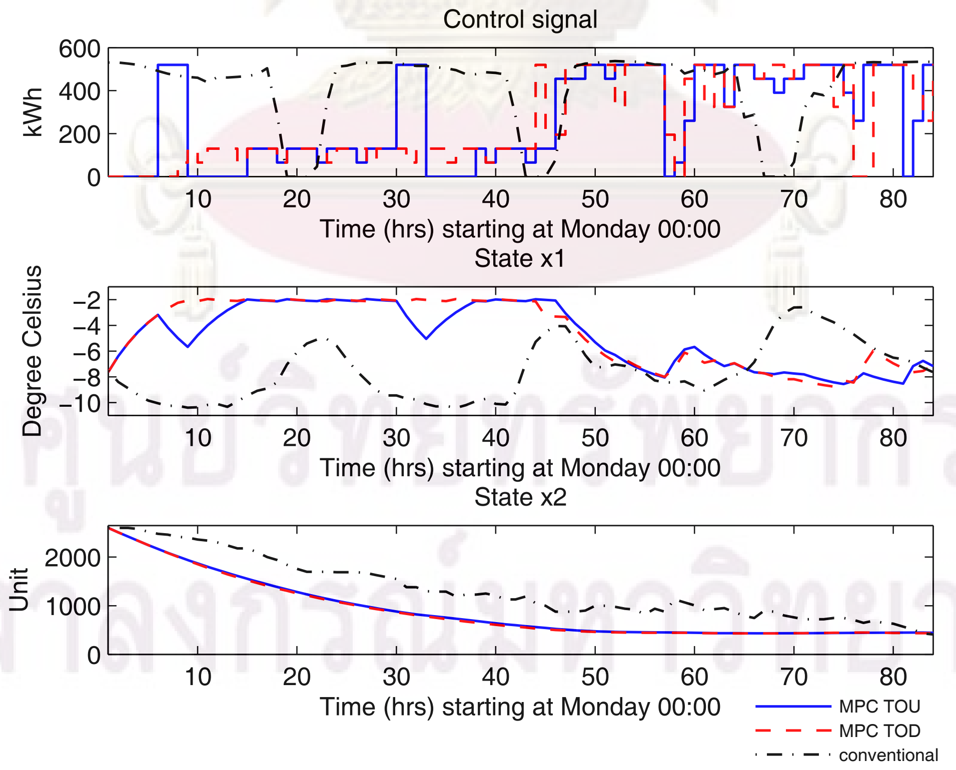

Figure 4.11: Comparison between MPC and conventional control strategies.

Table 4.4: Final conditions of compared control strategies.

Control strategies	Final condition	
	x_1 (degree Celsius)	x_2 (unit)
Optimal TOU	-6.3	440
Optimal TOD	-6.6	434
MPC TOU	-7.2	446
MPC TOD	-7.1	438
Conventional	-7.6	410

strategy and MPC strategy consume less energy than those using the conventional control strategy. Table 4.5 shows the benefit of the optimal control strategy and MPC strategy over the conventional control strategy in saving the energy consumption and reducing the electricity cost. The result reveals that the optimal control strategy using TOU tariff is the most effective. In particular, it is calculated that we can save the amount of money up to 26.15 percent when moving from conventional control strategy using TOD to the optimal control strategy using TOU and the percentage will be 37.21 if we move from conventional control strategy using TOU to the optimal control strategy using TOU.

Table 4.5: Electricity cost of compared control strategies.

Control strategies	Electrical energy (kWh)				Electricity cost (Bath)		
	Off-peak	On-peak	Partial-peak	Total	Demand	Energy	Total
Optimal TOU	106,600	66,560		173,160	69,123	306,382	375,505
Optimal TOD	67,340	17,940	77,480	162,760	148,226	277,245	425,471
MPC TOU	110,240	72,280		182,520	69,123	326,135	395,258
MPC TOD	78,000	21,840	72,280	172,120	148,226	293,189	441,415
Conventional TOU	151,420	128,629		280,049	71,017	527,058	598,075
Conventional TOD	136,640	0	143,410	280,050	31,456	477,036	508,492

4.6 Conclusion

In this chapter, we have investigated the MPC application for block-ice production process. The MPC strategy is constructed in which an optimal control strategy based on the framework in Chapter 3 is planned at every time step over a finite look-ahead time. The first actions of the optimal control sequence are executed and the process is repeated at the following time step. In addition, the effects of the length of the prediction horizon and the time interval were investigated and it was found that longer horizon and shorter time interval can reduce the cost. Then we compare the MPC, the optimal control and the conventional control strategies. The result indicates that the optimal control strategy using TOU tariff is the most effective in terms of operation cost.

CHAPTER V

CONCLUSIONS

5.1 Summary of results

An application of optimal control design to a block-ice production process is presented in this thesis. First, mathematical models for block-ice production process are built by using system identification techniques. Two parametric models, linear and neural network models, have been considered. Nonlinear models based on feedforward neural networks are constructed using the regressors provided by the best linear ARX models. The NNARX models are then pruned using OBS method. Comparing the results obtained from the ARX and NNARX models, it is shown that the performance of both linear ARX and NNARX models are very good. With the obtained models, we then examine the suitability of using TOU tariff and TOD tariff for an ice factory. We develop an optimal control design and a MPC design for block-ice production process which employs dynamic programming for solving the optimization problem. The optimal control strategy aims to minimize the operating cost for block-ice process over the finite-time horizon. In addition, a number of factors are analyzed to see how they affect the operating cost. It is observed that the initial and final conditions would affect the operating cost the most. The optimal controller and MPC strategy are then compared to the conventional control strategy. It is shown that the proposed optimal controller and MPC strategy have better performance than the conventional control strategy in terms of energy consumption and the operation cost. In particular, the optimal control strategy using TOU tariff can significantly reduce the operation cost when comparing to the conventional control strategy.

5.2 Further improvements

There are some improvements that can be considered to obtain better mathematical models and an ice demand predictor for block-ice production process.

1. In Section 2.5, although the NNAR models are much better than linear AR models but they still give poor performances in terms of the model fit. We can improve the results by choosing more complicated regressors in Equation (2.4), such as

$$\varphi(t) = \varphi(y(t-1), y^2(t-1), y(t-2), y^2(t-2), y(t-1)y(t-2)) \tag{5.1}$$

and apply the nonlinear black-box identification technique.

2. When doing system identification with neural network models in Section 2.4, we can take further improvements by different choices of the estimation and validation sets, by processing the data more times or by the use of recurrent neural networks.

5.3 Future works

1. In Section 2.5, we have considered the ice demand predictor using to predict the number of block-ices for sales in the next hours. To improve the performance of the system, it is possible to apply Demand Side Management (DSM) [27] to the number of block-ices on demand. Analyzing different patterns of the demand based on the real demand, we can find a suitable one which leads to the reduction in the operation cost.

2. In this research, we have developed a MPC strategy for block-ice production process in which the model of the process does not change over time. Future work could consider the MPC design with the process model is updated every time step.

3. Dynamic programming is sometimes thought to be of limited applicability in terms of computation due to the fact that the computation grows exponentially with the number of states. This is called the curse of dimensionality [12]. In future work we will look at more details about this.

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Biography

Hai Minh Le was born in Nam Dinh, Vietnam, in 1984. He received his Bachelor's degree in electrical engineering from Hanoi University of Technology, Vietnam, in 2007. He has been granted a scholarship by the Electricity Generating Authority of Thailand (EGAT) and AUN/SEED-Net (www.seed-net.org) to pursue his Master's degree in electrical engineering at Chulalongkorn University, Thailand, since 2007. Currently he works on his Master at the Control Systems Research Laboratory, Department of Electrical Engineering, Faculty of Engineering, Chulalongkorn University. His research interests are in the areas of system identification, analysis and design of optimal control systems via dynamic programming.