Multi-time scale identification for multi-energy system

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Abstract: Multi-energy systems (MES) are under development for a variety of benefits like energy conservation and emission reduction. Coupling components like CHP and CCHP transfer disturbance from one system to another system, thus, the multi-energy system has multi-time scale characteristic and broad bandwidth, which results in problem in dynamic modeling. A multi-time identification method is presented to solve the problem. Identification of a CHP unit with multi-time scale characteristics is presented as case study to verify the method, and simulation results show the effectiveness of the proposed method.

Keywords: System identification; Multi-energy system; Multi-time scale system;

1. Introduction

1.1 Research background and related work

In traditional energy management, different energy systems are always managed separately, for example, electricity grid is managed by national grid, heating network is managed by district heating companies and natural gas network is managed by gas companies, this leads to low overall efficiency of the power system. Over the past decade, with the increasing demand for energy and increasing serious environmental problem, there is an urgent need to integrate different energy systems for energy utilities.

Multi-energy system is under development for a variety of benefits like energy conservation and emission reduction. Coupling of different energy systems is the most significant character of multi-energy system. Coupling components such as combined heat and power units (CHP) [1], combined cooling, heating, and power units (CCHP), electric heating pumps couple the systems together.

Coupling between different energy systems lead to complex features of the integrated system, coupling components transfer disturbance from one system to another system bidirectional [2], but the response times of different systems are vastly different, which make it difficult to model multi-energy systems, many scholars have noticed this problem and carried out relevant research.

Many scholars worked on static modelling of multi-energy system for planning, scheduling of multi-energy system [3,4], however, the neglect of dynamic characteristics is obviously not conducive to the actual operation of the system [5], so that the static model is not enough for the system control when the multi-energy system is running [6]. Although the dynamic modeling of multi-energy system is important, it is rarely studied for there are many difficulties in the work: modelling through process mechanisms can better explain the physical processes of energy transfer, but modeling the mechanism of a process is very complicated and costly [7]; there is a growing emphasis on data-driven modeling, but most of the related works are limited to model a single system [8], which lack the description of coupling relationship in multi-energy system.

1.2 Contributions and outline

This paper focused on how to obtain the dynamic model of MES by system identification method and mainly studies the solution of multi-time scale problem in multi-energy system. A multi-time scale system identification method is proposed, and the primary energy input – power output model of CHP is identified as case study to verify the method.

The outline of the paper is as follows. In Section 2 two typical multi-time scale systems are presented and analyzed. In Section 3, the identification problem of multi-time scale systems is presented. In Section 4, a multi-time scale system identification is presented, and used in Section 5 to identify the primary energy input – power output model of CHP unit. Finally, the conclusions and further work are outlined in Section 6.
2. Multi-time scale characteristic of multi-energy system

Coupling of different energy systems lead to complex character of the integrated system, this is due to the wide difference in the physical properties of different systems and different coupling components:

The dynamic response of electrical power system is very fast (in seconds) for electric energy is transmitted at the speed of light; the dynamic response of hydraulic process is fast (in minutes) for pressure is transmitted at the speed of sound; the dynamic response of network thermal process is slow (in minutes or in hours) for thermal energy is transmitted at the speed of mass flow rate; the dynamic response of building temperature is very slow (in hours or in days) for the huge thermal capacity of buildings. Thus, the multi-energy system has multi-time scale characteristic and broad bandwidth,

To realize the control optimization of multi-energy flow system, it is necessary to describe its multi-scale characteristics mathematically and obtain accurate dynamic mathematical model

Based on automatic control theory, the above-mentioned integrated system can be summed up as a multi-time scale system because there are many subsystems with different time scales. The multi-time scale system can be described by the following formula:

\[
\begin{align*}
\dot{x} &= f(x, y, z) \\
\dot{y} &= g(x, y, z) \\
\mu \dot{z} &= h(x, y, z)
\end{align*}
\]  \hspace{1cm} (2.1)

The above state space models show that the change rate of \(x\) is much smaller than that of \(y\) and \(z\). To better represent the characteristics of a multi-time scale system, we took a transfer function form to illustrate the multi-time scale system, and gave the following definition:

**Definition 1.** A Single-in-single-out first-order transfer function matrix \(G_a(s)\) with two-time scale characteristic is presented below, where:

\[
\begin{align*}
G_a(s) &= G_1(s) * G_2(s) \\
G_1(s) &= a_1 / (b_1 s + 1) \\
G_2(s) &= a_2 / (b_2 s + 1)
\end{align*}
\]  \hspace{1cm} (2.2)

when \(a_1, a_2\) are in the same order, \(b_1 \ll b_2\).

Through a simple single-in-single-out model \(G_a(s)\), we can illustrate the characteristics of this model.

\[
G_a(s) = \frac{0.3}{0.019 s^2 + 0.166 s + 1} * \frac{25 s + 1}{30 s + 1}
\]

From the input-output relationship, it can be seen from the model that each output of the system has both fast and slow parts, that is, the system has a fast response to the model input first and reaches steady state quickly, while then superimposed a slow response and reaches steady state after a long time.

Such multi-time scale system can clearly demonstrate the coupling properties of energy systems and common in multi-energy system, for example, the response of back-pressure steam turbine power output to input energy has this multi-time scale characteristic.

Through a simple two-in-two-out model \(G_b(s)\), we can illustrate the characteristics of this model.

\[
G_b(s) = \begin{bmatrix} G_{11}(s) & G_{12}(s) \\ G_{21}(s) & G_{22}(s) \end{bmatrix}
\]

\[
\begin{align*}
G_{11}(s) &= \frac{a_{11}}{b_{11} s + 1} \\
G_{12}(s) &= \frac{a_{12}}{b_{12} s + 1} \\
G_{21}(s) &= \frac{a_{21}}{b_{21} s + 1} \\
G_{22}(s) &= \frac{a_{22}}{b_{22} s + 1}
\end{align*}
\]  \hspace{1cm} (2.2)

when \(a_{11}, a_{12}, a_{21}, a_{22}\) are in the same order, \(b_{11}, b_{12}, b_{21}, b_{22}\).

Through a simple two-in-two-out model \(G_b(s)\), we can illustrate the characteristics of this model.
\[ G_B(s) = \begin{bmatrix} \frac{1}{s+1} & 0.9 \\ 1.2 & \frac{2s+1}{1.5} \\ 100s+1 & 200s+1 \end{bmatrix} \]  

From the input-output relationship, it can be seen that the response speed of the output signal to the input signal can be measured in different time units, whether \( u_1 \) or \( u_2 \) as the input signal, \( y_1 \) always response faster than \( y_2 \).

Such multi-time scale system can demonstrate the response speed difference between different energy flows and common in multi-energy system, for example, the response of electric output power and thermal output power to input energy has this multi-time scale characteristic.

![Figure 2.2: Step response of \( G_B(s) \)](image)

3. Identification Problems of Multi-time scale system

3.1 Identification Problems

There is a mature solution for the identification of the model of the multi-in and multi-out (MISO) system shown in the \( G_B(s) \), model can be obtained by matrix transformation and input signal design. For the system corresponding to the \( G_B(s) \), the step response can be divided into two transients in the time domain, which is reflected in the large gap in the time constant, and the system has a large bandwidth; because of the large bandwidth of the system, it brings great challenges to the system identification work, and the main difficulties focus on sampling time selection and input signal design.

- **Sampling time selection problem**
  
  According to the sampling theory, if the sampling time is too large and the high frequency dynamic information contained in the data is too small, the information loss rate will increase sharply. Therefore, if the measurement hardware allows, reducing the sampling time can provide more effective dynamic information for identification. However, when the sampling time is too small, there are also some problems: when the sampling time is small compared with the system inherent time constant, all poles are concentrated near point \( z=1 \) in the complex plane, which makes the identification model very sensitive; fast sampling may also cause the model set to be more concentrated in high frequency band and too sensitive to noise, resulting in poor fitting accuracy in medium and low frequency band; and fast sampling model may turn the system into a non-minimum phase system, thus causing problems for controller design.

In general, the system sampling time usually selects 10% of the step response transition time, that is, the empirical value is a compromise choice for fast and slow sampling, which can reduce noise interference while providing enough dynamic information, and has certain guiding significance for non-multi-time scale system identification. For multi-time scale system, because of the wide bandwidth of the system, it is obviously contradictory to choose the sampling time of the system according to this method, so it is impossible to realize the balance of high and low frequency system from the sampling theory.

- **Excitation signal design problem**
  
  The design of input signal for system identification is a very important problem, which is due to the large selection space of input signal selection, and the selection of input signal plays a decisive role in what data set the system gets. Generally speaking, there are two key points in input signal selection: type of input signal (such as PRBS, GBN), spectrum of input signal. Input signal selection is not studied deeply in this paper. GBN signals are selected for input signal.

Under the condition that the model is chosen correctly, the optimal spectrum of the input signal is:

\[ \Phi_u^{opt}(\omega) = \mu \sqrt{\Phi_d(\omega) \Phi_c(\omega)} \]  

Where: \( \mu \) is a constant adjusted so that the input power is constrained, \( \Phi_d(\omega) \) is the spectrum of disturbance, \( \Phi_c(\omega) \) is the spectrum of the control signal.

From formula 3.1, we can see that the input signal design problem is the excitation signal spectrum selection problem: control the frequency point with high signal frequency, the excitation signal power increases accordingly, and at the frequency point with high disturbance power, the excitation
signal power should also be increased. Since the spectrum of both the disturbance signal and the control signal is determined by the system bandwidth, the signal frequency will be directly related to the system bandwidth.

On the basis of GBN signal power spectrum \( \Phi_{\text{GBN}}(\omega) \) formula 3.2\(^{[11]} \), the power spectrum design for GBN signals includes the design of sampling time \( T \) and conversion probability \( p \), it can be seen that although the excitation signal design and sampling time selection are discussed separately in this paper, the two are not independent problems.

All the variables related to optimal spectral design of excitation signal (GBN signal) are directly or indirectly related to system bandwidth. Therefore, it is difficult to design excitation signals which consider the high and low frequency subsystem together because of the wide frequency band of multi-time scale system.

\[
\Phi_{\text{GBN}}(\omega) = \frac{(1 - q^2)T}{1 - 2q \cos \omega T + \omega^2}
\]

Where: \( T \) is the sampling period, \( p \) is the transition probability.

3.2 Experimental example of identification problem

To better explain the problem of multi-scale system identification, three groups of identification experiments were carried out with the system shown in the \( G(s) \) as an example: (a) high frequency excitation, fast sampling; (b) low frequency excitation, slow sampling; (c) broadband excitation, fast sampling, three ways to identify the system. ARMAX method will be used to identify the models. To enhance the conclusion of the simulation, Monte Carlo simulation (MCS) method is used.

The sampling time and excitation signal are designed according to the response time of the high frequency part of the system, and the simulation conditions are shown in Table 3.1 below.

| Sampling time (T) | Transition probability (p) | Noise-to-signal ratio | Sampling number |
|-------------------|---------------------------|-----------------------|-----------------|
| (a) 0.04s         | 0.94                      | 20%                   | 1000            |
| (b) 4 s           | 0.94                      | 20%                   | 1000            |
| (c) 0.04s         | White noise               | 20%                   | 1000            |

Noise signal \( v_1(t) \) given by the white noise signal through different filters, and its sampling time is the same as that of the high frequency subsystem.

\[
v_1(t) = \frac{\alpha}{1 - 0.9q^{-1}} e(t)
\]

Where \( \alpha \) is adjusted so that the noise variance at the output is 20% of the measured output.

The simulation results are shown in Fig 3.1. It can be seen that all three results have some shortcomings:

As is shown in Figure 3.1(a), the identified model fits accurately to the high frequency part of the multi-scale system, but the effect on the low frequency part is very poor, so it can not reflect the low frequency characteristics.

As is shown in Figure 3.1(b). It can be seen that the model can fit accurately to the low frequency part of the multi-scale system, but the effect on the high frequency part is very poor, which can not reflect the dynamic characteristics of the high frequency part.

According to the identification results of the above two identification methods, it is obvious that only using high frequency excitation or low frequency excitation can not obtain satisfactory identification results for multi-scale systems. It is a natural idea to use white noise signal as excitation signal. At the same time, in order to ensure the integrity of the information after sampling, fast sampling is adopted. The simulation results are shown in Figure 3.1(c). It can be seen that the identified model can not consider the high frequency and low frequency characteristics of the multi-scale system together, the overall system identification effect becomes worse.
The main reason for the poor identification effect of traditional methods is the information loss caused by unreasonable design of experimental conditions. This problem can be better illustrated from the result of model order selection.

According to the FOE error criterion, the results of the three experiments in Section 3.2 are shown in Figure 3.2, the best order for all three experiment are all 2, while the actual system is a third order system.

4. Identification of Multi-time scale system

According to the above analysis, the interference between the high frequency and low frequency parts of the system is the difficulty of modeling. In order to ensure the accuracy of identification of high and low frequency parts of multi-score system and avoid the problem of poor overall identification effect caused by simultaneous excitation of high and low frequency systems, this paper presents a multi-time scale identification method for multi-time scale system.

4.1 Model structure selection

It is very important to determine the structure of the model to be identified for multi-time scale system identification. The choice of model structure involved in traditional model identification methods is mainly to determine the transfer function set and noise model. If the multi-time scale system is regarded as a system composed of subsystems with multiple time scales or frequency domain characteristics, the combination of multiple subsystem
models should also be included in the model structure selection work.

\[
R(s) = \frac{P(s)}{Q(s)} = \frac{a_0 s^m + a_1 s^{m-1} + \cdots + a_m}{b_0 s^n + b_1 s^{n-1} + \cdots + b_n}
\]

\[
= k + R_1'(s) + R_2'(s) + \cdots + R_m'(s)
\]

\[
= R_1(s) \ast R_2(s) \ast \cdots \ast R_n(s)
\]

Theorem 1: A rational function as \(R(s)\), where \(n, m\) is a nonnegative integer, and both are constants, if \(m<n\), is called a true fraction, if \(m\geq n\), is called a false fraction, the true fraction can always be expressed as the sum of several partial fractions, and the false fraction can always be expressed as the sum of one polynomial and more true fractions.

1. **Series model structure**

   \(R(s)\) is expressed as the way of the subsystem in series, that is \(R(s) = R_1(s) \ast R_2(s) \ast \cdots \ast R_n(s)\), for the convenience of description, a multi-time scale system is divided into two subsystems: high frequency subsystem and low frequency subsystem for subsequent analysis. If the time scale difference between the high and low frequency subsystem is large, there will be mutual filtering in the sampling process, just like the results in section 3.2. Obviously, it is not feasible to identify the model in series.

2. **Parallel model structure**

   According to the above analysis, whether the high frequency subsystem is in series or parallel with the low frequency subsystem, it can always be expressed as a parallel structure \(R(s) = k + R_1'(s) + R_2'(s) + \cdots + R_m'(s)\).

   From the characteristics of the model, when the high frequency subsystem is connected in parallel with the low frequency subsystem as a high frequency filter, there is no mutual filtering between the high and low frequency subsystems because the signal passes through different channels, which can avoid the lack of information caused by the filtering effect, so it is reasonable to use the parallel structure to identify the multi-time scale system.

4.2 Multi-time scale identification algorithm

According to the analysis of Section 3, although the traditional method can not balance the identification effect of high frequency system and low frequency system, it can still give us some enlightenments:

When the system is identified by high frequency excitation and fast sampling, although the low frequency partial identification is not accurate, it can guarantee the accuracy of high frequency subsystem, that is, the accuracy of high frequency subsystem identification can be improved by properly increasing the frequency of excitation signal and sampling;

When the system is identified by low frequency excitation and slow sampling, if the accurate high frequency subsystem model has been obtained, the low frequency partial identification accuracy can be guaranteed by filtering out the high frequency information.

The natural idea is to use high frequency excitation, fast sampling and low frequency excitation, slow sampling to identify the high and low subsystem model, and then integrate the two models in some way to obtain a final model.

4.2.1 Feasibility analysis of multi-time scale identification algorithm

Based on the above analysis, a multi-time scale identification scheme is proposed, the first step is to identify the high-frequency subsystem model in the multi-time scale
system by high-frequency excitation and fast sampling, and the second step is to obtain the data set by low-frequency excitation and slow sampling after obtaining the high-frequency subsystem.

Suppose that a second-order system can be decomposed into two first-order systems with the same gain and multi-time scale time constant, taking the first order constant system as an example, the feasibility of the above algorithm is illustrated as follows:

\[
G_{HF}(s) = \frac{k}{\tau_{HF}s + 1} \\
G_{LF}(s) = \frac{k}{\tau_{LF}s + 1} \tag{4.1}
\]

\[\tau_{LF} = f \ast \tau_{HF}\]

Where: \(k\) is the gain of the model, \(\tau_{HF}\) is the time constant of the high frequency subsystem, \(\tau_{LF}\) is the time constant of the low frequency subsystem, \(f\) is the time scale difference coefficient to calculate the time constant differences between high frequency system and low frequency subsystem.

According to the transformation relationship between discrete and continuous systems, as shown in formula 4.2, and then \(G_{HF}(q)\) and \(G_{LF}(q)\) are obtained as shown in formula 4.3.

\[
a = e^{(-\frac{T}{\tau})} \\
b = k \left(1 - e^{(-\frac{T}{\tau})}\right) \tag{4.2}
\]

Where: \(T\) is the sampling period, \(\tau\) is time constant of the continuous system.

\[
G_{HF}(q) = \frac{b_{HF}q^{-1}}{1 - a_{HF}q^{-1}} \\
G_{LF}(q) = \frac{b_{LF}q^{-1}}{1 - a_{LF}q^{-1}} \tag{4.3}
\]

For a good identification test, it is usually necessary to design the excitation signal so that the identification data set contains enough model information, that is, to maximize the information matrix \(J\):

\[
J = \det(Ez_zz_z^E) \tag{4.4}
\]

\(J\) can be expressed as formula 4.3 for the data set generated after the first order system is excited by the GBN signal.
The cross spectrum $\Phi_{y_2}^{LF}(w)$ and $\Phi_{y_2}^{HF}(w)$ under different situations is shown in figure 4.2.

As shown in Fig.4.2(a), the selected excitation signal spectrum has white noise characteristics when the sampling time is larger than the time constant of the high frequency system. The comparison between $\Phi_{y_2}^{HF}(w)$ and $\Phi_{y_2}^{LF}(w)$ shows that the white noise signal can excite both the high frequency subsystem and the low-frequency subsystem. Besides, the white noise signal impose heavy weighting at high frequencies, which will lead to the poor identification result to the gain part of the high frequency subsystem, so the white noise signal is not suitable as the multi-time scale system identification excitation signal.

From Fig.4.2(b)(c)(d), it is known that reducing the sampling time and increasing the excitation signal frequency can increase the power in the low frequency band and reduce the power in the high frequency band. At the same time, the signal cross spectrum $\Phi_{y_2}^{LF}(w)$ is significantly reduced, which means that the information of low frequency subsystem contained in the output signal is significantly reduced. This result can be understood as: the excitation signal and sampling frequency are designed according to the high frequency system, and the excitation frequency exceeds the cut-off frequency of the low frequency system, which makes the output of the low frequency system decay sharply. This feature is crucial for high and low frequency subsystem separation. It can ensure the accuracy of high frequency subsystem identification when applying high frequency excitation signal to multi-time scale system, which also verifies the conclusion in section 3.2.1 test. In addition, by comparing the spectrum characteristics under different standard differences, it can be found that the two systems with greater time standard differences, the easier it is to separate the high and low frequency models through this experimental method, as shown in formula 4.10. Although this property is derived from a first-order system, the same conclusion can also be drawn for a high-order stable system.

$$\lim_{\tau_{HF}/\tau_{LF} \to 0} b_{LF} e^{i\omega \tau_{HF}/\tau_{LF}} + a_{LF} e^{i\omega \tau_{HF}/\tau_{LF}} = 0$$  \hspace{1cm} (4.10)

However, the excitation signal frequency and sampling frequency used for model separation are not as high as possible. Compared with figure 4.2(b)(c)(d), we can see that excessive emphasis of excitation signal on low frequency band will reduce the identification information of middle frequency band, and when the noise signal is concentrated in middle frequency band, it will cause the identification effect of middle band to become worse.

The best sampling period of the first order system is given in some literatures, for the high frequency subsystem $G_{HF}(s)$, the best sampling period is $T_{HF}^* = \frac{\tau_{HF}}{8}$, thus, the best design parameters of the GBN signal can be obtained. Combined with formula 4.4 and formula 4.8, the recommended transition probability $p_{HF}^* = 0.94$, which is exactly the parameter used in the three tests in section 3.2.
Case 2: Low frequency excitation and slow sampling

According to the dynamic characteristics of low frequency subsystem, the model parameters under low frequency excitation and slow sampling conditions are obtained by combining the conclusion of case1, as shown in formula 4.11.

\[ a_{HF} = e^{\left( \frac{T_{LF}}{T_{HF}} \right)} \]

\[ a_{LF} = e^{\left( -\frac{T_{LF}}{T_{HF}} \right)} \]

\[ b_{HF} = k \left[ 1 - e^{-\left( \frac{T_{LF}}{T_{HF}} \right)} \right] \]

\[ b_{LF} = k \left[ 1 - e^{\left( -\frac{T_{LF}}{T_{HF}} \right)} \right] \]

\[ p_{LF} = \frac{1 + e^{\frac{T_{LF}}{T_{HF}}}}{2} \]  (4.11)

After substituting the parameters in formula 4.11 into the discrete transfer function of the low frequency subsystem, the frequency domain response of the low frequency system is obtained (formula 4.12). The greater the difference of time scale, the less dynamic information of high frequency subsystem is contained in the identification data. However, according to formula 4.12, with the increase of the time scale difference between high and low frequency subsystem, the gain information of high frequency subsystem is always present under the condition of low frequency excitation and slow sampling, which can be understood as a proportional element with proportion coefficient of \( k_{HF} \).

\[ \lim_{\tau_{LF}/\tau_{HF} \to \infty} \frac{b_{HF}e^{\tau_{ao}}}{1 - a_{HF}e^{\tau_{ao}}} = k_{HF} \]  (4.12)

According to the above analysis, if the gain \( k_{HF} \) is identified accurately, then after filtering the information of the high frequency subsystem, the information contained in the data will be able to ensure the accuracy of the identification of the low frequency subsystem.

4.2.2 Multi-time scale system identification algorithm

Based on the above analysis, this paper presents a two-step identification method for multi-time scale system. Its algorithm flow is as follows:
(1) Initial state, \( G_0(q) = 0 \);
(2) The high frequency signal \( u_a \) is used as the excitation signal to excite the system, and the data set \( A = [u_a, y_a] \) is obtained;
(3) Update data set \( A \) to get \( A' = [u_a, y_a'] \), update criterion is \( y_a' = y_a - G_0^0(q) * u_a \);
(4) Using data set \( A' \) to identify model \( G_0^1(q) \);
(5) The low-frequency \( u_b \) signal is used as the excitation signal, and the data set \( B = [u_b, y_b] \) is obtained;
(6) Update data set \( B \) to get \( B' = [u_b, y_b'] \), update criterion is \( y_b' = y_b - G_0^1(q) * u_b \);
(7) Using data set \( B' \) to identify model \( G_{1L}(q) \);
(8) \( \hat{G}_1(q) = G_{1H}(q) + G_{1L}(q) \) is used as the identified model.
If the accuracy condition is met, the model \( \hat{G}_1(q) \) is taken as the obtained model; if not, the model \( G_{1L}(q) \) is updated in the process (3) to get new data set, circle is repeated;
(9) End.

5. Simulation results and discussions

5.1 Simulation results

To verify the effectiveness of the multi-time scale system identification algorithm, the identification effect is also verified by taking the system shown in the \( G_1(s) \) as a simulation example, where the test conditions are the same as in tables 3.1 and 3.2.

From the previous discussion, it can be seen that there is a problem of order selection in the identification of the multi-time scale system. If the system order cannot be determined accurately, the parameter identification will be greatly affected. As the experiment condition is confirmed, the model structure determination result of \( \hat{G}_{1H}(q) \) and \( \hat{G}_{1L}(q) \) is shown in Figure 4.4, the best order of \( \hat{G}_{1H}(q) \) is 2 and the best order of \( \hat{G}_{1L}(q) \) is 1, so the order of the combined model \( \hat{G}(q) \) is 3, which is consistent with the true process. This shows that the proposed algorithm can solve the order selection problem of multi-time scale system.
1.2 Discussions

6. Simulation case of multi-energy system

6.1 System description

To verify the application of the algorithm in the multi-energy system, a multi-energy system is implemented in APROS as is shown in Figure 6.1. The main components of the system include a gas turbine, a heat recovery boiler, a backpressure steam turbine, two district heaters, an auxiliary cooling tower and two electric generators. Gas-steam combined cycle is adopted to supply energy:

After the natural gas is burned, the flue gas drives the gas turbine to generate electricity, and then enters the heat recovery boiler to heat the feedwater, which is converted into steam to drive the steam turbine to generate electricity. Heat power is supplied by the exhaust steam of steam turbine (in district heater A) and the exhaust flue gas of gas turbine (in district heater B). The auxiliary cooling tower is used to assist in cooling the return water to prevent excessive back pressure of the steam turbine.

For this multi-energy system, we focus on three input variables \((u_1, u_2, u_3)\) and three input variables \((y_1, y_2, y_3)\) as is shown in Table 6.1. There are coupling relationships between different variables: Firstly, there is a coupling relationship between the electric power generation of gas turbine and steam turbine, for the flue gas flows in sequence. Secondly, there is a coupling relationship between the electric power and the heat power, for the thermoelectric coupling characteristic of the multi-energy system.

The transformation relation of the system is expressed as the following three-in-three-out matrix form:

\[
\begin{bmatrix}
  E_{ST} \\
  E_{GT} \\
  Q_H
\end{bmatrix} =
\begin{bmatrix}
  G_{11}(q) & G_{12}(q) & G_{13}(q) \\
  G_{21}(q) & G_{22}(q) & G_{23}(q) \\
  G_{31}(q) & G_{32}(q) & G_{33}(q)
\end{bmatrix}
\begin{bmatrix}
  m_{gas} \\
  m_{air} \\
  m_{BPF}
\end{bmatrix}
\]

(6.13)

Where \(G_{ij}(q)\) \((i=1,2,3; j=1,2,3)\) are the dynamic models of different channels.

As is mentioned above, coupling relationships between different energy systems lead to complex features of the integrated system, coupling components transfer disturbance from one system to another system bidirectional. For example, disturbance from district heating system can transfer to electric system as the backpressure of ST changes with circulating water temperature, and the electric power of ST is directly related to back pressure; disturbance from electric system can also transfer to district heating system as
the thermoelectric coupling characteristic of ST.

![Diagram of the multi-energy system](image)

**Figure 6.1 Schematic diagram of the multi-energy system**

**Table 6.1 Description of input and output variables**

| Variable | Tag Name | Description |
|----------|----------|-------------|
| \(u_1\) | \(m_{\text{gas}}\) | Gas consumption rate, it determines the total energy input to the system |
| \(u_2\) | \(m_{\text{air}}\) | Air consumption rate, it controls the energy ratio between GT and ST by controlling the air-fuel ratio |
| \(u_3\) | \(m_{\text{BPF}}\) | Bypass flow of district circulating water, it controls the backpressure of ST by controlling return water temperature of district heating system |
| \(y_1\) | \(E_{\text{ST}}\) | Electric power of the steam turbine |
| \(y_2\) | \(E_{\text{GT}}\) | Electric power of the gas turbine |
| \(y_3\) | \(Q_u\) | Heat power supplied by the whole system |

**6.2 Identification of dynamic model**

To better illustrate the dynamic relationship between variables, our task is to identify the dynamic models of different channels.

Step test is carried out before identification of dynamic model to obtain a rough estimate of dominant process time constants, as is shown in Table 6.2. Obviously, this system is a representative multi-time scale system: it combines both properties of the two systems defined in Definition 1 and Definition 2, the output signal \(E_{\text{GT}}\) has both fast and slow response to the same input signals, and the response speed of different output signals \((E_{\text{ST}}, Q_u)\) to the input signals can be measured in different time units.

**Table 6.2 Time constants of different channels**

| \(m_{\text{gas}}\) | \(m_{\text{air}}\) | \(m_{\text{BPF}}\) |
|------------------|------------------|------------------|
| \(E_{\text{ST}}\) | \(-200 - 5000s\) | \(-200 - 5000s\) |
| \(E_{\text{GT}}\) | \(-70s\) | \(-70s\) | |
| \(Q_u\) | \(-2000s\) | \(-2000s\) | |

The test signals are designed based on the time constants of different channels. For the three outputs have different response times, the identification experiment is divided into two parts:

In the first part, models with faster response times are identified: Data A is used to identify \(G_{21}(q)\) and \(G_{22}(q)\), and Data B is used to identify high frequency parts of \(G_{11}(q), G_{12}(q)\) and \(G_{13}(q)\), the identified data is shown in Figure 6.2.

In the second part, models with slower response times are identified: Data C is used to identify \(G_{31}(q), G_{32}(q)\) and \(G_{33}(q)\); Data D is used to identify the low frequency parts of \(G_{31}(q), G_{32}(q)\) and \(G_{33}(q)\), the identified data is shown in Figure 6.3.

All data sets are separate into two parts, one part for identification and one part for validation of the identified model.
The identification conditions of different channels are shown in the following table 6.3: sample time and average switch time of GBN are design based on the time constants of different channels, multi-time scale identification method is used to identify models relative to $E_{ST}$, and ARMAX method is used to identify models relative to $E_{CT}$ and $Q_H$.

Step responses of the identified dynamic models are shown in Figure 6.4, from this, we can see that different channels have obvious multi-scale characteristics, in particular, the response speed of $E_{ST}$ has two parts. Identified models fits for $E_{ST}$, $E_{CT}$ and $Q_H$ are respectively shown in Figure 6.5, Figure 6.6 and Figure 6.7. The relative error (RE) is also used to measure the model quality, the relative error of $E_{ST}$ is 5.40%, the relative error of $E_{CT}$ is 5.05%, the relative error of $Q_H$ is 5.42%, which are all very small, therefore, the models are accurate.

Comments on the findings of the case are the following. The first good news is that the proposed multi-time scale identification method has a high accuracy for the multi-energy system, this is very encouraging as the prediction accuracy determines the performance of process control and economic optimization. The second good news is that for a new multi-energy system, the system model can be obtained efficiently through the rational design of experiments with few knowledge of process mechanism, the proposed method is efficient because it is very complex to study how different systems interact on each other, but the information is already contained in the operational data.

| Sample time | Average switch time of GBN | Identification method |
|-------------|----------------------------|-----------------------|
| $E_{ST}$    | 10s/200s                   | The proposed method   |
| $E_{CT}$    | 2s                         | ARMAX                 |
| $Q_H$       | 50s                        | ARMAX                 |

Figure 6.2 Identified data: identified data A (for $G_{21}(q)$, $G_{22}(q)$) and identified data B (for the high frequency parts of $G_{11}(q)$, $G_{12}(q)$, $G_{23}(q)$)
Figure 6.3 Identified data: identified data C (for $G_{11}(q)$, $G_{22}(q)$) and identified data D (for the low frequency parts of $G_{11}(q), G_{12}(q), G_{13}(q)$)

Figure 6.4 Step response of the identified dynamic models
7. Conclusion and further work

Multi-time scale system identification for multi-energy system has been studied. It has been shown that the proposed algorithm can give accurate dynamic models for multi-energy system, the multi-time scale modeling problems caused by system coupling are solved, the effectiveness of the method has been demonstrated using simulation examples. The analysis shows that the experimental design is very important to identified dynamic model, this also provides a reference for other data-driven methods of modeling for multi-energy system.

Future work will focus on closed-loop multi-time scale identification of multi-energy systems and multi-time scale predictive control method based on the identified models.

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