Adaptive Granular Control for HVDC Transmission System

By
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A Thesis Submitted to the Faculty of Graduate Studies
In Partial Fulfillment of the Requirements for the Degree of

Master of Science

In Computer Engineering

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A Thesis/Practicum submitted to the Faculty of Graduate Studies of The University

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I would like to dedicate this in memory of the love and spirit of my father Cheng He, who I miss dearly.

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I am pleased to take this opportunity to thank some special individuals and organizations for their help in my research work.

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Abstract

Considerable progress in control technology has been reported on solving a rapidly growing range of problems with a decision system. This occurs especially in those niches of control engineering where the classical approaches have been faced with some difficulties or have appeared to perform inherently weakly. In a non-liner and complicated plant system like High Voltage Direct Current (HVDC), it is very difficult to mathematically and accurately model its behaviors. It is a good approach to address this problem by measuring the input and output, and establish a relationship between the input and output. However, the relationship between input and output is not always one-to-one. When we apply any control to such a system, accurate control parameters are not easily obtainable by calculations. The classical PI control, which has been widely used in HVDC system, is one of these examples.

In this thesis, we study the application of rough set theory and granular computing techniques to the control of the HVDC systems. We propose an adaptive rough-set-based control scheme in place of the classical PI control. On the one hand, adaptive rough control deals with the dynamics and complexity of responses from a HVDC system in the operation points, by adjusting its control parameters adaptively. On the other hand, granular computing handles the issue of the unavailability of an accurate frequency domain model, which is usually required by adaptive control but is hardly established in a HVDC system. Our study includes a brief introduction to rough sets, rough control, and granular computing, both theory and application.

We also evaluate in the thesis the performance of adaptive rough control by simulation. The focus of our experiments is on the constant current control. The result shows there are many improvements offered by the rough control scheme in comparison with the conventional HVDC control scheme (i.e. classical PI control).

Keywords: HVDC system, Rough Sets, Adaptive Control, Granular Computing.

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1 Introduction

Recently, High Voltage Direct Current (HVDC) transmission has become increasingly important in the electrical power transmission system. It has attracted much more attention because of its advantages over alternative current (ac) transmission. The direct current voltage in conjunction with fast acting power electronic devices in an HVDC system makes HVDC transmission the most reliable method for power transmission over long distances. It also reduces our concerns about system stability with dynamic power injection into load buses.

1.1 HVDC Transmission

An HVDC transmission system is highly controllable, and its performance mostly depends on an appropriate utilization of this controllability to ensure the desired behaviors of the power system. As such, various levels of control are used for the common objectives of providing efficient and stable operation and maximizing flexibility of power control without compromising the safety of equipment. Applications of advanced methods (such as optimal control, adaptive control, and multi-variable control) and different approaches (such as microprocessor based on controllers, and digital signal processing) have been thoroughly investigated in recent years [8], [12], [70].

The most widely used control is the proportional-integral (PI) controller. It has been widely used in HVDC systems for the internal control loops. It is because that a PI controller is a static controller and the response of the HVDC 'plant' dynamically changes with variations in the operating point, the PI controller's performance is far from being optimal. On the other hand, adaptive control, in which the controller adapts itself to the observed changes in the operating point, is an active control technique for a HVDC system. However, adaptive controllers require for their design a frequency domain model of the controlled plant. Due to the non-linear operation of the HVDC system, such a model is difficult to establish. Thus, the rough set theory is introduced to deal with this dilemma. Because rough set theory makes it possible to set up a decision-making utility that approximates a control engineer's knowledge about how to tune the controller of a system to improve its behavior, rough sets can be used to design an adaptive controller.

Rough sets and rough set theory were introduced by Pawlak [36]-[38]. Since then we have witnessed a systematic, worldwide growth of interest in rough set theory and its application [31], [34], [41]-[45], [47]-[50], [56], [63], [71]. Rough sets are applicable in many problem domains such as neural network, medical diagnosis, signal analysis, robotics, telecommunications, vibration analysis, conflict resolution, intelligent agents, digital image processing, pattern recognition, control theory, web mining and web intelligence. Recently, a control system based on rough sets has been proposed and widely studied (see e.g. [41], [56]). However, we still lack the detailed study and evaluation of the application of rough set theory and granular computing to the implementation of an adaptive rough control scheme in service of HVDC transmission.

1.2 Scopes of the Thesis

In the thesis, we focus on the application of rough sets in the design of an adaptive HVDC transmission control system. The application of rough sets in a HVDC control system is investigated through a real-time rough-set-based control scheme. We will design and implement a rough controller, in which its parameters can be adaptively adjusted by using a rough set based tuning table and granular computation, in place of the classical PI controller in HVDC control system. The new control scheme utilizes the flexibility of dynamic input-output responses to improve the performance of the HVDC system. Our important development in this thesis includes the construction of the whole network, comprising plant, classical PI controller, sensors, granular data, tuning table, and the implementation of a real-time HVDC control system.

While attacking the problem "impreciseness", rough set theory views impreciseness not as a feature of the problem itself, but as the lack of knowledge. When extracting features and describing impreciseness, it utilizes the rule base obtained from experiments data or derived from expert conclusions. The main advantage of rough set control is that it is based on the availability of a set of rules that capture the knowledge of a control engineer on how to tune controller gains best.

1.3 Outline of the Thesis

The thesis consists of the following seven chapters.

Chapter 1 introduces the background of this study, and outlines the research scope of the thesis.

Chapter 2 studies the HVDC transmission and control system.

Chapter 3 presents some preliminary introduction about the rough set theory for control.

Chapter 4 exposes the principles of granular computation.

Chapter 5 deals with the design and application of rough control to HVDC systems. The simulated control system executes such duties as collecting data, granulating measurements, creating decision tables, generating decision rules, and applying rough control rules to improve the operation of a real-time HVDC system.

Chapter 6 analyzes the simulation results and discusses how to extend our rough control scheme to deal with a variable HVDC system. The advantages and disadvantages of the rough control scheme are also investigated.

Chapter 7 presents concluding remarks and presents future work.

In the Appendix, we will briefly introduce some important tools used in this study: Matlab Simulink and Rosetta, and record the main data from experiments.

2 HVDC Transmission and Control

In this chapter, we will study the High Voltage Direct Current (HVDC) transmission system and investigate the traditional approaches for efficient power transmission. For such purposes, we first introduce a simplified HVDC transmission system and its control system in Section 2.1. As we know, the HVDC transmission and control system is much complicated in reality. In order to investigate the performance of our rough control scheme on an HVDC system, we choose the CIGRE benchmark model to characterize HVDC transmission. With the simplified HVDC model, the traditional PI control scheme for HVDC transmission is studied in Section 2.2. It should be reiterated that the control method (PI control) is not the complete actual control method used in a real HVDC system. However, the conventional PI control comprises the main modes common to all control schemes. Various considerations and restrictions on the control method are discussed in detail. After that in Section 2.3, we propose an adaptive control scheme, in which some crucial parameters can be dynamically adjusted. Through the adjustment of those parameters, we expect that power transmission performance can be closely controlled and thus be greatly improved.

2.1 HVDC Transmission Modeling

We choose the CIGRE HVDC benchmark model [70] to characterize the HVDC system

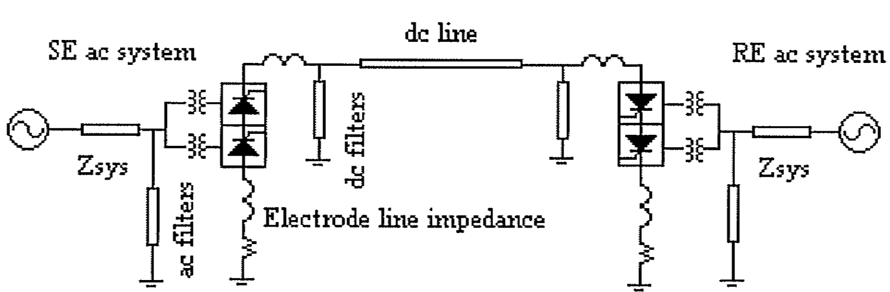

Fig. 2-1 CIGRE benchmark model

under study. The CIGRE HVDC benchmark model was designed by CIGRE study group 14.02 for conducting comparisons of performance of different dc control equipment and control strategies. It is a two-terminal dc scheme, depicted in Fig. 2-1. With a group of parameters, it represents a high degree of difficulty for control studies.

Short circuit ratio (SCR) and effective short circuit ratio (ESCR) are two important indices for characterizing the degree of expected operational problems in a dc transmission scheme. The SCR is defined as the ratio between the ac system short circuit MVA and the dc power. If the filter MVArs' are subtracted from the ac system MVA in the above calculation, the resultant quantity is the ESCR. The circuit under study has the following rectifier and inverter ac system characteristics:

Rectifier $SCR = 2.5\angle -85°$; $ESCR = 1.9\angle -82°$

Inverter $SCR = 2.5\angle -75°$; $ESCR = 1.9\angle -70°$

These short circuit ratios characterize a weak system. The combination of the weak inverter system, the dc side resonance (large admittance) near fundamental, and the ac side resonance (large impedance) near the second harmonic makes the benchmark system particularly onerous for dc control operation. In practice, HVDC transmission control is introduced to either partially or fully overcome this weakness.

2.2 Basic Theory of HVDC Control

Since the advent of HVDC transmission systems, their controls have been studied in great detail [8], [19]. The main objectives of HVDC transmission controls are to improve power transmission efficiency, enhance fault tolerance, etc. Many proprietary methods have been developed [2], [18]. Some of them have been utilized for many years and with ongoing modifications, are now considerably optimized.

However, all of these control schemes are quite complicated. Some of them are of proprietary and have not been published. Using a practical and complete control system for the studies conducted in this thesis is firstly very cumbersome, and secondly distracts one from the primary objective of the study. Our main objective is to investigate the feasibility of applying new techniques (mainly rough set theory) to the HVDC control. Therefore, only some main schemes of the HVDC control are implemented and studied in the thesis, without the addition of auxiliary modifications and improvements. Comprehensive HVDC control schemes are well explained and elaborated in [1].

2.2.1 Operating Point

Consider the dc transmission circuit shown in Fig. 2-2, with the assumption that the line resistance is negligible, we have $V_{dr} = V_{di} = V_d$ for the dc voltages at the rectifier and inverter ends respectively. Similarly, as the dc current at the sending and receiving ends must be equal, we obtain $I_{dr} = I_{di} = I_d$. Thus, the operating points for the converters can be easily determined as the intersection point of the voltage-current (V-I) characteristics of either converter (point E in Fig. 2-3). The actual operating point and the particular V-I characteristic is dependent on the selected control strategy.

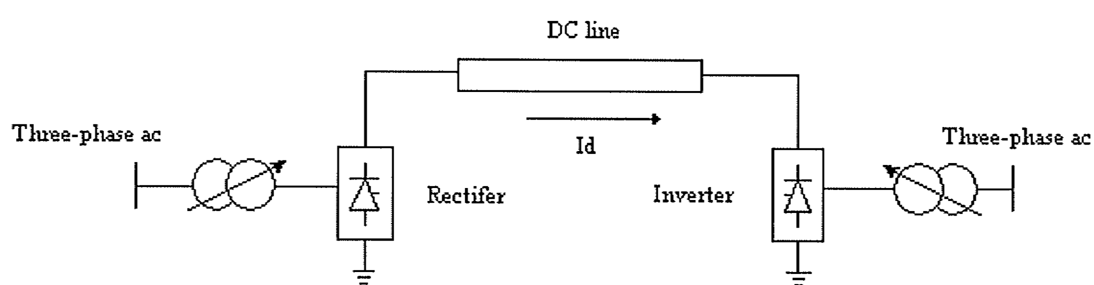

Fig. 2-2 The dc transmission system

2.2.2 Control Parameters α_{min} and γ_{min}

In the HVDC transmission system, power factor is one of most important parameters. We usually keep it as high as possible. Basically, there are four reasons for maintaining the power factor high, two concerning the converter itself and the other two concerning the ac system.

- To keep the rated power of the converter as high as possible for given current and voltage ratings of transformer and valve;
- To reduce stresses in the valves;
- To minimize losses and current rating of equipment in the ac system to which the converter is connected;
- To minimize voltage drops at the ac terminals as loading increases.

As we know,

$$\cos\phi_r \approx 0.5[\cos\alpha + \cos(\alpha + \mu)] \quad \textit{in the rectifier side}$$

$$\cos\phi_i \approx 0.5[\cos\gamma + \cos(\gamma + \mu)] \quad \textit{in the inverter side}$$

where α is the firing angle of a rectifier and γ is the extinction angle of an inverter. Therefore, both α for a rectifier and γ for an inverter should be kept as low as possible, so that ac can achieve high power factor.

The rectifier, however, has a minimum α about 5° (α_{min} = 5°) to ensure adequate voltage across the valve before firing. In the case of thyristors, the positive voltage appearing across each thyristor before firing is used to charge the supply circuit providing the firing pulse energy to the thyristor. Therefore, firing cannot occur earlier than about 5° [1]. Consequently, the rectifier normally operates at a value of α within the range of 15° to 20° (α_{min} = 15° or α_{min} = 20°), so as to leave some room for increasing rectifier voltage to control dc power flow.

In the case of an inverter, it is necessary to maintain a certain minimum extinction angle to avoid commutation failure. It is important to ensure that commutation is completed with sufficient margin to allow for re-ignition before commutating voltage reverses at $\alpha = 180^\circ$ or $\gamma = 0^\circ$. The extinction angle γ is equal to β-μ, with the overlap μ depending on I_d and the commutating voltage. Because of the possibility of changes in direct current and alternating voltage even after commutation has begun, sufficient commutation margin above the minimum γ limit must be maintained. Typically, the minimum value of γ with acceptable margin is 15° (γ_{min} =15°) for 50 Hz systems and 18° (γ_{min} = 18°) for 60 Hz systems.

2.2.3 HVDC Control Strategy

Both converter substations (rectifier and inverter) are provided with a current control loop including a current measuring device, a current controller and firing control equipment. Usually, one of the converters is current controlled, and the other operates in constant extinction angle as described below.

A general control system for HVDC transmission has two main parts.

- Rectifier constant current (CC),
- Inverter constant current (CC) or inverter constant extinction angle (CEA).

As stated in Section 2.2.1, the operating point is normally the intersection of the rectifier CC and inverter CEA (point E in Fig. 2-3), which results in the minimum reactive power demand [18], without an excessive risk of commutation failure. At this operating point, the firing angle to the rectifier is above that of the minimum value α_{min} (the minimum rectifier firing angle).

The rectifier maintains constant current by changing α. Once α_{min} is reached, no further voltage increase is possible, and the rectifier will operate at constant ignition angle (CIA).

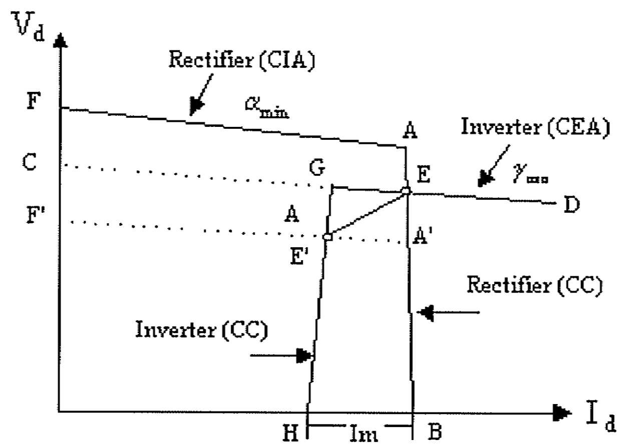

Fig. 2-3 Actual converter control steady-state characteristics

Therefore, the rectifier characteristic has really two segments (AB and FA) as shown in Fig. 2-3. The segment FA corresponds to minimum ignition angle and represents the CIA control mode; the segment AB represents the normal constant current mode. The complete rectifier characteristic at normal voltage is defined by FAB. At a reduced voltage, it shifts as indicated by F'A'B.

The CEA characteristic of the inverter intersects the rectifier characteristic at E at normal voltage. However, the inverter CEA characteristic (CD) does not intersect the rectifier characteristic at a reduced voltage represented by F'A'B. Therefore, a big reduction in rectifier voltage would cause the current and power to be reduced to zero after a short time period depending on the dc reactors. The system would thus run down. In order to avoid the problem, the inverter is also provided with a current controller, which is set at a lower value than the current setting for the rectifier. The complete inverter characteristic is given by DGH, consisting of two segments: one of CEA and one of constant current.

The difference between the rectifier current order and the inverter current order is called the current margin, denoted by I_m in Fig. 2-3. Under normal operating conditions (represented by the intersection point E), the rectifier controls the direct current and the inverter controls the direct voltage. In other words, the rectifier is in constant current mode, while inverter is in CEA mode. To work in the CC mode, the inverter is also provided with an inverter current controller. But, the current reference for this station is reduced by the amount I_m.

A rectifier current controller is used in a HVDC control system to adjust the voltage to keep the current constant at some point on the vertical line. During transients, e.g. line faults, there are excursions of voltage and the current is temporarily different from the set value. With a reduced rectifier voltage (possibly caused by a nearby fault), the operating condition is changed, represented by the intersection point E'. The reduction of rectifier voltage pushes the rectifier controller to hit the minimum firing angle limit ($\alpha = \alpha_{min}$), and forces it to act at the constant firing angle (or we call it as constant ignition angle e.t CIA). Normally, the inverter controller should switch from the CEA mode to the CC mode simultaneously. Therefore, the inverter will take over current control when the rectifier works at the minimum firing angle for a constant voltage. In this situation, the roles of the rectifier and inverter are reversed. The change from one mode to another is referred to as a mode shift.

2.2.4 PI Controller

The direct voltage at any point on the line and the current (or power) can be controlled by controlling the internal voltages ($V_{dor} \cos\alpha$) and ($V_{dor} \cos\gamma$). This is accomplished by grid/gate control of the valve ignition angle or control of the ac voltage through tap changing of the converter transformer.

In the thesis, our focus is on gate control, which is rapid (1 to 10 ms) and initially used for rapid action. This control system is basically a feedback loop that adjusts the output according to the input, where the input is the error of the measurement (Id or $\gamma_{mea.}$) and the reference value or called order value (Io or $\gamma_{ord.}$), such as ΔId (ΔId = Id – Io) for CC control or $\Delta\gamma$ ($\Delta\gamma = \gamma_{mea.} - \gamma_{ord.}$) for CEA control. But the output is always the value of the ignition angle to keep the constant current or constant extinction angle.

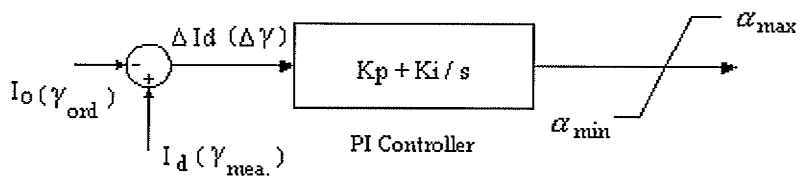

Fig. 2-4 Simple dc current controller

In such a HVDC control system, a classical proportional plus integral regulator (PI controller) is widely used (Fig. 2-4). It utilizes two parameters, integral time constant Ki and proportional gain Kp, to process inputs and obtain the firing angle α. Since Ki and Kp are predetermined parameters with fixed values, a PI controller is in fact a time-invariant system.

2.3 Adaptive Control Concept

In some cases where the system's mission is well known beforehand it is often possible to design preprogrammed time variations of controller parameters to achieve instantaneous optimum control at all times. This approach is called preprogrammed adaptive control. In reality, of course, such a controller is simply an optimum time-varying system, the control parameters being automatically set at the optimum values relative to instantaneous environmental conditions encountered at each point in time. This constitutes a logical and straightforward extension of concepts introduced in [41], [42], [44], [45], [56].

Adaptive control provides a potential solution to problems in the following general form. The system to be controlled is normally exposed to a time-varying environment, either in the form of a plant with changing parameters, input signals and disturbances with time-varying statistical characteristics, or changing performance objectives. Since changes encountered are not completely predictable, an optimum preprogrammed time-varying controller is not possible. If we assume that no feasible fixed-parameter controller provides acceptable response over the entire performance envelope, it is apparent that some means is required for adjusting controller parameters according to the short-term conditions encountered. If an IP, which is defined as the term index of performance, (abbreviated IP) is available which indicates the system's instantaneous or short-term average performance quality, and if a control loop is set up to optimize the IP automatically by adjusting controller parameters, the parameter-adjustment configuration is called an adaptive control loop. It is important to note that an adaptive controller has a parameter-adjustment loop above and beyond the normal feedback used to control position, velocity, and the like. Adaptive control is thus an effort to extend basic optimum-control concepts to time-varying systems.

We choose IP to denote any performance measure used in the adaptive loop to define optimum performance. Whereas many standard IP's available for use in the optimum-design problem, it is more difficult to find IP's practical value in adaptive controllers. This difficulty arises because the IP must be measured in real-time without appreciably disturbing normal operation of the major system. The standard IP's discussions are readily obtained, either analytically or computationally, if all system parameters are known, but this is not generally the case in adaptive applications.

The adaptive control process may be broken down into three major functions: identification, decision, and modification. Although it may be difficult to separate those parts of the system responsible for each, all three are necessary for adaptive action to take place. Identification is defined as the process by which the system is characterized or by which the IP value is measured. This is somewhat opposed to the usual definition as the process by which a system's impulse response or transfer function is measured. In general, when we mean IP measurement we will say just that is to decrease confusion. In some cases, as in the measurement of gasoline-engine manifold vacuum, IP measurement is relatively simple. In other applications, it may require complete plant identification and utilization of those results to determine some IP.

In the decision process, the IP measurements are used to decide how system performance relates to the desired optimum. If performance is inadequate, corrective adjustments are made according to the established strategy. Whenever an even-function IP is used, a decision is only possible after comparison of the effects of two or more parameter changes upon the IP value. In this case, parameter perturbations are used IP accumulates the information required for a decision. The eventual decision may be to increase x1 by Δ x1, decrease x2 by Δ x2, etc. the optimum parameter setting is not generally determined by a single set of measurements, even when odd-function IP is used, so the optimum is approached gradually by a succession of identification, decision, and modification steps.

Modification is the process of changing system parameters toward the optimum setting, as controlled by the identification and decision processes. In all adaptive systems, either the plant is modified directly by changing one or more of its parameters (least common), or the plant input signal is modified to provide improved performance relative to the IP assigned. The plant input, in turn, can be influenced in two ways. The first approach is to establish a controller topology and adjust the parameters of one or more equalizer networks within that topology to maintain optimum performance, thereby compensating for plant or input changes. The second approach is to synthesize, knowing (1) the plant transfer function, (2) the desired response, and (3) the IP, a plant control input which produces optimum response.

A block-diagram representation of the adaptive control process, schematically interrelating the three functions required of all adaptive controllers, is shown in Fig. 2-5. Although instrumentation of the process differs widely from one application to another, it is often convenient to interpret adaptive control in this general way. In most adaptive systems the plant is environmentally dependent and exposed to a sufficiently wide range of conditions during normal operation to cause significant time variation of its transfer function. Adaptive control is undertaken to compensate for those changes. The IP measurements environmental effects upon the system, and the remainder of the adaptive loop adjust parameters to assure optimum performance. Design of the adaptive controller therefore involves choice of the IP, the controller topology, and the adjustable parameters, as well as instrumentation of some means for changing those parameters as commanded by the modification process.

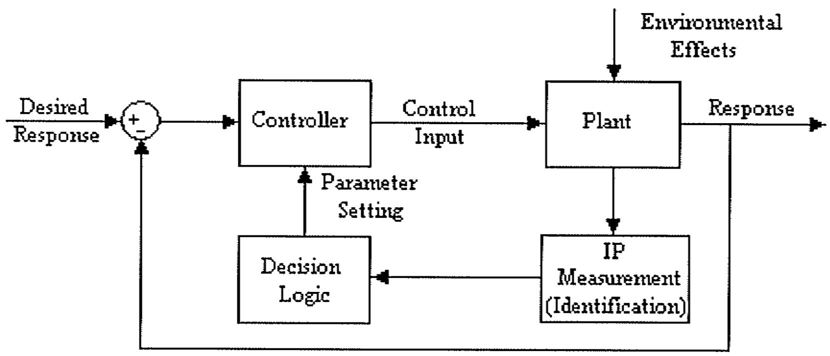

Fig. 2-5 A control system with a general adaptive controller appended

2.4 A Rough-Set-based Adaptive Control Scheme

In order to further improve the performance of HVDC control, we propose in the thesis a rough-set-based adaptive control scheme, or simply called rough control scheme. With this control scheme, the control parameters of the PI controller could be automatically set to be optimum values relative to the characteristics of the controlled HVDC transmission system. Rough set theory is applied to the design of the new control scheme. A high-level block diagram in Fig. 2-6 shows its principal components. A rough control scheme has the following features:

- A classic PI controller, which adapts the input of the controlled system according to the error between the values of reference and of measurement.

- A plant, which is the controlled HVDC transmission system.
- Data collection, which pre-processes data needed by the rough set tuner and rough controller.
- A rough set tuner, which dynamically constructs a real-time decision system in terms of a group of decision tables and rules.
- And a rough controller, which utilizes the established decision system and actually controls the work of the PI controller.

We will explain the design of the new control scheme, elaborate the details of its main components, and investigate its functionalities in the following few chapters.

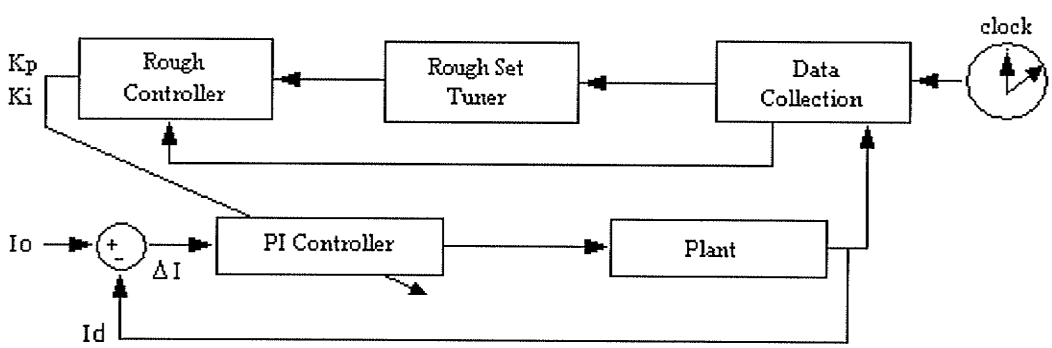

Fig. 2-6 General architecture of rough control system

3 Rough Set Theory for Control

This chapter deals with the basics of rough set theory and its application to an adaptive control system. Fundamental concepts of rough set theory are given in the first section. After that, the issue of knowledge representation within the adaptive control system is given in the second section. Lastly, there is an introduction to the core idea of the thesis, which is the construction of an adaptive control system by using rough set theory.

3.1 Preliminaries of Rough Set Theory

Rough sets have been introduced [22] as a tool to deal with inexact, uncertain or vague knowledge in artificial intelligence applications. Automatic control is only one of many application areas where rough set theory has shown to be of great practical use [28], [29], [45]. Among other areas are [38]:

- Medical data analysis
- Aircraft pilot performance evaluation
- Geology
- Pharmacology
- Vibration analysis
- Synthesis of switching circuits

This section contains basic notions related to rough set theory that will be necessary in order to understand our results.

3.1.1 Information Systems and Decision Tables

An information system is a pair S = (U, A), where U is a non-empty, finite set called the universe, A is a non-empty, finite set of attributes, i.e., a: U $\rightarrow$Va for a $\in$ A; where Va is called the value set of a. Elements of U are called objects. In this paper attributes are meant to denote the processes of the system, the values of attributes are understood as local states of processes and objects are interpreted as global states of the system.

Let S = (U, A) be an information system. With any subset of attributes $B \subseteq A$, we associate a binary relation ind (B), called an indiscernibility relation, which is defined by ind (B) = $\{(u, u') \in U \times U$ for every $a \in B$, $a(u) = a(u')\}$.

Any information system S = (U, A) determines an information function $Inf_A: U \rightarrow P(A \times V)$ defined by $Inf_A(u) = \{(a, a(u)): a \in A\}$; where $V = \bigcup_{a \in A} Va$ and P (X) denotes the powerset of X. The set $\{Inf_A(u): u \in U\}$ is denoted by INF(S). Hence, u ind (A) u' iff

$$Inf_A(u) = Inf_A(u').$$

The values of an information function will be sometimes represented by vectors of the form $(v_1, \ldots, v_m)$, $v_i \in V_a$, for $i = 1, \ldots, m$, where m = card(A). Such vectors are called information vectors (over V and A).

We also consider a special case of information systems called decision tables [22]. A decision table is any information system of the form $S = (U, A \cup \{d\})$, where $d \notin A$ is a distinguished attribute called decision. The elements of A are called conditional attributes (conditions).

Let S = (U, A) be an information system, where $A = \{a_1, \ldots, a_m\}$. Pairs (a, v) with $a \in A$; $v \in V$ are called descriptors. Instead of (a, v) we also write a = v or a_v. If τ is a Boolean combination of descriptors (over A and V) then by $\|\tau\|_S$ (or in short $\|\tau\|$) we denote the meaning of τ in the information system S.

3.1.2 Dependencies in Decision Tables

In this subsection, we recall some notions related to dependencies in decision tables and we introduce a new notion connected with an equivalence of attribute sets in decision tables. The last notion plays an important role in the rule reduction generated from a given decision table. Let S = (U, A) be an information system and let B, C $\subseteq$ A. We say that the set C depends on B in S in degree k ($0 \leq k \leq 1$); symbolically $B \xrightarrow[S,k]{} C$, if

$k = \frac{card(pos_B(C))}{card(U)}$, where POS_B (C) is the B-positive region of C in S [22].

If k = 1, we write $B \xrightarrow[S]{} C$ of $B \xrightarrow[S,k]{} C$ and we say that C is totally dependent on B in S. On this case $B \xrightarrow[S]{} C$ means that ind(B) $\subseteq$ ind(C). If the right hand side of a dependency consists of one attribute only, we say the dependency is elementary. If the set C is totally dependent on B and vice versa, then we say that C and B are equivalent in S. In this case B $B \xleftrightarrow[S]{} C$ means that ind(B) = ind(C). A pair (B, C) of subsets of A is called a strong component of S iff the following conditions are satisfied:

1) $B \cap C = 0$,

2) B and C are equivalent in S,

3) B and C are minimal (w.r.t. $\subseteq$) in A. By COMP(S) we denote the set of all strong components of S.

The condition 3) of the definition of the strong component of S we can also formulate in the following way. B and C are minimal (w.r.t. $\subseteq$) in A iff:

1) if (B, C) $\in$ COMP(S) then (B – {a}, C) $\notin$ COMP(S) for any a $\in$ B,

2) if (B, C) $\in$ COMP(S) then (B – {a}, C) $\notin$ COMP(S) for any a $\in$ C.

3.1.3 Rules in Decision Tables

Rules express some of the relationships between values of the attributes described in the information systems. This subsection contains the definition of rules as well as other related concepts.

Let S = (U, A) be an information system and let $B \subset A$. For every $a \notin B$, we define a function $d_a^B : U \rightarrow P(V_a)$ such that $d_a^B(u) = \{v \in V_a$: there exists $u' \in U$ u' ind (B) u and a(u') = v}, where P (V_a) denotes the powerset of V_a. Hence, $d_a^B(u)$ is the set of all the values of the attribute a on object indiscernible with u by attributes from B. If the set $d_a^B(u)$ has only one element, this means that the value a(u) is uniquely defined by the values of attributes from B on u.

A rule over A and V is any expression of the following form (Eq. 3.1):

$$(1) \quad a_{i\,1} = v_{i\,1} \Lambda \ldots \Lambda\, a_{i\,r} = v_{i\,r} \Rightarrow a_p = v_p \qquad (3.1)$$

where $a_p, a_{i\,j} \in A$, $v_p, v_{i\,j} \in V_{a\,i\,,\,j}$ for j = 1, …, r.

A rule of the form (1) is called trivial if $a_p = v_p$ appears also on the left hand side of the rule. The rule (1) is true in S (or in short: is true) if

$$0 \neq \| a_{i\,1} = v_{i\,1} \Lambda \ldots \Lambda\, a_{i\,r} = v_{i\,r} \| \subseteq \| a_p = v_p \|$$

The fact that the rule (1) is true in S is denoted in the following way (Eq. 3.2):

$$(2) \quad a_{i\,1} = v_{i\,1} \Lambda \ldots \Lambda\, a_{i\,r} = v_{i\,r} \underset{S}{\Rightarrow} a_p = v_p \qquad (3.2)$$

In the case (2) we also shall say that the values (local states) $v_{i1}, \ldots, v_{ir}, v_p$ of processes $a_{i1}, \ldots, a_{ir}, a_p$ can coexist in S. Let $S = (U, A \cup \{d\})$ be a decision table. A rule $\tau \Rightarrow d = v$, where τ is a term over A and V, d is a decision attribute of S, $v \in V_d$, is called a decision rule. We apply here the Boolean reasoning approach to the rule generation [59].

3.1.4 Reduction of Attributes

Let S = (U, A) be an information system. Any minimal subset $B \subseteq A$ such that ind(B) = ind(A) is called a reduct in the information system S [22]. The set of all reducts in S is denoted by RED(S). Now we recall two basic notions, namely those of discernibility matrix and discernibility function [49], which will help to compute minimal forms of rules w.r.t. the number of attributes on the left hand side of the rules.

Let S = (U, A) be an information system, and let us assume that $U = \{u_1, \ldots, u_n\}$, and $A = \{a_1, \ldots, a_m\}$. By M(S) we denote an $n \times n$ matrix (c_{ij}), called the discernibility matrix of S, such that $c_{ij} = \{a \in A: a(u_i) \neq a(u_j)\}$ for $i, j = 1, \ldots, n$.

Intuitively an entry c_{ij} consists of all the attributes discerning objects u_i and u_j. Since M(S) is symmetric and $c_{ii} = 0$ for $i = 1, \ldots, n$, M(S) can be represented using only elements in the lower triangular part of M(S), i.e., or $1 \leq j < i \leq n$. With every discernibility matrix M(S) one can uniquely associate a discernibility function $f_{M(S)}$ defined as follows. A discernibility function $f_{M(S)}$ for an information system S is a Boolean function of m propositional variables $a^*_1, \ldots, a^*_m$ (where $a_i \in A$ for $i = 1, \ldots, m$) defined as the conjunction of all expressions $\vee c^*_{ij}$, where $\vee c^*_{ij}$ is the disjunction of all elements of $c^*_{ij} = \{a^*: a \in c_{ij}\}$, where $1 \leq j < i \leq n$ and $c_{ij} \neq 0$. In the sequel we write a instead of a *. Proposition II.1 gives an important property that enables us to compute all reducts of S.

Proposition II.1: [49] Let S = (U, A) be an information system, and let $f_{M(S)}$ be a discernibility function for S. Then the set of all prime implicants of the function $f_{M(S)}$ determines the set RED(S) of all reducts of S, i.e., $a_{i1} \wedge \ldots \wedge a_{ik}$ is a prime implicant of $f_{M(S)}$ iff $\{a_{i1}, \ldots, a_{ik}\} \in$ RED(S) [42].

3.1.5 Minimal Rules in Decision Tables

In this section we present a method for generating the minimal form of rules in decision tables. The method is based on the idea of Boolean reasoning [22] applied to discernibility matrices defined in [34] and modified here for our purposes. This section presents the first step in the construction of a concurrent model of knowledge embedded in a given decision table.

Let S = (U, $A \cup \{d\}$) be a decision table and $d \notin A$. We are looking for all minimal rules (i.e., with minimal left hand sides) in S of the form:

$$a_{i1} = v_{i1} \wedge \ldots \wedge a_{ir} = v_{ir} \underset{S}{\Rightarrow} a_p = v_p \tag{3.3}$$

where $a \notin A \cup \{d\}$, $v \in V_a$, $a_{ij} \in A$, and $v_{ij} \in V_{a_{ij}}$ for j = 1,…, r.

The above rules express functional dependencies between the values of the conditional attributes of S as well as functional dependencies between the values of the conditional attributes of S and the values of the decision attribute of S. These rules are computed from systems of the form S'= (U, $B \cup \{a\}$) where $B \subset A$ and $a \in A\text{-}B$ or a = d.

First, for every $v \in V$, $ul \in U$ such that $d_a^B(u_l) = \{v\}$ a modification M (S'; a, v, ul) of the discernibility matrix is computed from M(S'). By M(S'; a, v, ul) = (c^*_{ij}), (or M, in short) we denote the matrix obtained from M(S') in the following way:

- if $i \neq l$ then $c^*_{ij} = 0$;
- if $c_{lj} \neq 0$ and $d_a^B(u_l) \neq \{v\}$ then $c^*_{lj} = c_{lj} \cap B$ else $c^*_{lj} = 0$.

Next, we compute the discernibility function f_M and the prime implicants of f_M taking into account the non-empty entries of the matrix M (when all entries c^*_{ij} are empty we assume f_M to be always true.

Finally every prime implicant $a_{i1} \wedge \ldots \wedge a_{ir}$ of f_M determines a rule

$$a_{i1} = v_{i1} \wedge \ldots \wedge a_{ir} = v_{ir} \underset{S}{\Rightarrow} a_p = v_p \tag{3.4}$$

where $a_{ij}(u_l) = v_{i1}$ for $j = 1, \ldots, r$, $a(u_l) = v$

The set of all rules constructed in this way for any $a \in A \cup \{d\}$ is denoted by OPT(S, a). We put $OPT(S) = \bigcup \{OPT(S, a): a \in A \cup \{d\}$. For any $a \in A \cup \{d\}$ and $u \in U$ we take $B = A$, if $a = d$; $B = (A \cup \{d\}) - \{a\}$ otherwise and we take $v = a(u)$. We compute all minimal rules true in $S' = (U, B \cup \{a\})$ of the form $\tau \Rightarrow a = v$, where τ is a term in conjunctive form over B and $V_B = \bigcup_{a \in B} V_a$, with a minimal number of descriptors in any conjunct. To obtain all possible functional dependencies between the attribute values it is necessary to repeat this process for all possible values of a and for all remaining attributes from $A \cup \{d\}$.

3.2 Rough Sets for Control

This section explains how to apply rough sets to automatic control system. It deals with creating rough set control algorithms in general. Like fuzzy logic control, rough set control is a rule based control paradigm.

The main advantage of rough logic control is the ability to reduce the rule base using the methods described in Section 3.1.5. Before the controller can be implemented, a few preliminary steps have to be taken. The whole process may be summed up as follows:

Step 1: (Attribute domain coding):

Choose suitable condition and decision attributes and code their domains. This corresponds to determining the boundaries of the equivalence classes. The sensor readings and control actions constitute the condition and decision attributes respectively.

Step 2: (Knowledge acquisition):

Create a decision table (Section 3.1.1) describing known relations between sensor readings and control actions. Such a decision table may be constructed from observing a human operator or interviewing an expert. Inconsistencies in the obtained decision table may be an indication that too few condition attributes have been chosen. Check also to see if the distribution of points in condition space is satisfactory.

Step 3: (Knowledge reduction):

Reduce and minimize the decision table by exploiting the dependency among decision tables as described in Section 3.1.2.

Step 3a: (Reduction of the system as a whole):

Find the reducts and remove all superfluous columns (Section 3.1.2 or 3.1.3). Eliminate redundant rules by removing duplicate rows in the reduced table.

Step 3b: (Reduction of each rules separately):

Identify and remove superfluous attributes in each separate rule (Section 3.1.3). Eliminate redundant rules by removing duplicate rows within each decision class in the reduced table.

Step 4: (Controller implementation):

Extract the control algorithm from the minimized decision table (Section 3.1.3) and apply the algorithm to the process in question. After the initial decision table has been minimized and the algorithm extracted, the control action decision process is reduced to a simple table lookup operation. Hence, the operation in practice is fast and simple, the computational load was done in the preprocessing stages.

3.3 The Construction of Rough Set Controller

The topology of a typical rough set controller is depicted in Fig. 3.1. When the sensor signals have been read, it has to be decided which equivalence classes they belong to. This is done by a lookup operation in the table describing the coding of the attribute domains. A lookup operation in the minimized control decision table is then performed on the basis of this classification. The entry in the decision table corresponding to the read condition attributes then determine a decision class that in turn is translated into suitable control signals. This translation is done by a second lookup operation in the attribute-coding table. Hence, the whole control loop consists of table lookup operations and is thus very fast.

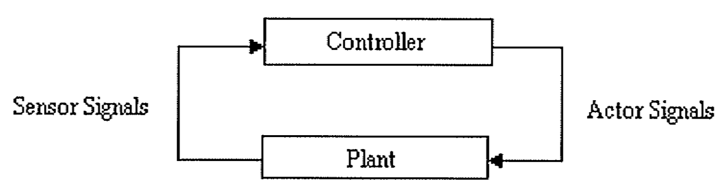

Fig. 3-1 The topology of a typical rough set controller

4 Granular Measurements

This chapter deals with the concept of information granules. It mainly consists of three sections. The first section is a brief summary of the basic concepts of information granules, and the second section is a section dealing with a general scheme for information granules. Membership functions are used to measure the probability (also termed the degree of membership) that an element belongs to an information granule. The last section gives some examples of information granules.

4.1 Basic Concepts of Information Granules

A basic assumption of rough set theory [4] is that any object x from the object universe U is perceived through an available information u expressed usually by a value vector of (conditional) attributes from a given set C. This information u is used to classify objects by matching the left hand sides of decision rules. We consider, by analogy with fuzzy set and rough mereological approaches, a more general case assuming that the language L_o in which the evidence about objects is represented and the language L_I used to describe knowledge about the problem to be solved are different and there is no direct translation of L_o into L_I preserving the semantical meaning. In this case it is often possible only to specify a set S_u of information vectors from L_I and a partial order $\leq_u$ over them with the following intuitive meaning: $v \leq_u v'$ iff v' is at least as likely as v to be a representation of u in L_I. One can treat this as a generalization of the fuzzification stage [53]. Using this example of input information granule $(S_u, \leq_u)$ one can fire the corresponding decision rules and to predict the final decision by resolving conflicts between received decisions. In a more general setting this process can be treated as a matching of input information granules against knowledge about the problem to be solved by using some logic. We obtain an output information granule as a result of inference based on the information granulation logic. Again some strategies should be applied (by analogy with the defuzzification stage) to construct a solution (e.g. decision). We discuss shortly how this general process is realized in rough mereology [50].

The rough set approach, due to Pawlak [4], is based on an assumption that information about objects is given by value vectors of (conditional) attributes. Hence, all objects with the same information are indiscernible. The indiscernibility relation is an equivalence relation. Some attempts were made to resolve limitations of this approach and some interesting extensions of the initial model ([77], [78]) have been proposed. In particular, it was observed that considering a similarity relation instead of an indiscernibility relation is quite relevant. In this more general case we obtain a covering of the object universe instead of the partition. One can consider many possible approaches to defining the lower and upper approximations of sets in this more general case. For example, one can take the components of a given covering. In this case we obtain a partition again. However, the received information granules are often not general enough and the decision rules generated on the basis of that partition would have, in many cases, not satisfactory quality of classification of new objects. One can consider another approach by taking the sum of all neighborhoods (similarity classes) containing x to create an information granule of x. However, this will not be satisfactory in many cases because we are not taking into account that some similarity classes are not reliable being influenced by noise. Hence, it is important to develop constructive methods (strategies) of searching for information granules corresponding to considered objects.

4.2 General Scheme of Information Granules

In this section we discuss a general scheme explaining how information granules can be constructed and dynamically tuned up in the process of solution construction.

We assume that an information vector u for any observed object x from the object universe U is given. Information vector u can be expressed as a value vector of attributes from a given set C i.e. $u = Inf_C(x) = \{(a,a(x)): a \in C\}$. In this way, available information can be expressed in a language, which we denote, by L_o. Knowledge about the problem to be solved is described in another language L_l (e.g. the decision rules representing knowledge about the problem are expressed in language L_l and expressions of the left hand sides of these decision rules are built using some attributes from the set A disjoint with *C*). In most cases it is not possible to translate expressions form L_o into the expressions from L_I if one would like to preserve the semantic meaning. However, using

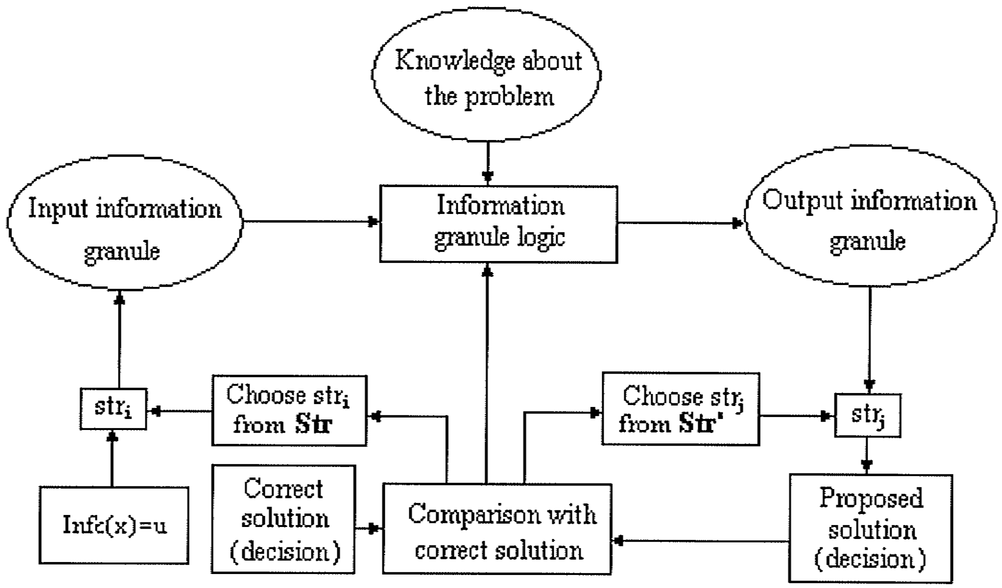

Fig. 4-1 General scheme of information granulates

some strategies from a predefined set of strategies $Str = \{str_i\}_i$, it is possible to define a set $S_u \subseteq L_I$ of possible information vectors under the evidence *u* together with e.g. a partial order $\leq_{u,A}$ in S_u. Usually the set S_u can be defined in two stages. In the first stage it is defined a superset of S_u using some strategies. Next some elements of S_u are deleted to make the final set more accurate for the decision prediction. In both stages some strategies from predefined classes of strategies Str and Str' are used.

The pair (S_u, $\leq_{u,A}$) can be treated as an example of information granules in the language L_I corresponding to the evidence *u*. S_u is the set of information vectors from L_I possibly corresponding to *u* and $v \leq_u v'$ means that *v'* is at least as likely as *v* to correspond to *u*. One can see an analogy of this stage to the fuzzification process. The main task is to develop strategies searching for information granules, tuned up into a satisfactory degree, from a given evidence *u* in the language L_o. We present some examples of such strategies. To check if an information granule is tuned up into a satisfactory degree the elements of S_u are matched against knowledge about the problem (e.g. against the decision rules representing knowledge about the problem) and the output information granule is constructed determining the set of possible solutions (e.g. decisions).

A process of matching input information granules against knowledge about the problem to be solved can be illustrated in the simplest case as a matching these granules against left hand sides of decision rules (creating a knowledge base about the problem to be solved). By analogy with fuzzy logic we call the logic involved in the inference during that matching process the information granule logic. This process can be much more complex than considered so far in fuzzy set theory.

In the next stage, by analogy with the defuzzification process, some strategies from a predefined set of strategies $Str' = \{str'_j\}_j$ should be chosen to construct from the output information granule a final solution corresponding to the evidence *u* to resolve possible conflicts between proposed solutions (e.g. decisions).

Finally, the quality of the solution is tested. The input and output information granules are tuned up into satisfactory degrees if the returned solutions are correct if the classification quality of decision rules on new objects is sufficiently high. The information granules can be tuned up to improve the quality of solutions (e.g. quality of new object classifications). This can be done by searching for optimal (sub-optimal) strategies in the predefined classes *Str* and *Str'* of strategies and by improving inference based on information granule logic. This is a complex optimization process in which information granules are adjusted to a given evidence *u* allowing to construct a satisfactory approximate solution.

We would like to stress that for real-life applications constructive methods of searching for information granules seem to be crucial.

4.3 Examples of Information Granules

In this section we would like to illustrate a general idea of information granule construction. Let $A = (U_0, A \cup \{d\})$ be a decision table [4] and another information system $C = (U, C)$, where $U0 \subseteq U$ be given. We assume here that for any $a \in A$, a function $P_{C,a}$ is given such that $P_{C,a} : INF(C) \to PART(a)$ where $PART(a)$ is the set of partial orders on $Va \times Va$ and $INF(C) = \underset{c \in C}{X} V_c$. The intuitive meaning of $P_{C,a}$ is the following: if $P_{C,a}(u) = \leq a,u$ and $v \leq a,u\ v'$ then (having the evidence u) v' is a correct value of a no less likely than v (see [7]). In the simplest case $\leq a,u$ is a linear order as the following example is showing.

<u>Example 1</u> Linear order $\leq a,u$.

Assume a decision system $(U, C \cup \{a\})$ is given for any $a \in A$. Then we define a partial order $\leq a,u$ as follows

$$v \leq_{a,u} v' \mathit{iff}\ card(u_C \cap \{x \in U : a(x) = v\}) \leq card(u_C \cap \{x \in U : a(x) = v'\}) \qquad (4.1)$$

where $v, v' \in Va$, $u \in INF(C) = \{Inf_C(x): x \in U\}$ and $u_C = \{x \in U: Inf_C(x) = u\}$. One can choose a threshold $t \in (0,1)$ and consider only values supported by $100*t\%$ of objects from u_C i.e.

$$v, v' \in V_a^t = \{v \in V_a : card(u_C \cap \{x \in U : a(x) = v\}) \geq t * card(u_C)\}. \qquad (4.2)$$

A parameter t should be tuned up in the optimization process.

One can consider a more general case with $\leq a,u$ defined in a family of subsets of Va.

<u>Example 2</u> Partial order $\leq_{u,a}^{t,k}$ with two thresholds $t, k \in (0,1)$.

Assuming notation from Example 1 we define

$$\delta_a(u) = \{v \in V_a : \exists x \in u_C \, a(x) = v\} \tag{4.3}$$

And,

$$\text{supp}_{u,a}(v) = \{x \in U : a(x) = v\} \cap u_C . \tag{4.4}$$

Now, a family *F(u,a,k,t)* of subsets of *Va* can be defined by

$$X \in F(u,a,k,t) \tag{4.5}$$

iff the following three conditions are satisfied

$$X \subseteq \delta_a(u) \tag{4.6}$$

$$card(X) \leq k * card(\delta_a(u)) \tag{4.7}$$

$$card\left(\bigcup_{v \in \delta_a(u) - X} \text{supp}_{u,a}(v) \right) \leq t * card(\delta_a(u)) \tag{4.8}$$

Hence we consider subsets of *Va*, which are enough *small* and supported by a *large* part of objects from u_C (this is an analogy to the boundary region thinning technique [48], [25]). We assume

$$X \leq_{u,a}^{t,k} Y \; iff \; Y \subseteq X \; for X, Y \in F(u,a,k,t). \tag{4.9}$$

Again the parameters *k, t* should be tuned up in the learning process.

5 Implementation of Rough Control in HVDC System

In Chapter 2, we have investigated the HVDC model and its control, and revealed the weakness of a traditional HVDC control scheme based on a classic PI controller. We then propose a rough set control scheme to address the weakness. In Chapters 3 and 4, we have reviewed the theory of rough set control and the principles of granular computation.

This chapter deals with the simulation of a typical HDVC system and the implementation of the rough control scheme. We will expose in detail the design methodology of our rough control scheme, which utilizes the combination of rough sets and granular computation. As an example, we will implement the rough control on the rectifier side, and illustrate that such a rough control scheme is applicable to constant current (CC) control on HVDC systems. Additionally, we will evaluate the performance of the new rough control scheme under different real-time scenarios, by adjusting the control parameters with the help of various generated decision rules.

This chapter comprises 5 sections. Section 5.1 describes in detail the rough control scheme of the HVDC systems. It consists of five components, i.e., PI controller, plant, data collection, rough set tuner, and rough controller. General introduction of all components is presented in this section. The actual simulation of a typical HVDC system (plant) with a classical PI controller is done in Section 5.2. Data collection that is the first step to apply rough control to the HVDC system is introduced in Section 5.3. After that, the rough set tuner, which establishes decision tables and derives decision rules, is discussed in Section 5.4. Finally, Section 5.5 investigates the rough controller. The rough controller performs the control action on the adaptive PI controller, which in turn applies actual CC control in the simulated HVDC system.

5.1 Overview of Rough Control Scheme

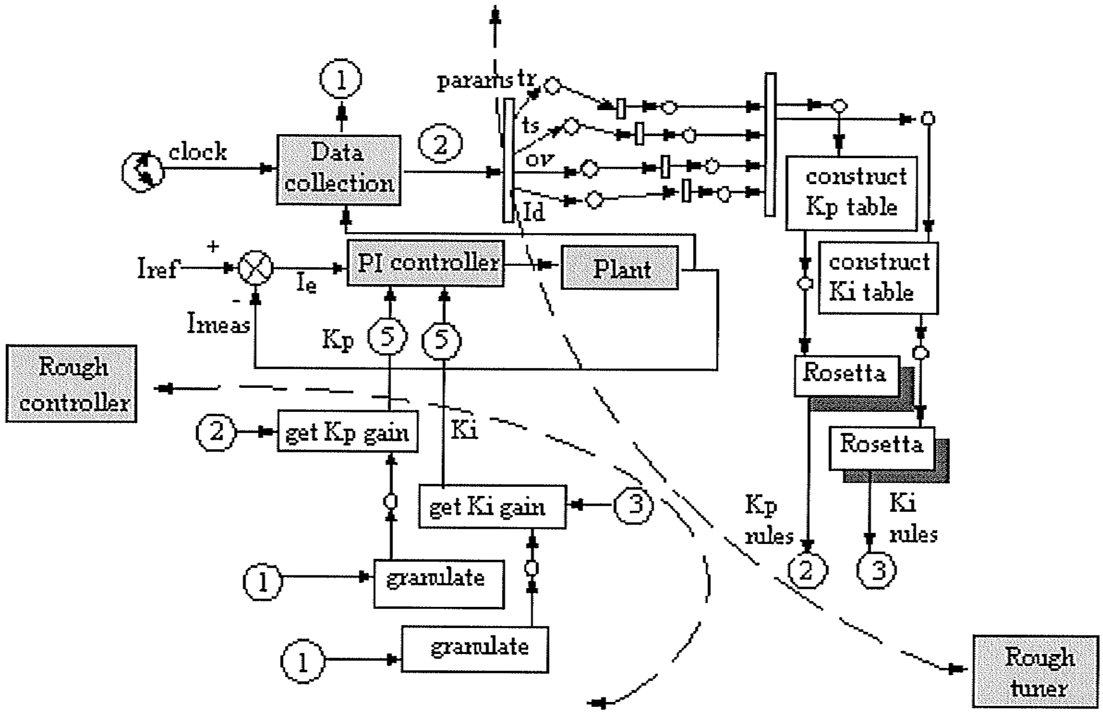

Fig. 5-1 Architecture of real-time rough control system

The architecture of real-time rough control system is shown as Fig. 5-1, which consists of five parts. The PI controller and the plant (HVDC system) constitute a traditional HVDC transmission and control system, which has been investigated in Chapter 2. The other three parts, data collection, rough set tuner, and rough controller, constitute our rough control scheme. On the one hand, data collection observes the plant, collects all responses from the plant, and analyzes all responses. On the other hand, the rough tuner generates decision tables and control rules by exploiting data obtained from data collection. Additionally, it is the rough controller that actually controls the behaviors of the PI controller.

- **Data Collection**

Data collection monitors the plant, and samples real-time responses from the plant. We will define an index of performance (IP) as "a functional relationship involving system characteristics in such a manner that the optimum operating conditions may be determined from it." Since optimum performance is based upon the IP used, the choice of a suitable IP for defining an optimum design (or an adaptive loop, as shown later) is a critical step to take. For that reason, only those most general interested and important characteristics, such as overshoot, rise time, and settling time, will be extracted and analyzed by data collection, and used by both the rough tuner and rough controller.

- **Rough Tuner**

A rough tuner consists of two main processes as follows.

❖ Roughly fuzzy Petri net, sensors, and approximate time window

In summary, a Petri net selects a subset of data collected by data collection and feed them into the next process to construct the required decision tables. In a Petri net, there exist a wide variety of sensors that granulate measurements needed to make decision tables. Sensors serve to aggregate and evaluate information (e.g., measurements from control systems), and provide a means of drawing conclusions based on various dependencies among sensor readings. In an approximate reasoning system, sensors are modeled with operators from fuzzy set theory. Sensors typically assess the degree of membership of an observation in a granule conceptualized as a cluster (collection, clump) of similar values [57], [76]. We call this process as data granulation.

❖ Decision tables, decision rules, and approximate reasoning system

The idea of information granules and rough sets is the creation of an approximate reasoning system (decision tables and rules) for making decisions. We will use the output of the sensors as the attribution and the corresponding Ki, Kp as decision column to construct the required decision tables. In particular, two decision tables, separately for Ki or Kp, will be constructed, and therefore two sets of rules will be established.

Combinations of sensor outputs and dependencies among sensor computations are expressed as rules. Rough sets theory provides a means of deriving rules from decision tables [26], and such a software package Rosetta is publicly available. Data from the decision tables go through Rosetta and result in a group of decision rules.

- **Rough Controller**

Three factors are part of the design of a rough controller to achieve rapid fine-tuning on control. They are real-time data, data granulation, and decision rules. In our case, the rough tuner derives the Ki and Kp correction rules for a PI controller by using a roughly fuzzy Petri net and Rosetta. Each step response of the rough controller is obtained from the firing of a pair of rules used to select appropriate changes in proportional and integral gains of the PI controller. Tuning information from a number of simulations was used to build an information system and to generate the tuning decision rules. Rough controller exploits these rules to tune the HVDC PI controller on-line. New information collected after each tuning are called real-time data, and are immediately added to the rough control system. Dynamic reductions based on real-time data are employed to modify decision rules in a timely way.

As we know, data learning and data training are two necessary steps in a real-time control system that exploits rough sets. A high level flowchart of the methodology underlying both the construction and computations performed by the rough control system is given in Fig.5-2. From dataflow's viewpoint, we can also partition the rough control scheme into three processes, data collection, data learning (state 2, right one), and data training (state 1, top one). On the one hand, data learning makes use of the rough set tuner to establish a decision system. This decision system is not a static system. It will be updated whenever a new decision rule can be established by the rough tuner and based on real-time responses from the data collection. As a result, we call this decision system a real-time decision system. On the other hand, data training exploits the rough controller to apply decision rule onto the control acceptant, i.e., PI controller. Whenever the real-time decision system is updated, new decision rule will be applied to the control of the PI controller, and generated new response from the plant. The new response will then be collected by data collection again, and thus it starts a new round of data circulation, data learning → data training → data collection. Therefore, a real-time dynamic loop of control-decision-control is established.

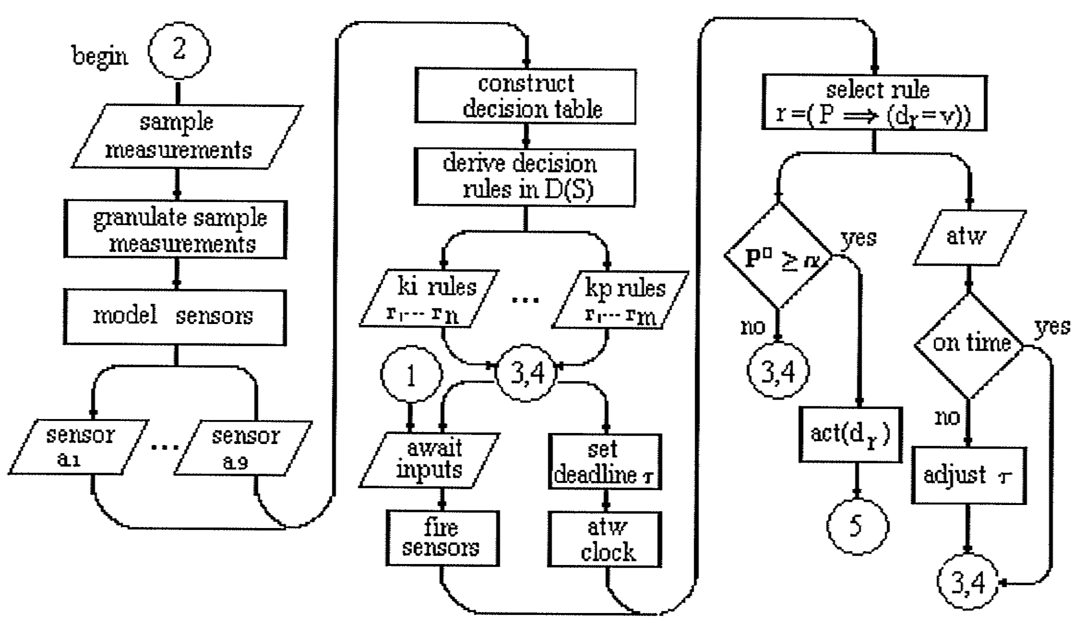

Fig. 5-2 Flowchart of approximate time rough control system

This flowchart depicts in detail all processes from data collection to data learning and to data training. It also explains the role of approximate real window and Petri Net in the implementation of the rough controller.

Let S = (U, A) be a decision system with a set of simulation cases U, a set of sensors A (the granulated measurements), and the decision d (di, dp). The construction of a decision system table and derivation of rules begins in state 2 and is completed with the derivation of rules in set D(S) for a system S before entering state 3 or 4. Actual approximate real-time reasoning begins in state 3 or 4, where reading inputs from experiments and selection of a timer setting t is done in parallel if necessary. Then enabled sensors evaluate inputs concurrently with the operation of an approximate time window (atw). Next an appropriate rule r is selected based on sensor readings. Let $r = (P \Rightarrow (d\, r = v)) \in D(S)$, where P is a premise of rule r. The notation P^0 is shorthand, which denotes the degree-of-membership of sensor readings (referenced in P) in corresponding granules.

Let $a \in A$, $x \in U$, and let $g_i\,(a_i\,(x)) \in [0,1]$ for membership function g_i for sensor a_i . Then $P^0 \geq \alpha$ means that $\forall a \in A.\ P\,(g_i\,(a_i\,(x)) \geq \alpha$. In the case P is a relationship with $g_i\,(a_i\,(x))$ and α is the conditions of the premise for a rule sensor readings satisfy, performance of some action act (dr) governed by the value of dr is carried out. Otherwise, the system waits for new sensor readings.

5.2 HVDC System with a Classical PI Controller

To develop and evaluate our new rough controller, we start with the simulation of a HVDC system with a classical PI controller as demonstrated by Fig. 5-3.

5.2.1 Description of HVDC Transmission System

- **HVDC System**

A basic two-terminal monopolar HVDC system with earth return is shown in Fig. 5-3. The 500 MW dc system transfers energy in the form of high-voltage direct current 2 kA and 250 kV, to the inverter ac bus through a 200 km dc transmission line. The rectifier substation consists of a converter bridge with a PI control system. The ac system has a short-circuit level of 5000 MVA, which is 10 times larger than the transmitted dc power, hence it is considered a strong ac system.

Equivalent	345 KV	5000 MVA		
Transformer	345:212 KV			
dc system	500MW	2.0 KA	250KV	200KM
Inverter	241.5KV			
Leakage impedance	12%			

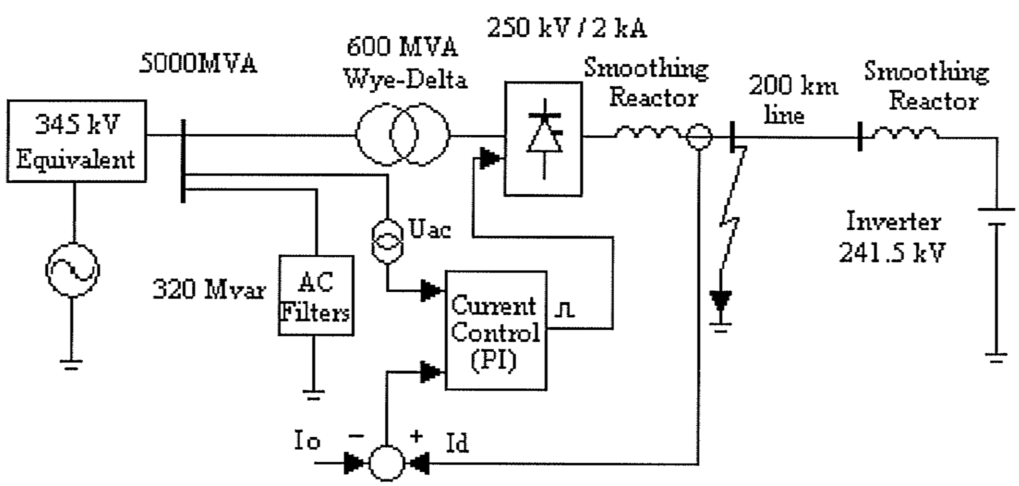

Fig. 5-3 Basic architecture of HVDC system

- **Formulations and Calculations in Steady-State**

To obtain the desired steady-state values and to reach them promptly at the beginning of the simulation, some calculations and artifices are needed.

The following values are known under the above HVDC system (the meaning of each symbol will be explained in the following part):

$Vd := 250$ kV $\quad Pd := 500$ MW $\quad T := \frac{345}{212}$ $\quad TMVA := 600$ MVA

$\eta := 0.12$ $\quad a := \frac{20.1}{180} \cdot 3.14$ rad $\quad Vlp := 345$ kV $\quad Rdc := 5\ \Omega$

Based on the theory of power system, the following formulations Eq. (5.1) are used to calculate the values of needed parameters:

$$Vl := \frac{Vlp}{T}$$

$$Id := \frac{Pd}{Vd} \qquad (5.1)$$

$Vd = 249.499$ kV

$Einv = 241.499$ kV

$$Xc := \eta \cdot \frac{Vl^2}{TMVA}$$

$$Vd6p := \frac{3 \cdot \sqrt{2}}{\pi} \cdot Vl \cdot \cos(a) - \frac{3}{\pi} \cdot Xc \cdot Id$$

$$Vd := Vd6p$$

$$\mu := \operatorname{acos}\left(\cos(a) - \frac{\sqrt{2} \cdot Xc \cdot Id}{Vl}\right) - a$$

$$Einv := Vd - (Rdc \cdot Id)$$

The following results in Eq. (5.2) are calculated from the above formulations:

$Xc = 8.82$ kV/kA (5.2)

$Id = 2$ kA

$Vl := 212$ kV

$\mu = 0.258$

where,

Rdc	Resistance of the line and smoothing reactance
Id	Direct current
Vd	Direct voltage
Xc	Commutation impedance
Vl	Line to line voltage on the second side
Vlp	Line to line voltage on the primary side
Vd6p	Direct voltage for each 6 pulse bridge
Pd	Direct power
T	Transformer turns ratio
TMVA	Transformer rated power
η	Leakage impedance
μ	Overlap angle
a	Firing angle
Einv	Voltage on the inverter side

5.2.2 Simulation of the HVDC System

To simulate the HVDC system in experiments, we construct the model shown in Fig. 5-4 with Matlab Simulink Power system tools. The model is used to illustrate the response of the HVDC System with a PI current control system to three conditions under that HVDC system recovery to the steady state. It consists of three main parts, which will be depicted as follows.

- Transformer: The 600 MVA three-phase converter transformer is represented by a linear model connected in Y/delta. The winding impedance of 0.12 p.u. is concentrated on the thyristor side.

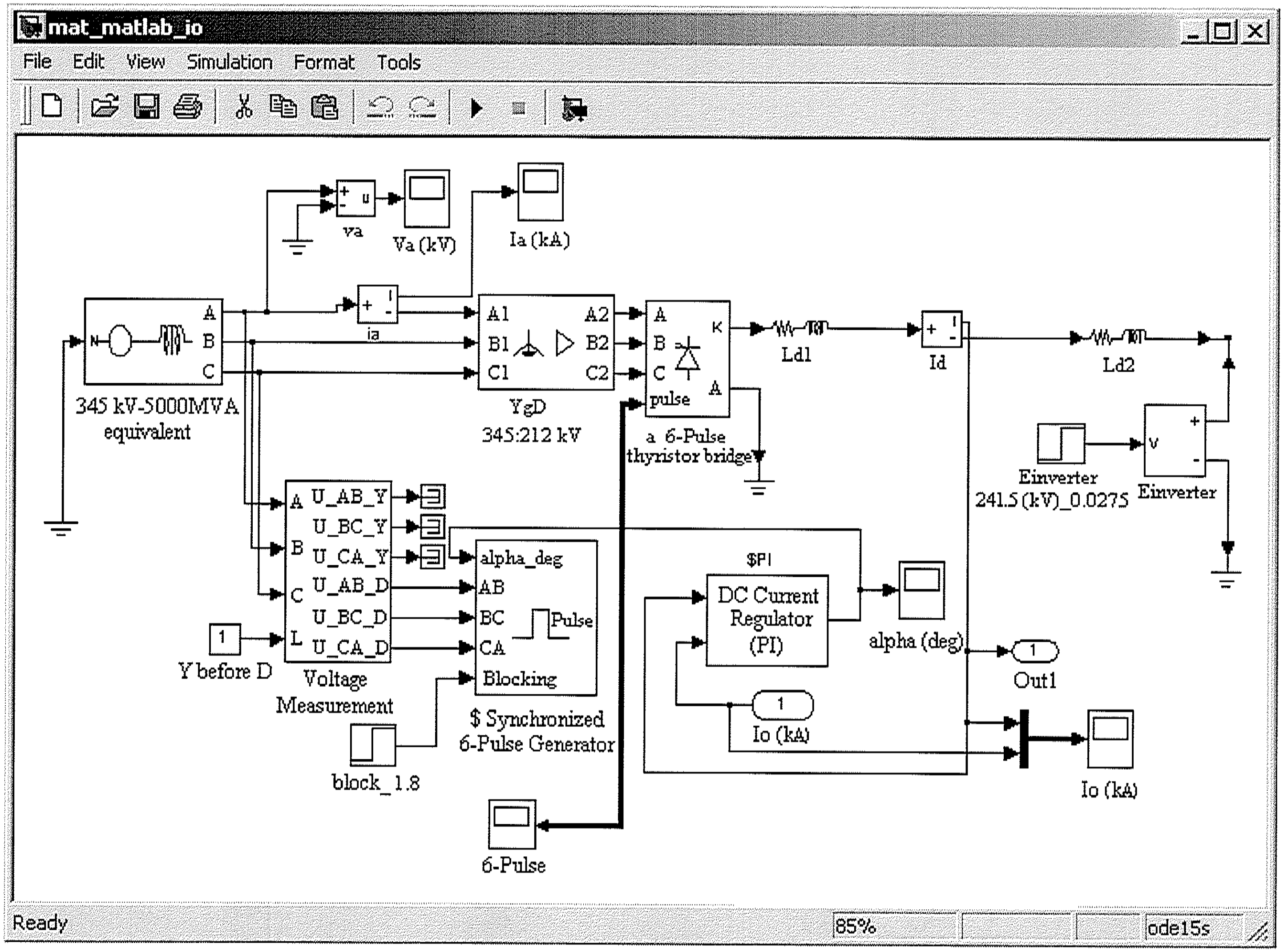

Fig. 5-4 HVDC system simulation model in Matlab Simulink

- Thyristor bridge: The six-pulse thyristor bridge uses six of the simple thyristor models connected in a three-phase bridge configuration. Snubbers are connected in parallel as damping circuits for each valve. They limit the rate of rise and peak value of inverse voltage across the thyristor valves.

- Current control system: It is composed of a current regulator, the voltage measurement subsystem, and synchronized pulse generator.

In order to fully evaluate the performance of the HVDC system, the following tests are conducted on the system to reveal the system's responses to varied changes.

- Current order reduction and restoration (20%)
- Inverter ac side voltage increase from zero to rated value
- The dc line fault and recovery

All changes happen in the time sequence as listed in Table 5-1.

Time (sec)	0.0275	0.4	0.7	1.2	1.8	2
Object	E_{inv}	I_o	I_o	Dc fault	Firing pulse	Simulation
Original value	0	1.0p.u.	0.8p.u.	Stop	Start	Start
Changed value	241.5kV	0.8p.u.	1.0p.u.	Start	Stop	Stop

Table 5-1 The sequences and values of various changes

Since we are only interested in the dc current and firing angle responses, only these two responses are separately presented in Fig. 5-5 and Fig. 5-6. They illustrate how the dc current and the firing angle respond to varied changes.

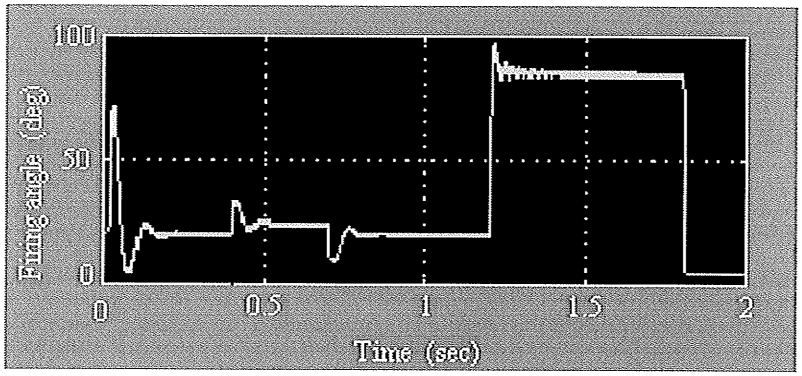

Fig. 5-5 Firing angle response

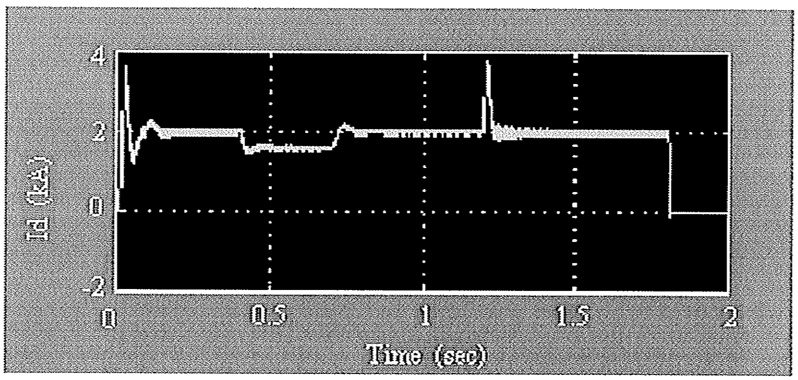

Fig. 5-6 Current Id response

5.2.3 Simulation of the Classical PI Controller

In the thesis, the rough control scheme will be evaluated in a HVDC system, where CC control is performed as an example. (Similarly, the evaluations of the rough control scheme based on other situations can also be carried on.) Therefore, the role of the controller is to change the firing angle value for keeping constant direct current (Id). The input to the controller is the measurement Id, the order value Io, and controller's integral and proportional gain parameters Ki and Kp. The output from the controller is a changed firing angle. The model shown in Fig. 5-7 is the model of a PI controller in Matlab Simulink.

- Current regulator

It has a proportional and integral characteristic (PI). It should have a high enough gain for low frequencies (about 10 Hz) to maintain the current response (Id) equal to the current order (Io), as long as α is within the minimum and maximum limits (5° and 16°). Also the current control system should be stable and fast.

- Ki and Kp

Ki and Kp are the parameters of integral gain and proportional gain respectively for a PI controller. They are constants in a classical PI controller. How to adjust and optimize them is the main task of our rough controller.

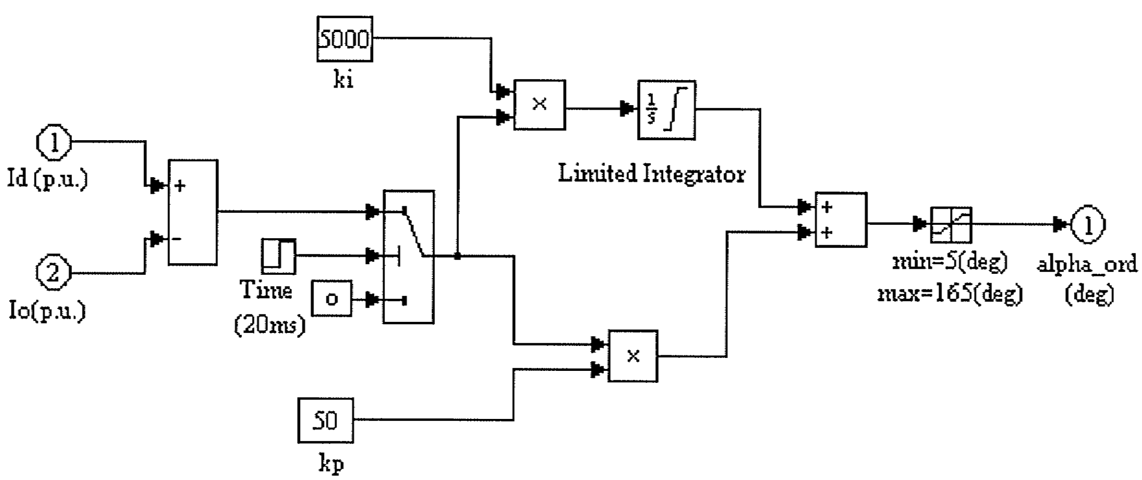

Fig. 5-7 Classical PI controller simulation model in Matlab Simulink

5.3 Data Collection

Data collection is the first step to apply the rough sets to HVDC control. It helps us find the information under different system conditions. The obtained information is used by data learning and data training to fine-tune the PI controller. The process to obtain needed information is named as "data collection", which is performed through a process called "select suitable IP".

5.3.1 Selection of Suitable IP

Since we are interested in CC control in the thesis, we need only to observe the variances of Id. Id is the measurement of direct current output from the HVDC system. As step response under the fault we assumed, Id can also be used to maintain the constant current in CC control. Therefore, Id is the concerning object in this thesis. Our work is to get the step response Id, and then control the HVDC system to maintain a constant current with a reference value Io.

However, the step response Id can have different values with different (Ki, Kp) pairs in the HVDC system, and will keep dynamically changing in response to the change of control parameters. The change of Id makes it very hard to model control-responses and identify their variances from the ideal case with a great accuracy.

Rough-logic-based data collection is introduced here to cope with this dilemma. As defined in the end of Chapter 3, an index of performance (IP) is defined as " a functional relationship involving system characteristics in such a manner that the optimum operating conditions may be determined from it". From the viewpoint of rough set theory, IP is the extracted features from the concerning object (Id in our case). The basic theory after IP is that, if we can obtain a few representing values, which reflect all important characteristics of the observed object, we then can reveal the internal relationship between the concerning object and the concerned system (HVDC in our case), by revealing the relationship between the IP and the system. We call this process "the selection of suitable

IP". In the thesis, we define the following three parameters as suitable IP for step response Id.

- Rise time (tr): It is defined as the time when the step response reaches 90% of its steady-state value for the first time. The tr indicates response speed to step inputs. Simulation is the standard means for measurement.

- Settling time (ts): It is defined as the time necessary for the output to settle and remain within ± 10% of the final value. The ts is a measure of the system-damping factor as well as of the speed of response. Simulation is suggested for measurement. Here we measure the settling time relative to the rise time, i.e. the clock for ts is reset at t = tr.

- Overshoot (ov): It is the biggest deviation of step response from steady state qss after the step response reached the tolerance band qss±ε for the first time. Overshoot is divided by the height of the step demand to obtain a relative quantity. In addition, percent overshoot used in all experiments of the thesis is defined as

$$overshoot = \left[\frac{peak\ \ response\ \ -\ \ final\ \ value}{final\ \ value}\right] \times 100 \tag{5.3}$$

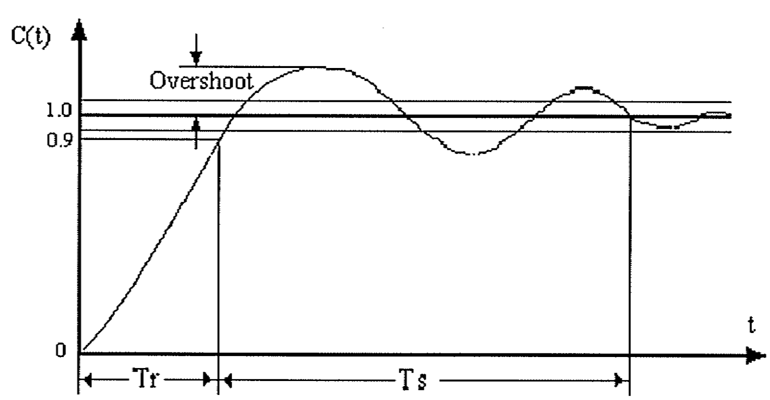

Fig. 5-8 IP defined from the step response

Fig. 5-8 illustrates the IP defined from the step response of Id. These three values tr, ts and ov are corresponding to a pair of Ki and Kp. Time itself is measured relative to a clock, which measures durations in the context of information granules named early, on time, and late.

5.3.2 Multiple IPs and System Initialization

As we explained, one IP (tr, ts, ov) can be obtained from one pair of (Ki, Kp). To build an information system and perform our experiments, we need establish an initial decision system with multiple IPs. It is done by observing the step responses of Id from systems with different controller gains (Ki, Kp). Ideally, we should initialize the control system with a large number of (Ki, Kp) pairs, which should be big enough to generate as many typical system step responses as possible.

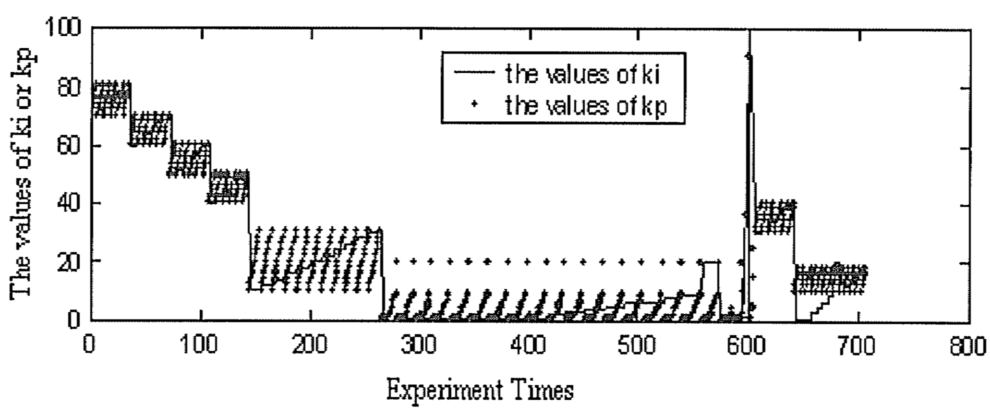

Fig. 5-9 Distribution of the values of ki and kp in simulation experiments

In this thesis, we first select the center values Ki* = 5000 and Kp* = 50, or denoted by (Ki*, Kp*) = (5000, 50). With the center values and assuming that Ki = ki x Ki* and Kp = kp x Kp* (ki, kp are the factors of Ki, Kp), we obtain a group of initial values of (Ki, Kp) by taking different parameters ki and kp. The distributions of ki and kp are drawn in Fig. 5-9. The X-axis is the series number of our experimental times and the Y-axis is the values of ki or kp. With the initial set of (Ki, Kp), we then simulate the HVDC and all responses are recorded. As we know, for each unique combination of Ki and Kp, we will get the corresponding step response of Id.

Some of these step responses may be almost similar, but most of them are more likely different from each other. These recorded responses are compared. All typical responses are retained and similar ones are discarded. It is a manual process. Of course, the final set of step responses obtained in this way does not include all possibilities. However, the sampling is good enough to reflect the important features of IP around the center (Ki*, Kp*). Fig. 5-10 shows some typical step responses Id from our experiments with different pairs of ki, kp.

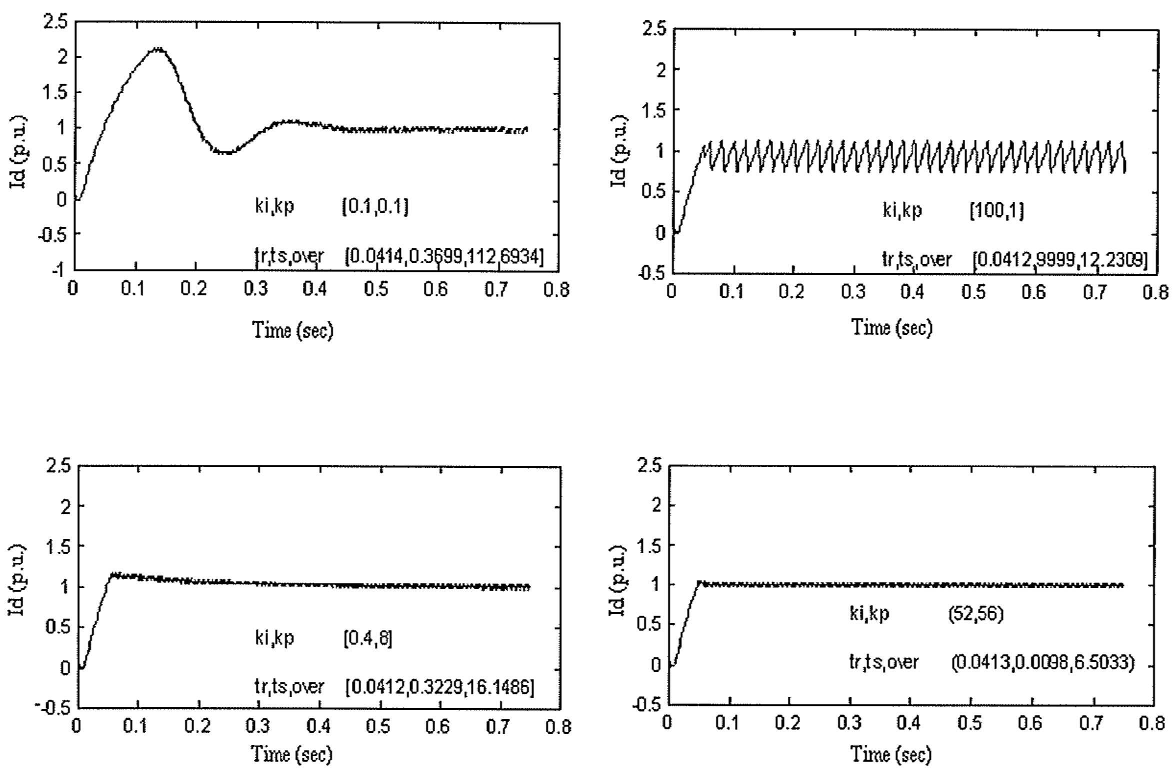

Fig. 5-10 Four examples of typical step responses

5.4 Rough Set Tuner

In this section, we will deal with the simulation of the rough set tuner. The main functions of a rough set tuner comprise data granulation, decision table construction, and decision rules generation. Rules of ki and kp, which are the final results of the tuner, are the essences of adapting the parameters of PI controller.

5.4.1 Granulate IP

In data collection, IP (such as tr, ts and ov) are used to characterize the step response Id. When all of IP are collected, they are fed into sensors by the rough tuner to be granulated. There are nine sensors, denoted as a1…a9, in which a1, a2, a3 are overshoot sensors, a4, a5, a6 are rise time sensors, and a7, a8, a9 are settling time sensors. Taken collectively, each trio of sensors constitutes what is known as an approximate time window (atw).

These membership functions for granular computation are made by a series of fuzzy membership function whose common types are Triangular, Monotonic, Gaussian and Trapezoidal. Overshoot sensors ai, $1 \le i \le 3$ take typical fuzzy membership function Trapezoidal for granular computation. In this case, the overshoot is a function of distance. Meanwhile, rise time and settling time sensors ai, $4 \le i \le 9$ take Gaussian function for granular computation. In this case, rise time and settling time are a function of time span.

The distribution of degree of membership values in a granule associated with a sensor ai, $4 \le i \le 9$, is assumed to be approximately normal in a Gaussian distribution with mean (modal point) m and standard deviation s (spread). Let g, x is the name of a granule associated with sensor ai and measurement (for example, overshoot at given instant in time), respectively. Hence, the membership function used in modeling sensor is given by

$$g(x) = e^{\left(\frac{-(x-m)^2}{s^2}\right)} \qquad (5.4)$$

Eq. (5.4). In modeling sensors a4,..., a9, we also introduce a modulator r and strength-of-connection w. A modulator imposes a threshold on stimuli, and a strength-of-connection raises or lowers the impact of an input in an atw. Then atw sensor ai is modeled as an aggregation of a fuzzy implication value and strength-of-connection w, in Eq. (5.5)

$$a_i(x) = (r \rightarrow g(x)) \text{ s w, where } (r \rightarrow g(x)) = \min\left(1, \frac{g(x)}{r}\right) \tag{5.5}$$

The granular computation results are shown in the following three sub-figures. The x-axes are respectively overshoot, rise time, or settling time. All of them are a crisp set. The y-axes are the corresponding membership grade of any value in the crisp, which is a granular set and only takes a value in the interval [0,1]. For example, the sensor 1 (shown as the solid line in Fig 5-11(a)) depicts granular computation of short overshoot. It shows that the membership grade has a high value when overshoot is short. Meanwhile, the membership grade decreases with the increase of overshoot, after overshoot is over a certain limitation. The sensor 2 (shown as the dashed line in Fig5-11(a)) demonstrates another situation of the membership grade, where overshoot is medial. It has a lower value when overshoot is very short. The value increases with the increase of the overshoot. Once the overshoot exceeds a certain value, the value of membership grade stops to increase and make a turn for decrease. But the value is biggest when overshoot is medial. Similarly, the following two figures Fig. 5-11(a) and Fig. 5-11(b) show the granular membership functions used for processing rise time and settling time, respectively.

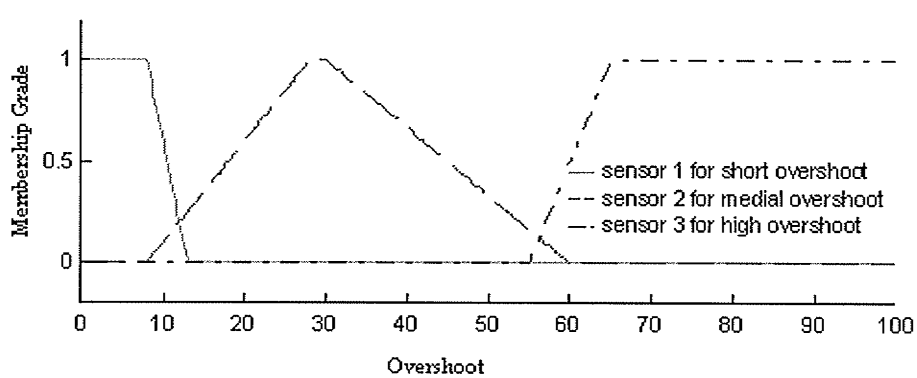

Fig. 5-11(a) Granular curve for overshoot

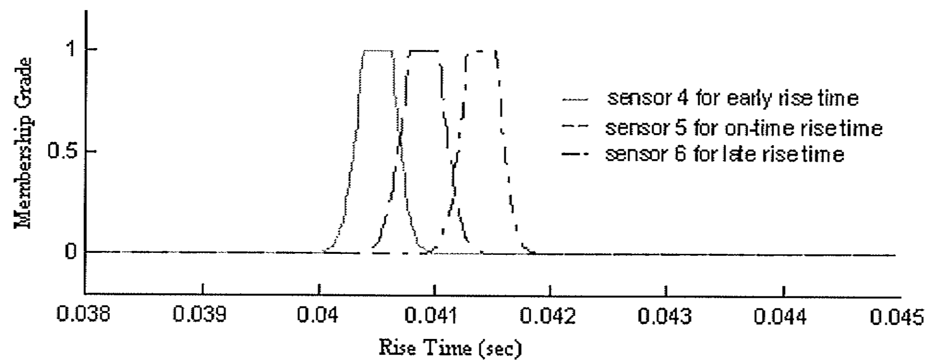

Fig. 5-11(b) Granular curve for rise time

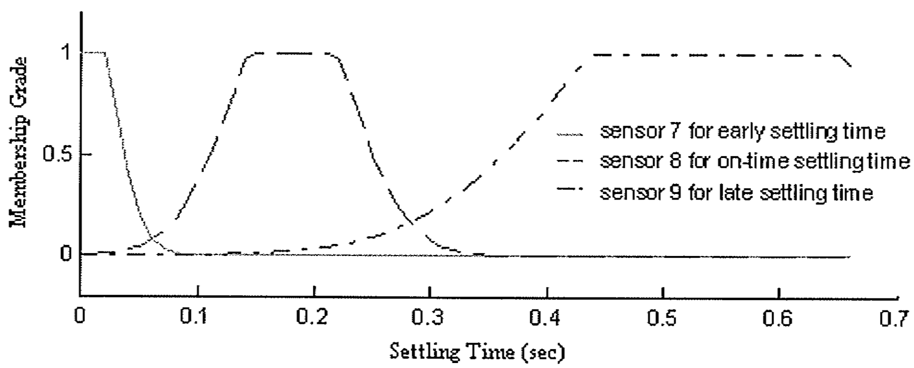

Fig. 5-11(c) Granular curve for settling time

5.4.2 Decision Table

The first step to establish a decision table is to characterize responses from the system for different controller gains, which has been done by data collection and data granulation. For each observed step response (i.e. Id is our case), we decide in the decision table the correction factors for both proportional and integral gains, which adjust the controller parameters in order to improve the performance. Controller parameter values (Ki and Kp) are inserted in a decision table by using a form of pattern recognition. Each decision value indicating a change in Ki and Kp is a judgment about the controller performance from a measured step response, and the observed response is compared to an ideal response. A decision table is constructed with nine condition attributes: a1, a2, a3 for granulations of overshoot measurement, a4, a5, a6 for rise time granulations, and a6, a7, a8 for settling time granulations. Sample rows from a rough controller tuning information table are given in Table 5-2 and Table 5-3.

	a1	a2	a3	a4	a5	a6	a7	a8	a9	di
1	0.00	0.01	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1
2	0.00	0.22	0.53	0.00	1.00	0.03	0.00	0.00	1.00	5
3	0.00	0.05	1.00	0.00	0.70	0.01	0.00	0.84	0.00	5
4	0.00	0.60	0.15	0.00	1.00	0.02	0.00	0.99	0.00	1
5	0.00	0.22	0.53	0.00	0.29	0.00	0.00	0.64	0.00	2

Table 5-2 Decision table for Ki

	a1	a2	a3	a4	a5	a6	a7	a8	a9	dp
1	0.00	0.01	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1
2	0.00	0.22	0.53	0.00	1.00	0.03	0.00	0.00	1.00	2
3	0.00	0.05	1.00	0.00	0.70	0.01	0.00	0.84	0.00	1
4	0.00	0.60	0.15	0.00	1.00	0.02	0.00	0.99	0.00	2
5	0.00	0.22	0.53	0.00	0.29	0.00	0.00	0.64	0.00	5

Table 5-3 Decision table for Kp

5.4.3 Obtain Decision Rules

Decision tables like Table 5-2 and Table 5-3 are processed by the rough set tool ROSSETA to derive rules to change proportional gain (Kp_new = Kp_old x dp), and integral gain (Ki_new = Ki_old x di). A sample of the rules is given in Table 5-5 and Table 5-6, and the intermediate process the reduction of attributes is shown in Table 5-4.

It can be noted that decision rules are derived from the real-time decision system table. To ensure the efficiency of decision rules, decision tables should be based on a sufficient number of prototypical experimental measurements on the controller's performance and the appropriate granulation of these measurements.

	Reduct for ki	Reduct for kp
1	{a2,a5,a8,a9}	{a2,a4,a5,a8}
2	{a2,a5,a6,a9}	{a2,a5,a6,a8}
3	{a2,a4,a5,a8}	{a2,a5,a8,a9}
4	{a2,a5,a7,a8}	{a2,a5,a7,a8}

Table 5-4 Reduct for Ki and Kp

	Rules for Ki
1	a2(0.01) AND a5(0.00) AND a8(0.00) AND a9(0.00) => di(1.00) OR di(2.00)
2	a2(0.22) AND a5(0.01) AND a6(0.00) AND a8(0.56) => di(5.00)
3	a2(0.01) AND a5(0.21) AND a7(0.00) AND a8(0.22) => di(2.00)
4	a2(0.22) AND a5(0.00) AND a7(1.00) AND a8(0.00) => di(0.50)

Table 5-5 Rule for Ki

	Rules for Kp
1	a2(0.01) AND a4(1.00) AND a5(0.00) AND a8(0.00) => dp(1.00) OR dp(1.20)
2	a2(0.22) AND a5(0.01) AND a6(0.00) AND a8(0.56) => dp(2.00)
3	a2(0.60) AND a5(0.22) AND a7(0.00) AND a8(0.55) => dp(4.00)
4	a2(0.05) AND a5(0.01) AND a7(1.00) AND a8(0.00) => dp(3.00)

Table 5-6 Rule for Kp

It should also be noted that each application of a relative rule to an observed step response of the control system results in changes in both Ki and Kp. Therefore, both rules for Ki and Kp will be updated at the same time.

5.5 Rough Controller

A rough controller will apply the derived decision rules to the real-time CC control. During real-time control process, the adjustment of the parameters Ki, Kp of the PI controller is done through looking up the rule tables and firing the suitable di, dp rules according to the measurements.

5.5.1 The Diagram of the Whole System

The following diagram depicts the control process including use of decision rules according the Id response and adjustment of the parameters Ki and Kp.

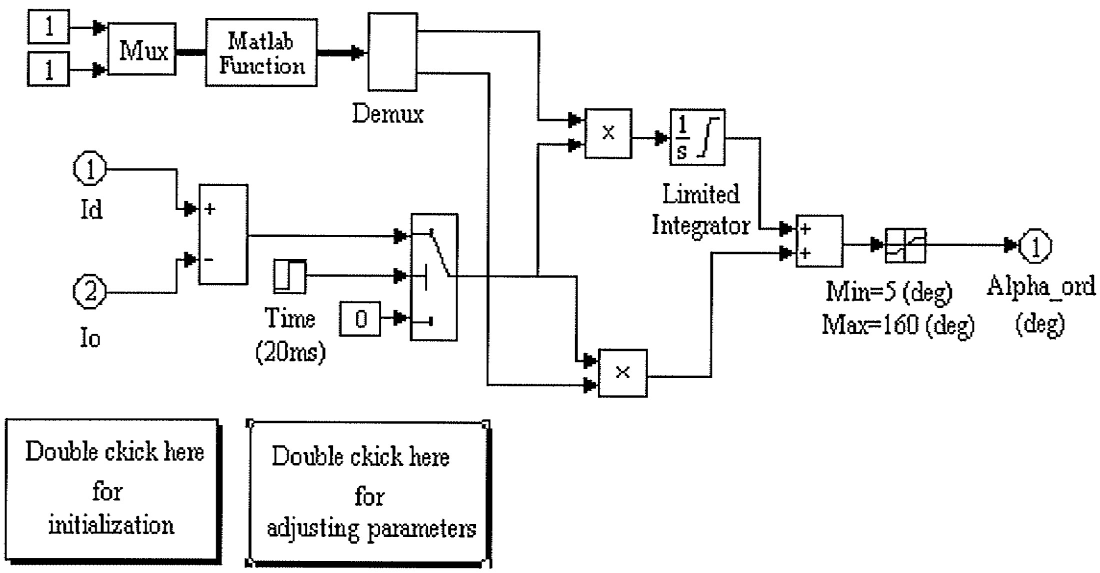

Fig. 5-12 Rough controller simulation model in Matlab Simulink

Circle 1 and circle 2, which are the input of the control system from HVDC system (plant), are respectively the order Id (or called reference Id) and the measurement Id. The bottom left rectangles have the functions of initialization the system under original ki, kp and adjusting ki, kp by rough control scheme. The inputs of the rectangle “MATLAB Function” are clock; reference Id, and error Id. Its outputs di and dp are used to adjust ki and kp. Its function is to get a pair of suitable di and dp. Through multiplications Ki x di and Kp x dp, the system controller gains (Ki, Kp) are changed.

5.5.2 Choice of a Pair of Suitable di, dp

In this section, we consider a method to determine changes in the system controller gains. There is a rule-firing algorithm to direct our choice of system controller gains (Ki, Kp), which is described as follows:

Step 1. Let x, ai, aj, ak, vai, vaj, vak be an experimental value observed during actual operation of a control system, sample decision system condition sensors for a sample control rule D(S), and sensor values from decision system table (U, A∪{d}, V), respectively. Let s be defined as a sum s = (ai(x) - vai) + (aj(x) - vaj) + (ak(x) - vak), where x is an input value (e.g. observed overshoot, rise time, or settling time) evaluated with sensor ai in A (for example) to produce a particular value vai.

Step 2. Let n, m be the number of Ki, Kp rules, respectively. Let si, $1 \leq i \leq n$, sj, $1 \leq j \leq m$ be sums of the form introduced in step 1 relative to n rules for Ki and m rules for Kp, respectively. Then let nki, mkp be functions defined as follows as follows:

nki: s1, ..., si, ..., sn → i such that d[i] = min(s1, ..., si, ..., sn)

mkp: s1, ..., sj, ..., sm → j such that d[j] = min(s1, ..., sj, ..., sm)

In other words, nki, mkp each finds the index (i, j) of the smallest sum, which identifies the premise of a rule, which is closest to the measured condition during the operation of a controller.

Step 3. Let Ki, Kp be the current values of proportional and differential coefficients. Then compute Ki_new = Ki_old × d[i] and Kp_new = Kp_old × d[j].

At this point, it should be observed that variations of step 3 of the rule-firing algorithm are possible. First, it has been found that it is helpful to change Ki, Kp only if the percent of overshoot exceeds some k (e.g. k = 0.1). Second, performance of the controller can be improved by constituting an experimental environment that will evolve. Such refinements of this algorithm are outside the scope of this thesis.

5.6 Summary

In this chapter, we have explained in detail how to construct the rough controlled HVDC system. The term "rough control scheme" is used to depict the whole rough control logic, which is applied to the plant and performed together by a data collector, rough set tuner, rough controller, and adaptive PI controller. The simulation details of individual components have been presented and explained. All analyses and explanations in this chapter are based on the static analysis of the system. The analyses on the dynamic behavior of the system and the simulation results obtained by tracking the dataflow in the system will be presented in the next chapter.

6 Experimental Results

We have constructed the simulation environment to apply rough set theory to the control of the HVDC transmission system. In summary, tuning information from a number of simulations is used to build an information system and to generate tuning decision rules. A suitable set of rules is used in real-time to tune a HVDC CC controller in order to improve HVDC performance. This chapter will present experimental results, which were produced under different control conditions.

6.1 Simulation Diagram

We establish our rough control system as described in Chapter 5. For the convenience of users to use the rough HVDC control system, we set up a user interface as shown in Fig. 6-1. The interface has the ability to get the system initialization from user's input of various system parameters such as Io, initial ki and kp, and then construct a basic decision system. It can extract features from step response and granulate those features. It can also generate decision tables and rough set rules on the fly. The key part is that it can then apply rough set rules to give the real-time decision, and guide the rough controller and adaptive PI controller to control the behavior of system.

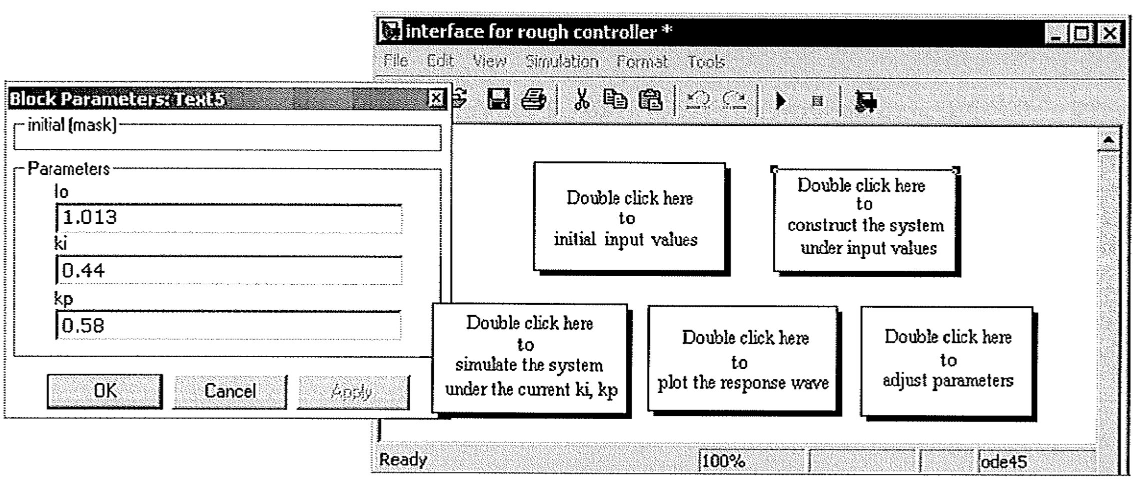

Fig. 6-1 The diagram of simulation process

When we use the interface, the first step is to initialize the system. The left button on the top row is an interface to input initial parameters such as random Io, ki, kp. (Here, Ki = ki x Ki* and Kp = kp x Kp*) The function of right button on the same row is to construct the system by using the input conditions. The left button on the second row is used to simulate this system under the current Ki and Kp. In the initial stage, they are the initial values of (Ki, Kp), which is (ki x Ki*, kp x Kp*). After the system has completed initialization, they are adjusted by rough control in the way of (Ki, Kp) = (Ki x di, Kp x dp). The middle button is intended to plot the waveforms of the step responses as the simulation results. In addition, the right button is to adjust the Ki and Kp through firing rough decision rules.

As explained, one measurement of direct current Id can be obtained from each (Ki, Kp) in the simulated HVDC system. We need a random pair of Ki, Kp to initialize the system. Therefore, the right top box has integrated this iteration function and all other initial processes. Double click it, the simulation system will carry all necessary initialization processes, and then the system is ready for our experiments.

The three blocks on the second row constitute a dynamic loop from dataflow's point of view. In our simulation, one loop corresponds to one firing of transit of fuzzy Petri Nets or one occurrence of system step change.

6.2 Simulation Results under Three Different Rough Control Schemes

The rough control scheme is designed, based on an assumption: the environment of HVDC system is constant except 1) a couple of random initial Ki and Kp, and 2) Io (the order direct current of this system) may be step signal, changing from 0 to 1 p.u. when t = 0, denoted by Io = 1.0 p.u.. Formula Io = x is used later in the thesis to represent the change of order direct current from 0 to x p.u.. We call the change of Io from 0 to x p.u. as system step change. If two system step changes have equal x values, they are called the same system step change; otherwise, they are different system step changes. We will perform the experiments in three groups, from simple to complex, to reveal the implementation of a flexible rough control system in a variable HVDC system with different behaviors of Io.

6.2.1 Rough Control with a Fixed Io

Following the processes as explained in Chapter 5, we construct the decision table shown

Completed decision table for ki

	a1	a2	a3	a4	a5	a6	a7	a8	a9	di
1	0.00	0.01	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
2	0.00	0.05	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
3	0.00	0.05	1.00	1.00	0.01	0.00	1.00	0.00	0.00	5.00
4	0.00	0.01	1.00	1.00	0.01	0.00	1.00	0.00	0.00	2.00
5	0.00	0.01	1.00	1.00	0.00	0.00	1.00	0.00	0.00	2.00
6	0.00	0.01	1.00	0.00	0.75	0.01	0.00	0.02	0.45	2.00
7	0.00	0.22	0.53	0.00	1.00	0.03	0.00	0.00	1.00	5.00
8	0.00	0.22	0.53	0.00	1.00	0.01	0.00	0.64	0.00	5.00
9	0.00	0.22	0.53	0.00	0.02	0.31	0.00	0.41	0.00	5.00
10	0.00	0.01	1.00	0.01	0.21	0.00	0.00	0.22	0.00	2.00
11	0.00	0.05	1.00	0.00	0.46	0.00	0.00	0.73	0.00	5.00
12	0.00	0.05	1.00	0.00	0.19	0.16	0.71	0.07	0.00	5.00
13	0.00	0.05	1.00	0.00	0.34	0.00	0.00	0.35	0.00	5.00
14	0.00	0.05	1.00	0.00	0.70	0.01	0.00	0.84	0.00	5.00
15	0.00	0.60	0.15	0.04	0.10	0.00	0.00	0.83	0.00	4.00
16	0.00	0.60	0.15	0.07	0.08	0.00	0.00	0.82	0.00	4.00
17	0.00	0.60	0.15	0.15	0.05	0.00	0.00	0.72	0.00	4.00
18	0.00	0.60	0.15	0.03	0.12	0.00	0.00	0.36	0.00	4.00
19	0.00	0.22	0.53	0.40	0.03	0.00	0.00	0.62	0.00	2.00
20	0.00	0.22	0.53	0.09	0.07	0.00	0.78	0.06	0.00	2.00

Table 6-1(a) Decision table for Ki with a fixed Io

Completed decision table for kp

	a1	a2	a3	a4	a5	a6	a7	a8	a9	dp
1	0.00	0.01	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
2	0.00	0.05	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
3	0.00	0.05	1.00	1.00	0.01	0.00	1.00	0.00	0.00	3.00
4	0.00	0.01	1.00	1.00	0.01	0.00	1.00	0.00	0.00	2.00
5	0.00	0.01	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.20
6	0.00	0.01	1.00	0.00	0.75	0.01	0.00	0.02	0.45	2.00
7	0.00	0.22	0.53	0.00	1.00	0.03	0.00	0.00	1.00	2.00
8	0.00	0.22	0.53	0.00	1.00	0.01	0.00	0.64	0.00	2.00
9	0.00	0.22	0.53	0.00	0.02	0.31	0.00	0.41	0.00	1.00
10	0.00	0.01	1.00	0.01	0.21	0.00	0.00	0.22	0.00	2.00
11	0.00	0.05	1.00	0.00	0.46	0.00	0.00	0.73	0.00	2.00
12	0.00	0.05	1.00	0.00	0.19	0.16	0.71	0.07	0.00	1.00
13	0.00	0.05	1.00	0.00	0.34	0.00	0.00	0.35	0.00	5.00
14	0.00	0.05	1.00	0.00	0.70	0.01	0.00	0.84	0.00	1.00
15	0.00	0.60	0.15	0.04	0.10	0.00	0.00	0.83	0.00	2.00
16	0.00	0.60	0.15	0.07	0.08	0.00	0.00	0.82	0.00	5.00
17	0.00	0.60	0.15	0.15	0.05	0.00	0.00	0.72	0.00	5.00
18	0.00	0.60	0.15	0.03	0.12	0.00	0.00	0.36	0.00	1.00
19	0.00	0.22	0.53	0.40	0.03	0.00	0.00	0.62	0.00	5.00
20	0.00	0.22	0.53	0.09	0.07	0.00	0.78	0.06	0.00	1.00

Table 6-1(b) Decision table for Kp with a fixed Io in Table 6-1(a), Table 6-1(b) for Ki and Kp respectively, and then we use the rough set tool ROSSETA for the rule generation as shown in Table 6-2 (a), Table 6-2(b).

Rules for ki

	Rule	LHS Support	RHS Support	RHS Accuracy
1	a2(0.01) AND a5(0.00) AND a8(0.00) AND a9(0.00) => di(1.00) OR di(2.00)	2	1, 1	0.5, 0.5
2	a2(0.05) AND a5(0.00) AND a8(0.00) AND a9(0.00) => di(1.00)	1	1	1.0
3	a2(0.05) AND a5(0.01) AND a8(0.00) AND a9(0.00) => di(5.00)	1	1	1.0
4	a2(0.01) AND a5(0.01) AND a8(0.00) AND a9(0.00) => di(2.00)	1	1	1.0
5	a2(0.01) AND a5(0.75) AND a8(0.02) AND a9(0.45) => di(2.00)	1	1	1.0
6	a2(0.22) AND a5(1.00) AND a8(0.00) AND a9(1.00) => di(5.00)	1	1	1.0
7	a2(0.22) AND a5(1.00) AND a8(0.64) AND a9(0.00) => di(5.00)	1	1	1.0
8	a2(0.22) AND a5(0.02) AND a8(0.41) AND a9(0.00) => di(5.00)	1	1	1.0
9	a2(0.01) AND a5(0.21) AND a8(0.22) AND a9(0.00) => di(2.00)	1	1	1.0
10	a2(0.05) AND a5(0.46) AND a8(0.73) AND a9(0.00) => di(5.00)	1	1	1.0
11	a2(0.05) AND a5(0.19) AND a8(0.07) AND a9(0.00) => di(5.00)	1	1	1.0
12	a2(0.05) AND a5(0.34) AND a8(0.35) AND a9(0.00) => di(5.00)	1	1	1.0
13	a2(0.05) AND a5(0.70) AND a8(0.84) AND a9(0.00) => di(5.00)	1	1	1.0
14	a2(0.60) AND a5(0.10) AND a8(0.83) AND a9(0.00) => di(4.00)	1	1	1.0
15	a2(0.60) AND a5(0.08) AND a8(0.82) AND a9(0.00) => di(4.00)	1	1	1.0
16	a2(0.60) AND a5(0.05) AND a8(0.72) AND a9(0.00) => di(4.00)	1	1	1.0
17	a2(0.60) AND a5(0.12) AND a8(0.36) AND a9(0.00) => di(4.00)	1	1	1.0
18	a2(0.22) AND a5(0.03) AND a8(0.62) AND a9(0.00) => di(2.00)	1	1	1.0
19	a2(0.22) AND a5(0.07) AND a8(0.06) AND a9(0.00) => di(2.00)	1	1	1.0
20	a2(0.60) AND a5(1.00) AND a8(0.99) AND a9(0.00) => di(1.00)	1	1	1.0

Table 6-2(a) Rule for Ki with a fixed Io

Rules for kp

	Rule	LHS Support	RHS Support	RHS Accuracy
1	a2(0.01) AND a4(1.00) AND a5(0.00) AND a8(0.00) => dp(1.00) OR dp(1.20)	2	1, 1	0.5, 0.5
2	a2(0.05) AND a4(1.00) AND a5(0.00) AND a8(0.00) => dp(1.00)	1	1	1.0
3	a2(0.05) AND a4(1.00) AND a5(0.01) AND a8(0.00) => dp(3.00)	1	1	1.0
4	a2(0.01) AND a4(1.00) AND a5(0.01) AND a8(0.00) => dp(2.00)	1	1	1.0
5	a2(0.01) AND a4(0.00) AND a5(0.75) AND a8(0.02) => dp(2.00)	1	1	1.0
6	a2(0.22) AND a4(0.00) AND a5(1.00) AND a8(0.00) => dp(2.00)	1	1	1.0
7	a2(0.22) AND a4(0.00) AND a5(1.00) AND a8(0.64) => dp(2.00)	1	1	1.0
8	a2(0.22) AND a4(0.00) AND a5(0.02) AND a8(0.41) => dp(1.00)	1	1	1.0
9	a2(0.01) AND a4(0.01) AND a5(0.21) AND a8(0.22) => dp(2.00)	1	1	1.0
10	a2(0.05) AND a4(0.00) AND a5(0.46) AND a8(0.73) => dp(2.00)	1	1	1.0
11	a2(0.05) AND a4(0.00) AND a5(0.19) AND a8(0.07) => dp(1.00)	1	1	1.0
12	a2(0.05) AND a4(0.00) AND a5(0.34) AND a8(0.35) => dp(5.00)	1	1	1.0
13	a2(0.05) AND a4(0.00) AND a5(0.70) AND a8(0.84) => dp(1.00)	1	1	1.0
14	a2(0.60) AND a4(0.04) AND a5(0.10) AND a8(0.83) => dp(2.00)	1	1	1.0
15	a2(0.60) AND a4(0.07) AND a5(0.08) AND a8(0.82) => dp(5.00)	1	1	1.0
16	a2(0.60) AND a4(0.15) AND a5(0.05) AND a8(0.72) => dp(5.00)	1	1	1.0
17	a2(0.60) AND a4(0.03) AND a5(0.12) AND a8(0.36) => dp(1.00)	1	1	1.0
18	a2(0.22) AND a4(0.40) AND a5(0.03) AND a8(0.62) => dp(5.00)	1	1	1.0
19	a2(0.22) AND a4(0.09) AND a5(0.07) AND a8(0.06) => dp(1.00)	1	1	1.0
20	a2(0.60) AND a4(0.00) AND a5(1.00) AND a8(0.99) => dp(2.00)	1	1	1.0

Table 6-2(b) Rule for Kp with a fixed Io

In a system with a classical PI controller, the step responses are almost identical to each other at every time when the same system step change occurs. In other words, Id will not change its shape, no matter how many times the same system step change has occurred. However, in a system with the rough control scheme, every occurrence of system step change will lead to a better rough set rule to be obtained and ready to be used in the next occurrence of the same system step change. It results in a better step response, which can be expected in the next time. As an example, Fig. 6-2 shows the evolution of the step response as a series of occurrences of the same system change (Io = 1.0). The evolution is easy to notice. Meanwhile, Table 6-3 lists the step response's features (tr, ts, ov) during the adjusting process of system with the rough control scheme.

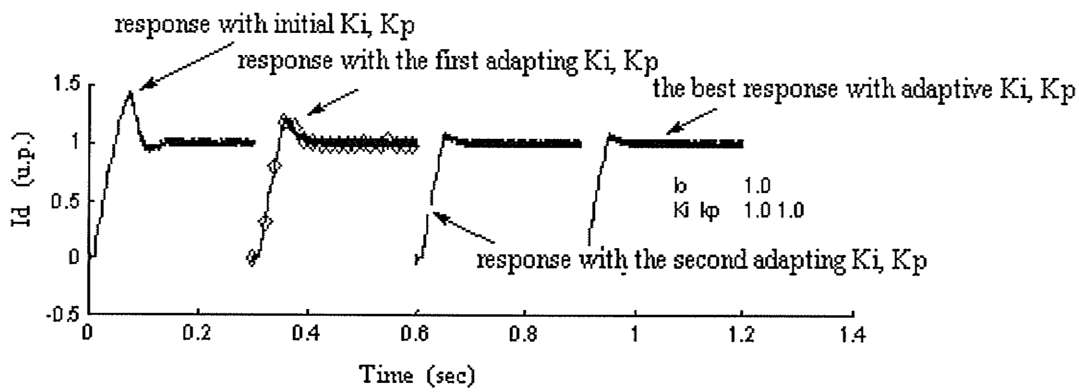

Fig. 6-2 The waveform comparison during the process of adaptation of Ki and Kp when Io = 1.0

Adjustment times	Rise time (tr)	Settling time (ts)	Overshoot (ov)
1	0.0411	0.0847	43.4092
2	0.0411	0.0530	22.4579
3	0.0412	0.0294	8.5659
4	0.0412	0.0097	6.6472

Table 6-3 The step response's features (tr, ts, ov) comparison during the process of adjustment of Ki and Kp, when Io = 1.0

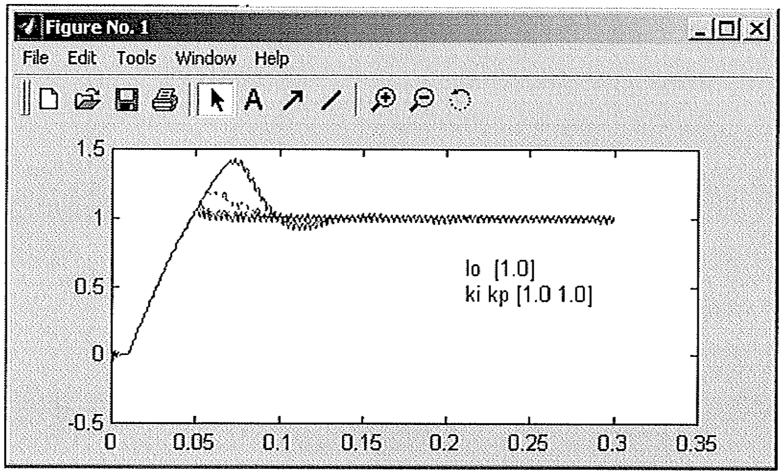

Fig. 6-3 The evolution of step responses with the rough control scheme.

Another example is shown by Fig. 6-3 to compare the step responses during the process of adaptation of Ki and Kp. As we can see, the most obvious change is overshoot. In the system with the rough control scheme, the learning-improving process, or called the adaptation of Ki and Kp, will continue until the step response will be "good enough". Approximate time window is used for the measurement. In this example, a very small overshoot means "good enough". We call the final "good enough" status as the "stable status". Two interesting things to notice are 1) that we have one "Stable Status" for each unique combination of Io, Ki, and Kp, 2) that the rough set control system may take a different "path" to reach the Stable Status, with different Id, or Io.

6.2.2 Rough Control with Variable Io

In preceding section, we have studied a simple rough control system that works in a constant HVDC system, parameters of which are invariable except random initial Ki and Kp. We will develop this rough control system into a more flexible rough control system, capable of controlling a more complicated HVDC system whose some parameters may be changed by requirements, such as Io (the order direct current value). Consider the situation when Io does not have a fixed value. It may take any value from a collection of possible values. In other words, $Io \in \{I_1, I_2, I_3, \ldots, I_n\}$, $n<\infty$. Under such situation, Io itself can be treated as one of IP features which affect the decision results in the rough information system. Therefore, we have 12 sensors in the rough set tuner, and each

Decision table for ki, completed

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	di
1	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.00	0.40	0.00	**1.00**
2	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	**1.00**
3	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.58	0.20	0.00	**5.00**
4	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.67	0.01	0.00	0.00	1.00	**2.00**
5	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.85	0.01	0.00	0.00	1.00	**2.00**
6	1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.01	0.00	0.40	0.00	**2.00**
7	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.32	0.12	0.00	0.50	0.00	**2.00**
8	1.00	0.00	0.00	1.00	0.00	0.00	0.01	0.19	0.00	0.00	0.00	1.00	**2.00**
9	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.43	0.00	0.00	0.33	0.00	**5.00**
10	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.33	0.12	0.18	0.30	0.00	**5.00**
11	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.29	0.00	0.00	0.00	1.00	**5.00**
12	1.00	0.00	0.00	1.00	0.00	0.00	0.05	0.10	0.00	0.00	0.53	0.00	**4.00**
13	1.00	0.00	0.00	1.00	0.00	0.00	0.45	0.02	0.00	0.00	0.90	0.00	**2.00**
14	1.00	0.00	0.00	1.00	0.00	0.00	0.06	0.09	0.00	0.18	0.30	0.00	**2.00**
15	1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.02	0.00	0.67	0.00	**1.00**
16	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.44	0.00	0.00	0.73	0.00	**1.00**
17	1.00	0.00	0.00	1.00	0.00	0.00	0.75	0.01	0.00	0.00	1.00	0.00	**5.00**
18	1.00	0.00	0.00	1.00	0.00	0.00	0.66	0.02	0.00	0.00	0.80	0.00	**5.00**
19	1.00	0.00	0.00	1.00	0.00	0.00	0.55	0.02	0.00	0.58	0.20	0.00	**5.00**
20	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.28	0.00	0.00	1.00	0.00	**2.00**

Table 6-4(a) Decision table for Ki with Io as one of features

Decision table for kp, completed

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	dp
1	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.00	0.40	0.00	**1.00**
2	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	**1.00**
3	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.58	0.20	0.00	**3.00**
4	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.67	0.01	0.00	0.00	1.00	**2.00**
5	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.85	0.01	0.00	0.00	1.00	**4.00**
6	1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.01	0.00	0.40	0.00	**4.00**
7	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.32	0.12	0.00	0.50	0.00	**1.00**
8	1.00	0.00	0.00	1.00	0.00	0.00	0.01	0.19	0.00	0.00	0.00	1.00	**2.00**
9	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.43	0.00	0.00	0.33	0.00	**2.00**
10	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.33	0.12	0.18	0.30	0.00	**1.00**
11	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.29	0.00	0.00	0.00	1.00	**5.00**
12	1.00	0.00	0.00	1.00	0.00	0.00	0.05	0.10	0.00	0.00	0.53	0.00	**2.00**
13	1.00	0.00	0.00	1.00	0.00	0.00	0.45	0.02	0.00	0.00	0.90	0.00	**5.00**
14	1.00	0.00	0.00	1.00	0.00	0.00	0.06	0.09	0.00	0.18	0.30	0.00	**1.00**
15	1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.02	0.00	0.67	0.00	**2.00**
16	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.44	0.00	0.00	0.73	0.00	**5.00**
17	1.00	0.00	0.00	1.00	0.00	0.00	0.75	0.01	0.00	0.00	1.00	0.00	**2.00**
18	1.00	0.00	0.00	1.00	0.00	0.00	0.66	0.02	0.00	0.00	0.80	0.00	**2.00**
19	1.00	0.00	0.00	1.00	0.00	0.00	0.55	0.02	0.00	0.58	0.20	0.00	**1.00**
20	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.28	0.00	0.00	1.00	0.00	**5.00**

Table 6-4(b) Decision table for Kp with Io as one of features

Rules for ki

	Rule
1	a2(0.00) AND a4(1.00) AND a7(1.00) AND a8(0.01) AND a9(0.00) AND a11(0.40) => di(1.00) OR di(2.00)
2	a2(0.00) AND a4(1.00) AND a7(1.00) AND a8(0.00) AND a9(0.00) AND a11(0.00) => di(1.00)
3	a2(0.00) AND a4(1.00) AND a7(1.00) AND a8(0.01) AND a9(0.00) AND a11(0.20) => di(5.00)
4	a2(0.00) AND a4(1.00) AND a7(0.00) AND a8(0.67) AND a9(0.01) AND a11(0.00) => di(2.00)
5	a2(0.00) AND a4(1.00) AND a7(0.00) AND a8(0.85) AND a9(0.01) AND a11(0.00) => di(2.00)
6	a2(0.00) AND a4(1.00) AND a7(0.00) AND a8(1.00) AND a9(0.01) AND a11(0.40) => di(2.00)
7	a2(0.00) AND a4(1.00) AND a7(0.00) AND a8(0.32) AND a9(0.12) AND a11(0.50) => di(2.00)
8	a2(0.00) AND a4(1.00) AND a7(0.01) AND a8(0.19) AND a9(0.00) AND a11(0.00) => di(2.00)
9	a2(0.00) AND a4(1.00) AND a7(0.00) AND a8(0.43) AND a9(0.00) AND a11(0.33) => di(5.00)
10	a2(0.00) AND a4(1.00) AND a7(0.00) AND a8(0.33) AND a9(0.12) AND a11(0.30) => di(5.00)
11	a2(0.00) AND a4(1.00) AND a7(0.00) AND a8(0.29) AND a9(0.00) AND a11(0.00) => di(5.00)
12	a2(0.00) AND a4(1.00) AND a7(0.05) AND a8(0.10) AND a9(0.00) AND a11(0.53) => di(4.00)
13	a2(0.00) AND a4(1.00) AND a7(0.45) AND a8(0.02) AND a9(0.00) AND a11(0.90) => di(2.00)
14	a2(0.00) AND a4(1.00) AND a7(0.06) AND a8(0.09) AND a9(0.00) AND a11(0.30) => di(2.00)
15	a2(0.00) AND a4(1.00) AND a7(0.00) AND a8(1.00) AND a9(0.02) AND a11(0.67) => di(1.00)
16	a2(0.00) AND a4(1.00) AND a7(0.00) AND a8(0.44) AND a9(0.00) AND a11(0.73) => di(1.00)
17	a2(0.00) AND a4(1.00) AND a7(0.75) AND a8(0.01) AND a9(0.00) AND a11(1.00) => di(5.00)
18	a2(0.00) AND a4(1.00) AND a7(0.66) AND a8(0.02) AND a9(0.00) AND a11(0.80) => di(5.00)
19	a2(0.00) AND a4(1.00) AND a7(0.55) AND a8(0.02) AND a9(0.00) AND a11(0.20) => di(5.00)
20	a2(0.00) AND a4(1.00) AND a7(0.00) AND a8(0.28) AND a9(0.00) AND a11(1.00) => di(2.00)

Table 6-5(a) Decision rule for Ki with Io as one of features

Rules for kp

	Rule
1	a4(1.00) AND a5(0.00) AND a7(1.00) AND a8(0.01) AND a10(0.00) AND a11(0.40) => dp(1.00) OR dp(5.00)
2	a4(1.00) AND a5(0.00) AND a7(1.00) AND a8(0.00) AND a10(1.00) AND a11(0.00) => dp(1.00)
3	a4(1.00) AND a5(0.00) AND a7(1.00) AND a8(0.01) AND a10(0.58) AND a11(0.20) => dp(3.00)
4	a4(1.00) AND a5(0.00) AND a7(0.00) AND a8(0.67) AND a10(0.00) AND a11(0.00) => dp(2.00)
5	a4(1.00) AND a5(0.00) AND a7(0.00) AND a8(0.85) AND a10(0.00) AND a11(0.00) => dp(4.00)
6	a4(1.00) AND a5(0.00) AND a7(0.00) AND a8(1.00) AND a10(0.00) AND a11(0.40) => dp(4.00)
7	a4(1.00) AND a5(0.00) AND a7(0.00) AND a8(0.32) AND a10(0.00) AND a11(0.50) => dp(1.00)
8	a4(1.00) AND a5(0.00) AND a7(0.01) AND a8(0.19) AND a10(0.00) AND a11(0.00) => dp(2.00)
9	a4(1.00) AND a5(0.00) AND a7(0.00) AND a8(0.43) AND a10(0.00) AND a11(0.33) => dp(2.00)
10	a4(1.00) AND a5(0.00) AND a7(0.00) AND a8(0.33) AND a10(0.18) AND a11(0.30) => dp(1.00)
11	a4(1.00) AND a5(0.00) AND a7(0.00) AND a8(0.29) AND a10(0.00) AND a11(0.00) => dp(5.00)
12	a4(1.00) AND a5(0.00) AND a7(0.05) AND a8(0.10) AND a10(0.00) AND a11(0.53) => dp(2.00)
13	a4(1.00) AND a5(0.00) AND a7(0.45) AND a8(0.02) AND a10(0.00) AND a11(0.90) => dp(5.00)
14	a4(1.00) AND a5(0.00) AND a7(0.06) AND a8(0.09) AND a10(0.18) AND a11(0.30) => dp(1.00)
15	a4(1.00) AND a5(0.00) AND a7(0.00) AND a8(1.00) AND a10(0.00) AND a11(0.67) => dp(2.00)
16	a4(1.00) AND a5(0.00) AND a7(0.00) AND a8(0.44) AND a10(0.00) AND a11(0.73) => dp(5.00)
17	a4(1.00) AND a5(0.00) AND a7(0.75) AND a8(0.01) AND a10(0.00) AND a11(1.00) => dp(2.00)
18	a4(1.00) AND a5(0.00) AND a7(0.66) AND a8(0.02) AND a10(0.00) AND a11(0.80) => dp(2.00)
19	a4(1.00) AND a5(0.00) AND a7(0.55) AND a8(0.02) AND a10(0.58) AND a11(0.20) => dp(1.00)
20	a4(1.00) AND a5(0.00) AND a7(0.00) AND a8(0.28) AND a10(0.00) AND a11(1.00) => dp(5.00)

Table 6-5(b) Decision rule for Kp with Io as one of features decision table consists of 12 attributes plus one decision result. Table 6-4(a) and Table 6-4(b) show the decision tables. Table 6-5(a) and Table 6-5(b) show the final decision rules.

We simulate this kind of variable rough control system under the situation where Io may take any one of values: Io∈{0.8, 0.9, 1.0, 1.1, 1.2}. In a system with a classical PI controller, its step response may vary from each other on the arrival of different system step changes, characterize by different Io values, although its step responses will always be identical to each other on each arrival of the same system step change. In a rough control system with an adaptive PI controller, it takes a learning-training process to reach the stable status. In this process, its step responses will vary on each arrival of system step change. After the rough control system reaches the stable status, the step response will not change any more. Similar to a classical PI controller's system, the rough control system will still generate different step responses with different system step changes, even on the stable status. The following figures show the step responses from a system with the classical PI controller and the step responses from a system with the rough control scheme on the stable status. We can notice that the first group of five figures illustrate the waveforms of the step response with different Io values and identical initial values of (ki, kp) which are (0.1, 0.1). Similarly, the second and third groups of figures are corresponding to the situations of (ki, kp) being (1.0,1.0) and (100, 100) respectively. In comparison with the classical PI controller, our rough control scheme can handle variable Io very well, in terms of faster tr and ts, and shorter overshoot.

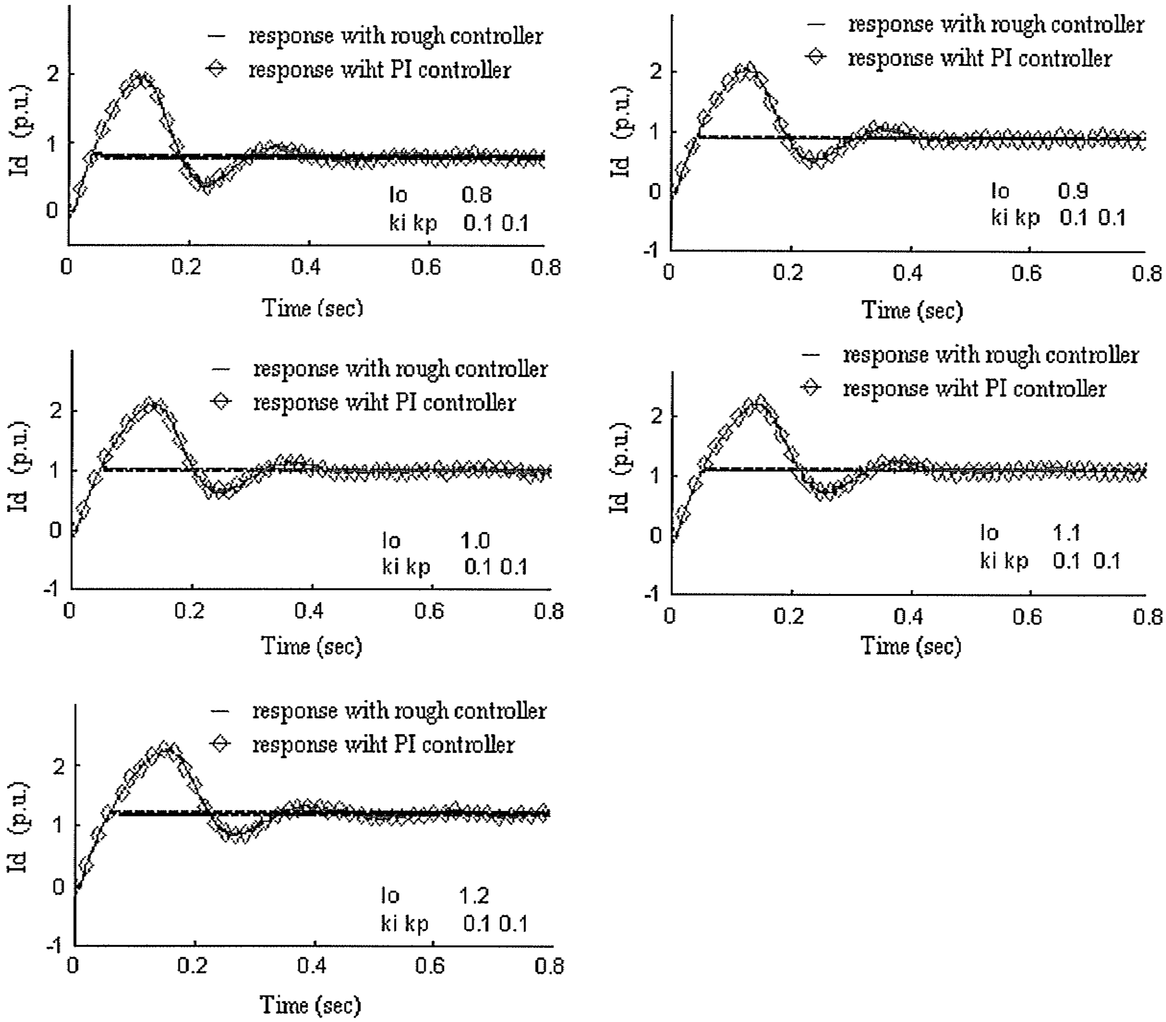

Fig. 6-4 The step response comparison between systems with a classical PI controller and with a rough controller when (ki, kp) = (0.1, 0.1) and variable Io

Io (p.u.)	Classical / Rough Control (ki, kp = 0.1, 0.1)					
	Rise time (tr)		Settling time (ts)		Overshoot (ov)	
0.8	0.0331	0.0327	0.2620	0.0110	147.3435	6.2884
0.9	0.0367	0.0366	0.4619	0.0110	128.5544	7.1543
1.0	0.0414	0.0414	0.3699	0.0097	112.6934	6.6472
1.1	0.0455	0.0450	0.4431	0.0044	100.8750	4.1055
1.2	0.0487	0.0489	0.5925	0.0120	89.7730	4.6735

Table 6-6 The step response's features (tr, ts, ov) comparison between systems with a classical PI controller and with a rough controller when (ki, kp) = (0.1, 0.1)

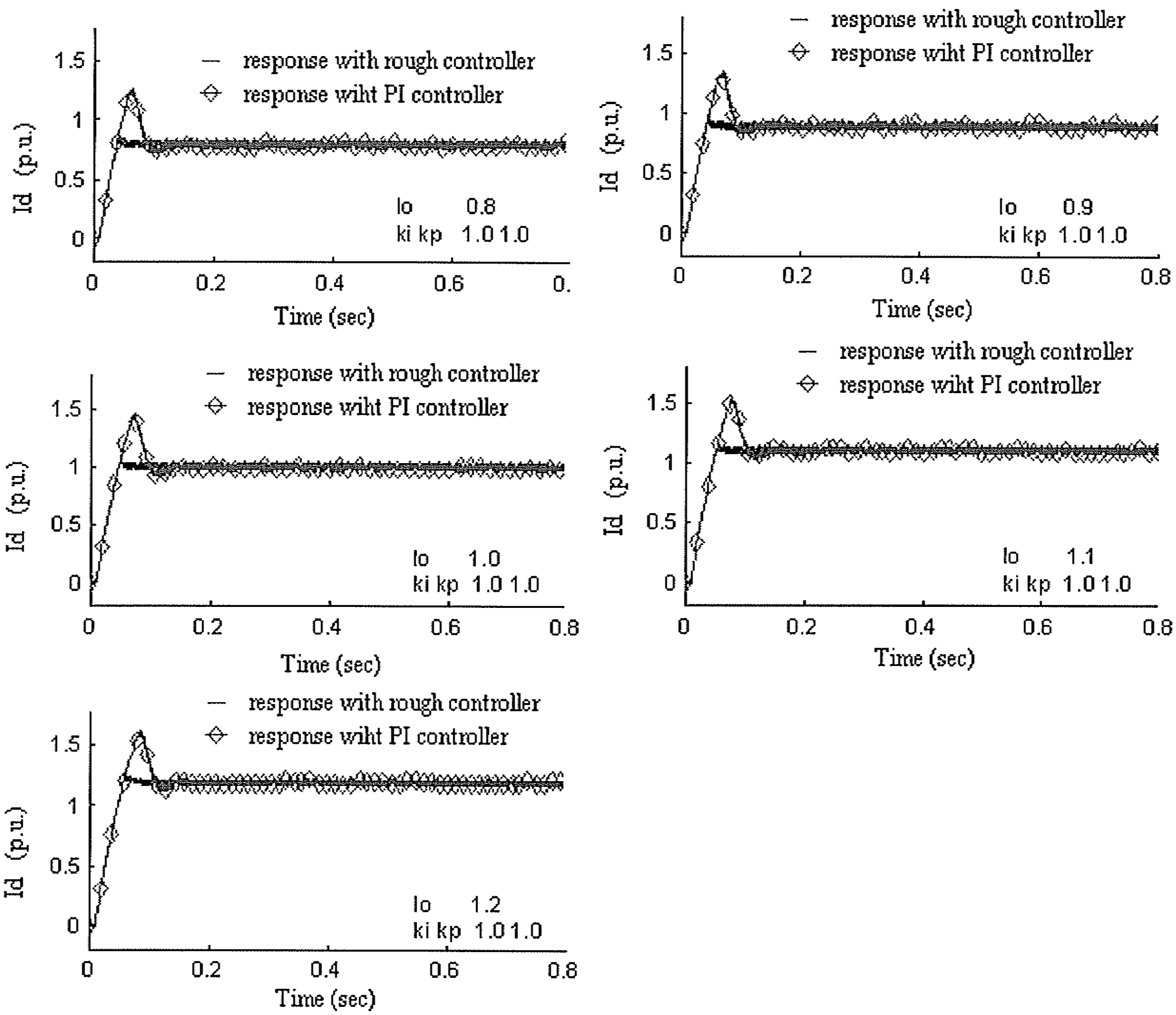

Fig. 6-5 The step response comparison between systems with a classical PI controller and with a rough controller when (ki, kp) = (1.0, 1.0) and variable Io

Io (p.u.)	Classical / Rough Control (ki, kp = 1.0, 1.0)					
	Rise time (tr)		Settling time (ts)		Overshoot (ov)	
0.8	0.0328	0.0327	0.0825	0.0110	57.7295	6.2884
0.9	0.0367	0.0366	0.0852	0.0110	49.0133	7.1543
1.0	0.0411	0.0414	0.0847	0.0097	43.4092	6.6472
1.1	0.0449	0.0450	0.0872	0.0044	38.1051	4.1055
1.2	0.0489	0.0489	0.0897	0.0120	34.4975	4.6735

Table 6-7 The step response's features (tr, ts, ov) comparison between systems with a classical PI controller and with a rough controller when (ki, kp) = (1.0, 1.0)

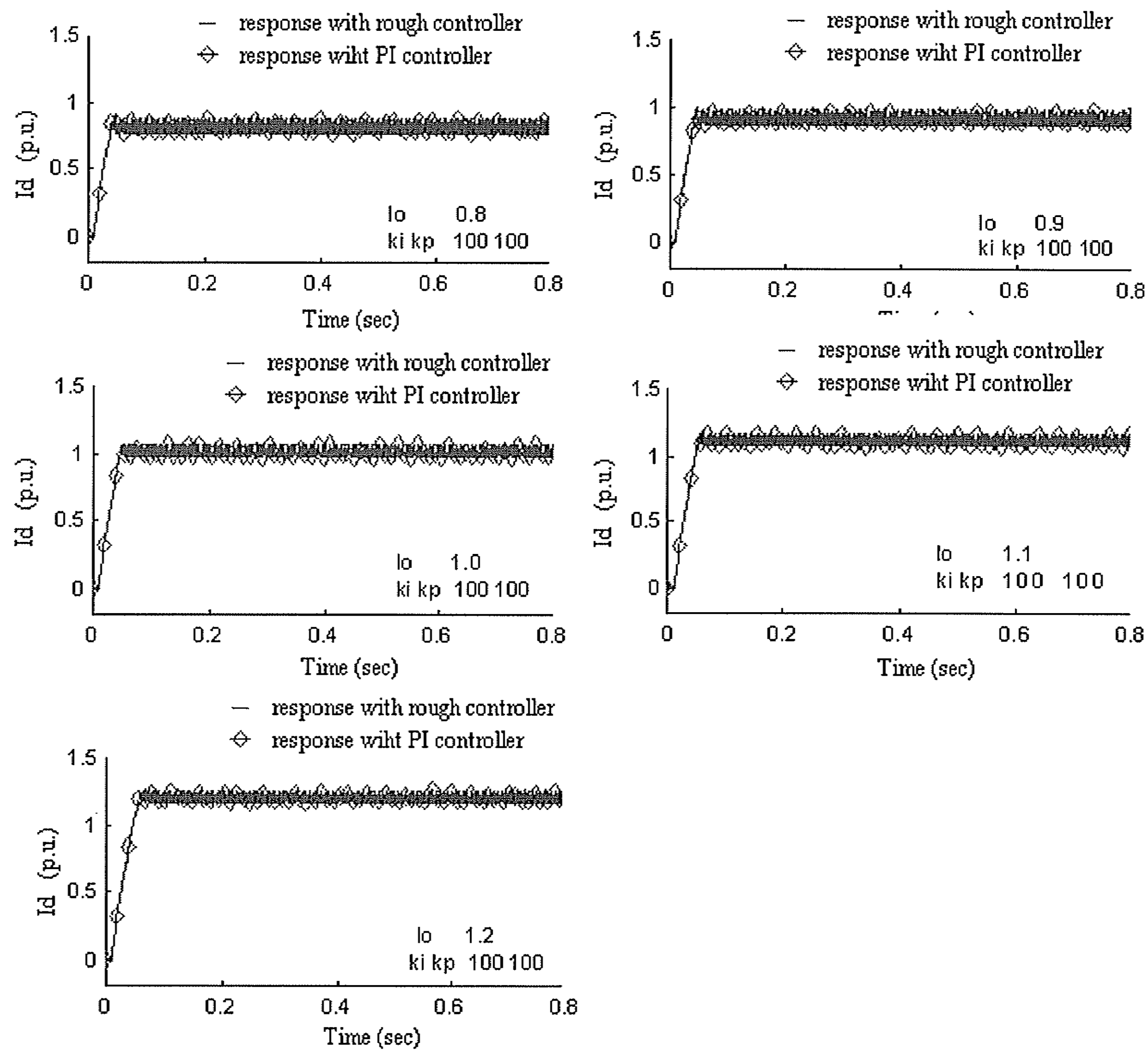

Fig. 6-6 The step responses: comparison between systems with a classical PI controller and with a rough controller when (ki, kp) = (100,100) and variable Io

Io (p.u.)	Classical / Rough Control (ki, kp =100, 100)					
	Rise time (tr)		Settling time (ts)		Overshoot (ov)	
0.8	0.0329	0.0327	99999	0.0110	13.5944	6.2884
0.9	0.0367	0.0366	99999	0.0110	10.5029	7.1543
1.0	0.0414	0.0414	99999	0.0097	7.9611	6.6472
1.1	0.0448	0.0450	99999	0.0044	8.8961	4.1055
1.2	0.0489	0.0489	99999	0.0120	6.0407	4.6735

Table 6-8 The step response's features (tr, ts, ov) comparison between systems with a classical PI controller and with a rough controller when (ki, kp) = (100, 100)

6.2.3 Rough Control with Io Varying in a Range

In a practical HVDC system, some parameters may vary continuously. Consider the situation where Io has neither a fixed value nor one of a set of values. Io may have any value in a range. In other words, Io satisfies $I_{min}<Io<I_{max}$. Under such a situation, our decision rules have been modified to support the selection of applicable decision rules. There is a special function named *discretization* in ROSETTA which can search for "cuts" that determine intervals to convert numerical attributes to attributes that can be treated as being categorical. In previous experiments, attributes a1, a2, and a3 are equal to 0, 0.5, and 1 separately. They correspond to the situations where Io has a value in the set {0.8, 0.9, 1.0, 1.1, 1.2}. In this experiment, the value of Io may be anywhere between 0.8 and 1.2, for example 1.078. As such, a1, a2, a3 should be an interval. For example, a1 on the first row of the following discretized decision Table 6-9(a) and it now represents an interval of [0.75, *). As a comparison, it was a single value 1 in Table 6-4(a). By this method we could divide the over range [0, 1] into three intervals (*, 0.25], (0.25, 0.75), [0.75, *), reflecting the original values 0, 0.5, 1. The generated decision rules after discretization can then match an attribute value varying in a range.

Decision table for ki,completed, discretized

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	di
1	[0.75, *)	(*, 0.25]	(*, 0.25]	1.00	0.00	0.00	1.00	0.01	0.00	0.00	0.40	0.00	**1.00**
2	[0.75, *)	(*, 0.25]	(*, 0.25]	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	**1.00**
3	[0.75, *)	(*, 0.25]	(*, 0.25]	1.00	0.00	0.00	1.00	0.01	0.00	0.58	0.20	0.00	**5.00**
37	(0.25, 0.75)	(0.25, 0.75)	(*, 0.25]	0.12	0.07	0.00	1.00	0.00	0.00	1.00	0.00	0.00	**1.00**
38	(0.25, 0.75)	(0.25, 0.75)	(*, 0.25]	0.12	0.07	0.00	1.00	0.00	0.00	0.98	0.10	0.00	**1.00**
39	(0.25, 0.75)	(0.25, 0.75)	(*, 0.25]	0.14	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	**1.00**
77	(*, 0.25]	[0.75, *)	(*, 0.25]	0.00	1.00	0.00	1.00	0.01	0.00	1.00	0.00	0.00	**5.00**
78	(*, 0.25]	[0.75, *)	(*, 0.25]	0.00	1.00	0.00	1.00	0.01	0.00	1.00	0.00	0.00	**2.00**
79	(*, 0.25]	[0.75, *)	(*, 0.25]	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	**2.00**
80	(*, 0.25]	[0.75, *)	(*, 0.25]	0.00	1.00	0.00	0.00	0.75	0.01	0.00	0.00	0.50	**2.00**
116	(*, 0.25]	(0.25, 0.75)	(0.25, 0.75)	0.00	0.14	0.15	0.00	0.97	0.01	0.00	0.00	0.50	**5.00**
117	(*, 0.25]	(0.25, 0.75)	(0.25, 0.75)	0.00	0.14	0.15	0.00	1.00	0.01	0.00	0.80	0.00	**5.00**
118	(*, 0.25]	(0.25, 0.75)	(0.25, 0.75)	0.00	0.14	0.15	0.00	0.23	0.00	0.00	0.40	0.00	**2.00**
180	(*, 0.25]	(*, 0.25]	[0.75, *)	0.00	0.00	1.00	0.75	0.01	0.00	1.00	0.00	0.00	**3.00**
181	(*, 0.25]	(*, 0.25]	[0.75, *)	0.00	0.00	1.00	0.84	0.01	0.00	0.58	0.20	0.00	**3.00**
182	(*, 0.25]	(*, 0.25]	[0.75, *)	0.00	0.00	1.00	0.73	0.01	0.00	0.98	0.10	0.00	**3.00**
183	(*, 0.25]	(*, 0.25]	[0.75, *)	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	**0.50**

Table 6-9(a) Completed discretized decision table for ki

Decision table for kp, completed, discretized

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	dp
1	[0.75, *)	(*, 0.25]	(*, 0.25]	1.00	0.00	0.00	1.00	0.01	0.00	0.00	0.40	0.00	**1.00**
2	[0.75, *)	(*, 0.25]	(*, 0.25]	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	**1.00**
3	[0.75, *)	(*, 0.25]	(*, 0.25]	1.00	0.00	0.00	1.00	0.01	0.00	0.58	0.20	0.00	**3.00**
41	(0.25, 0.75)	(0.25, 0.75)	(*, 0.25]	0.11	0.08	0.00	1.00	0.01	0.00	0.98	0.10	0.00	**3.00**
42	(0.25, 0.75)	(0.25, 0.75)	(*, 0.25]	0.09	0.10	0.00	1.00	0.00	0.00	0.98	0.10	0.00	**2.00**
43	(0.25, 0.75)	(0.25, 0.75)	(*, 0.25]	0.09	0.10	0.00	0.00	0.72	0.01	0.00	0.00	0.90	**5.00**
81	(*, 0.25]	[0.75, *)	(*, 0.25]	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	**1.20**
82	(*, 0.25]	[0.75, *)	(*, 0.25]	0.00	1.00	0.00	0.00	0.75	0.01	0.00	0.00	0.50	**2.00**
83	(*, 0.25]	[0.75, *)	(*, 0.25]	0.00	1.00	0.00	0.00	1.00	0.03	0.00	0.00	1.00	**2.00**
117	(*, 0.25]	(0.25, 0.75)	(0.25, 0.75)	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	**2.00**
118	(*, 0.25]	(0.25, 0.75)	(0.25, 0.75)	0.00	0.14	0.15	0.00	0.80	0.01	0.00	0.20	0.00	**2.00**
119	(*, 0.25]	(0.25, 0.75)	(0.25, 0.75)	0.00	0.14	0.15	0.00	0.97	0.01	0.00	0.00	0.50	**2.00**
184	(*, 0.25]	(*, 0.25]	[0.75, *)	0.00	0.00	1.00	0.84	0.01	0.00	0.58	0.20	0.00	**4.00**
185	(*, 0.25]	(*, 0.25]	[0.75, *)	0.00	0.00	1.00	0.73	0.01	0.00	0.98	0.10	0.00	**2.00**
186	(*, 0.25]	(*, 0.25]	[0.75, *)	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	**0.50**

Table 6-9(b) Completed discretized decision table for kp

Rules for ki

	Rule	LHS Suppor	R
1	a2((*, 0.25]) AND a4(1.00) AND a7(1.00) AND a8(0.01) AND a9(0.00) AND a11(0.40) => di(1.00) OR di(2.00)	2	1,
35	a2((0.25, 0.75)) AND a4(0.11) AND a7(1.00) AND a8(0.00) AND a9(0.00) AND a11(0.00) => di(1.00)	1	1
36	a2((0.25, 0.75)) AND a4(0.12) AND a7(1.00) AND a8(0.00) AND a9(0.00) AND a11(0.00) => di(1.00)	1	1
349	a3((*, 0.25]) AND a4(1.00) AND a7(1.00) AND a8(0.01) AND a9(0.00) AND a11(0.40) => di(1.00) OR di(2.00)	2	1,
350	a3((*, 0.25]) AND a4(1.00) AND a7(1.00) AND a8(0.00) AND a9(0.00) AND a11(0.00) => di(1.00)	1	1
461	a3((0.25, 0.75)) AND a4(0.00) AND a7(0.00) AND a8(0.23) AND a9(0.00) AND a11(0.40) => di(2.00)	1	1
462	a3((0.25, 0.75)) AND a4(0.00) AND a7(0.00) AND a8(0.45) AND a9(0.00) AND a11(0.87) => di(5.00)	1	1
719	a1([0.75, *)) AND a5(0.00) AND a7(0.77) AND a8(0.01) AND a9(0.00) AND a11(0.20) => di(5.00)	1	1
720	a1([0.75, *)) AND a5(0.00) AND a7(0.00) AND a8(0.35) AND a9(0.12) AND a11(0.00) => di(4.00)	1	1
748	a1((0.25, 0.75)) AND a5(0.06) AND a7(0.44) AND a8(0.02) AND a9(0.00) AND a11(0.80) => di(2.00)	1	1
749	a1((0.25, 0.75)) AND a5(0.06) AND a7(0.07) AND a8(0.08) AND a9(0.00) AND a11(0.10) => di(2.00)	1	1
784	a1((*, 0.25]) AND a5(1.00) AND a7(0.40) AND a8(0.03) AND a9(0.00) AND a11(0.60) => di(2.00)	1	1
785	a1((*, 0.25]) AND a5(1.00) AND a7(0.09) AND a8(0.07) AND a9(0.00) AND a11(0.10) => di(2.00)	1	1
996	a3((0.25, 0.75)) AND a5(0.15) AND a7(0.63) AND a8(0.02) AND a9(0.00) AND a11(0.00) => di(4.00)	1	1
997	a3((0.25, 0.75)) AND a5(0.14) AND a7(0.00) AND a8(0.33) AND a9(0.00) AND a11(0.60) => di(2.00)	1	1
1024	a3([0.75, *)) AND a5(0.00) AND a7(0.42) AND a8(0.03) AND a9(0.00) AND a11(0.40) => di(2.00)	1	1
1025	a3([0.75, *)) AND a5(0.00) AND a7(0.17) AND a8(0.05) AND a9(0.00) AND a11(0.00) => di(2.00)	1	1

Table 6-10(a) Discretized rule for ki

Rules for kp

	Rule	LHS Suppor
206	a2((*, 0.25]) AND a4(1.00) AND a7(1.00) AND a8(0.01) AND a10(0.98) AND a11(0.10) => dp(2.00)	1
207	a2((*, 0.25]) AND a4(1.00) AND a7(0.00) AND a8(0.00) AND a10(0.18) AND a11(0.30) => dp(0.50)	1
208	a2((0.25, 0.75)) AND a4(0.11) AND a7(1.00) AND a8(0.00) AND a10(1.00) AND a11(0.00) => dp(1.00)	1
209	a2((0.25, 0.75)) AND a4(0.12) AND a7(1.00) AND a8(0.00) AND a10(1.00) AND a11(0.00) => dp(1.00)	1
252	a2([0.75, *)) AND a4(0.00) AND a7(0.00) AND a8(0.02) AND a10(0.00) AND a11(0.40) => dp(1.00)	1
253	a2([0.75, *)) AND a4(0.00) AND a7(0.01) AND a8(0.21) AND a10(0.00) AND a11(0.20) => dp(2.00)	1
526	a3((*, 0.25]) AND a5(0.00) AND a7(0.00) AND a8(0.32) AND a10(0.00) AND a11(0.50) => dp(1.00)	1
527	a3((*, 0.25]) AND a5(0.00) AND a7(0.01) AND a8(0.19) AND a10(0.00) AND a11(0.00) => dp(2.00)	1
656	a3((0.25, 0.75)) AND a5(0.14) AND a7(0.96) AND a8(0.01) AND a10(0.98) AND a11(0.10) => dp(5.00)	1
657	a3((0.25, 0.75)) AND a5(0.17) AND a7(0.00) AND a8(0.00) AND a10(1.00) AND a11(0.00) => dp(0.50)	1
658	a3([0.75, *)) AND a5(0.00) AND a7(0.00) AND a8(1.00) AND a10(1.00) AND a11(0.00) => dp(0.50)	1
659	a3([0.75, *)) AND a5(0.00) AND a7(1.00) AND a8(0.00) AND a10(1.00) AND a11(0.00) => dp(1.00) OR dp(1.20)	2
1383	a1((*, 0.25]) AND a5(0.00) AND a7(0.00) AND a8(0.00) AND a10(1.00) AND a11(0.00) => dp(0.50)	1
1384	a1([0.75, *)) AND a5(0.00) AND a7(1.00) AND a8(0.01) AND a9(0.00) AND a11(0.40) => dp(1.00) OR dp(5.00)	2
1385	a1([0.75, *)) AND a5(0.00) AND a7(1.00) AND a8(0.00) AND a9(0.00) AND a11(0.00) => dp(1.00)	1
1842	a1((*, 0.25]) AND a5(0.17) AND a7(0.00) AND a8(0.51) AND a11(0.00) AND a12(0.00) => dp(1.00)	1
1843	a1((*, 0.25]) AND a5(0.17) AND a7(0.00) AND a8(0.38) AND a11(0.53) AND a12(0.00) => dp(5.00)	1
3504	a1((0.25, 0.75)) AND a2((0.25, 0.75)) AND a4(0.09) AND a7(0.00) AND a8(0.72) AND a9(0.01) AND a11(1.00) =>	1
3505	a1((0.25, 0.75)) AND a2((0.25, 0.75)) AND a4(0.09) AND a7(0.04) AND a8(0.11) AND a9(0.00) AND a11(0.67) =>	1

Table 6-10(b) Discretized rule for kp

Fig. 6-7 and Fig. 6-8 show the step responses by the rough control system for the case of random Io. More specifically, these two figures show the cases where Io = 0.816 and Io = 1.078 respectively.

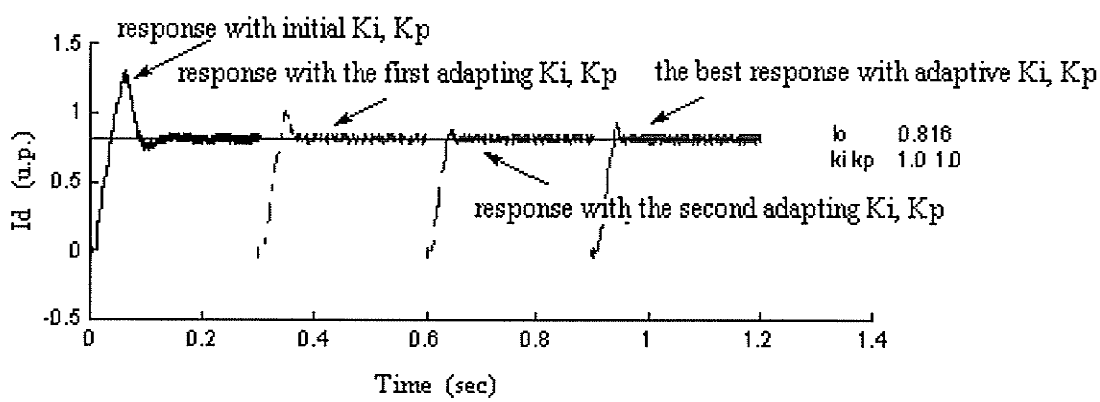

Fig. 6-7 The step response when Io = 0.816

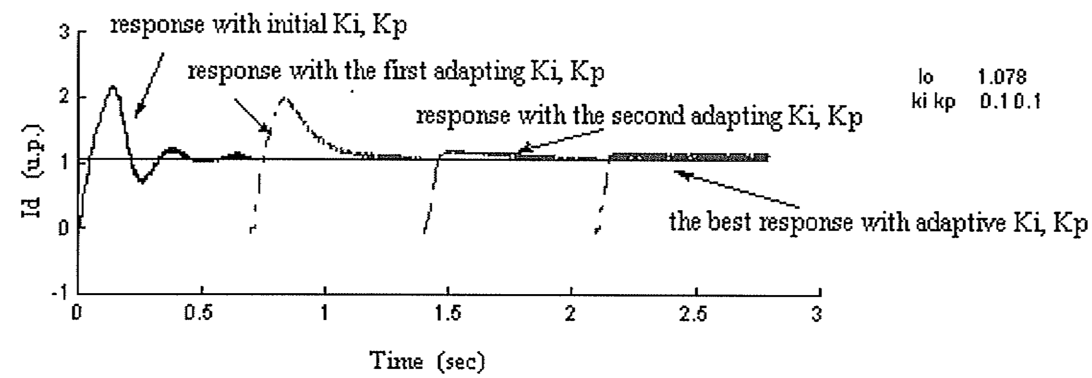

Fig. 6-8 The step response when Io = 1.078

Fig. 6-9 takes a step further to integrate the step responses comparison between two kinds of control scheme, on arrivals of a serious of different levels of system step change, as well as initial ki and kp are selected randomly. As we can see, it demonstrates that the rough control system is quite stable and can perform very well when HVDC system has been changed.

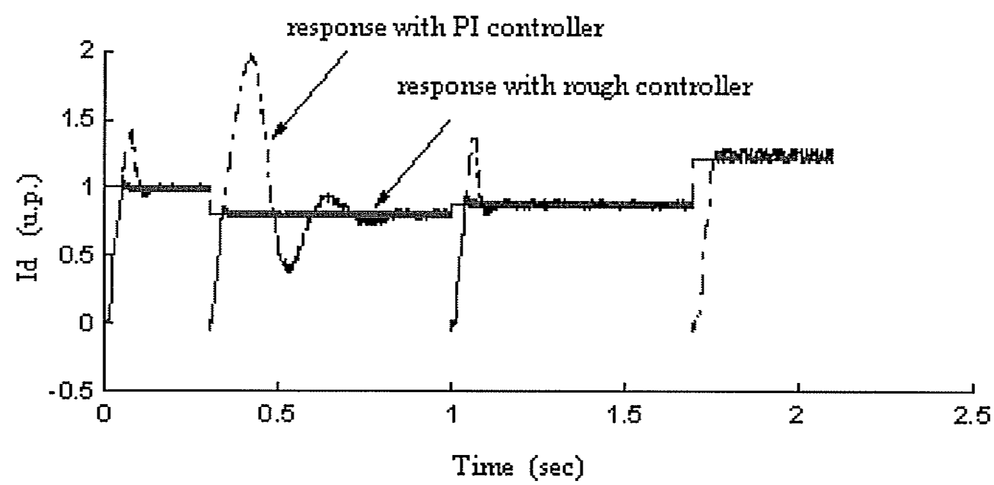

Fig. 6-9 The step response comparison when initial ki, kp and Io selected randomly

6.3 The Further Testing Results for Rough Controller

Until now, we have implemented a rough control scheme from basic one to more complex one and shown the simulation results. All work, however, is done under an assumption of an ideal HVDC system. The following work is to test whether constructed control system can keep the system stable status with variable system faults. Our testing experiments are based on the some typical faults assumed as Table 5-6, and the response is shown as Fig 6-10.

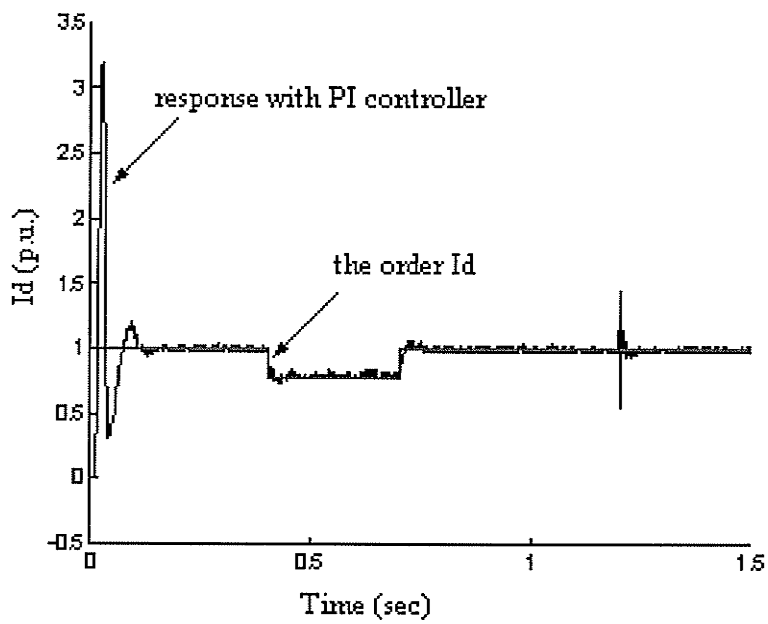

Fig. 6-10 Classical control system response on arrival of a serious of changes

Fig. 6-10 and Fig. 6-11 demonstrate the difference in step responses between a system taking classical PI control scheme and a system taking the rough control scheme. It clearly shows what happens at the first time when the system step change is observed. Since the PI controllers of both systems are running with the same initial parameters, they generate identical step responses when they encounter the first occurrence of system step change. As we can see, there is no difference between two systems in term of the first peak value, which is overshoot. Of course, there is no difference in terms of ts and tr, either. However, once the first overshoot is observed by rough control scheme through data collection, a suitable rough set rule is fired right away to adjust the adaptive PI controller. A new pair of (Ki, Kp) is set. It results that the continuous vibration of step response from the system with a rough control scheme is much reduced, as compared to a system with a classical PI controller.

In summary, the rough control scheme is suitable for a flexible HVDC system, where Io could be changed randomly in the thesis. If the other system parameters need to be changed, there will be some further work for us to do. It includes creating a similar decision system, constructing the corresponding rough tuner and controller, and finally obtaining the ideal results that we want.

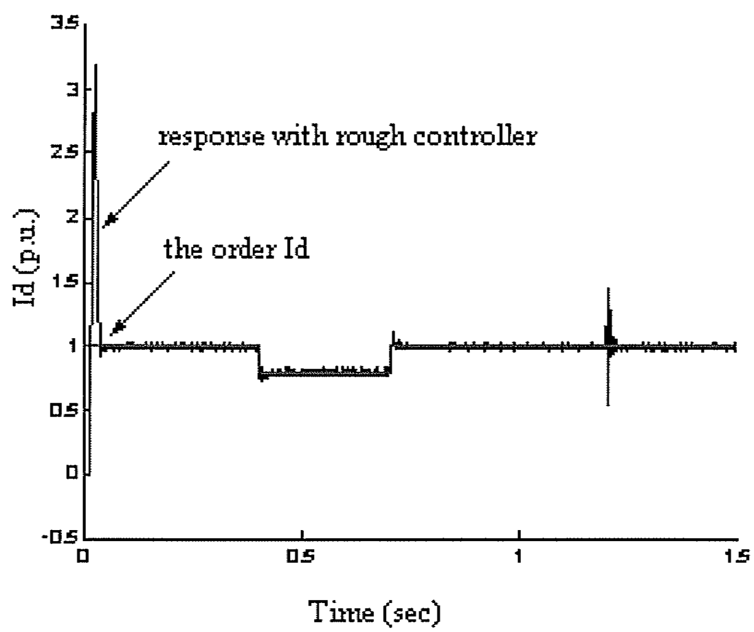

Fig. 6-11 Rough control system response on arrival of a serious of changes

7 Conclusion and Future Work

High Voltage Direct Current (HVDC) systems have been in service of electrical power transmission for over half a century. Their performance is greatly influenced by the control methods in use. It has been found that classical PI control is not able to make the best responses to the dynamical changes of HVDC system in the operating points. Based on this motivation, we have implemented the application of rough set theory for control system.

7.1 Conclusion

In the thesis, we have successfully proposed an adaptive rough control scheme, intended to improve the performance of HVDC transmission system. In the scheme, a series of processes are taken to control HVDC system in order to achieve better performance. These processes include measure of system performance, extraction of features from the measurement, granulating of obtained features, establishment of rough decision system, and firing of suitable decision rules.

We have demonstrated the performance of the adaptive rough control scheme in the thesis. The simulated HVDC system was working in a single control mode, and our control scheme was applied to the constant current control. The results show many improvements, as compared with the conventional HVDC control scheme.

In addition, we have demonstrated the stability and responsibility of our control scheme, when there are some kinds of dynamic variance existing in a HVDC system. The variance usually dynamically occurs on the users' demand or on various typical system faults, and they are characterized by the change of Io, ki, and kp.

In short, our adaptive rough control scheme performs in a manner comparable to or even superior to the classical PI control, and meanwhile it offers good system stability under various environments.

7.2 Future Work

The application of real-time decision-making in selecting gains for a HVDC constant current control system has been studied in the thesis. We have demonstrated the improved performance of our control scheme, as compared with classical PI control HVDC system. However, there are still many things we can do to improve the overall of performance offered by our rough control scheme.

First of all, we can apply the rough control scheme to constant extinction angle control, or both constant current control and extinction angle control at the same time. Extinction angle control is one of important control strategies widely deployed in HVDC transmission. It shares some common features with constant current control, while they also have some different characteristics from each other. When applying rough control scheme to extinction angle control, we need handle the unique issues of extinction angle control. It should not be scarified the improved performance obtained when the rough control scheme is applied to constant extinction angle control. The results should be studied and compared with the results obtained in this thesis.

Secondly, we can perform more experiments, so as to obtain a better initial decision system. In general, the more real experimental data we obtain, more accurately our decision system can approximate a real HVDC system. The experiments should be conducted under a wider range of variances of system conditions.

In addition, we should investigate other types of membership functions in an attempt to improve the performance of our rough control system. Membership functions are used to extracted important features from obtained responses. If the used membership functions can accurately characterize numerous responses with far less numbers of features, the control system will be high efficient and timely responsive.

Of course, the sensor models should be studied as well. The purpose of the sensors in our control scheme is similar to the functionality of membership functions. Better sensor models lead us to expect better results in characterizing the responses from HVDC.

Finally, the rough set based on controller concept can be further extended to high-level control problems such as the control of SSR and power swings. In short, we believe even better performance can be offered by our rough control scheme with those enhancements

Appendix

Appendix A: Introduction of the Tools

In the appendix, we will introduce the software tools used in the experiments. There is Matlab Simulink Power system Toolbox used to implement the model of HVDC system, and ROSETTA used to process the experimental data and construct the rough decision rules.

A-1 Power System Blockset

All functions implemented in the thesis to simulate the adaptive rough set control are coded by Matlab function. We select the Matlab Simulink to model the experimental environment, so that it is convenient to simulate HVDC system and run the functions of adjusting the adaptive controller.

The Power System Blockset was designed to provide a modern design tool that will allow user to rapidly and easily build models that simulate power systems. The Blockset uses the Simulink environment, allowing a model to be built using simple click and drag procedures. Not only can the circuit topology be drawn rapidly, but also the analysis of the circuit can include its interactions with mechanical, thermal, control, and other disciplines. This is possible because all of the electrical parts of the simulation interact with Simulink's extensive modeling library. Since Simulink uses Matlab as the computational engine, Matlab's toolboxs can also be used by the users.

Once we have built our circuit with the electrical blocks of PowerLib, we can start the simulation just like any other Simulink model. Each time we start the simulation, a special initialization mechanism is called. This initialization process computes the state-space model of our electric circuit and builds the equivalent system that can be simulated by Simulink.

The power2sys function is part of the process. It gets the state-space model and builds the Simulink model of our circuit. power2sys can also be called from the command line to obtain the state-space model of the linear part of the circuit. When called by the initialization process, power2sys performs the following four steps as also shown as Fig. A-1.

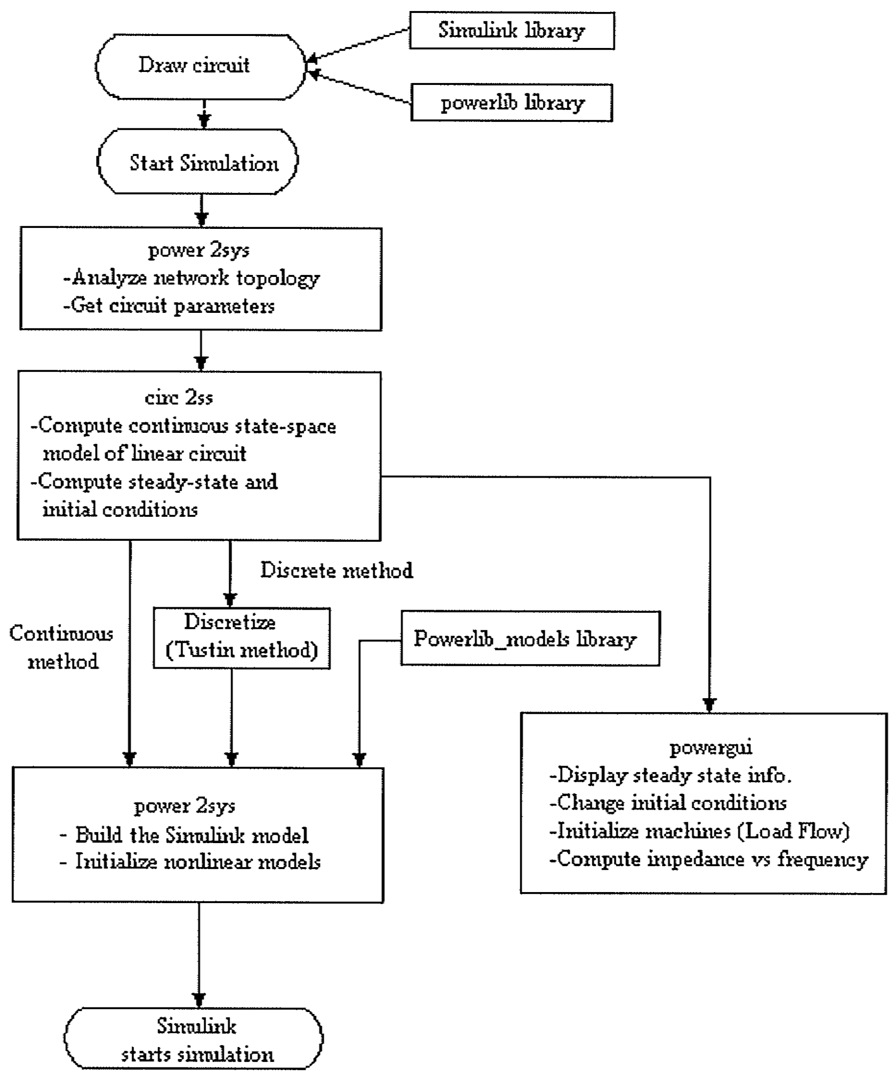

Fig. A-1 Power system blockset flowchart

At first, power2sys sorts all the blocks contained in the system into two categories: the

Simulink blocks and the Power System Blockset blocks. Then it gets the block parameters and evaluates the network topology. The Power System Blockset blocks are separated into linear and nonlinear blocks, and each electrical node is automatically given a node number.

Once the network topology has been obtained, the state-space model of the linear part of the circuit is computed by the circ2ss function. All steady-state calculations and initializations are performed at this stage.

If we have chosen to discretize our circuit, the discrete state-space model is computed from the continuous state-space model, using the Tustin method.

At last, power2sys builds the Simulink model of our circuit and stores it inside one of the measurement blocks. This means that we need at least one measurement block (Current Measurement block, Voltage Measurement block, or Multimeter block) in our model. The connections between the equivalent circuit and measurements blocks are performed by invisible links using the Goto and From blocks.

The Simulink model uses a State-Space block or an S-Function block to model the linear part of the circuit. Pre-defined Simulink models are used to simulate nonlinear elements. These models can be found in the Powerlib_models library available with the Power System Blockset. Simulink source blocks connected at the input of the state-space block are used to simulate the electrical sources blocks.

Fig. A-2 represents the interconnections between the different parts of the complete Simulink model. The nonlinear models are connected in feedback between voltage outputs and current inputs of the linear model.

Once power2sys has completed the initialization process, Simulink starts the simulation and we can observe waveforms on scopes connected at the outputs of our measurement

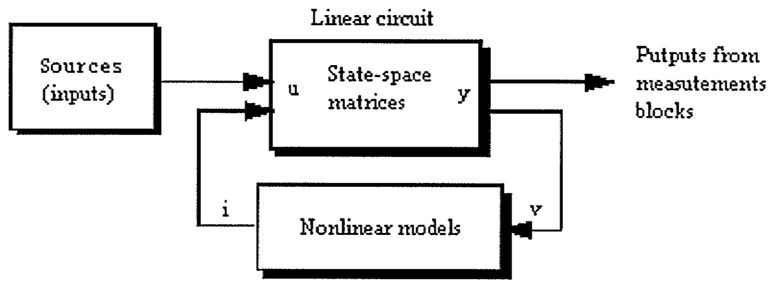

Fig. A-2 Interconnection of linear circuit and nonlinear model

blocks.

Once power2sys has completed the initialization process, Simulink starts the simulation and we can observe waveforms on scopes connected at the outputs of our measurement blocks.

If we stop the simulation and drag a copy of the Powergui block into our circuit window, we will have access to the steady-state values of inputs, outputs, and state variables displayed as phases. We can also use the interface to modify the initial conditions. The Powergui block interface allows us to perform a load flow with circuits involving three-phase machinery and initialize the machine models so that the simulation starts in steady state. This feature avoids long transients due to mechanical time constants of machines. Finally, if Impedance Measurement blocks are connected in our circuit, the Powergui block allows we to specify the desired frequency range, visualize impedance curves, and store results into our workspace.

A-2 Rosetta Software

Rough Sets theory and its application is concerned with empirical modeling necessarily to have a high experimental content, both because the sought after relationships are unknown in advance and because real-world data is often noisy and imperfect. The overall modeling process thus typically consists of a sequence of several steps that all require various degrees of tuning and fine-adjustments. Moreover, it may not beforehand be obvious which steps in the modeling pipeline that are required, nor which of several alternative algorithms that should be chosen for each step. It is therefore important to have a set of tools available that render possible this type of flexible experimentation. However, a complete model construction and experimentation tool must comprise more than a collection of clever algorithms in order to be fully useful. It is needed to set the tools in an environment such that intermediate results can be viewed and analyzed, and decisions for further processing made. Basically, an environment to interactively manage and process data is required.

Rough sets and methods based on discernibility have gained significant scientific interest as a framework for data mining and KDD, but successful research in this field undoubtedly requires good cooperation between theoreticians and practitioners. This interface can be enhanced by providing sophisticated tools and environments that support all aspects of the iterative nature of model construction and assessment. In response to these needs, the process of using rough sets for KDD has been investigated and process patterns typical to rough set KDD experiments been established. The ROSETTA system has been designed and implemented as a result.

This section introduces the ROSETTA system. ROSETTA is a toolkit for logical data analysis based on discernibility considerations. ROSETTA is designed to support the overall data mining and knowledge discovery process; from initial browsing and preprocessing of the data, via computation of minimal attribute sets and generation of if-then rules or descriptive patterns, to validation and analysis of the induced rules or patterns.

Another attribute of ROSETTA is that it is intended as a general purpose tool for discernibility-based modeling, and is not geared specifically towards any particular application domain.

- GUI Overview

The Appendix A-2 end runs under 32-bit Windows operating systems on Intel platforms, and offers an environment in which the user in a simple way can view and keep track of the individual data items in an analysis project. Emphasis has also been put on making it easy to manipulate the data items and initiate computations. The GUI is designed according to a strict object-oriented philosophy. Briefly, features include:

Project trees: Each item in a data analysis project is represented by its own icon specific to its type, and each project organizes these icons in a tree. The topology of the tree conveys how the data items relate to each other in an intuitive and immediate way. A branch from a parent item to a child item signifies a direct derivation relationship, while siblinghood typically represents alternative hypotheses being explored in the KDD

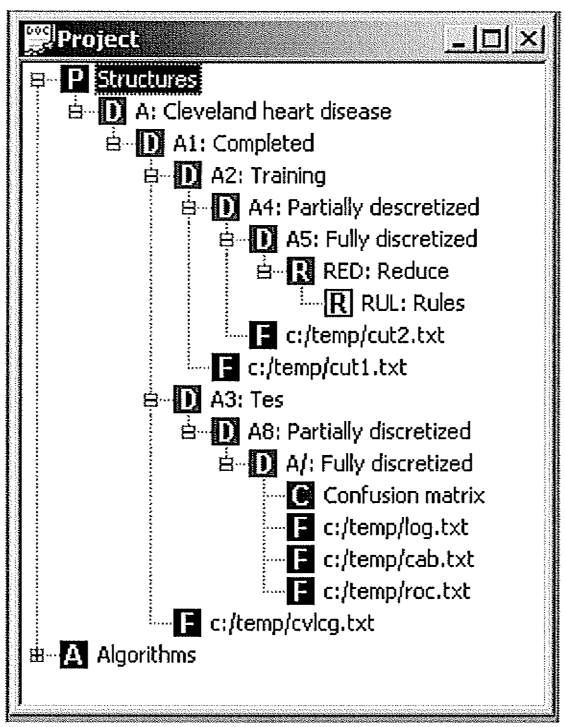

Fig. A-3 An example ROSETTA project tree process. A snapshot of a sample project tree is provided in Fig. A-3. Each data item is represented as a separate icon, with the branches in the tree reflecting how the items relate to each other. Right-clicking an icon brings up a pop-up menu for the selected object.

Data views: All data items in project trees can be viewed in individual windows, typically in grid views. Routed through data dictionaries, all data is displayed to the user in terms from the modeling domain. Together with the project trees, a collection of such views embodies a comprehensive workspace. A snapshot of a sample workspace is provided in Fig. A-4, which displays several different types of data views. A project tree, showing how all the current data relate to each other, is drawn in the top left corner. All views display data in terms from the modeling domain

Context-sensitive pop-up menus: Most GUI objects, e.g., icons in project trees and columns or rows in data views, are right-clickable and provide their own local pop-up menus. This gives intuitive and easy access to the set of operations currently applicable to that particular object.

Support for drag-and-drop: As an alternative to pop-up menus, the project tree also has support for drag-and-drop. In the tree, not only are data items represented by icons, but possible operations are iconified, too. Hence, to initiate a computation, an algorithm icon may be dragged and dropped onto a data icon, or vice versa.

Comprehensive parameter dialogs: Most algorithms need to be supplied with some parameters that determine details of their behavior. Often, default parameter settings are acceptable, but for flexibility and generality expert tuning must be possible. For some algorithms, combinations of parameters are only allowed according to certain rules. ROSETTA provides comprehensive support for this process by offering advanced parameter dialogs, which may adapt according to the currently specified settings.

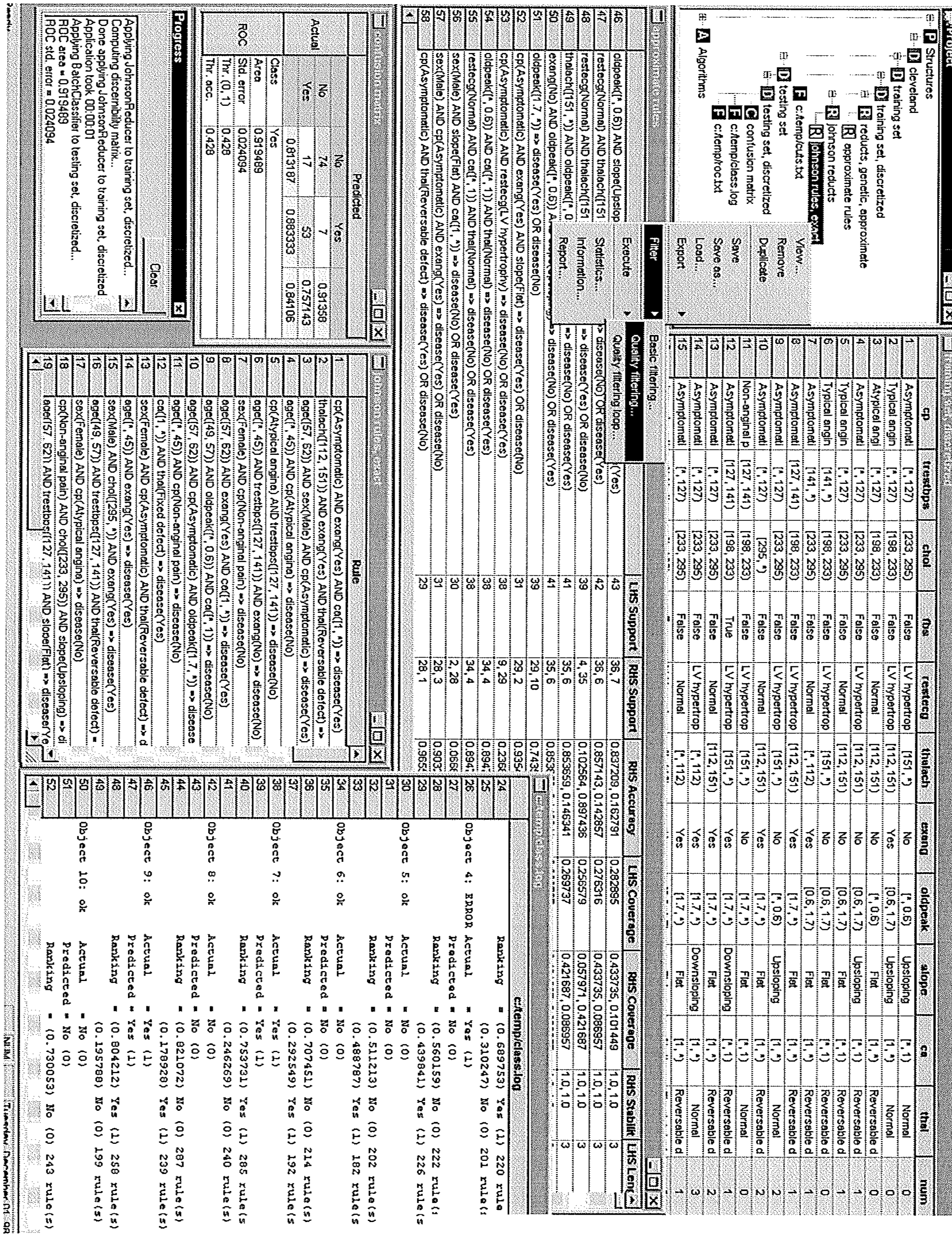

Fig. A-4 An example ROSETTA workspace

Annotations: Data items can be annotated with user comments. Also, as new data items are created or transformed, they get automatically stamped with history detail, revealing how they were created, which algorithms that were applied to them, which parameter settings that were used, etc. Hence, logs documenting the modeling sessions are automatically generated, thus promoting reproducibility of experiments between researchers when data is exchanged.

The ROSETTA GUI offers several other features, including a system for displaying detailed progress messages and intermediate results, the ability to prematurely terminate lengthy computations, and an on-line help system. The GUI is highly object-oriented in that all manipulable objects are represented as individual GUI items, each with their own set of context-sensitive menus.

- Computation kernel Overview

Exception a highly intuitive GUI environment, where data-navigational abilities are emphasized, ROSETTA also offers a very powerful computation kernel. The computational kernel has been developed for data analysis within the framework for rough set theory. The system implements feature relevant to build and evaluate rough set models in the medical domain, and offers a highly user-friendly environment in which to conduct experiments. Although by design equipped with several features that are relevant for analysis of medical data, ROSETTA is in itself a general-purpose system that is not geared towards any particular application domain. ROSETTA has been put to use by a large number of researchers worldwide, and has resulted in scientific publications in a wide variety of areas.

It is practical to differentiate between the computational kernel and the front-end of ROSETTA. The computational kernel is a general C++ class library for KDD within the rough set methodology, and offers an advantageous code base for researchers to quickly assemble and try out new algorithms and ideas. The front-end is a state-of-the-art graphical user interface (GUI) running under Windows NT / 98 / 95. Together, the kernel and the front-end constitute a powerful vehicle for practical discernibility-related research and applications.

The ROSETTA kernel can be employed in two modes: Together with the GUI front-end, and as a stand-alone command-line program. The former enable access to the computational engine in a user-friendly environment, while the latter enables ROSETTA to be used as a computational engine called from elsewhere, e.g., from Perl scripts.

ROSETTA is probably the most complete, flexible and advanced rough set software system of its kind currently available. The system also encompasses several stand-alone utility programs that operate directly on output from the main ROSETTA program, e.g., programs for statistical hypothesis testing.

Appendix B: Record of Experimental Data

The following data is recorded to construct the decision table for Ki and Kp

B-1 Experimental Data for Decision Table Ki

a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	di
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.00	0.40	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.58	0.20	0.00	5.00
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.67	0.01	0.00	0.00	1.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.85	0.01	0.00	0.00	1.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.01	0.00	0.40	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.32	0.12	0.00	0.50	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.01	0.19	0.00	0.00	0.00	1.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.43	0.00	0.00	0.33	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.33	0.12	0.18	0.30	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.29	0.00	0.00	0.00	1.00	5.00
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	1.00	0.00	0.00	0.05	0.10	0.00	0.00	0.53	0.00	4.00
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	1.00	0.00	0.00	0.45	0.02	0.00	0.00	0.90	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.06	0.09	0.00	0.18	0.30	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.02	0.00	0.67	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.44	0.00	0.00	0.73	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	0.75	0.01	0.00	0.00	1.00	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.66	0.02	0.00	0.00	0.80	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.55	0.02	0.00	0.58	0.20	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.28	0.00	0.00	1.00	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.99	0.01	0.00	0.00	0.60	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.88	0.01	0.00	0.00	0.40	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.77	0.01	0.00	0.58	0.20	0.00	5.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.00	0.40	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.00	0.40	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.35	0.12	0.00	0.00	1.00	4.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.02	0.00	0.00	1.00	4.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.40	0.00	4.00
1.00	0.00	0.00	1.00	0.00	0.00	0.96	0.01	0.00	0.00	0.50	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.58	0.20	0.00	2.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	0.01	0.20	0.00	0.00	0.07	0.30	4.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.50	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.01	0.19	0.00	0.00	0.47	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.02	0.00	0.60	0.00	5.00

NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.58	0.20	0.00	2.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.58	0.20	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.98	0.10	0.00	3.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.18	0.30	0.00	0.50
0.50	0.50	0.00	0.11	0.08	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.50	0.50	0.00	0.12	0.07	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.50	0.50	0.00	0.12	0.07	0.00	1.00	0.00	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.14	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.50	0.50	0.00	0.11	0.08	0.00	1.00	0.01	0.00	0.98	0.10	0.00	5.00
0.50	0.50	0.00	0.09	0.10	0.00	1.00	0.00	0.00	0.98	0.10	0.00	2.00
NaN	0.50	0.00	0.09	0.10	0.00	1.00	0.00	0.00	0.98	0.10	0.00	2.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.72	0.01	0.00	0.00	0.90	3.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.89	0.01	0.00	0.00	1.00	5.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	1.00	0.01	0.00	0.47	0.00	5.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.02	0.30	0.00	0.50	0.00	5.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.22	0.00	0.00	0.00	0.50	2.00
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.32	0.00	0.00	0.13	0.10	4.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.72	0.01	0.00	1.00	0.00	4.00
0.50	0.50	0.00	0.09	0.10	0.00	0.04	0.11	0.00	0.00	0.67	0.00	2.00
0.50	0.50	0.00	0.08	0.11	0.00	0.07	0.08	0.00	0.00	0.67	0.00	4.00
0.50	0.50	0.00	0.08	0.11	0.00	0.13	0.06	0.00	0.00	0.80	0.00	4.00
0.50	0.50	0.00	0.08	0.11	0.00	0.03	0.12	0.00	0.00	0.40	0.00	4.00
0.50	0.50	0.00	0.14	0.06	0.00	0.44	0.02	0.00	0.00	0.80	0.00	2.00
0.50	0.50	0.00	0.14	0.06	0.00	0.07	0.08	0.00	0.98	0.10	0.00	2.00
0.50	0.50	0.00	0.11	0.08	0.00	0.00	1.00	0.01	0.00	0.93	0.00	2.00
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.09	0.10	0.00	0.57	0.02	0.00	0.98	0.10	0.00	4.00
0.50	0.50	0.00	0.09	0.10	0.00	0.01	0.19	0.00	0.00	0.90	0.00	2.00
0.50	0.50	0.00	0.09	0.10	0.00	0.99	0.01	0.00	0.00	0.50	0.00	2.00
0.50	0.50	0.00	0.09	0.10	0.00	0.88	0.01	0.00	0.00	0.40	0.00	5.00
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.14	0.06	0.00	1.00	0.01	0.00	0.58	0.20	0.00	1.20
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.00	1.00	0.00	0.00	1.00	4.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.78	0.07	0.00	0.00	1.00	4.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.00	1.00	0.00	0.53	0.00	4.00
0.50	0.50	0.00	0.11	0.08	0.00	0.94	0.01	0.00	0.00	0.50	0.00	2.00
NaN	0.50	0.00	0.09	0.10	0.00	1.00	0.00	0.00	0.98	0.10	0.00	2.00
0.50	0.50	0.00	0.14	0.06	0.00	1.00	0.00	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.22	0.00	0.00	0.33	0.00	2.00
0.50	0.50	0.00	0.11	0.08	0.00	0.00	0.62	0.00	0.00	0.80	0.00	5.00
0.50	0.50	0.00	0.09	0.10	0.00	0.46	0.02	0.00	0.00	0.80	0.00	5.00
0.50	0.50	0.00	0.08	0.11	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00

0.50	0.50	0.00	0.09	0.10	0.00	1.00	0.00	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.08	0.11	0.00	1.00	0.00	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.09	0.10	0.00	0.37	0.03	0.00	0.18	0.30	0.00	4.00
0.50	0.50	0.00	0.16	0.06	0.00	1.00	0.01	0.00	0.98	0.10	0.00	3.00
NaN	0.50	0.00	0.11	0.08	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.14	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.14	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.14	0.06	0.00	1.00	0.00	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.16	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.16	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.11	0.08	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.09	0.10	0.00	0.99	0.01	0.00	0.00	0.50	0.00	2.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.00	0.00	0.98	0.10	0.00	0.50
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.01	0.00	1.00	0.00	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.01	0.00	1.00	0.00	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.75	0.01	0.00	0.00	0.50	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.03	0.00	0.00	1.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.67	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.02	0.31	0.00	0.40	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.01	0.21	0.00	0.00	0.20	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.46	0.00	0.00	0.73	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.19	0.16	0.98	0.10	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.34	0.00	0.00	0.33	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.70	0.01	0.00	0.80	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.04	0.10	0.00	0.00	0.87	0.00	4.00
0.00	1.00	0.00	0.00	1.00	0.00	0.07	0.08	0.00	0.00	0.80	0.00	4.00
0.00	1.00	0.00	0.00	1.00	0.00	0.15	0.05	0.00	0.00	0.70	0.00	4.00
0.00	1.00	0.00	0.00	1.00	0.00	0.03	0.12	0.00	0.00	0.40	0.00	4.00
0.00	1.00	0.00	0.00	1.00	0.00	0.40	0.03	0.00	0.00	0.60	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.09	0.07	0.00	0.98	0.10	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.02	0.00	1.00	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.30	0.00	0.00	1.00	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.69	0.01	0.00	0.00	0.70	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.70	0.01	0.00	0.00	0.60	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.60	0.02	0.00	1.00	0.00	0.00	4.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.29	0.00	0.00	0.60	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.92	0.01	0.00	0.00	0.40	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.92	0.01	0.00	0.18	0.30	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.72	0.01	0.00	1.00	0.00	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.01	0.00	0.18	0.30	0.00	1.20
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.01	0.00	0.58	0.20	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.55	0.00	0.00	1.00	4.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.06	0.24	0.00	0.00	1.00	4.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.67	0.00	4.00
0.00	1.00	0.00	0.00	1.00	0.00	0.91	0.01	0.00	0.18	0.30	0.00	2.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.01	0.00	1.00	0.00	0.00	2.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.22	0.00	0.00	0.53	0.00	2.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.50

0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	5.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	2.00
0.00	0.50	0.50	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.50	0.50	0.00	0.14	0.15	0.00	0.80	0.01	0.00	0.20	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	0.00	0.97	0.01	0.00	0.00	0.50	5.00
0.00	0.50	0.50	0.00	0.14	0.15	0.00	1.00	0.01	0.00	0.80	0.00	5.00
0.00	0.50	0.50	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.50	0.50	0.00	0.14	0.15	0.00	0.23	0.00	0.00	0.40	0.00	2.00
0.00	0.50	0.50	0.00	0.17	0.11	0.00	0.45	0.00	0.00	0.87	0.00	5.00
0.00	0.50	0.50	0.00	0.17	0.11	0.00	0.51	0.09	1.00	0.00	0.00	5.00
0.00	0.50	0.50	0.00	0.17	0.11	0.00	0.38	0.00	0.00	0.53	0.00	5.00
0.00	0.50	0.50	0.00	0.17	0.11	0.00	0.64	0.01	0.00	0.70	0.00	5.00
0.00	0.50	0.50	0.00	0.15	0.13	0.03	0.12	0.00	0.00	1.00	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	0.06	0.09	0.00	0.00	1.00	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	0.15	0.05	0.00	0.00	0.60	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	0.02	0.14	0.00	0.18	0.30	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	0.42	0.03	0.00	0.00	0.50	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	0.16	0.05	0.00	1.00	0.00	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	0.00	1.00	0.02	0.00	0.80	0.00	1.00
0.00	0.50	0.50	0.00	0.14	0.15	0.00	0.33	0.00	0.00	0.80	0.00	1.00
0.00	0.50	0.50	0.00	0.14	0.15	0.71	0.01	0.00	0.00	0.60	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	0.60	0.02	0.00	0.00	0.50	0.00	5.00
0.00	0.50	0.50	0.00	0.15	0.13	0.63	0.02	0.00	1.00	0.00	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	0.00	0.33	0.00	0.00	0.60	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	0.94	0.01	0.00	0.18	0.30	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	0.82	0.01	0.00	0.58	0.20	0.00	5.00
0.00	0.50	0.50	0.00	0.14	0.15	0.82	0.01	0.00	1.00	0.00	0.00	5.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	0.98	0.10	0.00	1.20
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	0.98	0.10	0.00	2.00
0.00	0.50	0.50	0.00	0.07	0.30	0.00	0.00	1.00	0.00	0.00	1.00	4.00
0.00	0.50	0.50	0.00	0.08	0.26	0.00	0.30	0.13	0.00	0.00	1.00	4.00
0.00	0.50	0.50	0.00	0.15	0.13	0.00	0.00	1.00	0.00	0.80	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	0.91	0.01	0.00	0.18	0.30	0.00	2.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	0.98	0.10	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	1.00
0.00	0.50	0.50	0.00	0.15	0.13	0.00	0.24	0.00	0.00	0.73	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	0.96	0.01	0.00	0.98	0.10	0.00	4.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	2.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	0.98	0.10	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	3.00
0.00	0.50	0.50	0.00	0.17	0.11	0.00	0.00	0.00	1.00	0.00	0.00	0.50
0.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.02	1.00	0.00	0.00	0.50
0.00	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	1.00	1.00	0.01	0.00	1.00	0.00	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	2.00

0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.79	0.01	0.00	0.40	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.02	0.00	0.27	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.02	0.00	0.93	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.03	0.29	0.58	0.20	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.25	0.00	0.00	0.60	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.48	0.00	0.00	1.00	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.53	0.09	1.00	0.00	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.37	0.00	0.00	0.73	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.63	0.00	0.00	0.60	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.02	0.13	0.00	0.00	1.00	0.00	4.00
0.00	0.00	1.00	0.00	0.00	1.00	0.06	0.09	0.00	0.00	1.00	0.00	4.00
0.00	0.00	1.00	0.00	0.00	1.00	0.12	0.06	0.00	0.00	0.50	0.00	4.00
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	1.00	0.42	0.03	0.00	0.00	0.40	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.17	0.05	0.00	1.00	0.00	0.00	2.00
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.36	0.00	0.00	0.70	0.00	1.00
0.00	0.00	1.00	0.00	0.00	1.00	0.62	0.02	0.00	0.00	0.50	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.62	0.02	0.00	0.18	0.30	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.64	0.02	0.00	1.00	0.00	0.00	4.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.36	0.00	0.00	0.50	0.00	1.00
0.00	0.00	1.00	0.00	0.00	1.00	0.87	0.01	0.00	0.58	0.20	0.00	1.00
0.00	0.00	1.00	0.00	0.00	1.00	0.86	0.01	0.00	0.98	0.10	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.86	0.01	0.00	1.00	0.00	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	1.00	0.01	0.00	0.98	0.10	0.00	1.20
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.55	0.09	0.00	0.00	1.00	4.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.87	0.00	4.00
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.26	0.00	0.00	0.87	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.59	0.02	0.00	0.18	0.30	0.00	1.00
0.00	0.00	1.00	0.00	0.00	1.00	0.75	0.01	0.00	1.00	0.00	0.00	3.00
0.00	0.00	1.00	0.00	0.00	1.00	0.84	0.01	0.00	0.58	0.20	0.00	3.00
0.00	0.00	1.00	0.00	0.00	1.00	0.73	0.01	0.00	0.98	0.10	0.00	3.00
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.50

B-2 Experimental Data for Decision Table Kp

a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	dp
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.00	0.40	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.58	0.20	0.00	3.00
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN

1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.67	0.01	0.00	0.00	1.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.85	0.01	0.00	0.00	1.00	4.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.01	0.00	0.40	0.00	4.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.32	0.12	0.00	0.50	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	0.01	0.19	0.00	0.00	0.00	1.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.43	0.00	0.00	0.33	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.33	0.12	0.18	0.30	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.29	0.00	0.00	0.00	1.00	5.00
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	1.00	0.00	0.00	0.05	0.10	0.00	0.00	0.53	0.00	2.00
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
1.00	0.00	0.00	1.00	0.00	0.00	0.45	0.02	0.00	0.00	0.90	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.06	0.09	0.00	0.18	0.30	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.02	0.00	0.67	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.44	0.00	0.00	0.73	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.75	0.01	0.00	0.00	1.00	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.66	0.02	0.00	0.00	0.80	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.55	0.02	0.00	0.58	0.20	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.28	0.00	0.00	1.00	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.99	0.01	0.00	0.00	0.60	0.00	4.00
1.00	0.00	0.00	1.00	0.00	0.00	0.88	0.01	0.00	0.00	0.40	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.77	0.01	0.00	0.58	0.20	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.00	0.40	0.00	5.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.00	0.40	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.35	0.12	0.00	0.00	1.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.02	0.00	0.00	1.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.40	0.00	4.00
1.00	0.00	0.00	1.00	0.00	0.00	0.96	0.01	0.00	0.00	0.50	0.00	5.00
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.58	0.20	0.00	4.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	0.01	0.20	0.00	0.00	0.07	0.30	4.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.32	0.00	0.00	0.00	0.50	4.00
1.00	0.00	0.00	1.00	0.00	0.00	0.01	0.19	0.00	0.00	0.47	0.00	2.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.02	0.00	0.60	0.00	0.50
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.58	0.20	0.00	3.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.58	0.20	0.00	3.00
1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.98	0.10	0.00	2.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.18	0.30	0.00	0.50
0.50	0.50	0.00	0.11	0.08	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.50	0.50	0.00	0.12	0.07	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.50	0.50	0.00	0.12	0.07	0.00	1.00	0.00	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.14	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.50	0.50	0.00	0.11	0.08	0.00	1.00	0.01	0.00	0.98	0.10	0.00	3.00
0.50	0.50	0.00	0.09	0.10	0.00	1.00	0.00	0.00	0.98	0.10	0.00	2.00

NaN	0.50	0.00	0.09	0.10	0.00	1.00	0.00	0.00	0.98	0.10	0.00	2.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.72	0.01	0.00	0.00	0.90	5.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.89	0.01	0.00	0.00	1.00	2.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	1.00	0.01	0.00	0.47	0.00	2.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.02	0.30	0.00	0.50	0.00	1.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.22	0.00	0.00	0.00	0.50	2.00
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.32	0.00	0.00	0.13	0.10	5.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.72	0.01	0.00	1.00	0.00	1.00
0.50	0.50	0.00	0.09	0.10	0.00	0.04	0.11	0.00	0.00	0.67	0.00	4.00
0.50	0.50	0.00	0.08	0.11	0.00	0.07	0.08	0.00	0.00	0.67	0.00	4.00
0.50	0.50	0.00	0.08	0.11	0.00	0.13	0.06	0.00	0.00	0.80	0.00	1.00
0.50	0.50	0.00	0.08	0.11	0.00	0.03	0.12	0.00	0.00	0.40	0.00	1.00
0.50	0.50	0.00	0.14	0.06	0.00	0.44	0.02	0.00	0.00	0.80	0.00	5.00
0.50	0.50	0.00	0.14	0.06	0.00	0.07	0.08	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.11	0.08	0.00	0.00	1.00	0.01	0.00	0.93	0.00	2.00
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.09	0.10	0.00	0.57	0.02	0.00	0.98	0.10	0.00	1.20
0.50	0.50	0.00	0.09	0.10	0.00	0.01	0.19	0.00	0.00	0.90	0.00	5.00
0.50	0.50	0.00	0.09	0.10	0.00	0.99	0.01	0.00	0.00	0.50	0.00	4.00
0.50	0.50	0.00	0.09	0.10	0.00	0.88	0.01	0.00	0.00	0.40	0.00	5.00
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.14	0.06	0.00	1.00	0.01	0.00	0.58	0.20	0.00	5.00
0.50	0.50	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.00	1.00	0.00	0.00	1.00	5.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.78	0.07	0.00	0.00	1.00	5.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.00	1.00	0.00	0.53	0.00	4.00
0.50	0.50	0.00	0.11	0.08	0.00	0.94	0.01	0.00	0.00	0.50	0.00	5.00
0.50	0.50	0.00	0.09	0.10	0.00	1.00	0.00	0.00	0.98	0.10	0.00	4.00
0.50	0.50	0.00	0.14	0.06	0.00	1.00	0.00	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.22	0.00	0.00	0.33	0.00	4.00
0.50	0.50	0.00	0.11	0.08	0.00	0.00	0.62	0.00	0.00	0.80	0.00	2.00
0.50	0.50	0.00	0.09	0.10	0.00	0.46	0.02	0.00	0.00	0.80	0.00	5.00
0.50	0.50	0.00	0.08	0.11	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.50	0.50	0.00	0.09	0.10	0.00	1.00	0.00	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.08	0.11	0.00	1.00	0.00	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.09	0.10	0.00	0.37	0.03	0.00	0.18	0.30	0.00	2.00
0.50	0.50	0.00	0.16	0.06	0.00	1.00	0.01	0.00	0.98	0.10	0.00	3.00
NaN	0.50	0.00	0.11	0.08	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.14	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.14	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.14	0.06	0.00	1.00	0.00	0.00	0.98	0.10	0.00	1.00
0.50	0.50	0.00	0.16	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.16	0.06	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.11	0.08	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.00	0.09	0.10	0.00	0.99	0.01	0.00	0.00	0.50	0.00	4.00
0.50	0.50	0.00	0.09	0.10	0.00	0.00	0.00	0.00	0.98	0.10	0.00	0.50
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.01	0.00	1.00	0.00	0.00	3.00

0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.01	0.00	1.00	0.00	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.20
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.75	0.01	0.00	0.00	0.50	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.03	0.00	0.00	1.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.01	0.00	0.67	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.02	0.31	0.00	0.40	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.01	0.21	0.00	0.00	0.20	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.46	0.00	0.00	0.73	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.19	0.16	0.98	0.10	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.34	0.00	0.00	0.33	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.70	0.01	0.00	0.80	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.04	0.10	0.00	0.00	0.87	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.07	0.08	0.00	0.00	0.80	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.15	0.05	0.00	0.00	0.70	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.03	0.12	0.00	0.00	0.40	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.40	0.03	0.00	0.00	0.60	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.09	0.07	0.00	0.98	0.10	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.02	0.00	1.00	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.30	0.00	0.00	1.00	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.69	0.01	0.00	0.00	0.70	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.70	0.01	0.00	0.00	0.60	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	0.60	0.02	0.00	1.00	0.00	0.00	1.20
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.29	0.00	0.00	0.60	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.92	0.01	0.00	0.00	0.40	0.00	4.00
0.00	1.00	0.00	0.00	1.00	0.00	0.92	0.01	0.00	0.18	0.30	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.72	0.01	0.00	1.00	0.00	0.00	2.00
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.01	0.00	0.18	0.30	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.01	0.00	0.58	0.20	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.55	0.00	0.00	1.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.06	0.24	0.00	0.00	1.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.67	0.00	4.00
0.00	1.00	0.00	0.00	1.00	0.00	0.91	0.01	0.00	0.18	0.30	0.00	5.00
0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.01	0.00	1.00	0.00	0.00	4.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.22	0.00	0.00	0.53	0.00	4.00
NaN	1.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.50
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	3.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	2.00
0.00	0.50	0.50	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.50	0.50	0.00	0.14	0.15	0.00	0.80	0.01	0.00	0.20	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	0.00	0.97	0.01	0.00	0.00	0.50	2.00
0.00	0.50	0.50	0.00	0.14	0.15	0.00	1.00	0.01	0.00	0.80	0.00	2.00
0.00	0.50	0.50	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.50	0.50	0.00	0.14	0.15	0.00	0.23	0.00	0.00	0.40	0.00	2.00
0.00	0.50	0.50	0.00	0.17	0.11	0.00	0.45	0.00	0.00	0.87	0.00	2.00
0.00	0.50	0.50	0.00	0.17	0.11	0.00	0.51	0.09	1.00	0.00	0.00	1.00
0.00	0.50	0.50	0.00	0.17	0.11	0.00	0.38	0.00	0.00	0.53	0.00	5.00
0.00	0.50	0.50	0.00	0.17	0.11	0.00	0.64	0.01	0.00	0.70	0.00	1.00
0.00	0.50	0.50	0.00	0.15	0.13	0.03	0.12	0.00	0.00	1.00	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	0.06	0.09	0.00	0.00	1.00	0.00	5.00

0.00	0.50	0.50	0.00	0.14	0.15	0.15	0.05	0.00	0.00	0.60	0.00	5.00
0.00	0.50	0.50	0.00	0.14	0.15	0.02	0.14	0.00	0.18	0.30	0.00	1.00
0.00	0.50	0.50	0.00	0.14	0.15	0.42	0.03	0.00	0.00	0.50	0.00	5.00
0.00	0.50	0.50	0.00	0.14	0.15	0.16	0.05	0.00	1.00	0.00	0.00	1.00
0.00	0.50	0.50	0.00	0.14	0.15	0.00	1.00	0.02	0.00	0.80	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	0.00	0.33	0.00	0.00	0.80	0.00	5.00
0.00	0.50	0.50	0.00	0.14	0.15	0.71	0.01	0.00	0.00	0.60	0.00	5.00
0.00	0.50	0.50	0.00	0.14	0.15	0.60	0.02	0.00	0.00	0.50	0.00	2.00
0.00	0.50	0.50	0.00	0.15	0.13	0.63	0.02	0.00	1.00	0.00	0.00	1.20
0.00	0.50	0.50	0.00	0.14	0.15	0.00	0.33	0.00	0.00	0.60	0.00	5.00
0.00	0.50	0.50	0.00	0.14	0.15	0.94	0.01	0.00	0.18	0.30	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	0.82	0.01	0.00	0.58	0.20	0.00	5.00
0.00	0.50	0.50	0.00	0.14	0.15	0.82	0.01	0.00	1.00	0.00	0.00	2.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	0.98	0.10	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	0.98	0.10	0.00	5.00
0.00	0.50	0.50	0.00	0.07	0.30	0.00	0.00	1.00	0.00	0.00	1.00	5.00
0.00	0.50	0.50	0.00	0.08	0.26	0.00	0.30	0.13	0.00	0.00	1.00	5.00
0.00	0.50	0.50	0.00	0.15	0.13	0.00	0.00	1.00	0.00	0.80	0.00	1.00
0.00	0.50	0.50	0.00	0.14	0.15	0.91	0.01	0.00	0.18	0.30	0.00	4.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	0.98	0.10	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	1.00
0.00	0.50	0.50	0.00	0.15	0.13	0.00	0.24	0.00	0.00	0.73	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	0.96	0.01	0.00	0.98	0.10	0.00	5.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	2.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	0.98	0.10	0.00	4.00
0.00	0.50	0.50	0.00	0.14	0.15	1.00	0.01	0.00	1.00	0.00	0.00	4.00
0.00	0.50	0.50	0.00	0.17	0.11	0.00	0.00	0.00	1.00	0.00	0.00	0.50
0.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.02	1.00	0.00	0.00	0.50
0.00	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	1.00	1.00	0.01	0.00	1.00	0.00	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.20
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.79	0.01	0.00	0.40	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.02	0.00	0.27	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	0.02	0.00	0.93	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.03	0.29	0.58	0.20	0.00	0.50
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.25	0.00	0.00	0.60	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.48	0.00	0.00	1.00	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.53	0.09	1.00	0.00	0.00	1.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.37	0.00	0.00	0.73	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.63	0.00	0.00	0.60	0.00	1.00
0.00	0.00	1.00	0.00	0.00	1.00	0.02	0.13	0.00	0.00	1.00	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.06	0.09	0.00	0.00	1.00	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.12	0.06	0.00	0.00	0.50	0.00	5.00
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	1.00	0.42	0.03	0.00	0.00	0.40	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.17	0.05	0.00	1.00	0.00	0.00	1.00
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.36	0.00	0.00	0.70	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.62	0.02	0.00	0.00	0.50	0.00	2.00

0.00	0.00	1.00	0.00	0.00	1.00	0.62	0.02	0.00	0.18	0.30	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.64	0.02	0.00	1.00	0.00	0.00	1.20
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.36	0.00	0.00	0.50	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.87	0.01	0.00	0.58	0.20	0.00	4.00
0.00	0.00	1.00	0.00	0.00	1.00	0.86	0.01	0.00	0.98	0.10	0.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.86	0.01	0.00	1.00	0.00	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	1.00	0.01	0.00	0.98	0.10	0.00	5.00
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.55	0.09	0.00	0.00	1.00	5.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.87	0.00	4.00
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	NaN
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.26	0.00	0.00	0.87	0.00	4.00
0.00	0.00	1.00	0.00	0.00	1.00	0.59	0.02	0.00	0.18	0.30	0.00	4.00
0.00	0.00	1.00	0.00	0.00	1.00	0.75	0.01	0.00	1.00	0.00	0.00	2.00
0.00	0.00	1.00	0.00	0.00	1.00	0.84	0.01	0.00	0.58	0.20	0.00	4.00
0.00	0.00	1.00	0.00	0.00	1.00	0.73	0.01	0.00	0.98	0.10	0.00	2.00
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
NaN	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00
0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.00	0.00	0.50

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