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SOFT COMPUTING METHOD BASED ON THOM'S CATASTROPHE THEORY FOR CONTROLLING OF LARGE-SCALE SYSTEMS

(with special regard to controlling of a heat power station)

Ph.D. Thesis
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Abbreviations

AI	Artificial intelligence
ANN	Artificial neural network
BP	Backpropagation
BPTT	Backpropagation through time
DCS	Distributed control system
ES	Expert system
EUC	Equipment Under Control
FC	Fuzzy control
FIS	Fuzzy inference system
FLC	Fuzzy logic control
FN	Fuzzy neuron
FNN	Fuzzy neural network
FS	Fuzzy system
HS	Hybrid system
IC	Intelligent control
IPL	*Independent protection layer*
LOPA	*Layer of protection analysis*
MNN	Multilayer neural network
NFC	Neuro-fuzzy control
NN	Neural network
PLC	*Programmable logic control*
RRF	*Risk reduction factor*
SA	*Safety availability*
SC	*Soft computing*
SIL	*Safety integrity level*
SIS	Safety instrumented system
SRS	Safety requirements specification

Symbols

R	Set of real numbers
R^n	n-dimension space
$Df\|_u$	Derivative of function
x, y, z	Variables
$Hf\|_u$	Hessian matrix of function $f(u)$
$Det(Hf\|_u)$	Determinant of Hessian matrix of function $f(u)$
$V_{ab..}(x)$	Canonic functions of catastrophes
$f: R^n \rightarrow R$	*Transformation of* R^{n} *into* R *by* f
p	Pressure
T	Temperature
V	Volume
ρ	Specific mass
m_{fa0}	Specific mass of fresh air for required by combustion of unit of earth gas
λ	Air xcess factor
$\dot{m}_{st}$	Mass flow of steam
$\dot{m}_{fw}$	Mass flow of feed water
$\dot{m}_{fl}$	Mass flow of fuel
$\dot{m}_{fg}$	Mass flow of flue gas
$\dot{m}_{fa}$	Mass flow of fresh air
$\dot{V}_{st}$	Volumetric flow quantity of steam
$\dot{V}_{fw}$	Volumetric flow quantity of feed water
$\dot{V}_{fl}$	Volumetric flow quantity of fuel
$\dot{V}_{fg}$	Volumetric flow quantity of flue gas
$\dot{V}_{fa}$	Volumetric flow quantity of fresh air
$\dot{V}_{fe}$	Volumetric flow quantity of flue gas transported by the exhauster
Δp_{cd}	Chimney draught
Δp_{fe}	Pressure difference of exhauster ventilator
Δp_{fo}	Output pressure difference of furnace chamber
Δp_{fa}	Pressure difference of blaster ventilator
n_{fa}	Revolution number of blaster ventilator
n_{fe}	Revolution number of exhauster ventilator

T_{fg}	Temperature of flue gas
T_{ea}	Temperature of environmental air
$\mu(\cdot)$	Membership function
U, $\tilde{A}$	Universe
w^i, w_{ij}	Weight
$A_i^{'}$	Fuzzy set
$a_{im_i}^{'}$	Membership grade
z_{COA}	Centroid of area of MF
z_{BOA}	Bisector of area of MF
z_{MOM}	Maximum of area of MF
z_{SOM}	Smallest of maximum of MF
z_{LOM}	Largest of maximum of MF
$a(f)$	Activation function
$max\|\ldots\|$	Max norm
σ_i^j	Width of bell-shape MF
m_i	*Centroid of MF*
E_m	Squared error
R^j	*j*th fuzzy rule
$\boldsymbol{u}(k)$	*Control action*
m	Coefficient of steam load
K_i	Cost of steam production on the *i*th boiler
k_i	Specific cost of steam production on the *i*th boiler
M	Symbol of finite-state machine
Q	Set of states of finite-state machine
Σ	Set of inputs of finite-state machine
δ	Set of operational rules of finite-state machine
F	Set of finite states of finite-state machine
S	Symbol of initial state of finite-state machine
U_{ep}	Excitatory potential
U_{ip}	Inhibitory potential
U_a	Membrane potential
U_{AC}	Action potential
gp	Generator potential
ep_j	Excitatory post-synaptic potential
ip_j	Inhibitory post-synaptic potential
Fnp	Unprotected risk frequency
Fp	Protected risk frequency
PFD_{avg}	*Probability of failure on demand (average value)*

PREFACE

Technical development in industry requires a harmony between the controlled process, the control system and the human. This requirement needs to use safety and fast bi-directional communication.

This time, the goal of production development is to achieve a short technological time with suitable quality. The tool for this goal is the efficient and accurate real-time control. Some technologies consist of extremely fast and extremely slow processes. Extremely fast processes require high-powered data collection and data conversion, high-speed process control system with extremely short real-time cycle, high computational capability, and high memory capacitance. Extremely slow processes require continuous communication with the process to perceive slow and fine changes, ability to distinguish a finite state of process from any temporary state of process, and capability to recognize and evaluate the relatively faster short-time events.

The goal of this dissertation is to develop a new method to achieve higher efficiency and safety in controlling of large-scale systems by Thom's catastrophe theory. The new method will be introduced by a large-scale system, the steam production technology which includes extremely fast and extremely slow processes.

In Chapter 1, there are introduced general methods and control systems used in industrial process control.

Chapter 2 includes the description of technological system of Heat Power Station of Nyíregyháza. The description is focused on the main technological subsystems. These technological subsystems are controlled by the process control software FREELANCE 2000.

In Chapter 3 there are described principal theory of applied soft computing method, Thom's catastrophe theory. This chapter includes the mathematical descriptions of individual technological units introduced in Chapter 2. The goal of description is to show that mathematical models of the individual technological processes are catastrophe functions, and Thom's catastrophe theory can be used as base of the applied soft computing, Zadeh's fuzzy logic control.

Chapter 4 introduces the steam production tas a large-scale technological system. There are described features of large-scale systems, and how the large-scale systems can be supervised. This chapter includes the description of hierarchical control methods applied fuzzy logic control and neural control. Chapter 4 introduces how to use Thom's catastrophe theory for determining the safety integrity level.

In Chapter 5, there is proved that the steam production system can be controlled by fuzzy logic control because van der Waals' functions are catastrophe functions. Van der Waals' functions compose a catastrophe surface. Over the catastrophe surface, membership functions can be drawn used to feature the process and to give opportunity to apply fuzzy logic control for a boiler and its safety system.

Chapter 6 includes the description of supervisory control of the heat power station consisted of individual steam production devices and their control subsystems. There is introduced the economical control, where the steam load distribution is running by the ratio of steam capacities of individual boilers.

In Chapter 7, there are described a new approach in fuzzy control systems, the application of analogue neural cells. The analogue neural network consists of typical neural cells described by the formal description method of regular languages by Chomsky. There is introduced the architecture of fuzzy catastrophe control system composed of analogue neural cells and reflex courses the "catastrophe bridge".

CHAPTER 1

Technological control for large-scale systems

1.1. Introduction

Universe is the set of inert objects and living creatures. Inert objects and living creatures have to take place in their environment with harmonious relationship, in accordance with rules of Universe, the rules of nature. The ability to be in harmonious relationship with the environment is *intelligence*. All the objects, either inert ones or living creatures, must have an essential intelligence for peaceful existence in their environment, where peaceful existence means some kind of opportunity to "collaborate" with the components of environment. That the ability can be called *own intelligence* belonged to the object, which is the minimum requirement to be part of environment. When own intelligence of an object would be out of harmony the object will disturb the environmental functions, and a revolution will be occurred. The required harmony will be established if the object occurred disturbance can change own intelligence, can involve the rules of environment and its components. This activity, completion of own intelligence is the *learning*, the most important capability to establish harmony either of the local environment, or the Universe.

Since the human had begun to use tools to improve vital conditions, the most important activity of human had been *recognition and learning*. Recognition has been focusing on the environment to observe and to study the operation of local environment, and to learn how to apply those the operational rules. That the knowledge, the *learnt knowledge* has been the basis of tool development, technical development, and social development.

Soft computing, an innovative approach to constructing computationally intelligent systems, has just come into the limelight. It is now realized that complex real-world problems require intelligent systems that combine knowledge, techniques, and methodologies from various sources. These intelligent systems are supposed to posses humanlike expertise within a specific domain, adapt themselves and learn to do better in changing environments, and explain how they make decisions or take actions. In confronting real-world computing problems, it is frequently advantageous to use several computing techniques synergically rather than exclusively, resulting in construction of complementary hybrid intelligent systems. The quintessence of designing intelligent systems of this kind is *neuro-fuzzy computing:* neural networks that recognize patterns and adapt themselves to cope with changing environments; fuzzy inference systems that incorporate human knowledge and perform inferencing and decision making. The integration of these two complementary approaches, together with certain derivative -free optimization techniques, results in a novel discipline called *neuro-fuzzy* and *soft computing.*

> "Soft computing is an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision." (Lotfi A. Zadeh, 1992)

1.2. Soft computing and conventional artificial intelligence

Soft computing consists of several computing paradigms, including neural networks, fuzzy set theory, approximate reasoning, and derivative-free optimization methods such as genetic algorithms and simulated annealing. Each of these constituent methodologies has its own strength, as summarized in Table 1.1.

Methodology	**Strength**
Neural network	Learning and adaptation
Fuzzy set theory	Knowledge representation via fuzzy IF-THEN rules
Genetic algorithm and simulated annealing	Systematic random search
Conventional AI	Symbolic manipulation

Table 1.1. Soft computing constituents (the first three items) and conventional artificial intelligence (Jang et al., 1997, p.2)

The seamless integration of these methodologies forms the core of soft computing: the synergism allows soft computing to incorporate human knowledge effectively, deal with imprecision and uncertainty, and learn to adapt to unknown or changing environment for better performance. For learning and adaptation, soft computing requires extensive computation. In this sense, soft computing shares the same characteristics as computational intelligence.

In general, soft computing does not perform much symbolic manipulation, so it can be seen it is as a new discipline that complements conventional artificial intelligence approaches, and vice versa. Table 1.2. is a list of conventional AI approaches and each of the soft computing constitutes in chronological order.

1.3. Way to computational intelligence

Conventional AI research focuses on an attempt to mimic human intelligent behavior by expressing it in language forms or symbolic rules. Conventional AI basically manipulates symbols on the assumption that such behavior can be stored in symbolic structured knowledge bases. This is the so-called *physical symbol system hypothesis* (Newell et al., 1976). Symbolic systems provide a good basis for

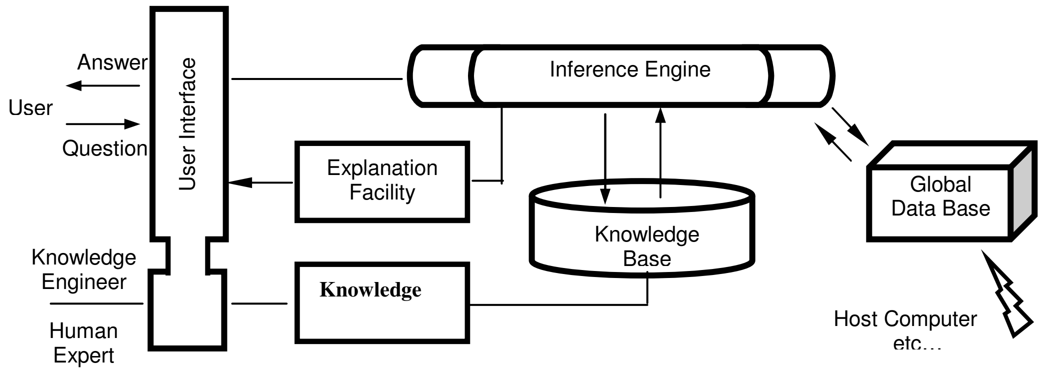


Figure 1.1. An expert system: one of the most successful (conventional) AI products

modeling human experts in some narrow problem areas if explicit knowledge is available. Perhaps the most successful conventional AI product is the knowledge-based system or expert system; it is represented in a schematic form in Figure 1.1.

Conventional AI literature reflects earlier work on intelligent systems. Many AI precursors defined AI in light of their own philosophy. These definitions provide a conspicuous AI framework although they may be somewhat ephemeral because the conceptual framework is metamorphosing rapidly.

Calling *soft computing constituents* "parts of modern AI" inevitably depends on personal judgement. It is true that today many books on modern AI describes neural networks and perhaps other soft computing components, as seen in (Russel et al, 1995)(Winston, 1992). This means that the AI field is steadily expanding; the boundary between AI and soft computing is becoming indistinct and, obviously, successive generation of AI methodologies will be growing more sophisticated.

Expert systems applied in power engineering are focused on high efficiency in power production, the environment protection and the safety (Neupert and Schlee, 1994)(Thierfelder, 1996)(Kogan et al., 2000).

	Conventional AI	Neural networks	**Fuzzy systems**	Other methodologies
1940s	*1947 Cybernetics*	1943 McCulloch-Pitts neuron model		
1950s	1956 Artificial Intelligence	1957 Percepton		
1960s	1960 LISP language	1960 Adalaine Madalaine	1965 Fuzzy sets	
1970s	mid-1970s Knowledge Engineering (expert systems)	1974 Birth of Back-propagation algorithm 1975 Cognitron Neocognitron	1974 Fuzzy controller	1970s Genetic algorithm
1980s		1980 Self-organizing map 1982 Hopfield Net 1983 Boltzman machine 1986 Backpropagation algorithm boom	1985 Fuzzy modeling (TSK model)	mid-1980s Artificial life Immune modeling
1990s			1990s Neuro-fuzzy modeling 1991 ANFIS 1994 CANFIS	1990 Genetic programming

Table 1.2. A historical sketch of soft computing constituents and conventional AI approaches (Jang et al.,1997. p. 4)

In practice, the symbolic manipulations limit the situations to which the conventional AI theories can be applied because knowledge acquisition and representation are by no means easy, but are arduous tasks. More attention has been directed toward biologically inspired methodologies such as brain modeling, evolutionary algorithms, and immune modeling; they simulate biological mechanisms responsible for generating natural intelligence. These methodologies are somewhat orthogonal to conventional AI approaches and generally compensate for the shortcomings of symbolicism.

The long-term goal of AI research is the creation and understanding of *machine intelligence*. From this perspective, soft computing shares the same ultimate goal with AI. Figure 1.2 is a schematic representation of an intelligent system that can sense its environment (perceive) and act on its perception (react). An easy extension of ES may also result in the same ideal computationally intelligent system sought by soft computing researchers. Soft computing is apparently evolving under AI influences that sprang from *cybernetics* (the study of information and control in humans and machines).

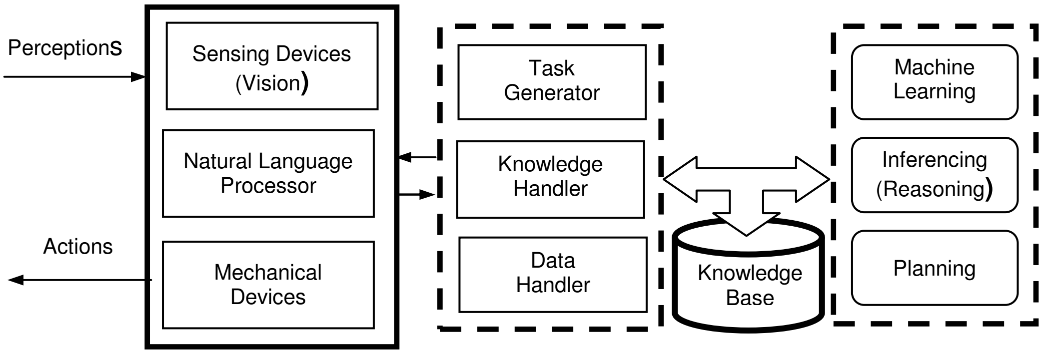


Figure 1.2. An intelligent system

Intelligence applied in process control can solve the application problems such as neural networks, fuzzy logic, genetic algorithms, expert systems, chaos theoretical methods. All objects are parametrized with default parameters. (SIEMENS Ag., 1999) (ABB Automation, 2000)(MATLAB,1997).

1.4. Tools for control of power station

The energy production requires more levels of process control. The process control system includes a data collecting module to collect and pre-process data originated from the process, a telematic system to operate the devices of influence, a central real-time control device with operator workstation. In the *indirect control system,* the open loop system, the central computer and the process has a communication by the human where the human's task is strategic decision making. In this case the computer is an expert system which can compute required data by inputs.

The *direct control system,* the closed-loop control system, consists of the process and the computer composed an integrated system. The computer has to operate in real-time operation system for a continuous collaboration with the process. In such a system the process control is running by analog devices but the reference signals are computed and set by the computer. In that case, the mathematical model of process must be programmed into the computer. If the control is realized by a computer implemented into the process then the computer is given all the functions of analog control devices. These direct control systems have high stability by the application of back-up control system, back-up computer, or twin-computer system.

The *divided control system* is a hierarchical architecture of computers, controllers. These systems have a central computer which communicates with the autonomous sub-systems and devices by field buses. In that case, all the autonomous systems and devices have own tasks, and the tasks are running independently, however, the results must be transferred ,directly or indirectly via any higher priority device, to the central computer.

The heat-power production systems can be controlled by all the methods described in the followings:

- The functions of *ARES Alarm Analysis Real-time Expert System* (Kogan and Halász, 2000) are identification of critical disturbances and their causes in real-time, and concurrently suggests appropriate corrective actions eliminating conjecture and potential human error. ARES optimizes a control room operator's capability by providing a fast, accurate solution even when many things go wrong at the same time. The high efficiency is achieved by the combining of general knowledge about the processes and their control of the specific power generation unit, the technical documents, the expert knowledge, and the detailed history of day-to-day measurements.
- The *standard IEC 61508* issued by the IEC covers a wide range of activities and equipment associated with functional safety. Programmable systems and network technologies have brought a new set of problems to *functional safety systems*. Software comes with new possibilities for performance failure due to program errors or untested combinations of coded instructions. Hence conventional precautions against defects in electrical hardware will not be sufficient to ensure reliability of a safety system. Newer standards such as the German VDE 0801 and DIN 19250 emerged in the late 1980s to incorporate quality assurance grading for both hardware and software matched to the class of risk being handled. In the USA the ISA S84.01 standard was issued in 1995 for use in process industry application including programmable systems. In the United Kingdom the HSE promoted the drive for an international standard. These and many other factors have resulted in the issue of a new general standard for functional safety using electronic and programmable electronic equipment. The new approach is to set down a framework of good practices and limitations leaving the designers room to find appropriate solutions to individual applications. Figure 1.3 shows the title of standard and its seven parts issued to date. The key elements of IEC 61508 are the following ones:
  - management of functional safety;
  - technical safety requirements;
  - documentation;
  - competence of persons.

  The IEC standard sets out procedures for managing and implementing a *safety life cycle* SLC of activities in support of a functional safety system.

Functional safety of electrical/electronic/programmable electronic safety-related systems

All sections of IEC 61508 now published

Part 1: General requirements

Part 2: Requirements for electrical/electronic/programmable electronic systems

Part 3: Software requirements

Part 4: Definitions and abbreviations

Part 5: Examples of methods for the determination of safety integrity levels

Figure 1.3. Standard IEC 61508

- The *ECANSE* Soft Computing Studio (SIEMENS, 1997) is an universal tool to develop, to analyse, to forecast and to control. It has a comfortable graphical user interface to work out the customized solution, to simulate process, or to control process. ECANSE supports the applications of neural networks, fuzzy logic and genetic algorithms. Main application areas of ECANSE are pattern recognition, classification problems, fuzzy controls, neuro-fuzzy controls, nonlinear modeling, automatic control of complex systems like a power station, optimization of computer programs by genetic algorithms.
- System *Freelance 2000* (ABB Automation, 2000) applied in Nyíregyháza Power Station is a scaleable control system that combines the benefits of conventional distributed control systems and programmable logic control systems within an integrated environment. The Freelance 2000 is divided into an operator system and a process level. The operator level includes traditional control system functions such as operation and observation, achieving and logs, as well as trends and alarms. At the process level, Freelance 2000 system can consist of one and several process stations or Field Controllers that can be extended with I/O units. The system employs two industry standard buses. The system utilizes the DigiNet P bus (CAN) which is used for field-area near communications. It is noted for its exceptional robustness and data reliability. Communications between the Freelance 2000 Process Stations, Freelance 2000 Operator Stations and the Engineering Station are carried over a DigiNet S (Ethernet) system bus.
- Control system *SCADA*, *Supervisory Control and Data Acquisition* is not a full control system, but rather focuses on the supervisory level. A purely software package that is positioned on top of hardware to which it is in general via programmable logic controllers (PLCs), or other commercial modules. SCADA systems used to run on DOS, VMS and UNIX, but in recent years vendors have moved to NT and some also to LINUX. The hardware architecture includes two layers, the “client layer” for the man-machine interaction, and the “data server layer” which handles process data control activities. The data servers communicate with devices through process controllers. Process controllers, e.g. PLCs, are connected to servers either directly or via networks or fieldbuses. Data servers are connected to each client stations via Ethernet LAN. The software architecture of SCADA system operates in multi-tasking and it is based upon a real-time database in one or more servers. Servers are responsible for data acquisition and polling controllers, alarm checking, calculations, logging and archiving parameters, typically those they are connected to. Server-client and server-server communication is in general on a publish-event-driven basis and uses a TCP/IP protocol.

  The SCADA system is able to detect, display, and long alarms and events. When there are problems the SCADA system must notify operators to take corrective action. Alarms and events are recorded so engineers or programmers can review the alarms to determine what caused the alarm and prevent them happening again. The SCADA can read data from PLCs and other hardware and then analyze and graphically present that data to the user. For simple control requirements, the system should be able to perform control instead of a PLC. However, for anything other than simplistic control a PLC or a soft PLC is preferred to do real-time control with SCADA doing the non-real-time control. SCADA is medium between the operator and the real-time controller.

  Most applications require receipes, data logging, and other means of reading and writing databases. The great thing about SCADA systems is that they can log incredible amounts of data to disk for later review. This is helpful for solving problems as well as providing information to improve the process.

Simulation system *MATLAB* with toolbox *Fuzzy Logic* and toolbox *Neural Networks* has been used to study and compose the applied neural fuzzy control. The simulated process control, the hierarchical fuzzy control system has been training with real technical data originated from Heat Power Station of Nyíregyháza.

All of these systems require data base which have to include the estimated heat-power requirement, meteorological data and estimated costs of steam production. Data are prepared by statistical methods. Data and the applied computational methods compose an expert system which occurs an operation having an appropriate stability in normal, planned circumstances. Stability of the system depends on the reliability of approximate calculations.

If any unexpected events occurred changing in the operation of technological system then the expert system will generate alarm signal, and system managers will have to interact. The system manager's activity will helped by the expert system which will propose more possible activities for solving problems .

1.5. Conclusion

Real-time control of technological processes has some problems during its operation. Although the real-time system has no troubles in its internal operation the synchronization of control system to the process requires special solutions by the followings:

- When a slow process has an internal high-speed changing in its state then the real-time control system may miss the changing because of the rate of real-time period and the changing period, or the business of its computational device. Although the controlled technology would be a slow process, any unexpected events could disturb the normal operation because unexpected events can generate effects which may occur unexpected statements in the technological system. These effects can be taken into consideration only if the control system could compute fast enough.
- If the high-powered control system is organized to make few computational operations, and the system is operating rather with logical functions then the process control system requires a referential data set of controlled technology, a sample of near-optimum-operation. In this case, computational functions would be replaced with logic functions when the temporary statement of technology will be compared with the referential data set. Therefore, the operation of control system will be faster, and unexpected events will always be taken into consideration.
- Data processing of unexpected events and preparation of answer on unexpected events can be powered by the application of *Thom's*

catastrophe theory used to compose description of controlled technology.

- Capability of control system used in slow technological processes will be increased by application of *soft computing methods* when the system description consists of a knowledge base and a rule base composed by the application of Thom's catastrophe theory. Knowledge base includes possible samples, the set of statements of controlled technology and set of activities of control system, and the rule base includes logical functions for the selection of proper activities answered on input statements, the decision making.

CHAPTER 2

Description of technological features

Power station Nyíregyháza has boilers GIB-60/37 M which can be heated either with gas or oil. The steam production of boiler GIB-60/37 M is 60 tons/hour, the temperature of outlet steam is 430 °C, the overpressure of outlet steam is 36 bar. Technological limits of GIB-60/37 M are the following: the minimum outlet quantity of steam is 20 tons/hour at 400 °C, and the maximum outlet quantity of steam is 60 tons/hour at 430 °C ± 20 °C and overpressure 40 bars.

2.1. Technological data of boiler GIB-60/37

The heat output of boiler depends on the parameters of input, such as fresh air temperature, air pressure, air quantity, and enthalpy of inlet water. Input and output features of boiler are shown in Figure 2.1.

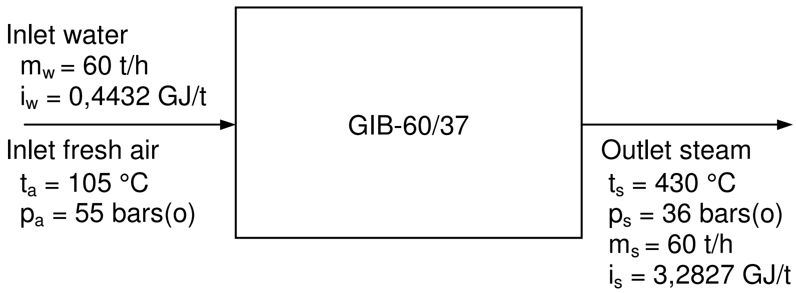


Figure 2.1. Input and output data of boiler GIB-60/37

The enthalpy of inlet water is i_w*=0,4432 GJ/t* and the enthalpy of outlet steam is i_s*=3,2827 GJ/t.* The available heat in boiler can be calculated by the following equation:

$$\dot{Q} = \dot{m}_s\, i_s - \dot{m}_w\, i_w\,, \qquad (2.1)$$

where $\dot{Q}$ is the specific heat output, $\dot{m}_s$ is the specific mass of steam, and $\dot{m}_w$ is the specific mass of inlet water. Therefore, the required heat output of GIB-60/37 boiler is:

$$\dot{m}_w = \dot{m}_s = 60 \text{ tons/hour}$$

$$\dot{Q} = 60 \text{ t/h } (3{,}2827 \text{ GJ/t} - 0{,}4432 \text{ GJ/t})\,/3{,}6$$

$$\dot{Q} = 47{,}325 \text{ MW/t}$$

2.2. Technological data of furnace chamber

The power of furnace chamber is decided by the burnt quantity of gas/oil, the caloric value of fuel, the inside pressure of furnace chamber, and the features of inlet fresh air.

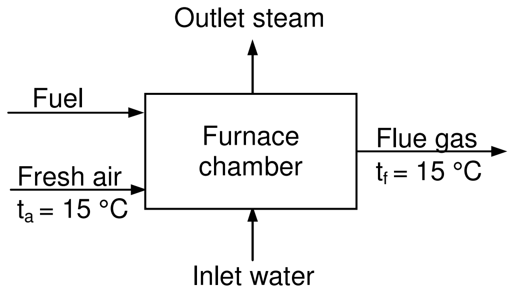


Figure 2.2. Inputs and outputs of furnace chamber

The thermal efficiency is:

$$\eta = \frac{\dot{m}_i \quad \Delta i}{3,6 \quad \dot{Q}_t} \tag{2.2}$$

where $\dot{Q}_t$ is the specific heat output, $\dot{m}_i$ is the specific mass of fuel mixture, and Δi is the enthalpy difference between the enthalpy of inlet fuel mixture and enthalpy of outlet flue gas. The specific heat output is computed by the equation (2.3):

$$\dot{Q}_t = \frac{0,03395 \quad \dot{V}_g}{3,6} \tag{2.3}$$

where $\dot{V}_g$ is the specific volume of inlet earth gas. The quantity of produced heat is regulated by the dosage of fresh air. The rate of mixture fresh air and earth gas in normal conditions is: $1m^3$ of earth gas requires $9,4541m^3$ of fresh air. The heat loss Δq in the furnace chamber can be calculated by the equation (2.4).

$$\Delta q \leq \frac{(1 + \lambda\, 9,4541)\, c_{fg}\, (t_{fg} - t_{fa})}{q} \; 100\% \tag{2.4}$$

where λ is the air excess factor for the inlet fuel quantity, c_{fg} is the specific heat of flue gas, t_{fg} is the temperature of flue gas, t_{fa} is the temperature of inlet fresh air, and q is the total value of produced heat. The required minimum value of heat loss Δq is about 1,3% at the maximum power of boiler.

2.3. Control of flue gas pressure in the furnace chamber

The scheme of control system is shown in Figure 2.3. The temperature in the boiler depends on the quantity and temperature of input fresh air and the quantity of fuel. The boiler has a convective heating system. The control of heating is operated by PI controllers which regulate the position of fresh air ventilator clack-valve and respiratory clack-valve. The fresh air temperature is set by a heater unit heated with smoke gas.

PI controllers are given input data of inlet air pressure before the boiler and outlet flue gas pressure of the furnace chamber, and position values of clack-valves. These input pressure data are compared with the setting values and both the clack-valves will be set into the suitable positions. The pressure in the furnace chamber depends on the quantity setting of input clack-valve and the setting of respiratory clack-valve. Clack-valves are operated by electric motors controlled by PI controllers.

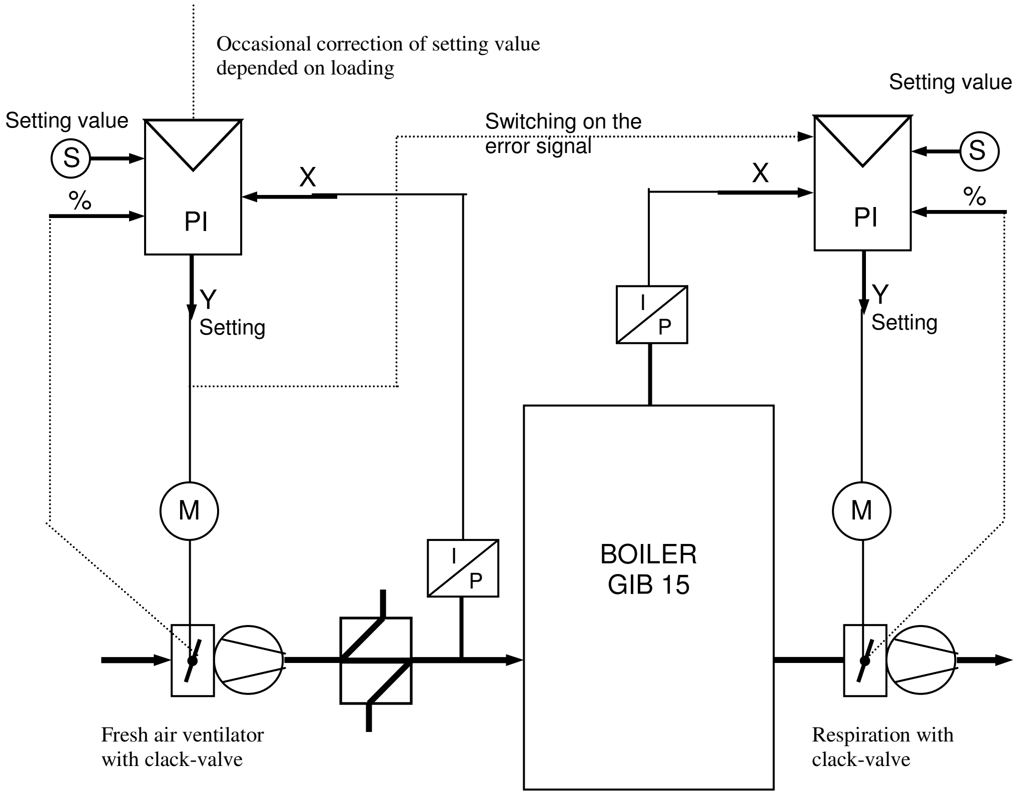


Figure 2.3. Control of air pressure and furnace chamber pressure

2.4. Power control of boiler

Power of boiler depends on the quantity of combusted fuel and rate of fresh air and fuel. The quantity of combusted fuel can be increased by duplicated flames. The pressure of steam is in accordance with the produced heat energy depended on volume of flames. The volume of combusted fuel might be change gradually, so speed of combustion changing requires a limitation because of a possible explosion risk. The power control of boiler by setting of active flames is seen in Figure 2.4.

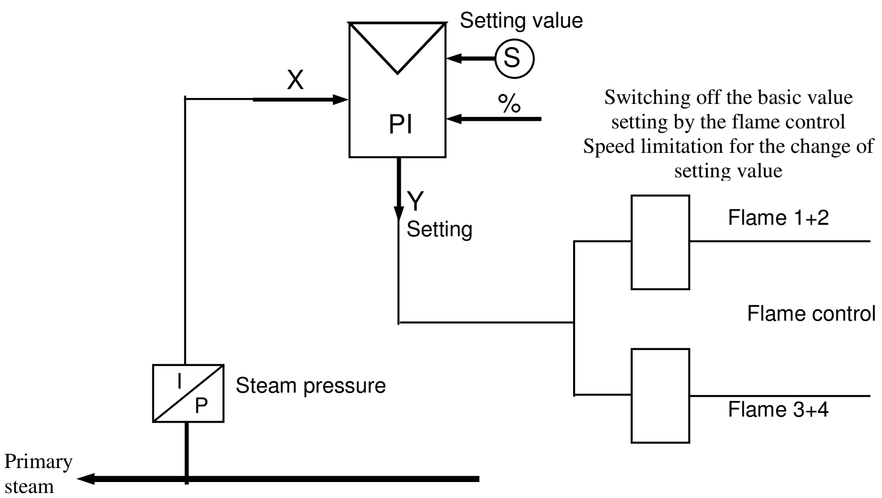


Figure 2.4. Power control of boiler

2.5. Level control of feed water in the steam drum

The heat production system has a double-drum steam-water storage system. The drums are used to store the inlet water and separate the steam from the hot water. The schematic diagram of level control in the steam drum is shown in Figure 2.5. The temperature of steam in the drum is 249 °C, and the pressure of steam is 40 bars.

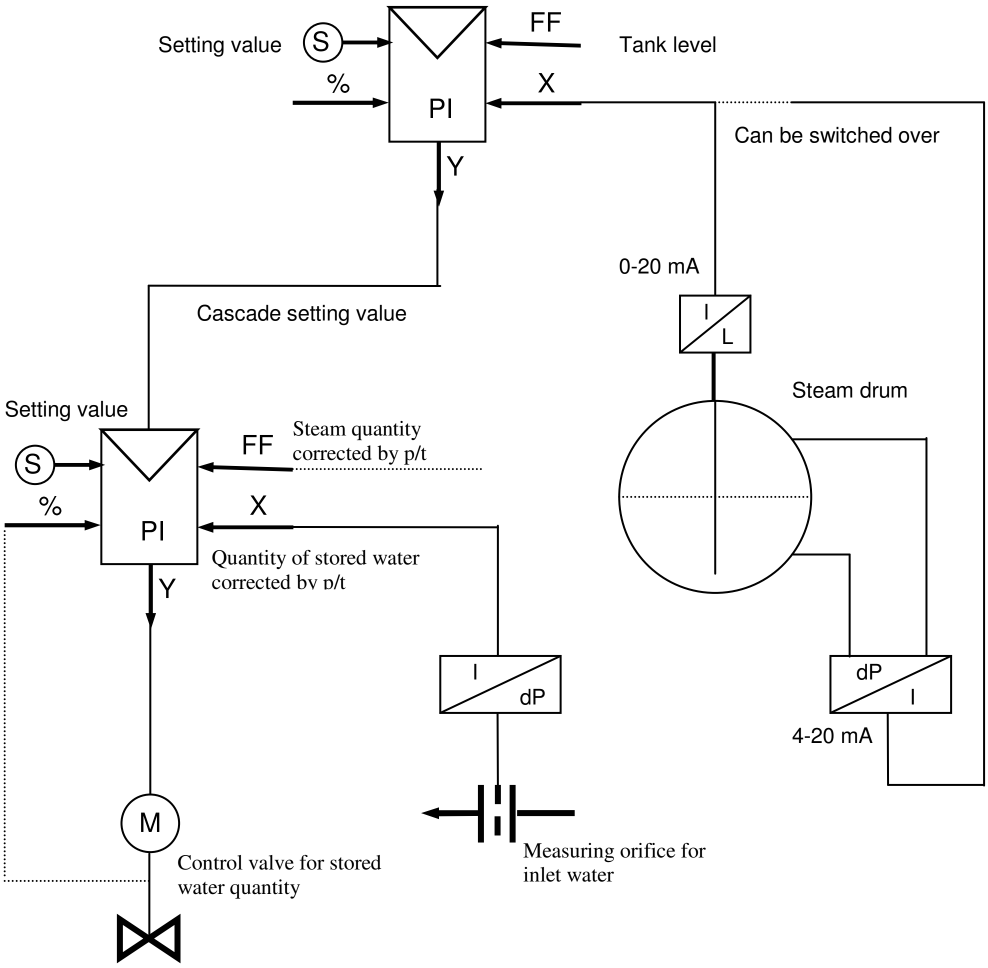


Figure 2.5. Level control of tank

The goal of water level control is to store a suitable quantity of water for the boiler. The level control is holding the water quantity in the tank at an average value required by the boiler. The average level is 100 mms over the medium water level of tank. The level of water is limited at a maximum value by high interlock and a minimum value by low interlock. The quantity of inlet water is measured by measuring orifice and the level of water is measured by differential pressure sensor.

2.6. Control of outlet steam temperature

The steam is separated by the steam drums and the most quantity of moisture of steam will be lost. The temperature of unsaturated and superheated steam is controlled by injected water. The control system measures temperature of inlet steam before the water injector, interim temperature after the water injector, and temperature of outlet steam which are compared with the setting values. Features of outlet steam is influenced by the water injection which is used to set temperature and to saturate the steam. Quantity of the outlet moisturized steam is measured by measuring orifice. The schematic diagram of control of steam temperature is shown in Figure 2.6.

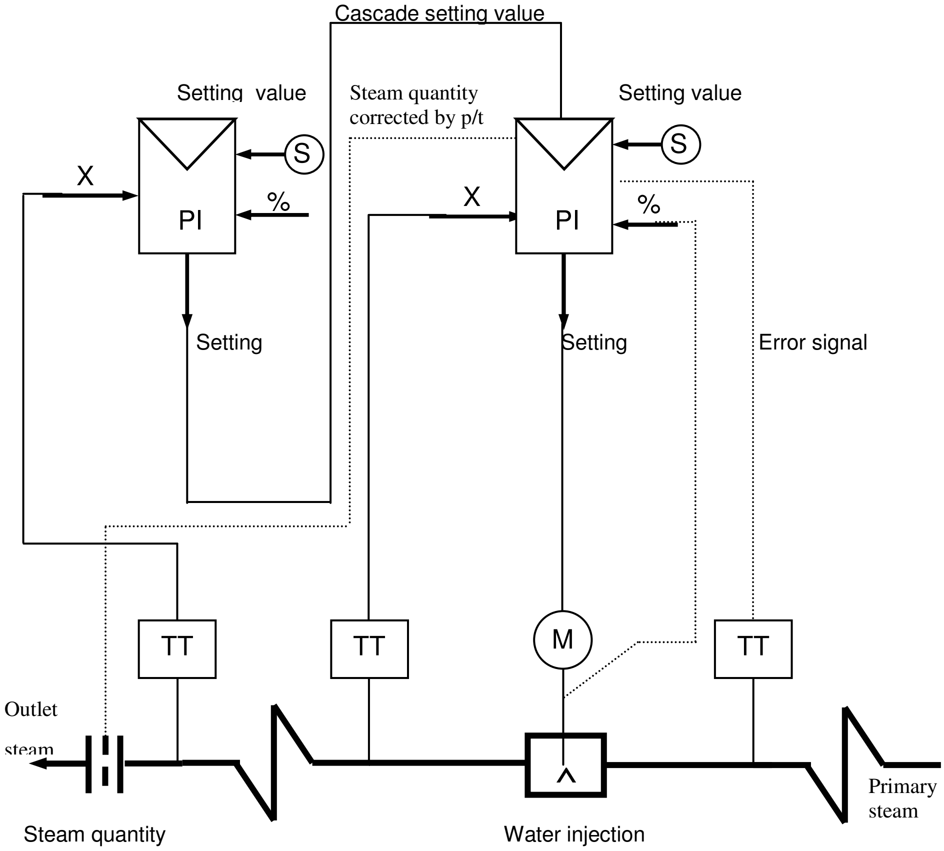


Figure 2.6. Control of steam temperature

2.7. Safety system of boilers

The safety system of heat production system GPIB-60/37 boiler consists of programmable logic system with shared sensors for the safety system of furnace chamber and steam drum and steam temperature setting. The logic control for safety functions uses *single channel system built with shared smart sensors* supervised by software FREELANCE 2000. The simplified schemes for safety instrumented system of boiler are shown in Appendix 1.

The burner controls will be fitted with a flame-out sensor, the flame detector that will trip out the fuel supplies as soon as the flame is lost. The level control of feed water level in the steam drum includes a level tester which will set the feed water valve, and it will trip out the water supplies as the water level is under the lower interlock or over the upper interlock, and then the flame will switched off. The temperature setting system of outlet steam has more measuring devices to sense the steam temperature, and water injection will be stopped if the quantity of outlet steam will be under the technical minimum.

Software protection is provided against transmitter failure which could cause malfunctions of technological devices. Connections to the boiler trip affect on the operation of safety system of boiler, alarm signals would be generated and the steam production will be interrupted when it is required because of sensor system errors or any error of actuators.

CHAPTER 3

Thom's catastrophe theory as tool for description of steam production

3.1. Introduction

Technological unit the boiler and its safety instrumented system of heat power station has been described in Chapter 2. In this part technological processes will be described by Thom's catastrophe theory, as inflection catastrophe and peak catastrophe.

Thom's catastrophe theory is based on the classification of critical points. The description of classification is made by Morse's lemma. Morse's lemma has been used to describe the critical points of functions, the inflection, the extreme values. These critical points by Morse have stability which means that perturbation does not occur the change of their types (Morse,1931)(Poston and Stewart, 1985).

3.2. Mathematical basis

Let $f:R^n \to R$ smooth function. The $u \in R^n$ is critical point of f if

$$Df\big|_u = 0, \quad \text{or}$$

$$\frac{\partial f}{\partial x_1}\bigg|_u = \ldots = \frac{\partial f}{\partial x_n}\bigg|_u = 0. \tag{3.1}$$

The $f(u)$ value belonged to critical point u is called the critical value of f. The tangent of function f is horizontal, and if $n=0$ then they are maximum, minimum and inflection points.

If $n=2$, $f:R^n \to R$ then critical points are local maximum, local minimum and saddle point, which are described the following functions $f(x,y)=-x^2-y^2$, $f(x,y)=-x^2+y^2$, $f(x,y)=x^2-y^2$ at the origin. There are much more complicated functions too, as function $f(x,y)=x^3-3xy^2$ or , $f(x,y)=x^2y^2$.

In according to the ***Morse lemma,*** it can be said that u is non-degenerated point of f if $Df\big|_u=0$ and $D^2f\big|_u$ is a non-degenerated quadratic form, that is,

$$Hf\big|_u = \left[\frac{\partial^2 f}{\partial x_i\, \partial x_j}\bigg|_u\right], \tag{3.2}$$

where the Hessian matrix is non-singular, or the Hessian determinant is

$$Det(Hf\big|_u) \neq 0. \tag{3.3}$$

Let the function $f:R^n \to R$ be a smooth function in the environment of 0, that is, $f(0)=0$. In this case, there are smooth functions function

$$f = \sum_{i=1}^{n} x_i g_i, \qquad g_i: R^n \to R \text{ that} \tag{3.4}$$

$$g_i = \frac{\partial f}{\partial x}\bigg|_u .$$

Let u be the non-degenerated critical point of the smooth function $f:R^n \to R$. In this case, in the universe U of u can be determined a local coordinate-system $y_1, \ldots, y_n$ that $y_i(u)=0$ by all of i, and the following is true for all $y \in U$:

$$f=f(u)-y_1^2-\ldots-y_i^2+y_{i+1}^2+\ldots+y_n^2. \qquad (3.5)$$

In accordance with the Morse lemma, a suitable *n* results that all non-degenerated critical points can be transformed into any Morse-saddle.

An other important definition is the *equivalency of families of functions.* Functions $f,g:R^n\to R$ are equivalent ones in the environment of *0,* when a local diffeomorphism $y: R^n\to R$ and a deformation constant γ can be given that

$$g(x)=f(y(x))+\gamma. \qquad (3.6)$$

In general, the diffeomorphism is $e:R^r\to R^r$, the smooth transformation is $y: R^n\times R^r\to R^n$, and it is true in case of $\forall s\in R^r$, that the following transformation is diffeomorphism

$$y_s: R^n\to R^n, \qquad (3.7)$$
$$y_s(x)=y(x,s),$$

and $\gamma: R^r\to R$ is a smooth function.

Then functions *f* and *g* are equivalent ones if there are *e, y,* and γ in the environment of *0* which satisfy the following rule:

$$g(s,x)=f(y_s(x),e(s))+\gamma(s), \qquad \forall(x,s)\in R^n\times R^r. \qquad (3.8)$$

This means that R^r will be deformed by *e* and *y*, and the origin will be able to be set by γ(Poston and Stewart, 1985).

3.3. Thom's theory

In any case of arbitrary variable *n* and $r\leq 5$, a *r*-parametric family consisted of functions $R^n\to R$ is stable structurally, and it is equivalent with anyone of following families in any point of its environment [Poston and Stewart,1985]:

- in case of non-critical point
  u_1,
- in a non-degenerated critical point or Morse-point
  $u_1^2+\ldots+u_i^2-u_{i+1}^2-\ldots-u_n^2 \qquad (0\leq i\leq n).$

These types have no catastrophe features. If the functions are influenced by control coefficients then they will be catastrophes. Let $u_1=x$ and $u_2=y$, and let *a, b, c,* and *d* be control coefficients of *x* and *y* variables, then the seven basic catastrophes described by Thom are the following ones:

- inflection:
  $$V_a(x)=\frac{1}{3}x^3+ax,$$
- peak
  $$V_{ab}(x)=\frac{1}{4}x^4+\frac{1}{2}ax^2+bx,$$
- swallow-tail
  $$V_{abc}(x)=\frac{1}{5}x^4+\frac{a}{3}x^3+\frac{b}{2}x^2+cx,$$
- butterfly
  $$V_{abcd}(x)=\frac{1}{6}x^6+\frac{a}{4}x^4+\frac{b}{3}x^3+\frac{c}{2}x^2+dx.$$
- elliptic umbilicus
  $$V_{abc}(x)=x^3-3xy^2+a(x^2+y^2)+bx+cy,$$

- hyperbolic umbilicus

  $V_{abc}(x)= x^3+ y^3+axy+bx+cy,$

- parabolic umbilicus

  $V_{abcd}(x)= x^2y+ y^4+ax^2+by^2+cx+dy.$

In the following parts, the inflection catastrophe and the peak catastrophe will be detailed only, because they will be used to describe the processes of steam production.

3.3.1. Description of peak catastrophe

In this session crucial points of equation $V_{ab}(x)$ expressed in analysis of Zeeman's catastrophe machine will be described(Zeeman, 1971)(Zeeman, 1973a) (Zeeman, 1976). Let equation $V_{ab}(x)$ be analyzed, where

$$V_{ab}(x) = \frac{1}{4}x^4 + \frac{1}{2}ax^2 + bx. \tag{3.9}$$

If variables a and b are fixed, crucial points of function (3.8) can be decided from the equation (3.9). The roots of equation depend on value (a,b), and the discriminant of third-degree equation in (3.10).

$$0 = \frac{d}{dx}(\frac{1}{4}x^4 + \frac{1}{2}ax^2 + bx) = x^3 + ax + b, \tag{3.10}$$

$$D = 4a^3 + 27 b^2. \tag{3.11}$$

If $D=0$ then the position of (a,b) related to the curve is computed by equation (3.11) (Salmon, 1885). The curve can be seen in Figure 3.1. The plane (a,b) is divide into five zones by the curve. Zone I is featured by term $4a^3 + 27 b^2 <0$, and zone E is characterized by term $4a^3 + 27 b^2 >0$ as follows:

- if $(a,b)\in E$ then there are single real roots;
- if $(a,b)\in I$ then there are three several real roots;
- if $(a,b)\in B_1$ or $(a,b)\in B_2$ then there are three real roots, but two of them are coincidental ones;
- if $(a,b)=(0,0)=P$ then the equation has three coincidental solutions (all of them are 0).

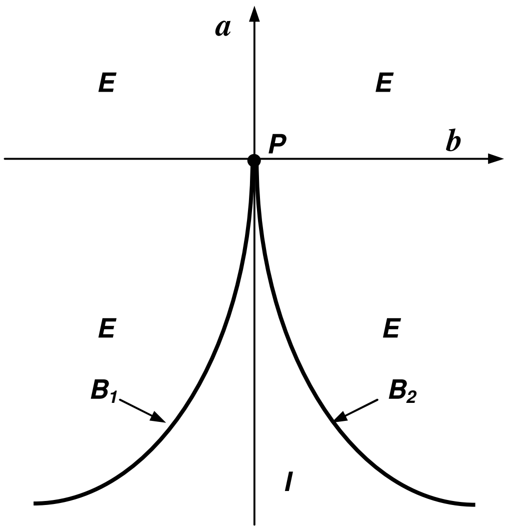


Figure 3.1. The transformation of (3.14)

Let the *catastrophe transformation* be introduced shown below:

$$\chi : M\rightarrow C, \tag{3.12}$$

where χ is the rule of transformation, and C means the catastrophe surface. Points of set M can be transformed into the environment of origin by the next rule:

$$(x, a, b) \to (a, b) \quad (x \in M), \tag{3.13}$$

where x replaces T the temperature, a replaces P the pressure, and b replaces V the volume according with Figure 3.2. The set M is a smooth subset of space R^3. Let Y sign the plane (x,a) and then the transformation of Y by rule π to surface M will be described by (3.14):

$$\pi : Y \to M, \tag{3.14}$$

and the rule of transformation is

$$\pi(x, a) = (x, a, b), \tag{3.15}$$

where

$$x^3 + ax + b = 0. \tag{3.16}$$

If variable b is expressed,

$$\pi(x, a) = (x, a, -x^3 - ax). \tag{3.17}$$

This process is the *mapping* of the set M (Poston and Stewart, 1985). In this case, the catastrophe set can be described by single map.

The *Jacobian matrix* of $\pi : Y \to R^3$ transformation is

$$\begin{bmatrix} \frac{\partial x}{\partial x} & \frac{\partial x}{\partial a} \\ \frac{\partial a}{\partial x} & \frac{\partial a}{\partial a} \\ \frac{\partial}{\partial x}(-x^3 - ax) & \frac{\partial}{\partial a}(-x^3 - ax) \end{bmatrix}, \tag{3.18}$$

and then let equation (3.16) be differentiated and replaced into (3.17):

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ -3x^2 - a & -x \end{bmatrix}. \tag{3.19}$$

The degree of matrix (3.19) is always 2 independently from values of a and x variables, therefore, the equation has no critical points, M is smooth.

Those points of set M are the critical points of the catastrophe transformation $\chi : M \to C$ where the surface folds back shown in Figure 3.2. These points can be decided by the set of equations (3.16) and (3.20):

$$0 = \frac{\partial^2 V}{\partial x^2} = 3\,x^2 + a. \tag{3.20}$$

The solution results $a = -3x^2$ and $b = 2x^3$, and the tangential planes of set M given by the points of parametric curve $(x, -3x^2, 2x^3)$ are vertical ones. Those cubical curves F projected onto catastrophe surface C are *inflextion curves* of set M.

If the projection of F transformed by expression $\Phi: F \to C$ whereby the rule of transformation is $\Phi(x) = (x, -3x^2, 2x^3)$. The parametric description of curve projected to plane C is $(-3x^2, 2x^3)$, therefore, the expressions $a = -3x^2$, and $b = 2x^3$ will result the equation $4a^3+27b^2=0$, which equation is the description of the curve shown in Figure 3.1 and it has the name *bifurcation curve.*

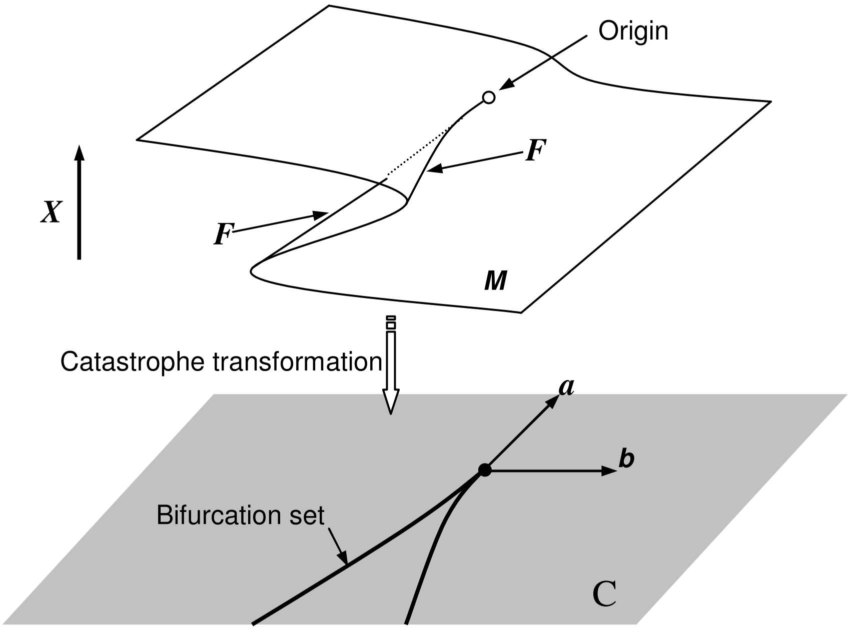


Figure 3.2. The catastrophe set M and its transformation

3.3.2. Description of inflection catastrophe

In this session, principal theory of the *inflection catastrophe* will be described for its application in water level control by setting of passage area of inlet valve (Bröcker and Lander,1975)(Thom, 1975)(Callahan, 1976).

Let the canonic description of inflection catastrophe be the following expression:

$$V_a(x) = \frac{1}{3}x^3 + ax. \qquad (3.21)$$

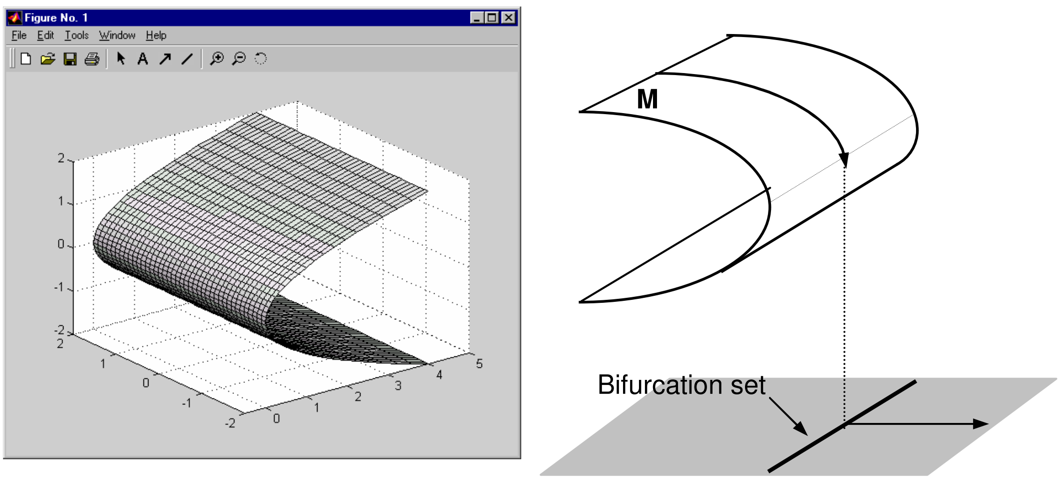


Figure 3.3. The inflection catastrophe and its transformation

The points of catastrophe set M shown in Figure 3.3 are featured by the equation (3.22):

$$0=\frac{d}{dx} V_a(x) = x^2 + a. \qquad (3.22)$$

Let a generalized point of M be

$$(x,a)=(x,\ -x^2). \tag{3.23}$$

In this case, Taylor's series around this point is

$$V_a(x+\Delta x)=\frac{1}{3}(x+\Delta x)^3+(-\Delta x^2)(x+\Delta x). \tag{3.24}$$

After the operations, if $x\neq 0$ then quadratic element $x\Delta x^2$ is non-degenerated element, else if x=0 then it is degenerated element. Therefore, set M has single degenerated point in (0,0). If x>0 then quadratic element is positive and function V has minimum, else if x<0 function has maximum. The catastrophe set M is a parabola and its bifurcation set is a single point on the catastrophe surface C shown in Figure 3.4.

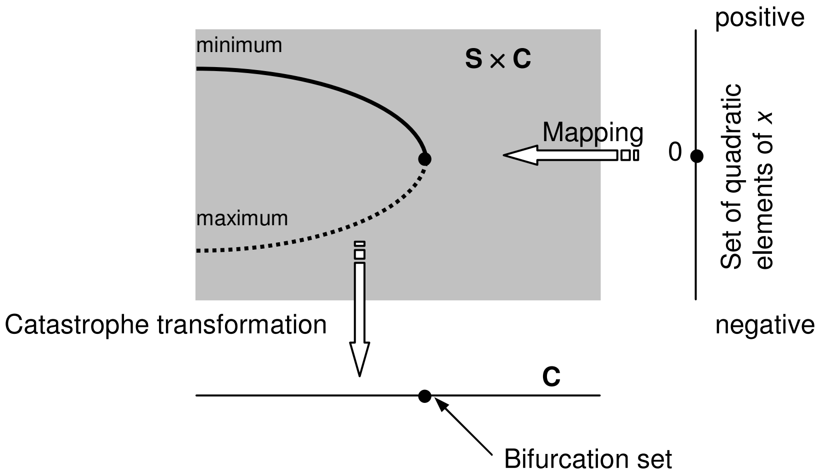


Figure 3.4. Catastrophe set and its transformation

3.4. Description of steam generation by Thom's catastrophe theory

In this session, the thermal process of steam production will be described by the application of Thom's catastrophe theory. Catastrophe theory by Thom describes events which has been occurring by continuous changes of variables, however, these changes occur sudden changes like water-steam transition in thermodynamics. Thom classified the catastrophe events into seven classes(Thom, 1969) (Thom, 1971) (Thom, 1975).

The most important features of steam production are the relationship of steam load and inlet feed water, and the relationship of steam load and fuel quantity. These relationships will be analyzed and described for fuzzy control thermal processes of steam production system by the application of catastrophe theory.

The features of steam generation can be described as fast changes of water states. The quantity changes and quality changes of components in the heated space can be seen by the van der Waals equations.

The application of catastrophe theory requires an other processing of thermodynamics, a higher ordered analysis, together with the mutual application of catastrophe theory and the re-normalizing method (Maslov, 1965).

Equation by van der Waals (1873) after the classic description of “ideal gas” $PV=RT$ of Boyle is

$$(P + \alpha / V^2)\,(V - \beta) = RT\,, \tag{3.25}$$

where P, V, and T are pressure, volume and temperature of the observed fluid, R is constant (its value is described by Nk, where N is the number of molecules, and k is the Boltzman’s constant). Values of α and β are empirical coefficients to a suitable approximation of reality.

Figure 3.5 shows the graphic representation of van der Waals’ expression, the P-V diagram. The diagram is much more clear if the graphs are shown in 3D space, the P-V-T space shown in Figure 3.6.

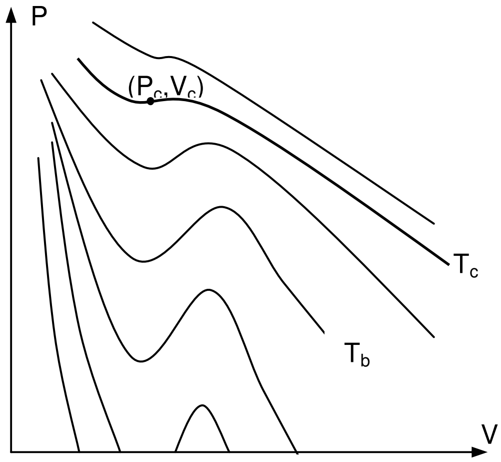


Figure 3.5. P-V diagram

In this case, the graph can be covered by a surface which is set of temporary states of water-steam mixture.

In 1875, Maxwell declared the theory of equivalency between the heat and the work, which can be seen as the equality of areas in the curve by the equations of van der Waals shown in Figure 3.7 where the piece of curve can be replaced with a straight line because of $F_a = F_b$.

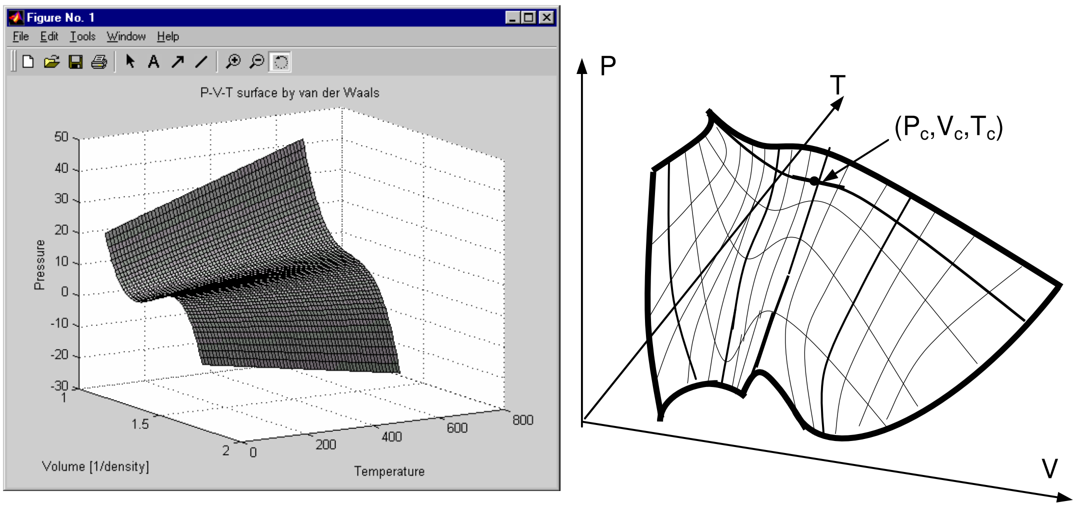


Figure 3.6. The water-steam constitution diagram as a catastrophe surface

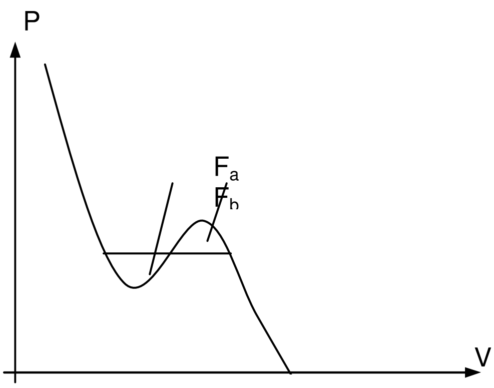


Figure 3.7. Geometrical explanation of Maxwell’s theory of equivalency between heat and work

If the surface P-V-T has a curve with single inflection then coordinates of P_c, V_c, and T_c

shown in Figure 3.6 can be substituted for the next expressions (Fowler,1972):

$$= \left[\frac{\alpha}{27\beta^2}, 3\beta, \frac{8\alpha}{27\beta R} \right]. \tag{3.26}$$

Let variables of equation (3.25) be replaced with $P'=P/P_c$, $V'=V/V_c$, and $T'=T/T_c$. Then the reduced form of equation by van der Waals is

$$(P' + \frac{3}{V'^2})\,(V' - \frac{1}{3}) = \frac{8}{3}\,T'. \tag{3.27}$$

Let the variable density ρ is taken into consideration against the volume, and let $V'=1/\rho$. By the transformation below point (1,1,1) will be replaced into the origin,

$$p = P' - 1, \qquad x = \rho - 1, \qquad t = T' - 1,$$

and the new form of equation will be the following:

$$x^3 + \frac{\mathbf{8t+p}}{3} x + \frac{8t - 2p}{3} = 0, \text{ or}$$
$$x^3 + ax + b = 0, \tag{3.28}$$

where

$$a = \frac{8t+p}{3} \text{ and } b = \frac{8t-2p}{3}.$$

Equation (3.28) is the parametric description of surface of the *peak catatstrophe* (Woodcock and Poston, 1974) (Bröcker and Lander, 1975) (Thom, 1975) (Poston and Stewart, 1985).

Let the thermodynamic potential be the free energy by Gibbs, and the calculations had been made by Bell and Lavis (Bell and Lavis). This potential is:

$$\Phi(x, p, t) = \frac{\mathbf{16\,(t+1)}}{9} \log \left[\frac{\mathbf{2+2x}}{2-x} \right] - \frac{\mathbf{2x\,(1+p)}}{\mathbf{3(1+x)}} - 2x. \tag{3.29}$$

It seems, this expression is different from the much more simple definition (3.30)

$$\Phi(x, p, t) = \frac{1}{4} x^4 + \frac{8t+p}{6} x^2 + \frac{8t-2p}{3} x, \tag{3.30}$$

which has the differentiated form being equal with (3.28), however, Φ has been composed to result the same equation like (3.28) .

Theory of Maxwell regarded to fixed pressure and temperature can be used to compute the volume (i.e. density) of liquid (Callen,1960). The rule of equal areas by Maxwell is not suitable for the minimalization of Φ. The goal is to achieve the absolute minimum has been called *Maxwell-convention* by Thom against the perfect delay. Bell and Lavis has come to the conclusion that the feature of "liquid van der Waals" does not correspond to the catastrophe Riemann-Hugoniot named by Thom (this catastrophe has been named *peak catastrophe* by Zeeman).

3.5. Feed water level in the steam drum

In this chapter requirements of primary steam production will be described. Primary steam is produced in the steam generator where the feed water is boiled. The generated steam is flown into the drum where hot water and steam are set together. The steam is conducted into the superheater where the output temperature will be set.

The inlet feed water quantity depends on the required quantity of outlet steam, the output load. Steam production is running on constant value of pressure inside the steam generator (Dr. Reményi, 1977)(Dr. Barótfi et al.,1993).

Let the heat power content of outlet steam be constant, then the feed water quantity will depend on the outlet steam quantity, and the quantity of outlet steam will be equal with the quantity of inlet feed water:

$$\dot{m}_{st1} = \dot{m}_{fw}, \tag{3.31}$$

where $\dot{m}_{st1}$ means the outlet steam quantity by time, and $\dot{m}_{fw}$ is the inlet feed water quantity by time.

$$\dot{Q}_{st1} = \dot{m}_{fw}\,(i_{st} - i_{fw}) = p_{st1}\,\dot{V}_{st1}, \tag{3.32}$$

$$\dot{m}_{fw} = \frac{\dot{Q}_{hq} - \dot{Q}_{fg}}{(i_{st} - i_{fw})} = \frac{\dot{Q}_{st1}}{(i_{st} - i_{fw})}, \tag{3.33}$$

where $\dot{Q}_{hq}$ is the produced heat quantity by combustion of fuel, and $\dot{Q}_{fg}$ is the heat content of flue gas, and $\dot{V}_{st1}$ is the volumetric flow quantity of outlet steam.

The required feed water quantity $\dot{m}_{fw}$ depended on the steam loading can be computed from the temporary water level difference between the previously measured value and the measured actual value. The volumetric quantity of required feed water $\dot{V}^{rq}_{fw}$ is expressed from equation (3.33):

$\frac{1}{\Delta t}$

$$\dot{V}^{rq}_{fw} = \frac{\dot{m}_{fw}}{\rho_{fw}} = \frac{\dot{m}_{st1}}{\rho_{fw}} = \sqrt{\frac{2p_{dr}}{\rho_{fw}}}\,[A_{fw}(t+1) - A_{fw}(t)], \tag{3.34}$$

where p_{dr} is the measured pressure inside the drum, quotient $\frac{\dot{m}_{st1}}{\rho_{fw}}$ is the outlet steam quantity, and $A_{fw}(\cdot)$ is the temporary discharge area of water inside the steam drum.

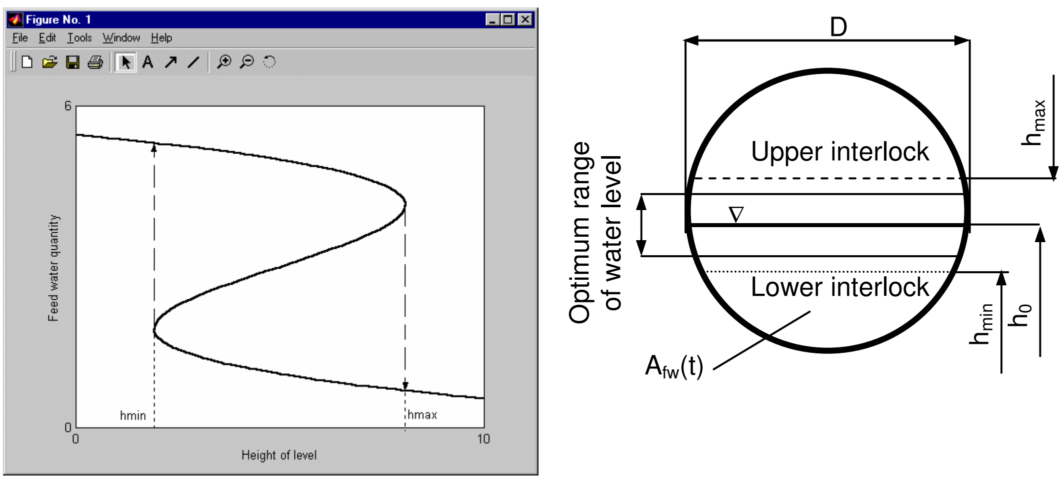


Figure 3.8. Level control in the drum

The level is setting by the ratio of outlet steam quantity and inlet water quantity. Figure 3.8 shows the limits of level control. The range of level limitation is active at 120 mm over medium level h_0, the upper interlock, and at 120 mm under the medium level h_0, the lower interlock. The level control between the maximum and minimum values is operated by a niveau sensor. The level control has to keep the water level height inside the range of 80 mm over and 80 mm under the medium water level, which is the optimum. The limits of water level height are the values of higher and lower interlock where the control system occurs alarm. The measured value of water level height affects on the control of inlet water valve dosing the feed water. The goal of control is to achieve a stable ratio of steam and water quantity in the drum.

The volumetric quantity of water in drum depends on the level h which is the measured value. The discharge area section of drum filled by water in accordance with Figure 3.8 is expressed by the following equation

$$A_{fw}=r^2\left[\pi-\arccos\left(\frac{\Delta h}{r}-1\right)+\left(\frac{\Delta h}{r}-1\right)\sqrt{1-\left(\frac{\Delta h}{r}-1\right)^2}\right], \tag{3.35}$$

where $r=D/2$ the radius of drum, $\Delta h=h_{up}-h_x$ for control of upper level, $\Delta h=h_x-h_{low}$ for control of lower level.

The inlet feed water quantity is measured with a measuring orifice in the feed water pipe. The quantity of inlet feed water $\dot{V}_{fw}^{in}$ measured by measuring orifice can be described by the equation (3.36), accordingly with Bernoulli's function

$$\dot{V}_{fw}^{in}=\alpha m\varepsilon\,\frac{D^2\pi}{4}\sqrt{\frac{2}{\rho_{fw}}(p_1-p_2)}, \tag{3.36}$$

where α is the discharge coefficient, $m=\frac{d^2}{D^2}$ is the rate of contracted passage area and non-contracted passage area, ε is the expansion coefficient, ρ_{fw} is the density of feed water, D is the diameter of pipe, and p_1 and p_2 are measured pressures (Kovács, 1981). As α, m, ε, ρ_{fw}, d and D are constant values the simplified expression of inlet volumetric quantity of feed water is:

$$\dot{V}_{fw}^{in}=k_{fw}A_p\sqrt{\frac{2\Delta p_{fw}}{\rho_{fw}}}, \tag{3.37}$$

where $\dot{V}_{fw}^{in}$ is the temporary inlet feed water quantity measured by orifice differential, and A_p is the discharge area of feed water pipe with diameter D. This quantity of inlet water has to be equal with the steam load if the water level height is stabilized.

However, feed water is pressurized on a stable value p_{in}, and the feed water is flown across a valve with controlled discharge area A_v. Therefore, the temporary inlet volumetric flow quantity to be set is expressed by Bernoulli's law by the following:

$$\dot{V}_{fw}^{va}=A_v\sqrt{\frac{2p_{in}}{\rho_{fw}}}. \tag{3.38}$$

The change of water volume inside the drum by (3.34) and (3.38) is the following:

$$\Delta\dot{V}=\dot{V}_{fw}^{va}-\dot{V}_{fw}^{rq},$$

$$\Delta\dot{V}=A_v\sqrt{\frac{2p_{in}}{\rho_{fw}}}-\Delta A_{fw}\sqrt{\frac{2p_{dr}}{\rho_{fw}}}. \tag{3.39}$$

When $\boldsymbol{\Delta\dot{V}=0}$, the valve of inlet feed water is set correctly.

The change of volumetric water quantity sensed as changing of water level h during a Δt period can be computed by the following:

$$\int_{(\Delta t)} \Delta\dot{V}\, dt = \Delta\dot{V}\Delta t = l\,[A_{fw0} - A_{fw1}(\Delta h)], \tag{3.40}$$

where l is the length of water room, $A_{fw1}(\Delta h)$ is the temporary water ratio of discharge area of drum which depends on the steam load, and A_{fw0} is the required water ratio of discharge area of drum. The volumetric feed water flow is computed by the following expressions where upper signs are valid for the upper limitation, and lower signs are valid for the lower limitation:

$$\Delta A_{fw} = [\pm A_{fw0} \mp A_{fw1}(\Delta h)], \tag{3.41}$$

$$\dot{V}_{fw}^{va} = A_v \sqrt{\frac{2p_{in}}{\rho_{fw}}} = \Delta A_{fw} \sqrt{\frac{2p_{dr}}{\rho_{fw}}}\,, \tag{3.42}$$

where

$$A_{fw0}(h_r) = r^2\left[\pi - \arccos\left(\frac{h_r}{r} - 1\right) + \left(\frac{h_r}{r} - 1\right)\sqrt{1 - \left(\frac{h_r}{r} - 1\right)^2}\right], \tag{3.43}$$

$$A_{fw1}(h) = r^2\left[\pi - \arccos\left(\frac{\Delta h}{r} - 1\right) + \left(\frac{\Delta h}{r} - 1\right)\sqrt{1 - \left(\frac{\Delta h}{r} - 1\right)^2}\right], \tag{3.44}$$

and h_r is the required height of level, and $\Delta h = h_{up} - h_x$ for control of upper level, $\Delta h = h_x - h_{low}$ for control of lower level.

The required discharge area of inlet feed water valve is the following:

$$A_v = \sqrt{\frac{\rho_{fw}}{2p_{in}}}\;[\pm A_{fw0} \mp A_{fw1}(\Delta h)]\sqrt{\frac{2p_{dr}}{\rho_{fw}}}\,,$$

$$A_v = \sqrt{\frac{p_{dr}}{p_{in}}}\;[\pm A_{fw0} \mp A_{fw1}(\Delta h)]. \tag{3.45}$$

The function of discharge area setting of feed water valve is shown in Figure 3.9.

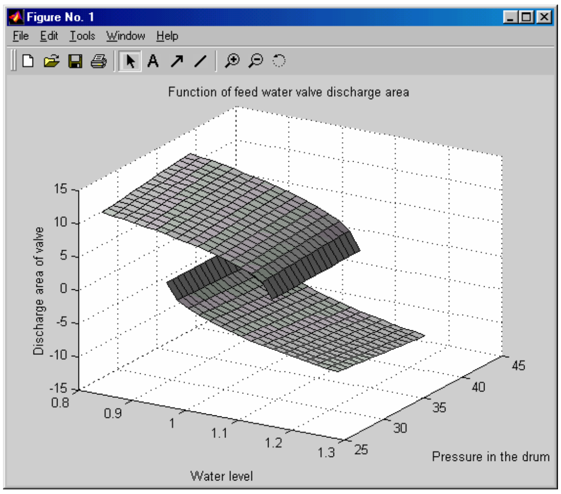


Figure 3.9. Function of discharge area of feed water valve

3.6. Temperature setting of outlet steam

In this chapter the setting of outlet steam features will be introduced, where the output steam load affects on the pressure of outlet steam, and the temperature of outlet steam is set by water injection into the superheated steam. The flow quantity and the temperature of steam load, the outlet steam pressure, and the temperature of saturated steam before and after the water injection are measured.

The saturated steam is flown into the superheater, the secondary heating course, for setting the required temperature of steam. The temperature of superheated steam is modified by water injection. This action influences on the temperature of steam in accordance with the temperature and quantity of injected water.

The scheme of technological device for setting the outlet temperature is shown in Figure 3.10.

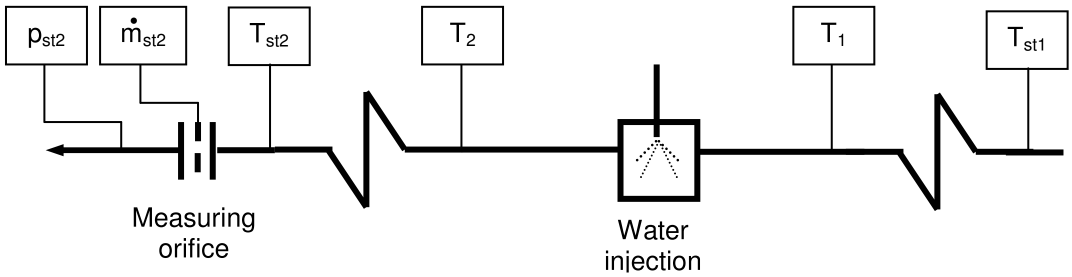


Figure 3.10. Setting of outlet steam temperature

The volumetric flow quantity $\dot{V}$ of outlet steam, the steam load is measured by measuring orifice at the output of steam generator:

$$\dot{V} = k_{2st} A_{st} \sqrt{\frac{2\Delta p_{st2}}{\rho_{st}}} = k_2 \sqrt{\frac{2\Delta p_{st2}}{\rho_{st}}}, \qquad (3.46)$$

where Δp_{st2} is the pressure difference measured by measuring orifice, A_{st} is the output discharge area of steam, and k_{2st} is measuring coefficient of the device. The mass flow of steam is described by the following equation:

$$\dot{m}_{st2} = \rho_{st} \dot{V}_{st2} = k_2 \sqrt{2\Delta p_{st2} \rho_{st}}\,.$$

The temperature of outlet steam depends on the injected water quantity. Therefore, the quantity of outlet steam $\dot{m}$ will be the composition of the generated superheated steam quantity $\dot{m}$ and the injected water quantity $\dot{m}$.

$$\dot{m} = \dot{m} + \dot{m} \qquad (3.47)$$

The required quantity of injected water is computed by equation (3.48):

$$\dot{m}_{inj} = \dot{m}_{st1} \frac{i_1 - i_2}{i_2 - i_{inj}}, \qquad (3.48)$$

where i_1 is the enthalpy of steam before the water injection, i_2 is the enthalpy of moisturized steam, and i_{inj} is the enthalpy of injected water for setting the temperature of outlet steam (Dr. Reményi, 1977).

The inlet steam has a temperature T_{st1} before the superheater. In the first stage of superheater, the temperature of inlet steam will be increased to temperature T_1. The steam heated to T_1 will be moisturized by injected water to set the suitable moisturized temperature T_2. The temperature of moisturized steam T_2 has to be set into a well defined temperature range because the required value of steam temperature will be achieved by addition of a fixed heat quantity. The temperature of annealed steam T_2 expressed from equation (3.48) is shown by equation (3.49).

$$T_2 = T_1 - \frac{\dot{m}_{st1} i_1 + \dot{m}_{inj} i_{inj}}{c_{st}(\dot{m}_{st1} + \dot{m}_{inj})} \qquad (3.49)$$

The quantity of injected water $\dot{m}_{inj}$ for setting the temperature of steam T_2 is expressed from the equations (3.48)and (3.49) by the following:

$$\dot{m}_{inj} = \dot{m}_{st1}\frac{i_1 - c_{st}(T_1 - T_2)}{c_{st}(T_1 - T_2) - i_{inj}}. \qquad (3.50)$$

After the annealing of steam, the temperature of outlet steam will be set by the second stage of superheater where the quantity of steam is . The outlet steam quantity, the steam load is measured by measuring orifice.

$$\frac{i_1 - c_{st}(T_1 - T_2)}{c_{st}(T_1 - T_2) - i_{inj}} \qquad (3.51)$$

The outlet heat power $\dot{Q}_{st2}$ is computed by the next equation:

$$\dot{Q}_{st2} = \dot{m}_{st1}(i_{st} - i_{fw}) + \dot{m}_{st1}\, c_{st}(T_1 - T_{st1}) + \dot{m}_{inj}\, i_{inj} + \dot{m}_{st2}\, c_{st}(T_{st2} - T_2), \qquad (3.52)$$

where T_{st1} is the temperature of steam at the output of steam generator.

The required temperature of outlet steam T_{st2} might be expressed by the following equation:

$$T_{st2} = T_2 + \frac{\dot{Q}_{st2} - [\dot{m}_{st1}(i_{st} - i_{fw}) + \dot{m}_{st1}\, c_{st}(T_1 - T_{st1}) + \dot{m}_{inj}\, i_{inj}]}{\dot{m}_{st2}\, c_{st}}. \qquad (3.53)$$

Let $\dot{m}_{st2}$ from equation (3.52) be replaced into equation (3.53) by the following:

$$T_{st2} = T_2 + \frac{\dot{Q}_{st2} - [\dot{m}_{st1}(i_{st} - i_{fw}) + \dot{m}_{st1}\, c_{st}(T_1 - T_{st1}) + \dot{m}_{inj}\, i_{inj}]}{c_{st}\left[\frac{i_{st1} - c_{st}(T_1 - T_2)}{c_{st}(T_1 - T_2) - i_{inj}}\right]}. \qquad (3.54)$$

It seems, the temperature of outlet steam T_{st2} depends on the difference of temperatures T_1, T_2, and the change of steam load also affects on the temperature of outlet steam T_{st2}.

Since the temperature of outlet steam is regulated by the quantity of injected water, the required quantity of injected water is expressed by the application of equation (3.52):

$$\dot{m}_{inj} = \frac{\dot{Q}_{st2} - [\dot{m}_{st1}(i_{st} - i_{fw}) + \dot{m}_{st1}\, c_{st}(T_1 - T_{st1}) + \dot{m}_{st1}\, c_{st}(T_{st2} - T_2)]}{c_{st}(T_{st2} - T_2) + i_{inj}}, \qquad (3.55)$$

$$= \dot{m}_{st2}(i_{st2} - i_{fw}) = k_2(i_{st2} - i_{fw})\sqrt{2\Delta p_{st2}\rho_{st}}, \text{ and } \dot{m}_{st1} = \dot{m}_{fw}.$$

The output heat power is rated with the orifice differential, and the difference of inlet water enthalpy i_{fw}, and outlet steam enthalpy i_{st2}.

Let the outlet heat power be replaced into the equation (3.55), then the expression of required quantity of injected water will be computed by the next equation:

$$\dot{m}_{inj} = \frac{k_2(i_{st2} - i_{fw})\sqrt{2\Delta p_{st2}\,\rho_{st}} - [\dot{m}_{st1}(i_{st} - i_{fw}) + \dot{m}_{st1}\, c_{st}(T_1 - T_{st1}) + \dot{m}_{st1}\, c_{st}(T_{st2} - T_2)]}{c_{st}(T_{st2} - T_2) + i_{inj}}, \qquad (3.56)$$

$$\dot{m}_{inj} = \rho_{fw} A_{iv} \sqrt{\frac{2p_{inj}}{\rho_{fw}}} = A_{iv} \sqrt{2p_{inj}\rho_{fw}} \, ,$$

where A_{iv} is the discharge area of valve of injected water, and p_{inj} is the pressure of injected water.

The discharge area setting of valve of injected water is expressed from (3.55)-(3.56) by the following equation:

$$A_{iv} = \frac{k_2(i_{st2} - i_{fw})\sqrt{2\Delta p_{st2}\,\rho_{st}} - k_{fw}A_v\sqrt{2\Delta p_{fw}\,\rho_{fw}}\,[(i_{st} - i_{fw}) + c_{st}(T_1 - T_{st1}) + c_{st}(T_{st2} - T_2)]}{\sqrt{2p_{inj}\rho_{fw}}\,[c_{st}(T_{st2} - T_2) + i_{inj}]}, \qquad (3.57)$$

where differential pressures Δp_{st2} and Δp_{fw}, and temperatures T_1, T_2, and T_{st1}, T_{st2} are measured quantities. The function of discharge are of injected water for setting the temperature of outlet steam is shown in Figure 3.11. where p_{inj}, Δp_{fw} and T_{st1}, T_{st2} are considered as temporary constant values.

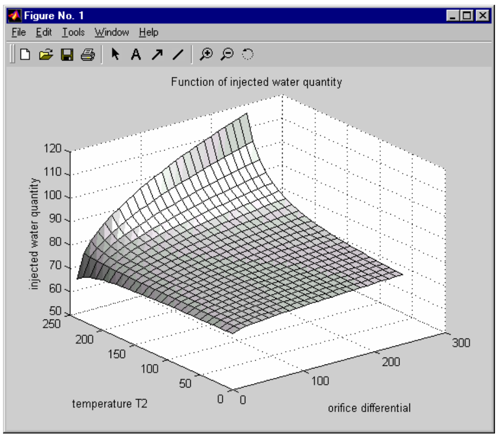


Figure 3.11. Function of discharge area of injected water

3.7. Description of combustion in the furnace chamber

In this session, changes of combustion parameters occurred by change of steam load will be described. The rate of steam load affects on the inlet feed water quantity, and the combusted fuel quantity, primarily. However, the change of steam load occurs secondary effects like the change of inlet fresh air quantity blasted into the furnace chamber, and the change of flue gas quantity (Reményi, 1968) (Dr. Reményi, 1977) (Schroedler and Cowell, 1968) (Dr. Berecz and Bereczki, 1972).

Hess' law declares that thermal effect of a chemical reaction depends on the initial state and final state of chemical reaction only, but it is independent from the process which occurred the change from the initial state to the final state.

The combustion heat on constant pressure generated during combustion of two-component mixture of *A* and *B* can be computed by the equation (3.58):

$$\Delta i = i - i = i - (i + i) \qquad (3.58)$$

where i_{ini} is the enthalpy in initial state of components and i_{fin} is the enthalpy in final state of combustion product. In case of heat production, the inlet components are fuel and fresh air, the outlet product is flue gas.

Since the reaction is running on constant pressure the change of combustion heat is:

$$\frac{}{\mathbf{d\Delta i}} = \frac{}{\mathbf{d\Delta i_{fin}}} - \frac{}{\mathbf{d\Delta i_{ini}}} = C_{pfin} - C_{pini} = \Delta C_p. \tag{3.59}$$

After the integration of equation (3.59) the enthalpy of mole quantity of component in the thermal reaction can be computed by *Kirchoff's* law:

$$\Delta i_T = \Delta\, i_{T0} + \int_{T_0}^{T} \Delta C_p\, dT\ , \tag{3.60}$$

where Δi_T is the enthalpy by final temperature T, Δi_{T0} is the enthalpy by initial temperature T_0, and ΔC_p is the mole heat. Enthalpy originated from the thermal reaction of n components can be decided by the equation (3.61):

$$\Delta i = \sum_{k=1}^{n} \Delta i_k = m_1 [i_{10} + \int_{T_0}^{T} C_{p1}\, dT\,] + \ldots + m_k\, [i_{k0} + \int_{T_0}^{T} C_{pk}\, dT\,], \tag{3.61}$$

where Δi_k is the enthalpy change of kth component, m_k is the quantity of kth component, i_{k0} is the enthalpy of kth component in the isobar reaction, C_{pk} is the mole heat of kth component on constant pressure, and T_0 is the initial temperature.

The produced heat quantity depends on the combusted volume V_{fl} of fuel in accordance with the equation (3.62):

$$Q_{hq} = H_{fl}\, V_{fl}. \tag{3.62}$$

The specific heat content of unit volume of combusted gas can be decided by the temperature of flue gas inside the furnace chamber by equation (3.63):

$$\mathbf{Q_{fg0} = (\mathit{1} + \lambda m_{fa0})\, c_{fg}\, (T_{fg} - T_{ea})}, \tag{3.63}$$

where λ is the air excess factor, c_{fg} is the specific heat of flue gas, T_{fg} is the temperature of nascent flue gas, and T_{ea} is the temperature of environmental air, and $V_{fa0}=9{,}4541nm^3$ is the required volumetric quantity of fresh air for the combustion 1nm^3 of fuel. The produced heat included by the flue gas is rated to the quantity of burnt earth gas – fresh air mixture.

The generated heat quantity Q_{hq} by equation (3.62) is divided into two parts, the heat content of produced steam Q_{st}, and the heat content of flue gas Q_{fg}. The generated heat power is the differentiated value by time t of generated heat quantity:

$$\frac{dQ_{hq}}{dt} = \frac{dQ_{st}}{dt} + \frac{dQ_{fg}}{dt}, \tag{3.64}$$

$$\dot{Q}_{hq} = \dot{Q}_{st} + \dot{Q}_{fg}\,,$$

where

$$\dot{Q}_{hq} = H_{fl}\, \dot{V}_{fl}\,, \tag{3.65}$$

$$\dot{Q}_{st} = \dot{m}_{st} (i_{st} - i_{fw}), \tag{3.66}$$

$$\dot{Q}_{fg} = \dot{m}_{fl} (1 + \lambda\, m_{fa0})\, c_{fg}\, (T_{fg} - T_{ea}). \tag{3.67}$$

These equations describe thermal processes inside the furnace chamber. Equation (3.65) means the produced heat quantity by combustion, equation (3.66) means the heat quantity transferred into the produced steam, and equation (3.67) means the heat quantity included by the flue gas.

3.7.1. The required fuel quantity

In this session, the burner control system will be described by Thom's catastrophe theory. The burner control decides the energy content of steam generated in the boiler which is direct rated with load and pressure of the outlet steam. The quantity of combusted fuel depends on the steam load and the output pressure of outlet steam. The temporary steam load is measured by a differential orifice, and the pressure of outlet steam is measured by pressure gauge in the output pipe.

The pressure of outlet steam p_{st2} depends on the steam load as the equations (3.68) and (3.69) describe by the following:

$$\mathbf{p_{st2}} = \frac{\dot{Q}_{st2}}{\dot{V}_{st2}}\,, \tag{3.68}$$

$$p_{st2} = \frac{\dot{m}_{st2}\,(i_{st2} - i_{fw})}{\dot{\ }}\,, \tag{3.69}$$

where the outlet volumetric flow quantity of steam is $\dot{V} = k_2\sqrt{2\Delta p_{st2}/\rho_{st}}$, and value of the orifice differential is measured at the steam output.

Since the mass flow is rated with the volumetric flow by the specific gravity ρ_{st}, therefore the equation of pressure (3.69) will be modified by the following:

$$p_{st2} = \rho_{st}(i_{st2} - i_{fw}). \tag{3.70}$$

The specific gravity ρ_{st} at the output and the enthalpy of feed water i_{fw} at the input can be taken into consideration as constant values, so the pressure depends on the heat content of outlet steam, the enthalpy i_{st2}. The value $\rho_{st}(i_{st2} - i_{fw})$ from equation (3.70) can be expressed by the following:

$$\rho_{st}\,(i_{st2} - i_{fw}) = \frac{\dot{m}_{inj}\,[c_{st}(T_{st2} - T_2) + i_{inj}] + \dot{m}_{st1}(i_{st} - i_{fw}) + \dot{m}_{st1}\,c_{st}(T_1 - T_{st1}) + \dot{m}_{st1}\,c_{st}(T_{st2} - T_2)}{k_2\sqrt{2\Delta p_{st2}/\rho_{st}}}, \tag{3.71}$$

$$p_{st2} = \frac{\dot{m}_{inj}\,[c_{st}(T_{st2} - T_2) + i_{inj}] + \dot{m}_{st1}(i_{st} - i_{fw}) + \dot{m}_{st1}\,c_{st}(T_1 - T_{st1}) + \dot{m}_{st1}\,c_{st}(T_{st2} - T_2)}{k_2\sqrt{2\Delta p_{st2}/\rho_{st}}}. \tag{3.72}$$

It can be seen that the pressure of outlet steam depends on the heat content of outlet steam, and inverse proportional with the steam load. The affect of steam load might be corrected by the heat content, only. Therefore, the changing of pressure can be balanced by the changing of heat power.

The generated heat power is computed by the following equation:

$$\dot{Q}_{fl} = \dot{V}_{fl}\,H_{fl}\,,$$

where $\dot{Q}_{fl}$ is the heat power produced by burning volumetric quantity $\dot{V}_{fl}$ of fuel with heating value H_{fl}. Since the required heat power is $\dot{Q}_{st2} = \dot{Q}_{fl} - \dot{Q}_{fg}$, so the modified formula of equation (3.68) will describe the relationship of pressure of outlet steam and the required volumetric quantity of fuel:

$$\mathbf{p_{st2}} = \frac{\dot{Q}_{fl} - \dot{Q}_{fg}}{\dot{V}_{st2}} = \frac{\dot{V}_{fl} H_{fl} - \dot{Q}_{fg}}{k_2 \sqrt{2\Delta p_{st2}/\rho_{st}}}. \tag{3.73}$$

The required fuel quantity is described by the following equation:

$$\dot{V}_{fl} = \frac{p_{st2}\, k_2 \sqrt{2\Delta p_{st2}/\rho_{st}}}{H_{fl} - \rho_{fl}(1+\lambda m_{fa0}) c_{fg}(T_{fg} - T_{ea})}. \tag{3.74}$$

Figure 3.12 shows the function of required volumetric fuel quantity.

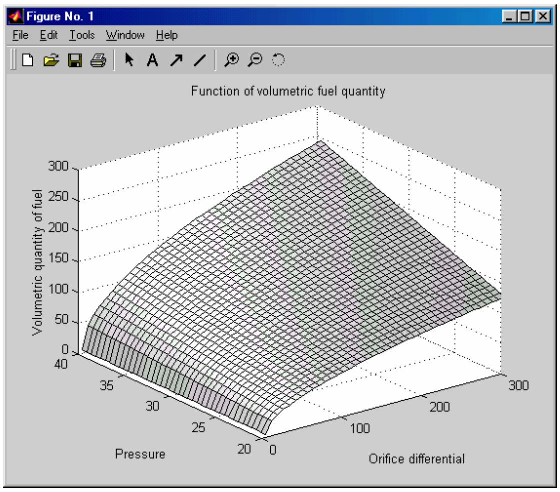


Figure 3.12. Function of volumetric fuel quantity

3.7.2. Inlet fresh air quantity

Chemical reactions of combustion are imperfect ones, therefore, perfect reactions require more oxygen which has to be inlet by fan. The generated heat is originated from the burning of fuel and air components. In the burning process, 1nm^3 of earth gas requires V_{fa0} = 9,4541nm^3 of fresh air, where the specific value of the combustion heat of earth gas is H_{fl} = 0,03395 GJ/nm^3.

The heat production requires a higher air quantity related to the theoretical air quantity to burn all the components of fuel because the theoretical fresh air quantity V_0 includes less oxygen than it would be required by perfect burning. Therefore, the real inlet fresh air quantity V_r must be higher than theoretical quantity. The rate of V_0 and V_d is the *air excess factor* λ:

$$\lambda_0 = \frac{V_r}{V_Q} \tag{3.75}$$

The required value of air excess factor of the operating boiler must be known to reach a high combustion efficiency. That the air excess factor can be computed by an other expression, too:

$$\lambda = \frac{RO_{2max}}{RO_2}, \tag{3.76}$$

where RO_{2max} is the RO_2 content at λ=1, and $RO_2= CO_2+ SO_2$ means the sum of volumetric rate CO_2 and volumetric rate SO_2 (Dr. Reményi,1977).

The combusted fuel and fresh air occur the generation of flue gas. The heat quantity of flue gas is described by the following equation:

$$\dot{Q}_{fg} = \dot{V}_{fl}\, \rho_{fl}\, (1+ \lambda\, V_{fa0}\, \rho_{fa}\,)\, c_{fg}\, (T_{fg}-T_{ea}\,), \tag{3.77}$$

$$\dot{Q}_{fg} = \dot{m}_{fl}(1+ \lambda\, m_{fa0}\,)\, c_{fg}\, (T_{fg}-T_{ea}\,),$$

where λ is the air excess factor, c_{fg} is the specific heat of flue gas, T_{fg} is the temperature of nascent flue gas, and T_{ea} is the temperature of environmental air.
The quantity of flue gas originated from the mixture of fuel and fresh air is

$$\dot{m}_{fg} = \dot{m}_{fl}\, (1+ \lambda\, m_{fa0}\,). \tag{3.78}$$

The required inlet fresh air quantity is:

$$\dot{m}_{fa} = \dot{m}_{fl}\, \lambda\, m_{fa0}\, . \tag{3.79}$$

3.7.3. Removal of flue gas from the furnace chamber

In this session the computation of blasted air quantity will be described. The required quantity of blasted air is affected by the height and discharge area of chimney, and the environmental features, and the quantity and temperature of flue gas.

Let the chimney draught computed from the following expression:

$$\Delta p_{cd} =\Delta p_{gr}+\Delta p_{w}\, , \tag{3.80}$$

where Δp_{gr} is the gravitational pressure difference and Δp_w is the pressure difference occurred by the wind. The exhauster device has to be able to produce the chimney draught Δp_{cd}.

The gravitational pressure difference depends on the height of chimney h_c, and the density of environmental air ρ_{ea}, and the density of flue gas ρ_{fg}:

$$\Delta p_{gr}=gh_c(\rho_{ea}-\rho_{fg}\,), \tag{3.81}$$

$$\rho_{ea}= p_{ea}\, \rho_{ea0}\, \frac{273}{T_{ea}},$$

$$\rho_{fg}= p_{ea}\, \left[\rho_{ea0} + \frac{CO_2}{100}(0{,}713- \frac{4{,}2}{CO_{2max}})\right]\frac{273}{T_{fg}},$$

where p_{ea} is the temporary pressure of environmental air, and ρ_{ea0} is the density of normal air, CO_2 is the carbon dioxide percentage content of flue gas, and CO_{2max} is the maximum of carbon dioxide percentage content of flue gas (Macskássy,1975).

The pressure difference occurred by wind can be computed by the following equation:

$$\Delta p_w =\mu\, \rho_{ea}\, \frac{v^2}{2}, \tag{3.82}$$

where μ is pressure coefficient, and v is the speed of wind.

The measured pressures are shown in Figure 3.13. The internal pressure p_{fo} of boiler is

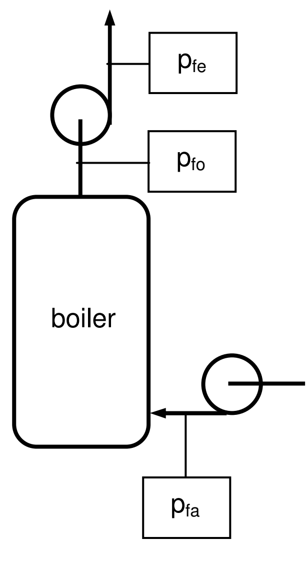


Figure 3.13. Pressures on the boiler

$$p_{fo}V_{fg}=p_{fa}V_{fa}+\Delta p_{fg}V_{fg}-(p_{fe}V_{fg}-\Delta p_{cd}V_{fg}),$$

$$p_{fo}=p_{fa}\frac{\dot{V}_{fa}}{\dot{V}_{fg}}+\Delta p_{fg}-(p_{fe}-\Delta p_{cd}), \qquad (3.83)$$

where $\Delta p_{fg}=c_{fg}\rho_{fg}(T_{fg}-T_{ea})$.

The revolution number of ventilator to blast fresh air into the furnace chamber is controlled to set the suitable air delivery. If the inlet fresh air quantity is $\dot{V}_{fa}$ then the required revolution number of ventilator tuned by frequency converter is computed by the following equation:

$$\dot{V}_{fa}=\varphi\frac{D_{fa}^2\pi}{4}v_{fa}, \qquad (3.84)$$

where φ is the pressure coefficient, D_{fa} is the rotor diameter of ventilator, and v_{fa} is the peripheral speed of rotor.

Let $v_{fa}=D_{fa}\,\pi\,n_{fa}$ be replaced into equation (3.84), then the volumetric flow quantity is computed by the following equation:

$$\dot{V}_{fa}=\varphi\frac{D_{fa}^3\pi^2}{4}n_{fa}=k_{fav}\,n_{fa}=\frac{\dot{m}_{fl}}{\rho_{fa}}\lambda\,m_{fa0}\,. \qquad (3.85)$$

It seems that the control of revolution number n_{fa} by changing the output frequency of frequency converter occurs proportional change of volumetric flow quantity of inlet fresh air.

Volumetric flow quantity and required revolution number of exhauster ventilator has to be computed similarly to equations (3.84)-(3.85) as it seems in equation (3.86):

$$\dot{V}_{fe}=\varphi\frac{D_{fe}^3\pi^2}{4}n_{fe}=k_{fev}\,n_{fe}=\frac{\dot{m}_{fl}}{\rho_{fg}}(1+\lambda\,m_{fa0}). \qquad (3.86)$$

The pressure of inlet fresh air Δp_{fa} can be computed by equation (3.83). After $v_{fa}=D_{fa}\,\pi\,n_{fa}$ had been replaced in (3.83), the following equation will be formed:

$$p_{fa}=\frac{1}{2}\rho_{fa}\psi_{fa}\,v_{fa}^2=k_{fap}n_{fa}^2. \qquad (3.87)$$

It seems that the pressure of inlet fresh air depends on quadratic value of revolution number n_{fa} (Dr.Menyhárt,1990).

The required pressure produced by the exhauster p_{fe} is computed by the following:

$$p_{fe}=\frac{\dot{V}_{fa}}{\dot{V}_{fg}}\,p_{fa}+\Delta p_{fg}-(p_{fo}-\Delta p_{cd}), \qquad (3.88)$$

$$p_{fe}=\frac{\dot{V}_{fa}}{\dot{V}_{fg}}\,k_{fap}n_{fa}^2+c_{fg}\rho_{fg}(T_{fg}-T_{ea})-(p_{fo}-\Delta p_{cd}). \qquad (3.89)$$

The exhauster ventilator must be able to produce the pressure p_{fe}, which pressure can be computed by equation (3.90):

$$p_{fe}=\frac{1}{2}\rho_{fg}\psi_{fe}\,v_{fe}^2=k_{fep}n_{fe}^2, \qquad (3.90)$$

where $n_{fe}=\dfrac{\dot{V}_{fe}}{k_{fev}}$, and

$$p_{fe}=k_{fep}\left(\frac{\dot{V}_{fe}}{k_{fev}}\right)^2 \qquad (3.91)$$

.

The required pressure produced by the exhauster ventilator is the following:

$$p_{fe}=\frac{\dot{V}_{fa}}{\dot{V}_{fg}}k_{fap}\left(\frac{\dot{V}_{fa}}{k_{fav}}\right)^2+c_{fg}\rho_{fg}(T_{fg}-T_{ea})-(p_{fo}-\Delta p_{cd}). \qquad (3.92)$$

The volumetric flow quantity of flue gas transported by the exhauster ventilator is expressed from equation (3.92):

$$\dot{V}_{fe}=k_{fev}\sqrt{\frac{\frac{\dot{V}_{fa}}{\dot{V}_{fg}}k_{fap}\left(\frac{\dot{V}_{fa}}{k_{fav}}\right)^2+c_{fg}\rho_{fg}(T_{fg}-T_{ea})-(p_{fo}-\Delta p_{cd})}{k_{fep}}}. \qquad (3.93)$$

The volumetric flow quantity of outlet flue gas $\dot{V}_{fe}$ depends on the volumetric flow quantity of inlet fresh air $\dot{V}_{fa}$, and the chimney draught Δp_{cd}, and the temperature difference between the flue gas temperature T_{fg} and the environmental temperature T_{ea}.

3.7.4. Revolution numbers of blaster ventilator and exhauster ventilator

Efficient combustion in furnace chamber requires a suitable rate of fuel and fresh air. The outlet of generated flue gas and inlet of fuel and fresh air must be satisfied continuously. The volumetric flow quantity depends on the revolution number of ventilator.

The revolution number of inlet fresh air ventilator is the following:

$$n_{fa}=\frac{\dot{V}_{fa}}{k_{fav}}=\frac{\dot{m}_{fl}\,\lambda\, m_{fa0}}{k_{fav}\,\rho_{fa}}. \qquad (3.94)$$

Let equation (3.74) be replaced into (3.94), then

$$\mathbf{n_{fa}}=\frac{p_{st2}\,k_2\sqrt{2\Delta p_{st2}/\rho_{st}}}{H_{fl}-\rho_{fl}(1+\lambda m_{fa0})c_{fg}(T_{fg}-T_{ea})}\,\frac{\rho_{fl}}{\rho_{fa}}\cdot\frac{\lambda\, m_{fa0}}{k_{fav}} \qquad \mathit{(3.95)}$$

Figure 3.14 includes the function of revolution number of blaster ventilator.

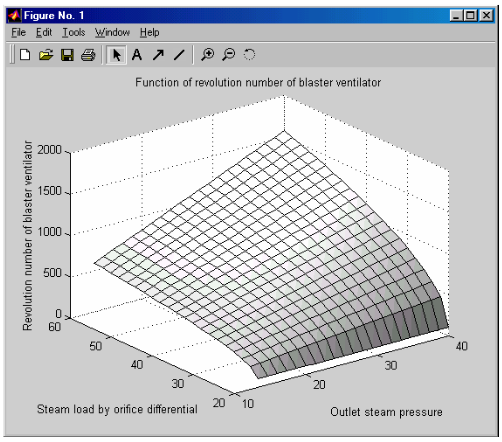


Figure 3.14. Function of revolution number of blaster ventilator

Since the exhauster ventilator must produce the suitable volumetric transportation and the required pressure to outlet flue gas, the revolution number of exhauster ventilator is computed from equation (3.96):

$$n_{fe} = \sqrt{\frac{\frac{\dot{V}_{fa}}{\dot{V}_{fg}} k_{fap} \left(\frac{\dot{V}_{fa}}{k_{fav}}\right)^2 + c_{fg}\rho_{fg}(T_{fg} - T_{ea}) - (p_{fo} - \Delta p_{cd})}{k_{fep}}} \,. \tag{3.96}$$

and after replacing equation (3.94) into (3.96):

$$n_{fe} = \sqrt{\frac{\frac{\dot{V}_{fa}}{\dot{V}_{fg}} k_{fap} \left(\frac{\dot{m}_{fl}\,\lambda\, m_{fa0}}{k_{fav}\,\rho_{fa}}\right)^2 + c_{fg}\rho_{fg}(T_{fg} - T_{ea}) - (p_{fo} - \Delta p_{cd})}{k_{fep}}} \,. \tag{3.97}$$

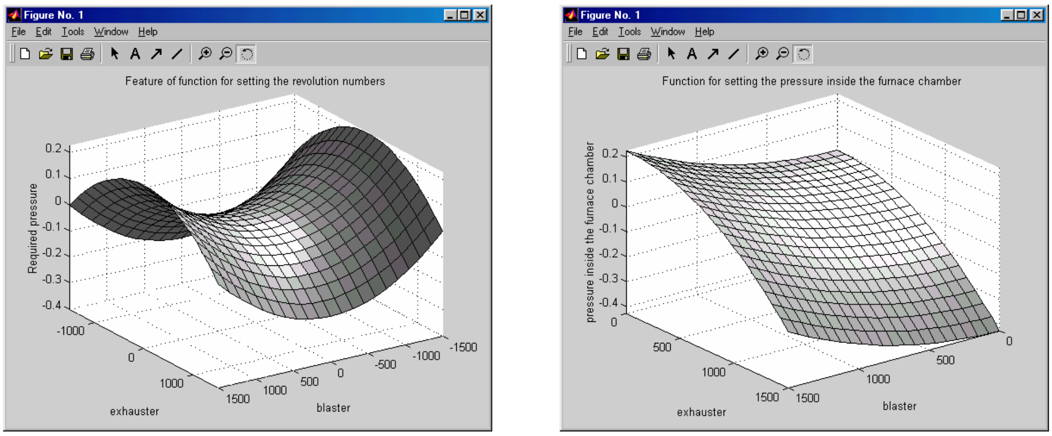
It seems in equation (3.97) that the required revolution number of exhauster ventilator depends on the inlet fuel quantity $\dot{m}_{fl}$, and the volumetric flow quantity of fresh air $\dot{V}_{fa}$, and the chimney draught Δp_{cd}.

The required internal pressure p_{fo} is expressed from equation (3.97) by the following:

$$k_{fep}\, n_{fe}^2 - \frac{\dot{V}_{fa}}{\dot{V}_{fg}} k_{fap}\, n_{fa}^2 = c_{fg}\rho_{fg}(T_{fg} - T_{ea}) - (p_{fo} - \Delta p_{cd})\,, \tag{3.98}$$

$$p_{fo} = c_{fg}\rho_{fg}(T_{fg} - T_{ea}) + \Delta p_{cd} - (k_{fep}\, n_{fe}^2 - \frac{\dot{V}_{fa}}{\dot{V}_{fg}} k_{fap}\, n_{fa}^2)\,, \tag{3.99}$$

The produced internal pressure of furnace chamber depends on the quadratic values of revolution numbers of inlet fresh air ventilator and exhauster ventilator as it can be seen in equation (3.99). Figure 3.15 shows the function of internal pressure by revolution numbers.



a) b)

Figure 3.15. Function for setting internal pressure of furnace chamber depended on revolution numbers of blaster and exhauster: a) locus of possible operating points; b) applied session of function

3.7.5. Request for changing the distribution of stem load

The efficiency of steam production depends on the temporary steam load distributed among boilers. The energy requirement of furnace chamber can not be reduced under a minimum while the steam load can decrease. Therefore, limitation of lower outlet steam quantity is necessary. The computation of volumetric flow quantity of outlet steam is the following:

$$\dot{V}^{i} = \dot{V}^{i} - k_0\sqrt{2(\Delta p_{st2,i} - \Delta p_{min,i})/\rho_{st}}\ , \qquad (3.100)$$

where $\Delta p_{min,i}$ is the minimum differential pressure measured by orifice differential and $\dot{V}^{i}$ is the minimum of steam load on the *i*th boiler.

When the temporary outlet steam quantity on an individual boiler has been reduced to a minimum value then the ratio between the burnt fuel quantity and the outlet steam quantity will be too high, which means the lower quantity of outlet steam the higher steam production cost.

When the steam load is at the specified minimum then the control system of boiler occurs a distribution request by the *i*th boiler as it seems in Figure 3.16. It seems in the figure that under a minimum there is no valuable outlet steam quantity. Then a request for changing the steam load of *i*th boiler will be occurred. The minimum value of orifice differential means the critical point of function outlet steam quantity the *i*th boiler. Critical points are decided in accordance with the technical features of individual boilers.

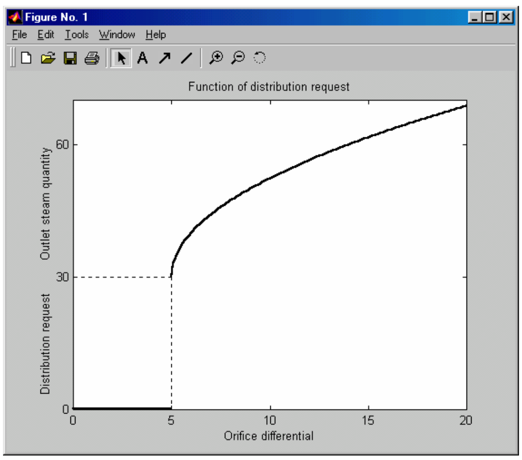


Figure 3.16. Function of distribution request

3.8. Conclusion

Previous sessions 3.5.–3.7. of this chapter include descriptions of technological variables of steam production system, the boiler. It seems, all of the parameters are results of non-linear functions. Those functions have bifurcation zones.

All the functions have limits where the slope of function is increased until ∞. Then output values will be set out of the production range, continuity will be interrupted, and working points will transfer to the catastrophe surface. Therefore, it can be declared, that

- all the functions being used to describe processes of steam production system have input range of independent variables where the changing of output variables is not linear,
- interruption of continuity is not a sharp cut-off event but a zone, where the slope of function is changing faster, and this zone is the *bifurcation zone* where output variables can get two or more values computed from single input, depended on the class of function,
- *all the functions are catastrophe functions because they have bifurcation zones,* and they can be transformed into the form of equations (3.10) and (3.20),
- the control system has to influence on technological parameters to product a stable value for setting the output variable,
- the appropriate control method is the *fuzzy logic control*, because decision making to influence on the technological process does not require a lot of computation, membership value can be computed fast and simply,
- the applied control system might be *Sugeno's fuzzy control system* because technological equipment settings by fuzzy logic control require continuous changing of output values.

Following chapter, Chapter 4 includes the description of soft computing methods which will be applied for the control of steam production system. Since the steam production system is a large-scale system the control system has to be useful for controlling the multi-layer, hierarchical technological system.

CHAPTER 4

Soft computing as tool for large-scale system control

4.1. Introduction

In this chapter the applied soft computing methods will be introduced. The expansion of computer technology resulted an intelligent heat production system which was one step towards a new digital computer area. Fuzzy systems supplanted conventional technologies in many scientific applications and engineering systems, especially in control systems and pattern recognition. But the fuzzy logic has grown rapidly in a wide range of consumer products and industrial systems. Fuzzy technology, in the form of approximate reasoning, is also resurfacing in information technology, where it provides decision-support and expert systems with powerful reasoning capabilities bound by a minimum of rules. It is this wealth of deployed, successful applications of fuzzy technologies that is responsible for current interest in fuzzy systems.

4.2. Control strategy of steam production

The technological system at of steam production at the Heat Power Station of Nyíregyháza has been involved into a multilevel dynamical control system. The control system has been divided into hierarchical units which have been running autonomously, and are connected to any subsystem. The central control system has been collecting the pre-processed data originated from the subsystems, and computes the generalized data to describe the temporary statement of steam production technology. Those data are shown in computer screen for the technology manager who can influence the features of steam production process. Those modified or no-modified data are transferred to the control subsystems of the particular technological units to change technological operations, and make correction of outlet steam parameters. The control subsystem is the local supervisory control of a technological unit of steam production. Subsystems of steam production are the following ones:

- feed water level control in the steam drum,
- temperature control of outlet steam,
- combustion control which consists of the following subsystems:
    - burner control,
    - control of inlet fresh air quantity,
    - control of removal of flue gas,
    - control of outlet steam pressure.

Technological units described in Chapter 2 are operated by autonomous controllers which have been connected to a local supervisory control system where the pre-processing of data is running. A part of pre-processed data is used to operate some secondary functions of technological unit, and there are some results of data pre-processing to transfer for the control unit of the technological subsystem. It seems, the control system of steam production divided into subsystems has internal feedbacks on the level of technological units, and has external feedback via PCs operated by the managers of technology. The process control is based on a hierarchical control strategy with the following features:

- the hierarchical system consists of decision-making components structured in a pyramid shape,

- the system has an overall goal, the required quantity of steam with required features,
- the various levels of hierarchy in the system exchange information among themselves iteratively,
- as the level of hierarchy goes up, the lower-level components are faster than the higher-level ones.

The hierarchical control system of steam production in the heat power station of Nyíregyháza includes three levels as it can be seen in Figure 4.1. They are the following: level of technological operations, level of large-scale subsystem control, and level of supervisory control of technology. The controlled output parameters of the system are the outlet steam quantity, the outlet steam pressure, and the outlet steam temperature which are influenced by the following input features: the temporary steam load, the required steam pressure, and the required steam temperature. Input parameters have been ordered by the users and they are set and supervised by the technology manager. Output parameters have to be set to those ordered values and the control of them is divided into two groups, the furnace chamber control and the steam drum control.

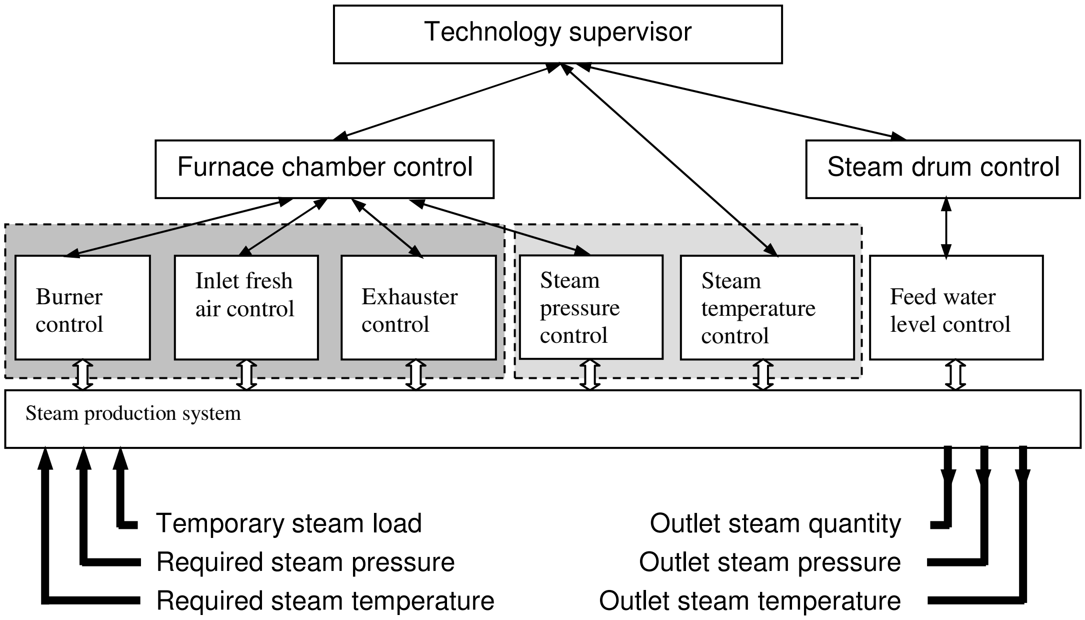


Figure 4.1. Hierarchical control strategy for the large-scale system of steam production

The steam production system has three subsystems, the system of steam generator colored with gray, the system for adjusting output parameters colored with light gray, and the feed water level control. The control system includes a large-scale system for the furnace chamber, a large-scale system for setting the output steam parameters, and a large-scale system to regulate the level of feed water in the steam drum. These large-scale systems have to be divided into small-scale subsystems by decomposition, and the supervisory process makes the coordination of subsystems.

4.3. Large-scale fuzzy control systems

A great number of today's problems in energy production are brought about by present-day technology and social and environmental processes which are highly complex, large in dimension, and uncertain by nature. Large-scale is a subjective one: how large is large? A system is considered large-scale if it can be coupled or partitioned into a number of interconnected subsystems or small-scale systems for either computational or practical reasons. This definition is shown in Figure 4.2.

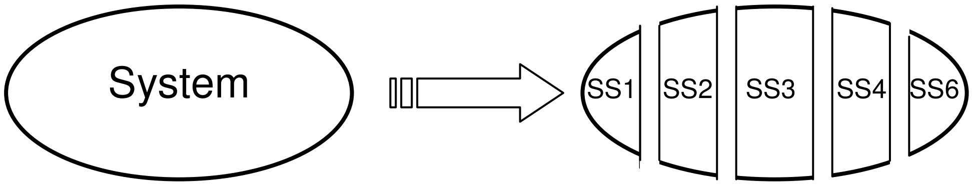


Figure 4.2. Large-scale system based on notion of decomposition

An other viewpoint is that a system is large-scale one when its dimensions are so large that conventional techniques of modeling, analysis, control, design, and computation fail to give reasonable solutions with reasonable computational efforts. In other words, a system is large when it requires more than one controller. Large-scale systems posses the following features (Jamshidi, 1983) (Jamshidi, 1997):

1. Large-scale systems are often controlled by more than one controller or decision maker involving decentralized computations.
2. The controllers have different but correlated information available to them, possibly at different times.
3. Large-scale systems can also be controlled by local controllers at one level whose control actions are being coordinated at another level in a hierarchical (multilevel) structure.
4. Large-scale systems are usually represented by imprecise aggregate models.
5. Controllers may operate in a group as a team or in a conflicting manner with single- or multiple-objective or even conflicting-objective functions.
6. Large-scale systems may be satisfactorily optimized by means of suboptimal or near-optimum controls, sometimes termed a satisfying strategy.

4.3.1. Hierarchical structures

The decoupled approach divides the original system into a number of subsystems involving certain values of the decoupling parameter, whose value is subsequently adjusted by a coordinator in an appropriate fashion so that the subsystem resolve their problems and the solution to the original system is obtained.

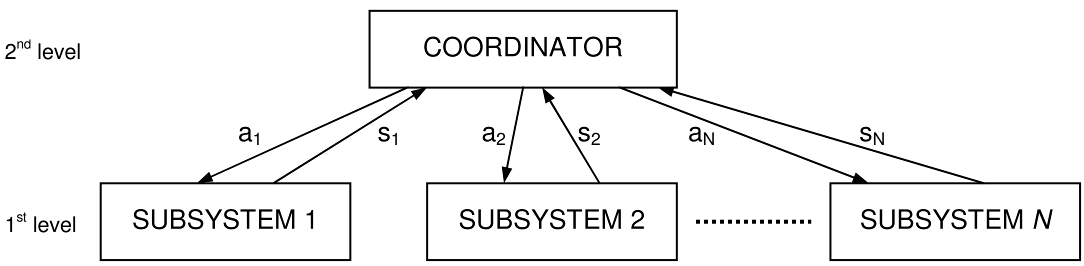


Figure 4.3. Scheme of a two-level hierarchical system

This approach, sometimes termed as the multilevel or hierarchical approach shown in Figure 4.3. At the first level, N subsystems of the original large-scale system are setting. At the second level a coordinator receives the local solutions of the N subsystems, s_i, $i=1,2,\ldots,N$, and then provides a new set of interaction parameters, a_i, $i=1,2,\ldots,N$.

The goal of coordinator is to arrange the activities of subsystems to provide feasible solution to the overall system. This exchange of solution s_N by the subsystems and coordination vector a_N by the coordinator will continue until convergence has been achieved. Such a system is both feasible and optimum, in the sense of minimizing a cost function of the overall system (Ho and Mitter, 1976)(Jamshidi et al., 1992).

In a hierarchical control, a decomposition in system structure will lead to computational efficiency.

When a fuzzy controller is designed for a large-scale system, often several measurable output and actuating input variables are involved. Each variable is represented by a finite number l of linguistic labels which would indicate that the total number of rules is equal to l^n where n is number of system variables. Even for a low-order system with as few as possible label's per variable exponential expression would become large. Figure 4.4 shows a schematic representation of a hierarchical fuzzy controller (Raju et al.,1991).

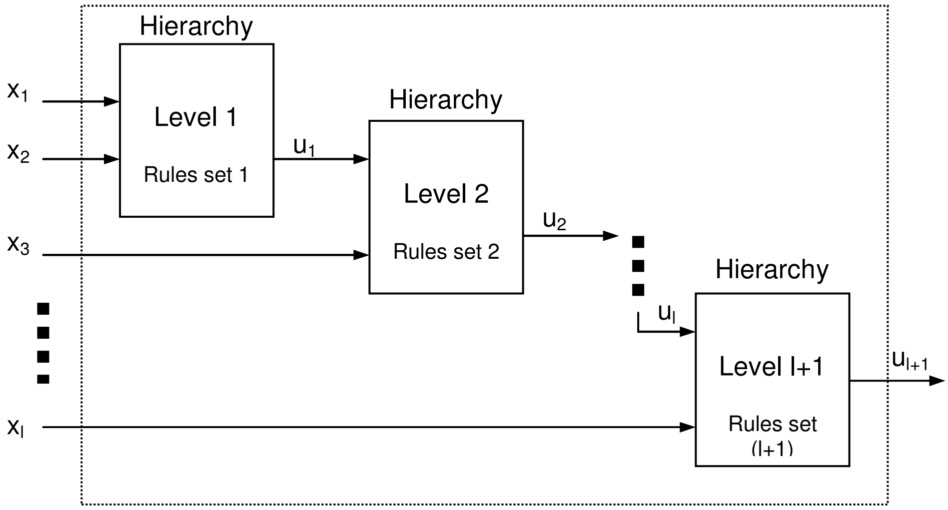


Figure 4.4. Scheme of hierarchical fuzzy controller

4.3.2. Multilayer control strategy for steam production system

The control strategy offered to use in large-scale control system of steam production is *multilayer control strategy* which is a direct outcome of the complexities involved in a decision-making process. Control tasks are distributed in a vertical division shown in Figure 4.5 (Singh and Titli,1978). The multilayer structure consists of regulation layer which acts as a direct control activity, an optimization layer which can compute the required set points of regulators, an adaptation layer which is a direct adaptation of control law and model, and a layer of self-organization which selects the suitable model of control and control as a function of environmental parameters. Successful operation of hierarchical system is best described by two processes known as *decomposition* and *coordination.* Decomposition means the large-scale

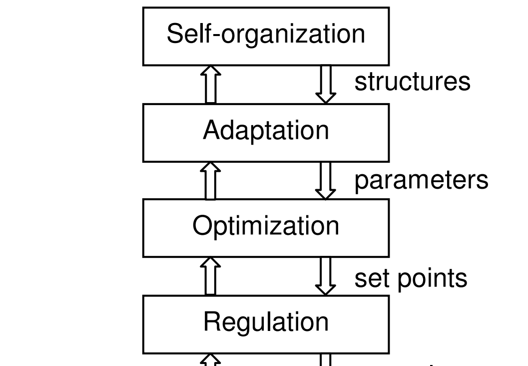


Figure 4.5. The multilayer control strategy

system is given as a number of small-scale subsystems, and the coordination means that these subsystems' solutions will be coordinated until feasibility and optimality of the overall system are achieved through a multilevel iterative algorithm. However, subsystems of steam production system are complicated 'internal large-scale systems' as they has been described in Chapter 2.

4.3.3. Decentralized control

Most large-scale systems are featured by a great multiplicity of measured outputs and inputs. For example, a heat power station has several control substations, each of them being responsible for the operation of the overall system. This situation is arising in a control system design is often referred to as decentralization. There are determined a structure for control which assigns system inputs to a given set of local controllers, which observe only local system outputs. This approach attempts to avoid difficulties in data gathering, storage requirements, computer program debuggings, and geographical separation of system components.

The basic characteristic of any decentralized system is that the transfer of data from one group of sensors or actuators to others is quite restricted. System in Figure 4.6 uses only the output y_1, and input v_1 to find the control u_1, and likewise the control u_2 is obtained through only the output y_2 and external input v_2.

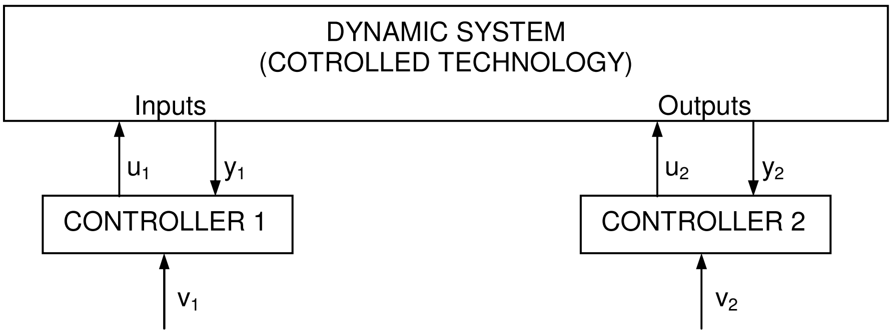


Figure 4.6. A two-controller decentralized system

4.4. Fuzzy logic systems

The human brain interprets imprecise and incomplete sensory information provided by perceptive organs. Fuzzy set theorem provides a systematic calculus to deal with such information linguistically, and it performs numerical computation by using linguistic labels stipulated by membership functions. Moreover, a selection of fuzzy if-then rules forms the key component of a fuzzy inference system (FIS) that can effectively model of human expertise in a specific application (Zadeh,1965) (Zadeh, 1969)(Zimmermann,1976)(Takagi and Sugeno, 1985)(Sugeno and Kang,1988) (Lee, 1990a)(Lee, 1990b)(Kosko, 1991)(Trautzl, 1991a)(Trautzl, 1991b) (Yager and Zadeh, 1992) (Yager and Zadeh, 1994) (Wang,1994)(Ajtonyi,1998).

A classical (crisp) set is a collection of distinct objects. It is defined in such a way as to dichotomize the elements of a given universe of discourse into two groups: members and non-members. A crisp set can be defined by the so-called *characteristic function*. Let *U* be a universe of discourse. The characteristic function $\mu_A(x)$ of a crisp set *A* in *U* takes its values in (0,1) and is defined such that $\mu_A(x)=1$ if *x* is a member of *A* (i.e., $x \in A$) and 0 otherwise. That is,

$$\mu_A(x) = \begin{cases} 1 & \text{if and only if } x \in A, \\ 0 & \text{if and only if } x \notin A. \end{cases} \qquad (4.1)$$

Note that

- **the boundary of set A is rigid and sharp and performs a two-class dichotomization** (i.e., $x\in A$ or $x\notin A$) **,**
- **and the universe of discourse U is a crisp set.**

A fuzzy set $\tilde{A}$ in the universe of discourse U can be defined as a set of ordered pairs.

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in U\}, \qquad (4.2)$$

where $\mu_{\tilde{A}}(\ )$ is called the *membership function* of $\tilde{A}$ and $\mu_{\tilde{A}}(x)$ is the *grade* or degree of membership of x in $\tilde{A}$, which indicates the degree that x belongs to $\tilde{A}$. The membership function $\mu_{\tilde{A}}(\ )$ maps U to the membership space M, that is $\mu_{\tilde{A}}: U\to M$. When $M=\{0, 1\}$, set is nonfuzzy and $\mu_{\tilde{A}}(\ )$ is the characteristic function of the crisp set A. For fuzzy sets, the *range of the membership function* (i.e., M) is a subset of the nonnegative real numbers whose supremum is finite. In most general cases, M is set to the unit interval [0, 1].

Fuzzy set is a type of imprecision that stems from a grouping of elements in the classes. It is worth pointing out that $\mu_A(x)\in [0,1]$ indicates the membership grade of an element $x\in U$ in fuzzy set A and that is not a probability because $\sum\mu_A(x) \neq 1$. The grades of membership basically reflect an ordering of the objects in fuzzy set A.

An other way of representing a fuzzy set is through use of the support of a fuzzy set. The support of a fuzzy set A is the crisp set of all $x\in U$ such that $\mu_{\tilde{A}}(x)>0$. That is,

$$\text{Supp}(A) = \{ x\in U \mid \mu_A(x)>0\}. \qquad (4.3)$$

A fuzzy set A whose support is a single point in U with $\mu_A(x)=1$ is referred to as a *fuzzy singleton*. Moreover, the element $x\in U$ at which $\mu_A(x)=0.5$ is called *crossover point*. The *kernel* of fuzzy set A consists of the element x whose membership grade is 1. That is, $ker(A) = \{ x \mid \mu_A(x)=1\}$. Then *height* of a fuzzy set A is the supremum of $\mu_A(x)$ over U.

A fuzzy set is *normalized* when the height of the fuzzy set is unity, otherwise it is *subnormal.* A non-empty fuzzy set A can always be normalized by dividing $\mu_A(x)$ by the height of A.

The representation of a fuzzy set can be expressed in terms of the support of the fuzzy set. For a discrete universe of discourse $U=\{x_1, x_2, \ldots, x_n\}$, a fuzzy set A can be represented using the ordered pairs concept and written as

$$A = \{(x_1, \mu_A(x_1)), (x_2, \mu_A(x_2)), \ldots,(x_n, \mu_A(x_n))\}. \qquad (4.4)$$

If U is not discrete, but is an interval of real numbers, we can be use the notation

$$A = \int_U \mu_A(x)/x, \qquad (4.5)$$

where $\int$ indicates the union of the elements in A.

Let A be a fuzzy set in the universe of discourse U. Let αA_α denote a fuzzy set with the membership function

$$\mu_\alpha A_\alpha(x) = [\alpha \wedge \mu_{A_\alpha}(x)] \qquad \forall x \in U. \qquad (4.6)$$

In this case, resolution principle states that a fuzzy set *A* can be expressed by the following form:

$$A = \int_0^1 \alpha A_\alpha. \qquad (4.7)$$

The resolution principle indicates that a fuzzy set A can be decomposed into αA_α, $\alpha \in (0,1]$. A fuzzy set A can be retrieved as a union of its αA_α, which is the representation theorem. A fuzzy set can be expressed in terms of its α-cuts without resorting the membership function.

Fuzzy logic system is a name of systems which have direct relationship with the fuzzy concepts like fuzzy sets, linguistic variables, etc., and fuzzy logic. There are four classes of fuzzy systems in the literature: pure fuzzy logic systems, fuzzy systems of Takagi and Sugeno, fuzzy logic systems with fuzzifier and defuzzifier, and adaptive fuzzy systems.

4.4.1. Pure fuzzy logic system

Basic configuration of pure fuzzy logic systems is shown in Figure 4.7 where the fuzzy rule base includes the collection of fuzzy *IF-THEN* rules, and the fuzzy inference engine uses these *IF-THEN* rules to determine a mapping from fuzzy sets in the input inverse of discourse $U \subset R^n$ to fuzzy sets in the output inverse of discourse $V \subset R^n$ based on fuzzy logic principles. Fuzzy *IF-THEN* rules have the following form:

$$R^n\text{: } IF\ x_1\ is\ F_1^l\ AND\ x_2\ is\ F_2^l\ AND \ldots AND\ x_n\ is\ F_n^l\ THEN\ y\ is\ G^l, \qquad (4.8)$$

where F^l and G^l are fuzzy sets, $\underline{x}=(x_1, x_2, \ldots, x_n)^T \in U$ and $y \in V$ are input and output linguistic variables, respectively, and $l=1,2,\ldots,M$.

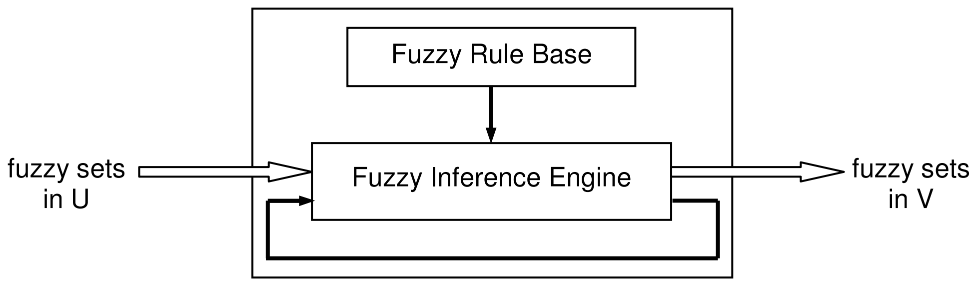


Figure 4.7. The pure fuzzy logic system

Each *IF-THEN* fuzzy rules described by equation (4.8) define fuzzy set shown by (4.9) in the product space $U \times V$. Most of commonly used fuzzy logic principle in the fuzzy inference engine is the so-called *sup-star* composition.

$$F_1^l \times F_2^l \times \ldots \times F_n^l \rightarrow G^l. \qquad (4.9)$$

Let A' be an arbitrary fuzzy set in U. When A' is the input to the pure fuzzy logic system in Figure 4.4, then the output determined by each fuzzy *IF-THEN* rule shown in expression (4.8) is a fuzzy set $A' \circ R^{(l)}$ in whose membership function is the following

$$\mu_{A' \circ R^{(l)}}(y) = sup_{\underline{x} \in U} [\mu_{A'}(\underline{x}) * \mu_{F_1^l \times \ldots \times F_1^l \to G^l}(\underline{x}, \underline{y})], \quad (4.10)$$

where operator "*" may be min, product, or others. The μ_A is used as the fuzzy membership function of fuzzy set A. The output of the pure fuzzy logic system is a fuzzy set $A' \circ [R^{(1)}, R^{(2)}, \ldots, R^{(M)}]$ in V which is a combination of the M fuzzy sets of expression (4.10); that is,

$$\mu_{A' \circ [R^{(1)}, R^{(2)}, \ldots, R^{(M)}]}(y) = \mu_{A' \circ R^{(1)}}(y) + \mu_{A' \circ R^{(2)}}(y) + \ldots + \mu_{A' \circ R^{(M)}}(y), \quad (4.11)$$

where the operator "+" may be "max", "algebraic sum", or others.

If the pure logic system includes internal feedback as it is shown by the Figure 4.6 then it is the so-called *fuzzy dynamic system*, the pure fuzzy logic system depended on its output.

4.4.2. Fuzzy logic system by Takagi and Sugeno

The Sugeno fuzzy model shown its scheme in Figure 4.8 has been proposed by Takagi, Sugeno and Kang in an effort to develop a systematic approach generating fuzzy rules from a given input-output data set (Sugeno and Kang, 1985)(Takagi and Sugeno,1985). Typical fuzzy rule in a Sugeno model is

$$L^{(l)}: IF\ x_1\ is\ F_1^l\ AND\ x_2\ is\ F_2^l\ AND \ldots AND\ x_n\ is\ F_n^l\ THEN\ y^l = c_0^l + c_1^l x_1 + \ldots + c_n^l x_n, \quad (4.12)$$

where F_i are fuzzy sets, c_i are real-valued parameters, y^l is the system output due to rule L^l, and $l=1,2,\ldots,M$. while $z=f(x,y)$ is a crisp function in the consequent.

When y^l is a first-order polynomial the resulting fuzzy inference system is *first-order Sugeno fuzzy model*, and if y^l is constant then it is called a *zero-order Sugeno fuzzy model*. The output of a zero-order Sugeno fuzzy model is a smooth function of its input variables as long as the neighboring membership functions in the antecedent have enough overlap. The first-order Sugeno fuzzy model has a crisp output, the overall output is obtained via *weighted average*. For a real valued input vector $\underline{x}=(x_1, x_2, \ldots, x_n)^T$, the output $y(\underline{x})$ of fuzzy system by Takagi and Sugeno is a weighted average of y^l:

$$y(x) = \frac{\sum_{l=1}^{M} w^l y^l}{\sum_{l=1}^{M} w^l}, \quad (4.13)$$

where the weight w^l implies the overall truth value of the premise of rule $L^{(l)}$ for the input. The weight is computed as

$$w^l = \prod_{l=1}^{M} \mu_{F_1^l}(x_i). \quad (4.14)$$

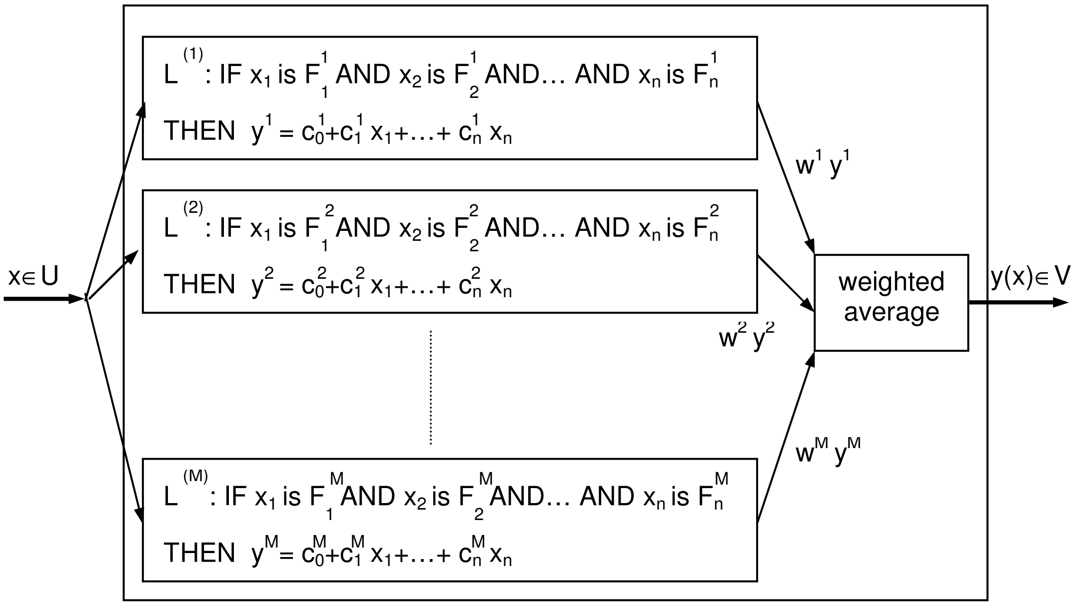


Figure 4.8. Scheme of fuzzy system by Takagi and Sugeno

4.4.3. Fuzzy logic system with fuzzifier and defuzzifier

The pure fuzzy logic system applied in technologies requires fuzzifier and defuzzifier to the input and output when inputs and outputs are real-valued variables. The basic configuration of fuzzy logic system with fuzzifier and defuzzifier is shown in Figure 4.9.

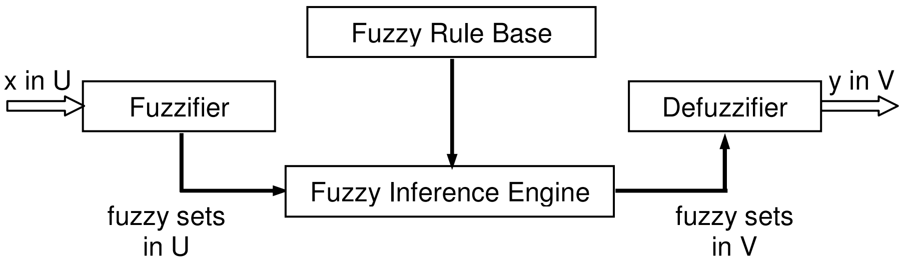


Figure 4.9. Fuzzy logic system with fuzzifier and defuzzifier

The fuzzifier transforms crisp point in *U* to fuzzy set *U*, and the defuzzifier maps the fuzzy sets in *V* to crisp points in *V*. The fuzzy rule base and the fuzzy inference system are the same as they in the pure fuzzy logic system. This system is called the fuzzy logic controller since it has been used as controller which has been used successfully to industrial processes and consumer products.

The fuzzy logic systems with fuzzifier and defuzzifier have a lot of attractive features. It can be used for engineering systems because its inputs and outputs are real-valued variables. That system provides a natural framework to incorporate fuzzy IF-THEN rules from human experts. Users have freedom in the choice of fuzzifier, fuzzy inference system and defuzzifier, therefore, it can be obtained the most suitable fuzzy logic system for any particular problem If that the system provides an effective framework to integrate numerical and linguistic data there are different training algorithms developed for this fuzzy logic system.

4.4.4. Adaptive fuzzy systems

An adaptive fuzzy system is defined as a fuzzy logic system equipped with training algorithm, where the fuzzy logic system is constructed from a set of IF-

THEN rules using fuzzy logic principles, and the training algorithm adjusts parameters and the structures of the fuzzy logic system based on numerical information. Adaptive fuzzy systems can be seen as fuzzy logic system which includes rules generated automatically through training.

There are two strategies of combining numerical and linguistic data using adaptive fuzzy systems:

- use linguistic data to construct an internal fuzzy logic system, and then adjusts parameters of the initial fuzzy logic system based on numerical data;
- use numerical data and linguistic data to construct two separated fuzzy logic systems, and then average them to obtain the final fuzzy logic system.

4.5. Structure of fuzzy control systems

A common definition of fuzzy systems is that it is a system which can emulate a human expert to control by fuzzy methods.

Fuzzy controls are good engineering approaches which would be able to make effective use of all available data. Data can be originated from sensors and from human experts. Fuzzy control is a *model-free approach* which means it does not require mathematical description of controlled system. The fuzzy control provides *non-linear controllers*, which are justified due to the Universal Approximation Theorem. These fuzzy logic controllers are general enough to perform non-linear control activities.

4.5.1. Fuzzyfication

The operation of fuzzyfication represents a mapping form a crisp value into a fuzzy set. There are two categories of fuzzifiers, the singleton and non-singleton ones.

Singleton fuzzifier has one value x_p as its fuzzy set support, and the membership function is governed by the following expression:

$$\mu_A(x) = \begin{cases} 1 & \text{if } x=x_p \in X, \\ 0 & \text{if } x\neq x_p \in X. \end{cases} \qquad (4.15)$$

Non-singleton fuzzifiers are those ones in which support is more than one a point. These fuzzifiers are left-shoulder (L), right shoulder (Γ), triangular (Λ), trapezoidal (Π),Zadeh's S-function, Gaussian function (G).

The function of right-shoulder fuzzyfication $\Gamma: U\rightarrow[0,1]$ is defined with two parameters as it seems in the following:

$$\Gamma(u,\alpha,\beta)=\begin{cases} 0 & \text{if } u<\alpha, \\ (u-\alpha)/(\beta-\alpha) & \text{if } \alpha\leq u\leq\beta, \\ 1 & \text{if } u>\beta. \end{cases} \qquad (4.16)$$

The function of left-shoulder fuzzyfication $L: U\rightarrow[0,1]$ is defined by the following expression:

$$L(u,\alpha,\beta)=\begin{cases} 1 & \text{if } u<\alpha, \\ (u-\alpha)/(\beta-\alpha) & \text{if } \alpha\leq u\leq\beta, \\ 0 & \text{if } u>\beta. \end{cases} \qquad (4.17)$$

. The function of triangular fuzzyfication $\Lambda:U\to[0,1]$ is defined by the following expression:

$$\Lambda(u,\alpha,\beta,\gamma,\delta)=\begin{cases} 0 & \text{if } u<\alpha, \\ (u-\alpha)/(\beta-\alpha) & \text{if } \alpha\leq u<\beta, \\ 1 & \text{if } u=\beta, \\ (\beta-u)/(\gamma-\beta) & \text{if } \beta<u\leq\gamma, \\ 0 & \text{if } u>\gamma. \end{cases} \tag{4.18}$$

These functions can be seen in Figure 4.10.

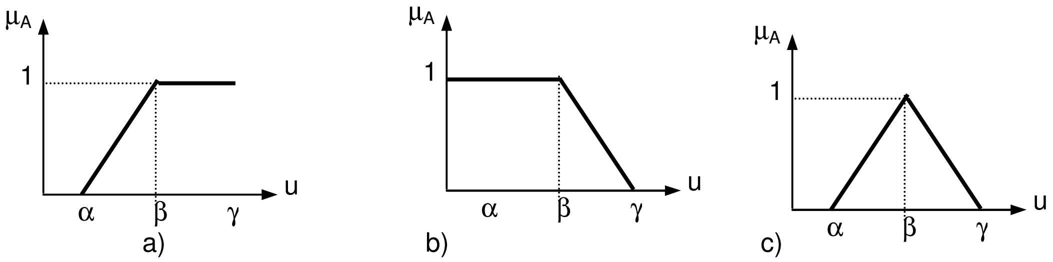


Figure 4.10. Non-singleton fuzzifier types
a) right-shoulder, b) left-shoulder, c) triangle

The function of trapezoidal fuzzyfication $\Pi:U\to[0,1]$ is defined by the following expression:

$$\Pi(u,\alpha,\beta,\gamma,\delta,)=\begin{cases} 0 & \text{if } u<\alpha, \\ (u-\alpha)/(\beta-\alpha) & \text{if } \alpha\leq u\leq\beta, \\ 1 & \text{if } \beta<u<\gamma, \\ (\gamma-u)/(\delta-\gamma) & \text{if } \gamma\leq u\leq\delta, \\ 0 & \text{if } u>\delta. \end{cases} \tag{4.19}$$

The Zadeh's S-function is the following:

$$S(u,\alpha,\beta,\gamma)=\begin{cases} 0 & \text{if } u\leq\alpha, \\ 2\left[\dfrac{u-\alpha}{\gamma-\alpha}\right]^2 & \text{if } \alpha<u\leq\beta, \\ 1-2\left[\dfrac{u-\alpha}{\gamma-\alpha}\right]^2 & \text{if } \beta<u\leq\gamma, \\ 1 & \text{if } u>\gamma. \end{cases} \tag{4.20}$$

The Gaussian membership function $G:U\to[0,1]$ is defined below:

$$G(u,\beta,a)=\begin{cases} 1 & \text{if } u=\beta, \\ g(u) & \text{otherwise,} \end{cases} \tag{4.21}$$

where β is the centroid, and a represents the width of membership function., and the expression of $g(u)$ is the following:

$$g(u)=\exp\left[-\frac{(u-\beta)^2}{2a^2}\right], \tag{4.22}$$

where $\{u,\beta, a_i\}$defines the gaussian membership function. These functions are shown in Figure 4.11.

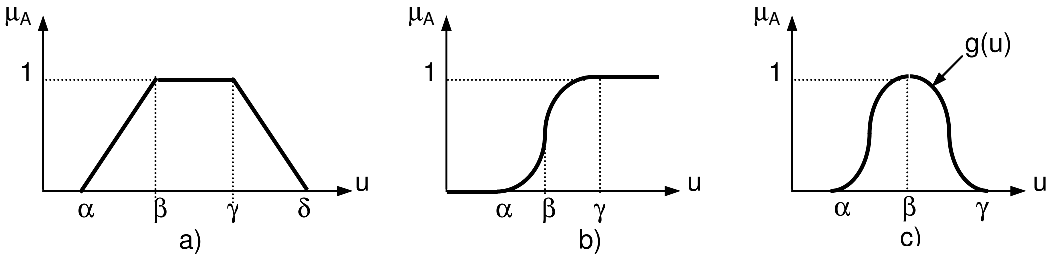


Figure 4.11. Non-singleton fuzzifier types
a) trapezoidal, b) Zadeh's S function c) Gaussian function

4.5.2. Fuzzy inference engine

Fuzzy inference systems are the most important modeling tools based on fuzzy sets theorem (Zadeh, 1965) (Zadeh,1969)(Mamdani, and Assilian, 1975)(Tsukamoto, 1979)(Takagi and Sugeno, 1985)(Sugeno and Kang,1988)(Lee, 1990a)(Lee, 1990b)(Kosko, 1991)(Ajtonyi,1998). This session presents three of the frequently used fuzzy inference systems, the Mamdani, Sugeno and Tsukamoto fuzzy models.

The fuzzy inference system is a framework based on concepts of fuzzy set theorem, fuzzy if-then rules, and fuzzy reasoning. Conventional fuzzy inference systems are typically built by domain experts and have been used in automatic control, decision analysis, and expert systems. Optimization and adaptive techniques expand the applications of fuzzy inference systems to fields such as adaptive control, adaptive signal processing, nonlinear regression, and pattern recognition.

Fuzzy inference system can take either fuzzy inputs or crisp inputs, but the outputs it produces are almost always fuzzy sets. Sometimes it is necessary to have a crisp output, especially in a situation where a fuzzy inference system is used as a controller. Therefore, a method of defuzzification is required to extract a crisp value that best represents the fuzzy set.

With crisp inputs and outputs, a fuzzy inference system implements a nonlinear mapping from its input space to output space. This mapping is accomplished by a number of fuzzy if-then rules, each of which describes the local behavior of the mapping.

Mamdani's fuzzy inference system (Mamdani and Assilian, 1975) was proposed to control a steam engine and boiler combination by a set of linguistic control rules obtained from experienced human operators. Adopting the *max* and *algebraic product* as a choice for the T-norm and T-conorm operators, respectively, and using max-product composition instead of the max-min composition, then the resulting fuzzy reasoning is inferred output of each rule where the fuzzy set is scaled down by its firing strength via algebraic product. Although this type of fuzzy reasoning was not employed in Mamdani's original paper, it has often been used in the literature. Mamdani used two fuzzy inference systems which were used as two different controllers to generate the heat input to the boiler and throttle opening of the engine cylinder to regulate the steam pressure in the boiler and the speed of engine. Since the plant has taken only crisp values as inputs, a *defuzzifier* has had to be used to convert a fuzzy set to a crisp value.

Fuzzy reasoning of Mamdani's minimum implication rule R_c; in this mode of reasoning, the *i*th fuzzy control rule leads to the control decision:

$$\mu_{C_i'}(w)=\alpha_i\wedge\mu_{C_i}(w), \qquad (4.23)$$

$$\mu_C(w)=\mu_{C_1'}\wedge\mu_{C_2'}=[\alpha_1\wedge\mu_{C_1}(w)]\vee[\alpha_2\wedge\mu_{C_2}(w)]. \qquad (4.24)$$

The ***Sugeno fuzzy model*** has been proposed by Takagi, Sugeno and Kang in an effort to develop a systematic approach generating fuzzy rules from a given input-output data set (Sugeno and Kang, 1985)(Takagi and Sugeno,1985). Typical fuzzy rule in a Sugeno model is

$$\text{if } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z=f(x,y), \tag{4.25}$$

where A and B are fuzzy sets in the antecedent, while $z=f(x,y)$ is a crisp function in the consequent.

When $f(x,y)$ is a first-order polynomial the resulting fuzzy inference system is *first-order Sugeno fuzzy model*, and if $f(.)$ is constant then it is called a *zero-order Sugeno fuzzy model*.

The output of a zero-order Sugeno fuzzy model is a smooth function of its input variables as long as the neighboring membership functions in the antecedent have enough overlap.

In case of first-order Sugeno fuzzy model, since each rule has a crisp output, the overall output is obtained via *weighted average*. Waited average operator is sometimes replaced with the *weighted sum* operator to reduce computation further, especially in the training of fuzzy inference system.

In ***Tsukamoto fuzzy models*** the consequent of each fuzzy IF-THEN rule is represented by a fuzzy set with a monotonical membership function. The inferred output of each rule is defined as a crisp value induced by the rule's firing strength. The overall output is taken as the weighted average of each rule's output (Tsukamoto, 1979).

Since rules infers crisp output, the Tsukamoto fuzzy model aggregates each rule's output by the method of weighted average and thus avoids the time-consuming process of defuzzification.

$$\text{if } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z = \frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i}, \tag{4.26}$$

where f_i is the output of each rule included by the firing strength w_i and membership function.

Since the reasoning mechanism of the Tsukamoto fuzzy model does not follow strictly the compositional rule of inference, the output is always crisp even when the inputs are fuzzy (Jang et al., 1997).

4.5.3. Defuzzification methods

A brief explanation of each defuzzification strategy is the following:

- Centroid of area z_{COA}

$$z_{COA} = \frac{\int_{(z)} \mu_A(z) z \, dz}{\int_{(z)} \mu_A(z) \, dz}, \tag{4.27}$$

where $\mu_A(z)$ is the aggregated output membership function.

- Bisector of area z_{BOA} : z_{BOA} is the following

$$\int_{\alpha}^{z_{BOA}} \mu_A(z)\, dz = \int_{z_{BOA}}^{\beta} \mu_A(z)\, dz, \qquad (4.28)$$

where $\alpha = min\{z \mid z \in Z\}$ and $\beta = max\{z \mid z \in Z\}$. This vertical line $z=z_{BOA}$ partitions the region between $z=\alpha$, $z=\beta$, $y=0$ and $y=\mu_A(z)$ into two section with the same area.

- Mean of maximum z_{MOM} : z_{MOM} is the average of the maximizing z at which the MF reach a maximum of μ^*:

$$Z_{MOM} = \frac{\int_{(Z')} z\, dz}{\int_{(Z')} dz}, \qquad (4.29)$$

where $Z' = \{z \mid \mu_A(z)= \mu^*\}$.

- Smallest of maximum z_{SOM} : z_{SOM} is the minimum of the maximizing z.
- Largest of maximum z_{LOM} : z_{LOM} is the maximum of the maximizing z.

Figure 4.12. shows the various defuzzification schemes for obtaining a crisp output. The calculation required to carry out any of these defuzzification operations is time-consuming unless special hardware support is available.

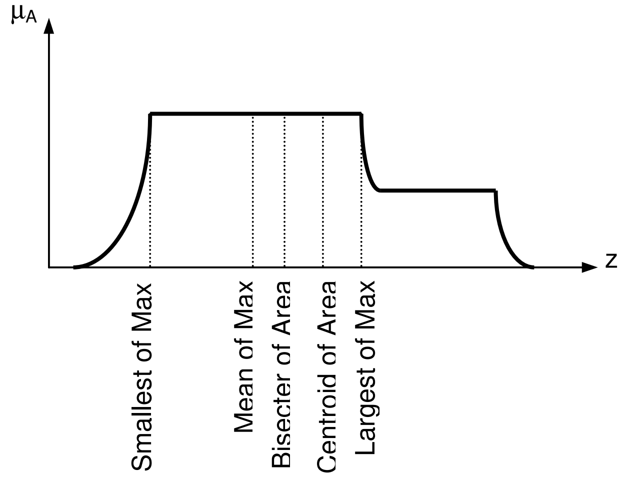


Figure 4.12. Various defuzzification schemes for obtaining a crisp output (Jang et al.1997, p. 77)

Furthermore, the MOM strategy yields a better transient performance, while the COA strategy yields a better steady-state performance (Lee,1990a).

4.6. Neural networks

Neural networks have a large number of highly interconnected processing elements (nodes) that usually operate in parallel and are configured in regular architectures. They are featured by their collective behavior, like a human brain. Their collective behavior demonstrates the ability to learn, recall, and generalize from training patterns or data. Neural networks are inspired by modeling networks of real neurons in the brain. A schematic diagram of a typical biological neuron is shown in Figure 4.13a. The typical neuron has the following parts: the *cell body* or soma, where the cell nucleus is located, the *dendrites,* and the *axon.* Dendrites are treelike networks of nerve fiber connected to the cell body. An axon is a single, long, cylindrical connection extending from the cell body and carrying impulses from the neuron. The end of axon split into strands or a fine arborization. Each strand terminates in a small bulblike organ called a *synapse*, where the neuron introduces its

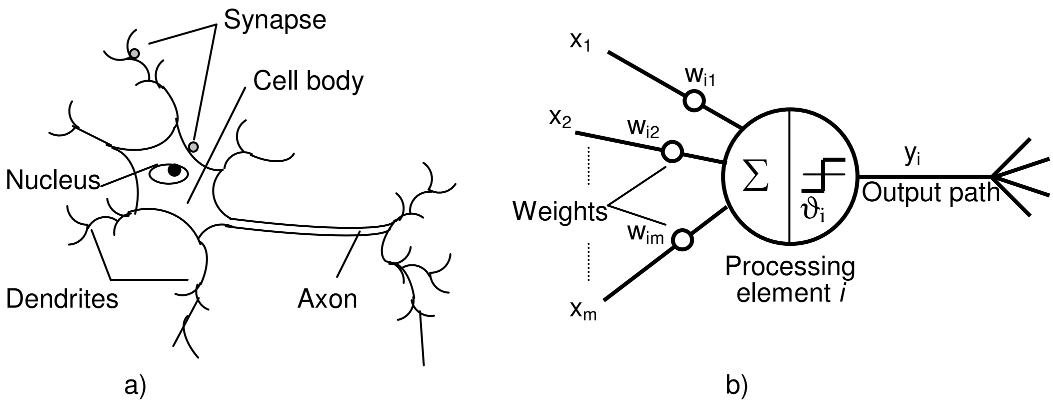


Figure 4.13. Correspondence between a biological and an artificial neuron a) Schematic diagram of a biological neuron, b) McCulloch and Pitts neuron (after Lin és Lee, 1996: p.206)

signal to the neighboring neurons. Receiving ends of these junctions on the neighboring neurons can be found both on the dendrites and on the cell bodies themselves.

The signals reaching a synapse and received by dendrites are electric signals. They raise or lower the electric potential inside the body of receiving cell. The receiving cell *fires* if its electric potential reaches a threshold, and a pulse or *action potential* of fixed strength and duration is sent out through the axon to the axonal arborization to synaptic junctions to other neurons. After firing, neuron has to wait for a period of time called *refractory period* before it can fire again. Synapses are *excitatory* if they let passing impulses cause the firing of the receiving cell, or *inhibitory* if they passing impulses hinder the firing of the neuron.

Figure 4.13b shows a simple mathematical model of biological neuron proposed by McCulloch and Pitts (McCulloch and Pitts, 1943). In this model, the *i*th processing element computes a weighted sum of its inputs and outputs $y_i=1$ (firing) or 0 (not firing) according to whether this weighted input sum is above or below a certain threshold ϑ_i.

$$y_i(t+1)=a\left(\sum_{j=1}^{m} w_{ij}x_j(t)-\vartheta_i\right), \tag{4.30}$$

where the activation function $a(f)$ is a unit step function:

$$a(f)=\begin{cases} 1 & \text{if } f\geq 0, \\ 0 & \text{otherwise.} \end{cases} \tag{4.31}$$

The weight w_{ij} represents the strength of the synapse connecting neuron j (source) to neuron i (destination). A positive weight corresponds to an excitatory synapse, and a negytive weight corresponds to an inhibitory synapse. If $w_{ij}=0$ then there is no connection between the two neurons.

Although simplicity models a biological neuron as a binary threshold unit, a McCulloch-Pitts neuron has substantial computing potential. It can perform the basic logic operations NOT, OR, and AND when weights and thresholds are selected accordingly. Since any multivariable combination function can be implemented by these logic operations, a synchronous assembly of such neurons is capable of performing universal computations.

4.6.1. Fuzzy-neural hybrid systems

There are two opportunities for bringing neural network techniques into fuzzy systems to form *neural fuzzy systems* or introducing fuzzy logic into neural networks to form *fuzzy neural networks.* An advanced straightforward approach is to put them together to form a fuzzy logic and neural network incorporated system called *fuzzy-neural hybrid system.* In such systems, fuzzy logic techniques and neural networks can be viewed as two individual systems. Both of them do their own jobs by serving different purposes. By making use of their individual strengths, they incorporate and complement each other to accomplish a desired task. Typical architecture of a fuzzy-neural hybrid system is shown in Figure 4.14. The neural network is used for input signal processing and the fuzzy logic subsystem is used for output action decision. This system makes use of the strength of a neural network in its processing speed and the strength of fuzzy logic in its flexible reasoning capability for decision making and control.

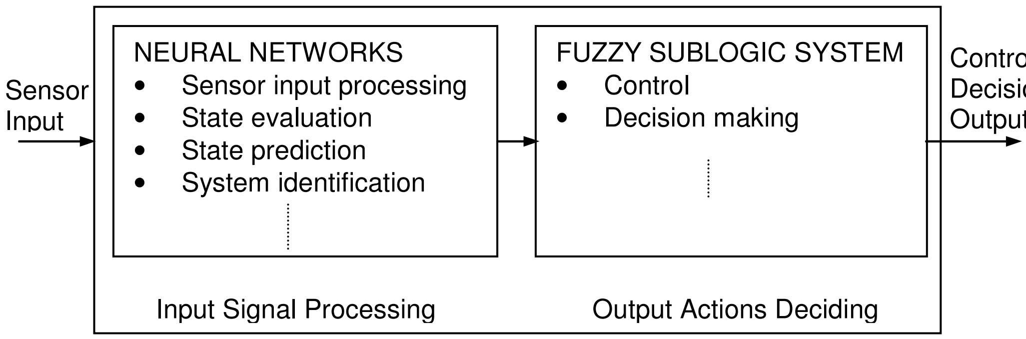


Figure 4.14.A typical architecture of fuzzy-neural hybrid system (Lin and Lee, 1996; p.696)

4.6.2. Description of neural network-based fuzzy logic inference

Let we consider a neural network realization of fuzzy logic inference which is kernel of a fuzzy inference system. Fuzzy inference systems can be used to learn and extrapolate complex relationships between possibility distributions for the preconditions and consequents in rules. The non-adaptive behavior of original fuzzy inference systems can be improved by using neural networks. Since different rules with same variables may be encoded in a single network, the use of neural networks as realization of fuzzy logic inference can provide a natural mechanism for rule conflict resolution. The common application of fuzzy logic and neural network can lead to the development of new algorithms and structures. They provide adaptive behavior while the strong knowledge representation characteristic of fuzzy inference systems are maintained.

Each basic network structure implements a rule in the rule base of the form

$$\text{IF } X_1 \text{ is } A_1 \text{ AND } X_2 \text{ is } A_2 \text{ AND} \ldots \text{AND } X_n \text{ is } A_n \text{ THEN } Y \text{ is } B. \quad (4.32)$$

The fuzzy sets that characterize the possibility distribution of the facts, X_1 is A_1' ,.., X_n is A_n' are presented to the input layer of the network. The fuzzy set A_n' is denoted by the following expression:

where $a'_{i1}, a'_{i2},\ldots, a'_{im_i}$ are the membership grades of the fuzzy set A'_i at sampled points over its domain of discourse.

One of the variations of the activities in the precondition is the clause-checking layer which is the first hidden layer. The weights w_{ij} are the fuzzy complement of the precondition clause that is, for the ith clause

$$w_{ij}= \overline{a}_{ij}= 1-a_{ij}, \quad (4.34)$$

where the clause "X_i is A_i" is translated into ith possibility distribution

$$\Pi x_i=A_i=\{a_{i1}, a_{i2},\ldots, a_{im_i}\}. \quad (4.35)$$

The second form for the precondition clause-checking layer uses the fuzzy sets A_i themselves as the weights; that is, in this case

$$w_{i1}, w_{i2},\ldots, w_{im_i}=\Pi x_i=A_i=\{a_{i1}, a_{i2},\ldots, a_{im_i}\}. \quad (4.36)$$

The combination at the kth node in the precondition clause-checking layer then becomes

$$d_k=max\| a_{kj}-a'_{kj}\|, \quad (4.37)$$

which is the max norm difference between the two functions μ_{A_k} and $\mu_{A'_k}$.

4.6.3. Neural network-driven fuzzy reasoning system

Let we consider a network realization of the Takagi-Sugeno-Kang fuzzy inference model (Sugeno and Kang, 1988). The basic idea to use neural networks to realize or generalize a Takagi-Sugeno-Kang model is to implement the membership functions in the preconditions as well as the inference function in the consequents by proper neural networks. The neural networks in the precondition part can learn proper membership functions, and those in the consequent part can learn the proper action of rule. One scheme for generalization of the Takagi-Sugeno-Kang model using neural networks is the *neural network-driven fuzzy reasoning* (Takagi and Hayashi, 1991). The fuzzy inference rules in the neural network-driven fuzzy reasoning have the following format:

$$R^s\text{: IF } \boldsymbol{x}=(x_i,\ldots,x_n) \text{ is } A_s \text{ THEN } y_s=NN_s(x_1,\ldots,x_m);\ s=1,2,..,r, \qquad (4.38)$$

where r is the number of inference rules, A_s represents a fuzzy set of the precondition part of each inference rule, and $NN_s(\cdot)$ denotes a structure of model function characterized by a back-propagation network with input $(x_1, x_2,\ldots,x_m)$ and output y_s.

Assume that in a neural network-driven fuzzy reasoning system there are m inputs $x_1, x_2,\ldots,x_m$ and a single output y. The architecture of the system is shown in Figure 4.15, where NN_{mem} is the neural network that determines the membership values of the precondition part of all rules, NN_s are the neural networks that determine control values and output y^* is the final control value, x_m is the input variable, and m^s is the membership value of the precondition part of the rule.The input-output data are divided into into N_t training data and N_c checking data, where $N_t+N_c=N$, the total number of input-output data. Training data are divided into r classes of R^s, where $s=1, 2,\ldots, r$. Training data for $\hat{m}_i^s$ each R^s are expressed by $(\boldsymbol{x} , y)$ where $i=1, 2,\ldots, N_s$, and N_s is the number of training data for R^s.

The membership function of the IF part is defined as the inferred value   that is the output of the learned NN_{mem}, that is,

$$\mu_{A_s}(\boldsymbol{x}_i)=\hat{m}_i^s, \qquad i=1, 2,\ldots,N; \quad s=1,2,\ldots,r, \qquad (4.39)$$

where A_s is the fuzzy set of the preconditioning part of the sth rule as described in

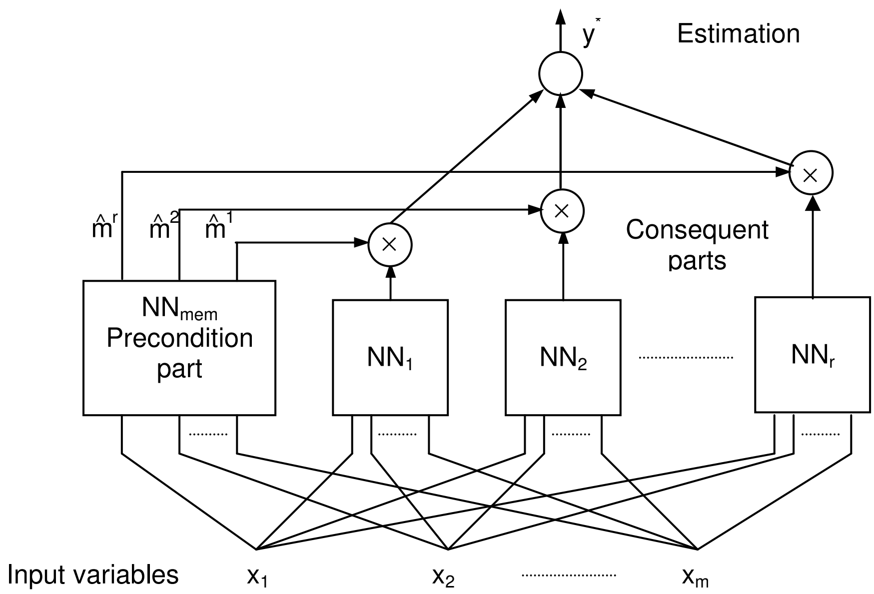


Figure 4.15. Block diagram of neural network-driven fuzzy reasoning (Lin and Lee, 1996; p. 508)

equation (4.38).

The membership function of the IF part is defined as the inferred value $\hat{m}^s$ that is the output of the learned NN_{mem}, that is,

$$\mu_{A_s}(\boldsymbol{x}_i)=\hat{m}_i^s, \quad i=1, 2,\ldots,N; \quad s=1,2,\ldots,r, \tag{4.39}$$

where A_s is the fuzzy set of the preconditioning part of the sth rule as described in equation (4.38).

Training NN_s corresponding to the THEN part of the sth fuzzy inference rule. The checking data input values $x_{i1}, x_{i2},\ldots, x_{im}$, $i=1, 2,\ldots,N_c$, are substituted into the obtained NN_s to obtain the sum ^s_m of the squared error by the following:

$$^s_m=\sum_{i=1}^{N_c} \{y_i-\mu_s(\boldsymbol{x}_i)\mu_{A_s}(\boldsymbol{x}_i)\}^2. \tag{4.40}$$

Among the m input variables of an NN_s, one an input variable x_p is arbitrarily eliminated, and NN_s is trained again by using the training data. Then equation (4.40) gives the squared error $^s_{m-1}$ of the control value of the sth rule in case of eliminating the pth input variable $(p=1, 2,\ldots, m)$:

$$^{sp}_{m-1}=\sum_{i=1}^{N_c} \{y_i-\mu_s(\boldsymbol{x}_i)\mu_{A_s}(\boldsymbol{x}_i)\}^2. \tag{4.41}$$

The final control value y^* can be computed by the following equation:

$$y^*=\frac{\sum_{s=1}^{r}\mu_s(\boldsymbol{x}_i)\mu_{A_s}(\boldsymbol{x}_i)}{\sum_{s=1}^{r}\mu_{A_s}(\boldsymbol{x}_i)}. \qquad i=1, 2,\ldots, N \tag{4.42}$$

4.6.4. Neural fuzzy controller with Sugeno fuzzy rules

In this session, the neural fuzzy control system with Sugeno fuzzy rules will be described which has consequents with linear combinations of their preconditions. Rules are described by the following forms:

$$R^j\text{: IF } x_1 \text{ is } A_1^j \text{ AND } x_2 \text{ is } A_2^j \text{ AND} \ldots \text{AND } x_n \text{ is } A_n^j,$$
$$\text{THEN } y=f_j= a_0^j+ a_1^j x_1+ a_2^j x_2+\ldots+ a_n^j x_n, \tag{4.43}$$

where x_i is an input variable, y is the output variable, ^j_i are linguistic terms of the precondition part with membership functions $\mu_{A_i^j}(x_i)$, $a_i^j \in R$ are coefficient of linear equations $f_j(x_1, x_2, \ldots, x_n)$, and $j=1, 2,\ldots,m$, $i=1, 2,\ldots,n$.

Assume that the fuzzy control system under consideration has i inputs x_j and one output y and that the rule base contains j fuzzy rules as follows:

$$R^1\text{: IF } x_1 \text{ is } A_1^1 \text{ AND } x_2 \text{ is } A_2^1 \text{ AND} \ldots \text{AND } x_n \text{ is } A_n^1,$$
$$\text{THEN } y=f_1= a_0^1+ a_1^1 x_1+ a_2^1 x_2+\ldots+a_n^1 x_n, \tag{4.44}$$

$$R^2\text{: IF } x_1 \text{ is } A_1^2 \text{ AND } x_2 \text{ is } A_2^2 \text{ AND} \ldots \text{AND } x_n \text{ is } A_n^2,$$
$$\text{THEN } y=f_2= a_0^2+ a_1^2 x_1+ a_2^2 x_2+\ldots+a_n^2 x_n, \tag{4.45}$$

$$R^j\text{: IF } x_1 \text{ is } A_1^j \text{ AND } x_2 \text{ is } A_2^j \text{ AND } \ldots \text{ AND } x_n \text{ is } A_n^j,$$

$$\text{THEN } y=f_j= a_0^j+ a_1^j x_1+ a_2^j x_2+\ldots+ a_n^j x_n . \qquad (4.46)$$

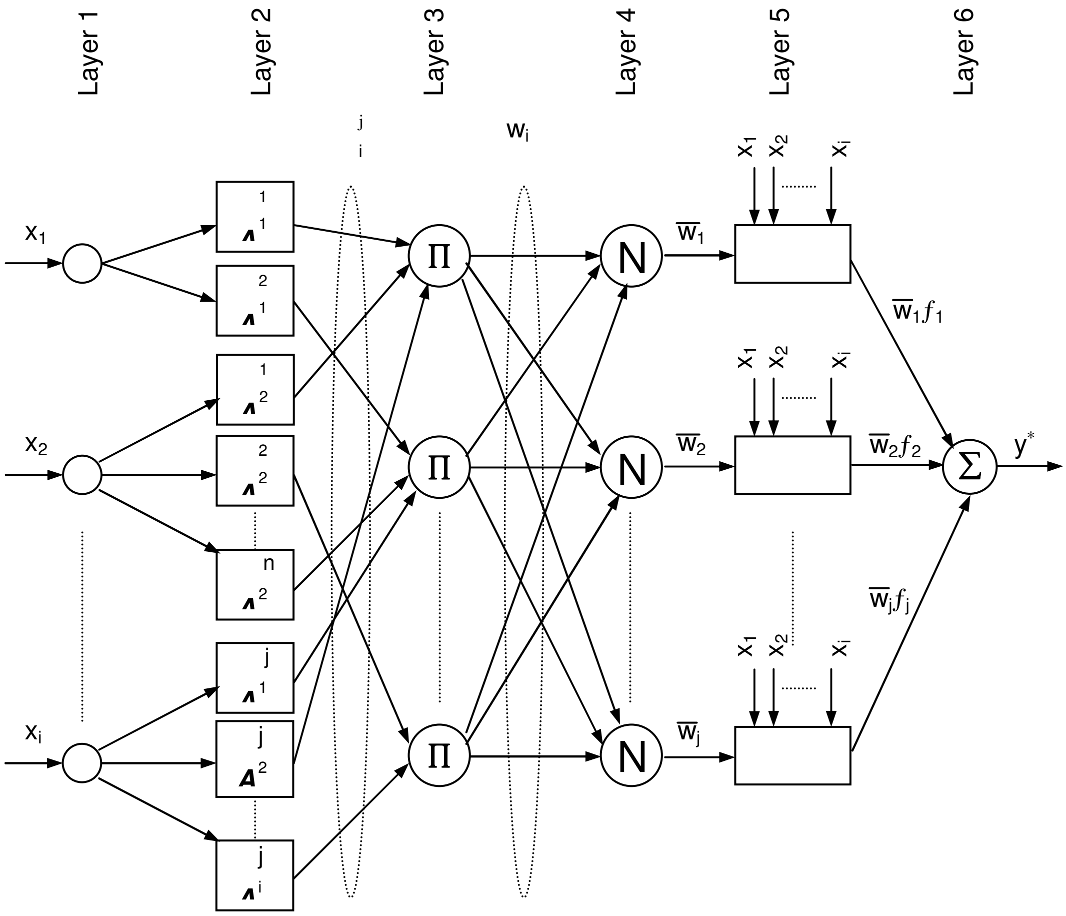
For the given input values $x_1, x_2, \ldots, x_n$ the inferred output y^* is computed by the following:

$$y^* = \frac{w_1 f_1+w_2 f_2+\ldots+w_j f_j}{w_1+w_2+\ldots+w_j}, \qquad (4.47)$$

where w_j are firing strengths of R^j, $j=1, 2, \ldots, m,$ and are given by

$$w_j = \mu_{A_1^j}(x_1)\cdot\mu_{A_2^j}(x_2)\cdot\ldots\cdot\mu_{A_i^j}(x_i), \qquad i=1, 2, \ldots, n \qquad (4.48)$$

if product inference is used. The corresponding architecture is shown in Figure 4.16.



Figue 4.16. Structure of neural fuzzy controller with Sugeno fuzzy rules (after Lin and Lee, 1996; p.557)

The architecture consists of layers with the following functions and outputs:

- *Layer 1* is an input node to transfer input signals to the next layer,
- *Layer 2* consists of nodes which operate as membership functions, and parameters in this layer are precondition parameters,

- *Layer 3* includes nodes which ones multiply the incoming signals, and the product represents the firing strength of a rule (see equation (4.48)),
- *Layer 4* has nodes to calculate the normalized firing strength of a rule where

$$O_{4,j}= \overline{w_j} = \frac{w_j}{w_1+ w_{2+ \dots +} w_j}, \tag{4.49}$$

- *Layer 5* consists of nodes which calculate the weighted consequent value where parameters are consequent parameters:

$$O_{5,j}=\overline{w_j}f_j= \overline{w_j}(a_0^j+ a_1^j x_1 + a_2^j x_2 +\dots+ a_n^j x_n), \tag{4.50}$$

where $O_{5,j}$ means the output of nodes in Layer 5, and $\{a_0^j, a_1^j, a_2^j, \dots, a_n^j\}$ is the parameter set,

- *Layer 6* has one a node to sum all incoming signals to obtain the final inferred result for the whole system.

$$O_{6,j}=\sum_j \overline{w_j}f_j=\frac{\sum_j w_j f_j}{\sum_j w_j}. \tag{4.51}$$

The membership function of every node chosen to be bell-shaped is computed by equation (4.52):

$$\mu_{A_i^j}(x_1)=\frac{1}{1+\left\{\left[\frac{x_i - m_{\text{j}}}{\sigma_{\text{j}}}\right]^2\right\}^{b_{\text{j}}}}, \tag{4.52}$$

where $\{ m_{\text{j}}, \sigma_{\text{j}}, b_{\text{j}}\}$ is the parameter set to be tuned.

4.7. Number of rules in large-scale fuzzy control system

There are three important aspects of fuzzy control systems have to be considered. They are fuzzy control architectures, adaptive fuzzy control systems, and stability of fuzzy control systems.

When a fuzzy controller is designed for a large-scale system, often several measurable output and actuating input variables are involved. Each variable is represented by a finite number l of linguistic labels which would indicate that the total number of rules is equal to l^n, where n is the number of system variables.

Consider a fuzzy controller with n rules of the following type:

IF y_1 is A_{1i} and y_2 is A_{2i} and … and y_n is A_{ni} THEN u_1 is B_1 , (4.54)

where y_i, $i=1,2,\dots,n$ are the output variables of the system (a subset of all variables), u_i, $i=1,2,\dots,n$ are the control variables of the system, and A_{ij} and B_i, $i, j=1,2,\dots,n$ are fuzzy sets.

For a fuzzy system with n variables and m fuzzy sets per variable, the total number of rules is given by $k=m^n$. It is clear that application of fuzzy control to any system of significant size would result in a "curse of dimensionability", much like standard dynamic programming. This exponential explosion of the size of the rule base can be handled in a variety of ways:

- fuse sensory variables before feeding them to the inference engine, thereby reducing the size of the inference engine,
- group the rules in prioritized levels to design a hierarchical fuzzy controller,
- reduce the size of the inference engine directly using notions of passive decomposition of fuzzy relations,
- decompose a large-scale system into a finite number of reduced-order subsystems, thereby eliminating the need for a large sized inference engine.

4.7.1. Rule-base reduction in hierarchical control systems

In the proposed hierarchical fuzzy control structure, the first-level rules are those related to the most important variables and are gathered to form the first-level hierarchy. The second most important variables, along with output of the first-level, are chosen as inputs to the second-level hierarchy, and so on. The first and ith rule of the hierarchically categorized sets are given by the following ones:

IF y_1 is A_{11} and y_2 is A_{21} and … and y_{n_1} is A_{1n_1} THEN u_1 is B_1 ,

.
.
.

IF $y_{N_{i+1}}$ is $A_{N_i 1}$ and $y_{N_{i+2}}$ is $A_{N_i 2}$ and … and $y_{N_i n_i}$ is $A_{N_i n_i}$ THEN u_i is B_i , (4.55)

where $N_i=\sum_{j=1}^{i-1} n_j \leq n$ and n_i is the number of jth level system variables used as inputs.

The following theorems evaluate the number of overall rules for a hierarchical fuzzy controller and minimum number of rules (Raju et al., 1991).

Consider a hierarchical fuzzy controller with L levels of rules, n system variables, and n_i variables contained in the ith level including the output of the $(i-1)$th level for $i>1$. Then the total number of rules is given by

$$k=\sum_{i=1}^{L} m^{n_i}, \tag{4.56}$$

where m is the number of fuzzy sets and

$$n_i + \sum_{i=2}^{L}(n_i - 1)=n. \tag{4.57}$$

Thus, the total number of rules for all levels is m^{n_i}. The overall numbers of rules is given as a sum of the rules at all levels, i.e.,

$$k=\sum_{i=1}^{L} m^{n_i}. \tag{4.58}$$

If there is a constant number of rules at each level, i.e., $n_i=a$ is equal with a constant for $i=1, 2, \ldots, L$, then by (4.58), one has

$$a+\sum_{i=2}^{L}(a-1)=a+(a-1)(L-1)=n, \tag{4.59}$$

and solving for L, one has

$$L=1+(n-a)/(a-1). \tag{4.60}$$

Hence, the total number of fuzzy rules, using equations (4.56) and (4.60), will be

$$k=\sum_{i=1}^{L} m^a = L\, m^a =[\ 1+(n-a)/(a-1)\ m^a\ , \tag{4.61}$$

which indicates that through this hierarchical structure, the total number of fuzzy rules is now a linear function of the number of system variables and not exponential.

For a hierarchical fuzzy control structure with n variables, if m and n_i satisfy conditions $m\geq 2$ and $n_i\geq 2$, the total number of rules in the rule set will take on its minimum value when $n_i=a=2$ and on its maximum when $n_i=n_1=n$.

Let n_i variables be involved at the ith level and assume that $n_i\geq 3$, and the number of rules at ith level is m^{n_i}. Now assume that one splits this level into two sublevels containing 2 and n_i-1 variables (the output from the previous level is also counted here). The total number of rules for both sublevels combined is

$$k_{i2}=m^2+m^{n_i-1}. \tag{4.62}$$

Since $n_i \geq 3$ or $n_i - 1 \geq 2$, it follows that $m^2 \leq m^{n_i - 1}$ and hence

$$m^2 + m^{n_i - 1} \leq 2m^{n_i - 1}. \tag{4.63}$$

It is assumed that $m \geq 2$, then

$$2m^{n_i - 1} \leq m^{n_i}. \tag{4.64}$$

Considering this,

$$m^2 + m^{n_i - 1} \leq m^{n_i}. \tag{4.65}$$

Thus, the total number of rules in the hierarchical structure would be reduced if one would be split any level with three or more variables into two sublevels, one of which has two variables. If this process is repeated for all levels, it is asserted that the total number of rules will reach its minimum if every hierarchical level would contain only two variables.

Let the number of variables be n_i and n_j at their respective levels with the assumption that $n_i \geq n_j$, then these two levels would have

$$k_{ij} = m^{n_i + n_j - 1} \tag{4.66}$$

rules. The following inequality would then follow:

$$m^{n_i} + m^{n_j} \leq m^{n_i} + m^{n_i} \leq 2\, m^{n_i}. \tag{4.67}$$

In a similar fashion one infers that $n_j \geq 2$, $n_j - 1 \geq 1$ and $m \geq 2$, hence

$$2\, m^{n_i} \leq m \cdot m^{n_i} \leq m^{n_i + n_j - 1}. \tag{4.68}$$

Utilizing (4.66)-(4.68), it follows that

$$m^{n_i} + m^{n_j} \leq m^{n_i + n_j - 1} = k_{ij}. \tag{4.69}$$

Thus, it is concluded that the total number of rules would decrease if one begins combining two levels into one. Repetition this process would eventually lead to the maximum number of rules when $n_i = n_j = n$.

4.7.2. Rule-base reduction and structural stability by Thom's catastrophe theory

Now, let the operation of the hierarchical fuzzy logic system be based on Thom's catastrophe theory. In this case, the number of rules are reduced by catastrophe events because the catastrophe events neglect rules which control variables over the district of any catastrophe event. It means that effects occurred by variables out of the bifurcation zone do not require analysis because they belong to any structurally stable statement of a function f, and variables from the unstable zone, the bifurcation zone require control, only.

The catastrophe theory had been developed from the classification of types of critical points. The method of classification of critical points is based on the Morse-lemma. Reduction of the number of variables can be realized by the application of lemma decomposition.

Critical points by Morse have a stability feature which means that a small perturbation does not occur the change of type of critical points.

Let $f: R^n \to R$ be a continuous function. The point $u \in R^n$ is a critical point, if

$$\left.\frac{\partial f}{\partial x_1}\right|_u = \left.\frac{\partial f}{\partial x_2}\right|_u = \ldots = \left.\frac{\partial f}{\partial x_n}\right|_u = 0. \tag{4.70}$$

The function value $f(u)$ in the point u is called critical value of f. The tangent of f in the critical point is horizontal. If $n=1$ then these points are locally *maximum, minimum,* and *inflection* points. If $n=2, f: R^2 \to R$ then these points are locally *maximum, minimum,* and *saddle* points.

The u is *non-degenerated critical point* in f when $\left.\frac{\partial f}{\partial x_n}\right|_u = 0,$ and $\left.\frac{\partial^2 f}{\partial x_n^2}\right|_u$ is non-degenerated quadratic form.

This is adequate that

$$Hf\Big|_u = \left[\left.\frac{\partial^2 f}{\partial x_i \partial x_j}\right|_u\right] \tag{4.71}$$

the Hessian matrix is not singular, or the determinant of Hessian matrix is

$$Det(Hf\big|_u) \neq 0. \tag{4.72}$$

It seems that critical points are *non-degenerated and isolated points.* The function f in the environment of a non-degenerated point can be transformed into simple form.

Let the value of $f{:}R^n \to R$ function be in the environment of 0 $f(0)=0$. Then, there are functions $g_i{:}R^n \to R$, that

$$f=\sum_{i=1}^{n} x_i\, g_i, \tag{4.73}$$

$$g_i(0)= \frac{\partial f}{\partial x}\Big|_0 . \tag{4.74}$$

and

Let we consider the following expression:

$$f(x_1, x_2,\dots, x_n)=\int_0^1 \frac{d}{dt}\,(f(tx_1, tx_2,\dots, tx_n))dt=\int_0^1 \sum_{i=1}^{n} \frac{\partial f}{\partial x_i}\Big|_{(tx_1,\, tx_2,\dots,\, tx_n)} \cdot x_i\, dt,$$

and

$$g_i(x_1, x_2,\dots, x_n)=\int_0^1 \frac{\partial f}{\partial x_i}\Big|_{(tx_1,\, tx_2,\dots,\, tx_n)} dt\, . \tag{4.75}$$

The partial derivative of f by x_i is

$$g_i(0)= \frac{\partial f}{\partial x_i}\Big|_0 . \tag{4.76}$$

Let u be the non-degenerated critical point of the function $f{:}R^n \to R$. Then, in the environment U of u can be given a local coordinate system $y_1, y_2,\dots, y_n$ where $y_i(0)=0$ for all i, and

$$f=f(u) - y_1^2 - y_2^2 - \dots - y_i^2 + y_{i+1}^2 + \dots + y_n^2 \tag{4.77}$$

for all of $y \in U$.

Lemma by Morse will be proved by the following: let the origin of coordinate system be transferred into U, then it can be supposed that $u=0$, $f(u)=f(0)=0$. In that case, it is true in the environment of 0, that

$$f(x)=\sum_{j=1}^{n} x_j\, g_j(x). \qquad (4.78)$$

As 0 is critical point, therefore

$$g_i(0)=\frac{\partial f}{\partial x_i}\bigg|_0=0. \qquad (4.79)$$

There are such h_{ij} functions, that

$$g_j(x)=\sum_{i=1}^{n} x_i\, h_{ij}(x), \text{ and} \qquad (4.80)$$

$$f(x)=\sum_{i,j=1}^{n} x_i\, x_j\, h_{ij}(x). \qquad (4.81)$$

Let h_{ij} be replaced with the function $h_{ij}=0.5(h_{ij}+h_{ji})$, then this equation will be valid, and $h_{ij}=h_{ji}$. The second-order partial derivative of equation (4.81) is

$$\frac{\partial^2 f}{\partial x_i \partial x_j}\bigg|_0=2\, h_{ij}(0), \text{ and} \qquad (4.82)$$

$$[h_{ij}(0)]=\left[\frac{1}{2}\frac{\partial^2 f}{\partial x_i \partial x_j}\bigg|_0\right] \qquad (4.83)$$

matrix is non-singular as 0 is a non-degenerated critical point.

Let we consider that local coordinates $u_1, u_2,\ldots, u_n$ can be given in the environment U_1 of 0, that

$$f=\pm u_1^2 \pm u_2^2 \pm \ldots \pm u_{r-1}^2+\sum_{i,j\geq r} u_i\, u_j\, H_{ij}(u_1, u_2,\ldots, u_n), \tag{4.84}$$

where $H_{ij}= H_{ji}$. Let the following function be composed by the following:

$$g(u_1, u_2,\ldots, u_n)=\sqrt{|H_{rr}(u_1, u_2,\ldots, u_n)|}\ . \tag{4.85}$$

Let a co-ordinate transformation be made by the following ones:

$$v_i= u_i \quad (i\neq r),$$

$$v_r= g(u_1, u_2,\ldots, u_n)\Big[u_r+\sum_{i>r}\frac{u_i H_{ir}(u_1, u_2,\ldots, u_n)}{H_{rr}(u_1, u_2,\ldots, u_n)}\Big], \tag{4.86}$$

and in accordance with function (4.84)

$$f(u_1, u_2,\ldots, u_n)=\pm v_1^2 \pm v_2^2 \pm \ldots \pm v_r^2+\sum_{i,j\geq r+1} v_i\, v_j\, H_{ij}(v_1, v_2,\ldots, v_n), \tag{4.87}$$

which function is similar to the expression use u_i but r has been replaced with $r+1$, and the theorem is proved.

The following type of functions $z_1^2+ z_2^2+\ldots+ z_{n-l}^2- z_{n-l+1}^2-\ldots- z_n^2$ are called as *l-saddle by Morse*. Morse's lemma declares that all of non-degenerated critical points can be transformed by a reversible co-ordinate transformation into a *l-saddle by Morse,* by selection a proper value of l. Number l is an invariant of the topological type of critical point. If $l=n$ then maximum is in the critical point, if $l=0$ then there is a minimum.

Since the origin is the isolated critical point of *l-saddle by Morse*, and a smooth co-ordinate transformation occurs that the isolated critical point will be transformed into an isolated one, therefore, non-degenerated points are always isolated.

A critical point is stable structurally, only if it is not degenerated, therefore all the degenerated points are unstable structurally.

Let it be said, that function p is *small* enough if its partial derivatives are small in the environment of 0. Let 0 the critical point of function f, and add a proper small p to f. Let we suppose that f is Morse-type function, that is, critical point 0 is not degenerated. Then the determinant of Hessian matrix is

$$\det Hf\big|_0 \neq 0. \tag{4.88}$$

If p is small enough, then

$$\det H(f+p)\big|_0 \neq 0, \tag{4.89}$$

because the determinant of Hessian matrix is a continuous function. Therefore, function $f+p$ is also Morse-type function, both of critical points are *l-saddle*s and they are equivalent ones.

It can be said, that *f is stable structurally* when function p is arbitrary small, if f and $f+p$ have the same type, that is, f and $f+p$ will remain equivalent after the displacement of origin. Therefore, *a function is stable structurally in the environment of its critical points Morse.*

The functions used to describe the technological processes of steam production have critical points, the catastrophe points described in Chapter 3. If the control range can be set nearby the critical points of those functions then the fuzzy rules to control the process would be required out of the environment of critical points, only. *That is, the number of fuzzy rules can be reduced because functions for description of technological processes are Morse-type ones*. It is true, because the fuzzy rules for the control system has only to check if the working point is out of the environment of critical points or not.

4.8. Safety and shutdown systems for heat power station

There have been some steadily developing trends in the last ten years which have moved the subject of so-called *functional safety* from a specialized domain of a few engineers into the broader engineering and manufacturing fields.

The term *functional safety* is a concept directed at the functioning of the safety device or safety system itself. It describes the aspect of safety that is associated with the functioning of any device or system that is intended to provide safety. A short description of functional safety is the following: "*Functional safety is that part of the overall safety of a plant that depends on the correct functioning of its safety related systems.*"(from IEC 61508 part 4.).

4.8.1. Hazard and risk analysis

It seems, specification errors contribute a large proportion of safety system failures. Recognizing and understanding the safety problem to be solved is the first essential step in avoiding this problem. The foundation for any system application is a thorough understanding of the problem to be solved. The process industry seems to have reached consensus on the use of a top down methodology and is generally known as the hazard study method.

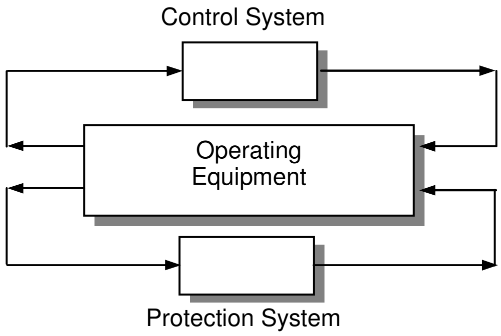


Figure 4.17. Separation of safety controls from process controls

Safety functions were originally performed in different hardware from the process control functions. This was a natural feature because all control systems were discrete single function devices. It was not really inconvenient for instrument design to achieve the separation and extra features needed for the safety shutdown devices. Only with the advent of DCS and PLC controllers did engineers have to pay attention to the question of combining safety and control in the same systems. All standards and guidelines clearly recommend the separation of the control and safety functions. The diagram in Figure 4.17 (Macdonald, 2004, p. 41) shows the separation of safety control from process control.

4.8.2. Risk reduction and classification

The problem of risk classification is that risk does not come in convenient units like volts or kilograms. There is no universal scale of risk. The method of calculation is generally consisted and it is possible to arrive at a reasonable scale of values for a given industry. As a result IEC have suggested using a system of risk classification that is adaptable for most safety situations.

The risk reduction factor *RRF* can be computed by the expression (4.90):

$$RRF = \frac{Fnp}{Ft}, \tag{4.90}$$

where *Fnp* is given by demands/year.

The safety availability *SA* is

$$SA = \frac{(RRF-1)}{RRF} 100[\%]. \tag{4.91}$$

The probability of failure on demand PFD_{avg} is computed by equation (4.92):

$$PFD_{avg} = \frac{1}{RRF} = \frac{Ft}{Fnp} = \Delta R, \tag{4.92}$$

and the protected risk frequency *Fp* is

$$Fp = Fnp\ PFD_{avg}, \qquad (4.93)$$

where the target value of *Fp* is the tolerable risk frequency *Ft*. The alternative name of *PFD* is fractional dead-time. Its meaning is the fraction of time that safety system is dead.

4.8.3. Safety integrity level (SIL)

The question is, how to decide when to use a safety instrumented system *SIS*, and how good must it be. It depends on the amount of risk reduction required after the other devices have been taken into account. The measure of the amount of risk reduction provided by a safety system is the *safety integrity*.

In order to get a scale of performance safety practitioners have adopt the concept of safety integrity levels *SIL*s. The SILs are derived from earlier concepts of grading or classification of safety systems. The SIL table provides a class of safety integrity to meet a range of PFD_{avg} values. Hence the performance level of safety instrumentation needed to meet the SIL is divided into categories shown in Table 4.1 (Macdonald, 2004). There are some choices about how to the SIL is determined. Basically there is a choice between using real numbers (quantitative method) and some variations on fuzzy logic (qualitative methods).

Safety integrity level	Low demand mode of operation (average probability of failure to perform its design function on demand)
4	$\geq 10^{-5}$ to 10^{-4}
3	$\geq 10^{-4}$ to 10^{-3}
2	$\geq 10^{-3}$ to 10^{-2}
1	$\geq 10^{-2}$ to 10^{-1}

Table 4.1. Safety integrity level by IEC61508

4.8.4. Determining the safety integrity

The most important tasks in the SRS development is to specify the safety integrity of each SIS functions. This needs to be done fairly early in the development stages to see that the proposed solutions are realistic, achievable and of course affordable. The cost of the SIS will rise steeply with the SIL values even if a logic solver is used that meets SIL 3 the cost of sensors and actuators and engineering work will still be influenced strongly by the SIL rating.

The reason for diversity in methods of determining SILs is probably due to the difficulties of arriving at reliable and credible estimates of risk in the wide variety of situation faced in industries. Whilst a quantitative risk assessment is desirable it may be worthless if the available data on fault rates is minimal or subject to huge tolerances. Qualitative methods allow persons to use an element of judgement and experience in the assessment of risk without having to come up with numeral values that are difficult to justify.

One advantage of the SIL concept is that provides a 10:1 performance band for risk reduction and for SIS in each safety integrity level. Hence the classification of the safety system can be matched to a broad classification of the risk and the whole system is able to accept a reasonable tolerance band for estimates of risks and risk reduction.

4.9. Quantitative method for determining safety integrity level

The quantitative method is used to assist in development of the SRS and the defining of the SIL by historical data. The steps of quantitative method are:

- evaluation of hazard event rate without protection, definition of target risk frequency, and record of all details under phase 4 of the SLC;
- addition of external and non-SIS protection and evaluation of effect on risk frequency;
- proposition of an SIS risk reduction measure which reduces the hazard event rate and hence the risk frequency;
- conclusion of a practical risk reduction factor for the SIS consistent with being below the target risk frequency;
- conversion of the risk reduction factor to an SIL value for the SIS;
- draft the SRS with a reference to the calculation sheet and risk reduction model;
- finalization SIS detail SRS.

4.10. Qualitative methods for determining safety integrity level

The qualitative method is a very attractive alternative for arriving at SILs because it avoids the need to place actual quantitative figures on the hazard demand rates, risk frequency and the consequences.

4.10.1. Qualitative method by IEC 61508

Since in many cases the used figures are very approximate it is perhaps more realistic to use an approximate description. The following diagram in Figure 4.18 will show the risk parameter chart (Macdonald,2004).

In practice the process industries there are separate versions for three categories of hazard:

- harm to persons,
- harm to environment,
- loss of assets (production and equipment losses/repair costs).

All three versions of the risk graph can have the same basic layout but for environment and asset loss the parameter *F*, for exposure, is considered to be permanent and can be left out of the diagram.

For a full determination of SIL requirements each safety function should be evaluated for the three categories of hazard and the SIL target rating must be set to meet the highest value found from the three categories.

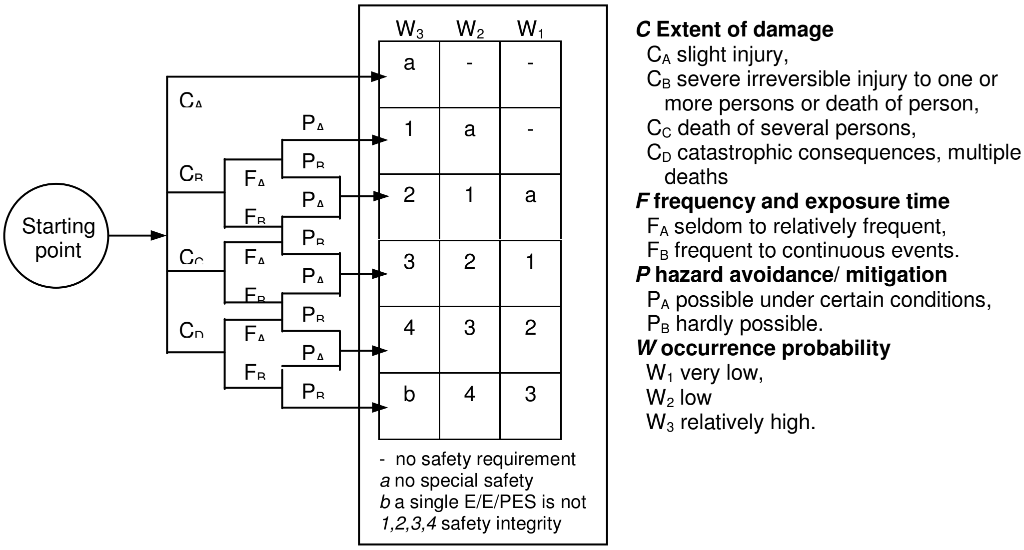


Figure 4.18. Risk parameters charts based on IEC 61508

IEC 61511 has generated a very useful version of the factors affecting the parameters *C, F, P* and *W* shown in Table 4.2. It must be cleared that for each application it is the responsibility of individual companies or safety departments to establish their own agreed parameters for the risk graph they wish to use. In particular it is important to note the interpretation of the term *W* as being based on the assumption that no SIS is present.

4.10.2. The safety layer matrix method for SIL determination

Another qualitative method described by IEC standards is called safety layer matrix method which is described in Annex E of IEC 61508. The same principles have been included in the ISA standard S84.01 Annex A.3.1, and in the recently issued IEC 61511-3 in annex along with the risk graph. IEC states some basic requirements for safety layers before the logic of the matrix diagram can be used:

- independent SIS and non-SIS risk reduction facilities,
- each risk reduction facility is to be an independent protection layer,
- each protection layer reduces the SIL by 1,
- only one SIS is used.

The method then determines the SIL for the SIS by applying the situation to a severity matrix chart such as the one shown in Figure 4.19. It seems even easier than the risk

***C* Consequence**	average number of fatalities likely to result from the hazard. It is determined by calculating the average numbers in the exposed area when the area is occupied taking into account the vulnerability to the hazardous event.
***F* Occupancy**	probability that the exposed area is occupied. It is determined by calculating the fraction of time the area is occupied.
***P* Probability of avoiding the hazard**	the probability that exposed persons are able to avoid the hazard if the protection system fails on demand. This depends on there being independent methods of alerting the exposed persons to the hazard and manual methods of preventing the hazard or methods of escape.
***W* Demand rate**	the number of times per year that the hazardous event would occur if no SIS was fitted. This can be determined by considering all failures which can lead to one hazard and estimating the overall rate of occurrence.

Table 4.2. Parameter description table from IEC 61511

matrix but it depends on a calibrated scale of severity and the correct identification of valid protection layer. Obviously it must be sure that each safety layer has a suitable integrity to qualify as a protection layer.

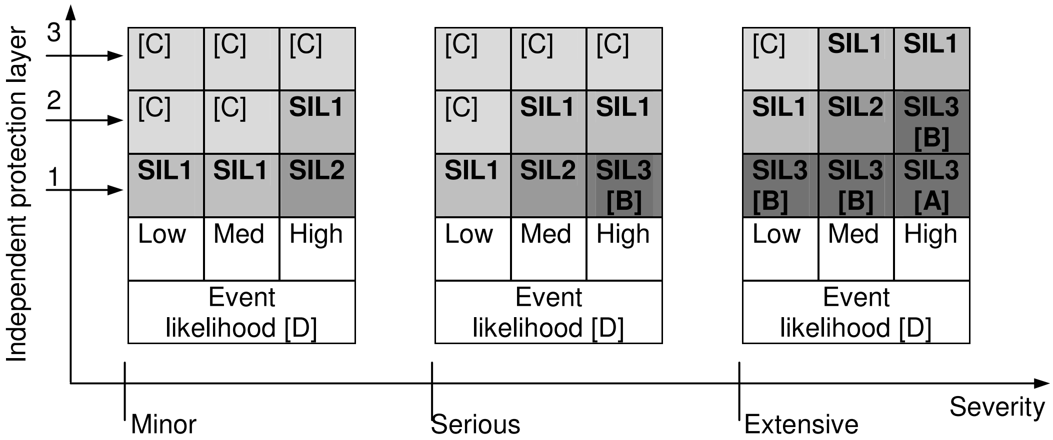


Figure 4.19. Hazardous event severity matrix (Macdonald,2004 p.133)

4.10.3. The LOPA method for SIL determination

The term LOPA is an abbreviation for *layer of protection analysis*. The version of LOPA described in IEC 61511 part 3 Annex F is very useful because it includes suggested or typical PFD values for factors such as operator responses and alarm system integrities. It also suggests a range of frequency values for demand categories. This method is effectively a general-purpose implementation of the quantitative method.

The method accounts for each identified hazard by documenting the initiating cause and the protection layers that prevent or mitigate the hazard. The total amount of risk reduction recognized in the plant design and the protection system is evaluated typically using a table or spreadsheet format.

4.11. Thom's catastrophe theory as tool for the qualitative method

The events affected on SIL value form a set of conditions and occur moving to other catastrophe layer described by functions (Poston and Stewart, 1985). Typical feature of switch catastrophes is the separation which means the continuous changing will be modified to sudden changing when any environmental condition has changed. Special form of switch catastrophe is the *conditional catastrophe* when functions are directed or switched to different catastrophe surfaces by *control variables*, i.e. the conditional variables. The catastrophe surface is a peak catastrophe shown in Figure 4.20. As it seems control variables affect on the functions of processes, and the direction of changing is influenced by the control variable. The SIL

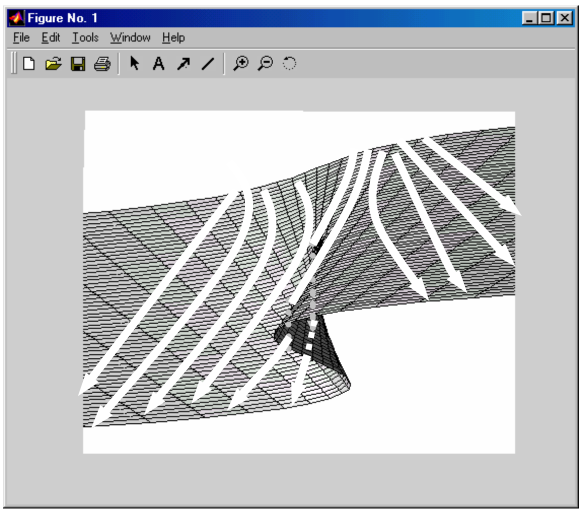


Figure 4.20. The conditional catastrophe

determination is based on the rules of conditional catastrophes.

4.12. Conclusion

Technological processes controlled by soft computing methods require one or more membership functions depended on the number of input data. The fuzzy logic control requires many MFs. The operational speed and the stability of fuzzy logic system depends on the number of rules, therefore, the goal is the reduction of the number of rules by the following:

- variables out of the bifurcation zone do not require analytic process because they belong to the stable statement of the controlled process,
- functions for description of technological processes in Chapter 3 are Morse-type ones, and they are stable structurally, therefore, fuzzy rules are used out of the environment of critical points, only,
- rules focused on variables belonged to the stable statement can be neglected,
- safety system analysis is running in accordance with standard IEC 61508 and standard IEC 61511.

In Chapter 5 the introduced methods will be used to solve control tasks. The fuzzy logic controllers will be described in accordance with Thom’s catastrophe theory. The control systems belonged to the individual boilers are the basic units in the complex control of large-scale system where many technological units have to be composed into single technological system by a central supervisory control. I shall determine the safety integrity of the large-scale subsystems. The method will based on the hazardous event severity matrix for classification of SIL, and results will be compared with results of quantitative method in Appendix 1.

Data processing and control in the steam production system

5.1. Introduction

In this chapter, the previously described large-scale system will be completed with the proper control based on soft computing methods.

Most variables of continuous technological processes use to be changed around an average. The continuous processes also have periodic parts but their set of features is continuous such as the energy flow, typically. Figure 5.1 shows a process consisted of technological units. The process includes n units of technology ($B_1, B_2, \ldots, B_n$) which have inputs (x, y) and outputs (S).

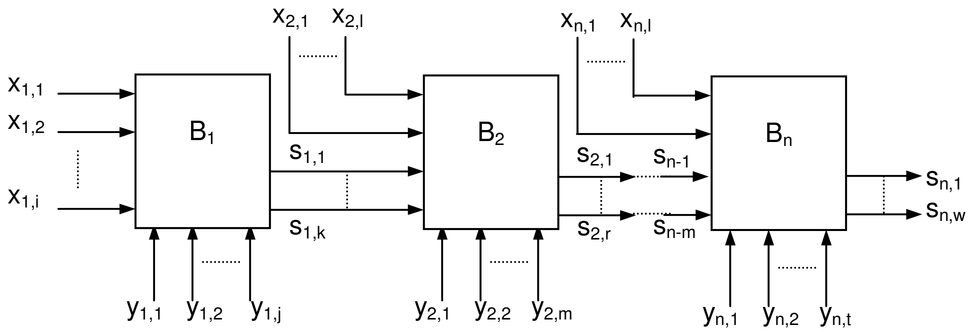


Figure 5.1. The scheme of a continuous process

External inputs are signed with x, and influential parameters are signed with y, and output of the blocks are signed with s. These features depend on time. The relationship between them are the following:

$$
\begin{aligned}
&S_1=f_1(x_1, \ldots, x_i ; y_1, \ldots, y_j) \\
&S_2=f_2(x_2, \ldots, x_i ; y_1, \ldots, y_j) \\
&S_k=f_k(x_k, \ldots, x_i ; y_k, \ldots, y_j) \\
&x_1= x_1(t), \ldots, x_i= x_i(t);\ y_1= y_1(t), \ldots, y_j= y_j(t)
\end{aligned}
\tag{5.1}
$$

These expressions can be described by matrices:

$$
\begin{bmatrix} \varphi_{1,1}, & \varphi_{1,2}, & \ldots, & \varphi_{1,i+j} \\ \varphi_{k,1}, & \varphi_{k,2}, & \ldots, & \varphi_{k,i+j} \end{bmatrix}
\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \\ y_1 \\ y_2 \\ \vdots \\ y_j \end{bmatrix}
=
\begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ \\ \vdots \\ \\ \vdots \\ S_k \end{bmatrix}
\tag{5.2}
$$

where the φ functions ,in general cases, include time functions. The φ functions mean static relationships between the input and output variables (Mendek, 1971).

5.2. Data processing in the steam production

The boiler system consists of two technological parts, the *furnace chamber* and the *steam generator*. The system architecture is shown in Figure 5.2.

The external input parameters of furnace chamber are the following ones: x_{t1} is the calorific value of fuel, x_{t2} is any other feature of fuel, x_{t3} is the value of air pressure, and x_{t4} is the temperature of insufflated air. Influential input features of the furnace chamber are the following parameters: y_{t1} is the quantity of injected fuel, and y_{t2} is the quantity of insufflated air. The output features of furnace chamber are s_{t1} the quantity of flue gas and s_{t2} the temperature of outlet flue gas.

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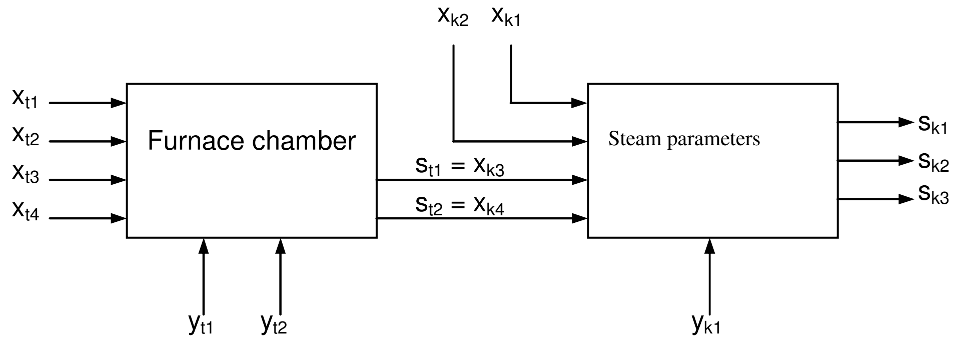


Figure 5.2. The scheme of boiler

The external input parameters of steam generator are the following: x_{k1} is temperature of inlet water, x_{k2} is the separated steam, x_{k3} is the quantity of inlet flue gas, and x_{k4} is the temperature of inlet flue gas. Influential input parameter of steam parameters setting device is y_{k1} the quantity of inlet water. The output features of steam parameters setting device are the quantity of outlet steam s_{k1}, the pressure of outlet steam s_{k2}, and the temperature of outlet steam s_{k3}.

The burning efficiency z of fuel described by (5.3) depends on the calorific value, the quantity, and the quality features of fuel, the quantity and temperature of inlet air, and the quantity and temperature of outlet flue gas:

$$z = f(x_{t1}, x_{t2}, x_{t3}; y_{t1}, y_{t2}; s_{t1}, s_{t2}) \qquad (5.3)$$

The result of process Z can be described as function based on variables shown in (5.4):

$$Z = f(x_i, y_j, s_k) \qquad (5.4)$$

where x_i means input data, y_j means influential input, and s_k means any interim variables. The interim variables can be described as functions of input data and influential data of the same set:

$$S_k = f(x_l, y_m) \qquad (5.5)$$

and the result can be expressed by the input data and influential data only, shown in (5.6):

$$Z = f(x_i, y_j) \qquad (5.6)$$

The expression of result can be characterized like a surface in an n dimensional space. That the surface describes the known relationships which means that the same results always belong to the same set of independent variables.

norm difference between the two functions μ_{A_k} and μ_{A_k}.

In according with the rule of van der Waals, the content of steam generator has three possible states. These states can be seen in Figure 5.3 where the rates of components in the content are terminated by the curves of membership functions, and $\mu(\cdot)$ means the membership grades. When the working point is inside the bifurcation space then the working point characterizes a two-component composition, the mixture of hot water and steam where the rate of hot water and steam depends on the temperature and the pressure. If the working point is out of the bifurcation zone then the product will be consisted of single component, steam or hot water.

As the definition of states requires if-then rules which can be fuzzy rules so

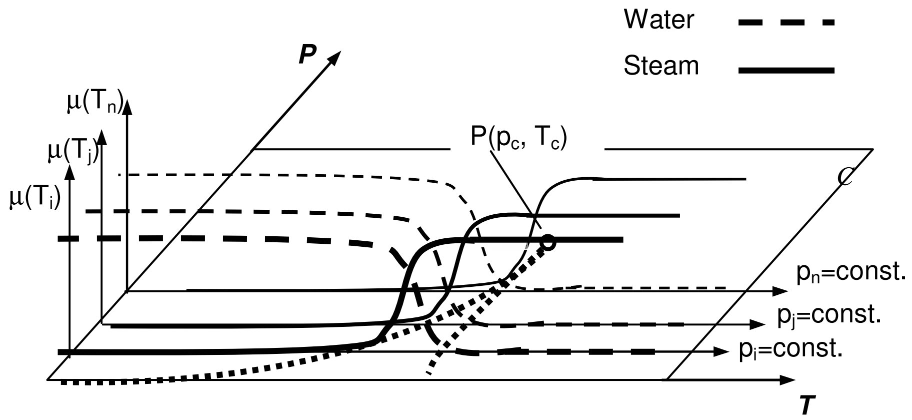


Figure 5.3. The membership function over the catastrophe space

the control system of hot water-steam rate can be fuzzy control system. The membership functions decide three fuzzy sets, one for unsaturated steam, one for the mixture of boiling water and saturated steam, and one for boiling water.

The control of steam production can be considered as a *two-input single-output fuzzy logic system*, where output is steam in the steam drum of boiler, and the membership grade is computed from the temporary temperature and pressure. Then rules of the fuzzy model of steam production by the boiler are the followings:

- if (p,t) is out of bifurcation zone and t is larger than T_c then there are unsaturated steam;
- if (p,t) is inside the bifurcation zone then there are composition of hot water and saturated steam;
- if (p,t) is out of bifurcation zone and t is smaller than T_c then there are hot water.

where $(p,t)\big|_{p<p_c}$ are the coordinates of a working point, and $(p_c\ ,T_c)$ are the coordinates of critical point *P,* the peak of catastrophe.

Since the pressure p can be seen as constant value by Maxwell's rule because the pressure in the steam production system is set to be constant value, therefore, the fuzzy control can be modified to a *single-input single output fuzzy model.*

The linguistic description of fuzzy rules are the followings while the pressure $p<p_c$ is considered as constant value:

- if T_s is low then there are hot water, no steam;
- if T_s is high then there are boiling water and saturated steam;
- if T_s is higher than T_c then there are unsaturated steam.

5.3. Steam production system in the Heat Power Station of Nyíregyháza

Steam production technology requires a large-scale system which includes more technological units with autonomous control devices. The energy management of industrial steam production has been developed fast in the first big energy crisis. The oil crisis was the driving force of the intelligent energy production. An other driving force of intelligent heat power production was the raising awareness of environmental pollution by inefficient production of energy.

The heat power station supplies heat power for domestic users and industrial users, and the waste heat power is used to generate electric energy. The technological device of heat generation is described in Chapter 2. The power station has fifteen different boilers which are connected to the central steam line. All the boilers have autonomous control system built with analog PI controllers introduced in Chapter 2. The boilers are supervised from a central managing station where PCs are used to give opportunity for the power managers if they would have to influence the operation of technological system.

Generation and consumption of heat power for industrial and domestic demand should consider economical and ecological aspects. Optimal demand-oriented heat power generation by a cascade heat center requires sustainable evaluation of measurement data of the whole system.

The managing stations use the software of FREELANCE 2000 which requires Windows NT operation system. The managers can configure different emulated control devices in the DIGIMATIC, like fuzzy control, PID, different logical devices, analog control device, etc., and they can modify technological parameters.

The system includes operator stations, engineering station on the side of central managing station, and process stations and field controllers on the side of steam production technology. The DIGIMATIC system is shown in Figure 5.4.

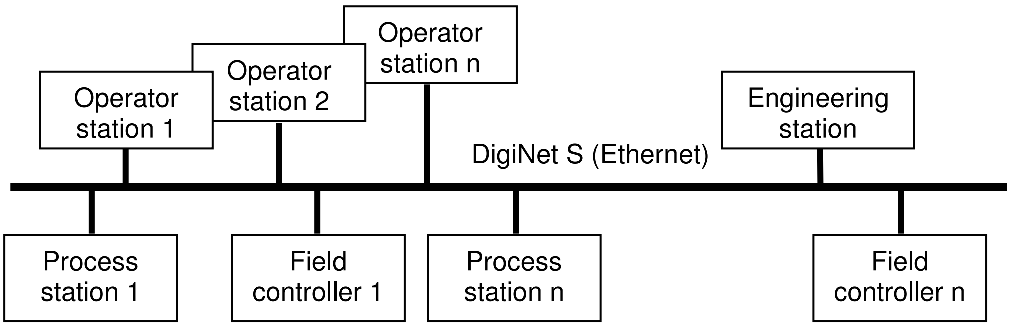


Figure 5.4. System DIGIMATIC with DigiNet S

Process stations communicate with I/O units through CAN bus, and they are connected to the DigiNet S bus, directly. Field controllers are connected to technological devices by Profibus and Modbus, and they are also connected to the DigiNet S bus, directly.

5.4. Control system for the steam production technology

The steam production technology has two main units, the steam generator, and the

temperature setting unit shown in Figure 5.5. The steam generator produces the steam featured with

p_{st1}, T_{st1}, and the temperature setting unit, the superheater will regulate the temperature of output steam. Black colored arrows mean controlled parameters.

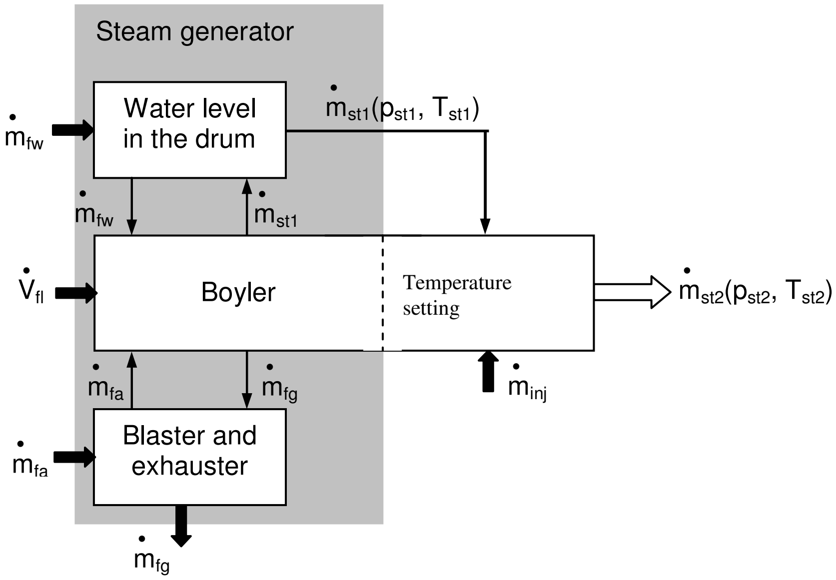


Figure 5.5. Controlled parameters of steam production technology

The heat production is set by the combusted quantity of fuel $\dot{V}_{fl}$, water level in the drum is set by the regulation of feed water quantity $\dot{m}_{fw}$. The combustion requires a proper quantity of fresh air $\dot{m}_{fa}$, and the flue gas must be exhausted.

The output steam of steam generator $\dot{m}_{st1}$ is flown to the superheater, where the required

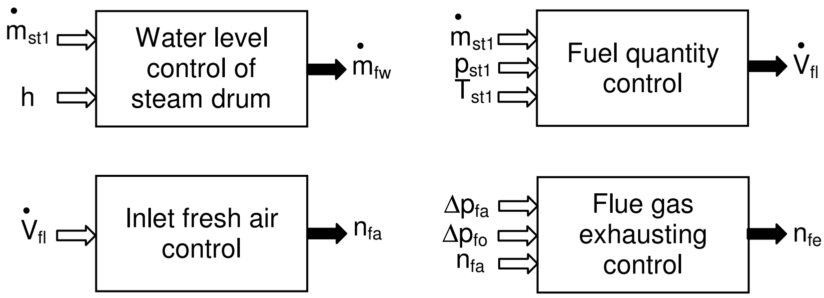


Figure 5.6. *Measured and controlled parameters of the steam generator*

temperature of outlet steam is set by superheating and water injection. All of these parameters, the pressure and the temperature of outlet steam depends on the steam load. In Figure 5.6 measured input data and controlled output data of steam generator are shown, and the measured input data and controlled output steam parameters can be seen in Figure 5.7.

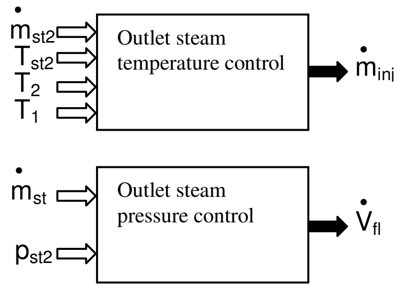


***Figure 5.7** Measured and controlled parameters of the output steam*

5.5. Control system for the steam generator

In this session the structure of control system for steam production technology will be described. Traditional methods of power station control always involve the primary position of human role because of the safety of operation (Jamshidi, 1997). These methods have been using stand-alone subsystems for the control of different technological processes which subsystems could operate individually, too. All the subsystems have been connected to a communicational network, which network belonged to the interactive supervisory system. Interactivity means the human supervisor has to synchronize autonomous subsystems by supervisory messages.

In this control system the goal of control is to achieve the production of steam with constant energy content being independent of temporary steam load and minimum quantity of energy consumption. All the technological parameters, the height of feed water level, the combusted fuel quantity, the blasting of required fresh air quantity, the flue gas removal, the quantity of injected water for setting the temperature of output steam will be controlled by fuzzy control devices. Parametric values of the fuzzy control systems are tuned by a back-propagation neural network.

Figure 5.8 shows the schematic diagram of steam generation control. Input data are the change of feed water level *h* measured in the drum, and the pressure of inlet fresh air p_{fa} measured at the input of fresh air into the furnace chamber, and the flue gas pressure p_{fo} measured at the output of flue gas from the furnace chamber. Output data to next subsystem, the control system of outlet steam parameters are the steam mass flow $\dot{m}_{st1}$, and the steam temperature T_{st1}, and the pressure of outlet steam p_{st1}.

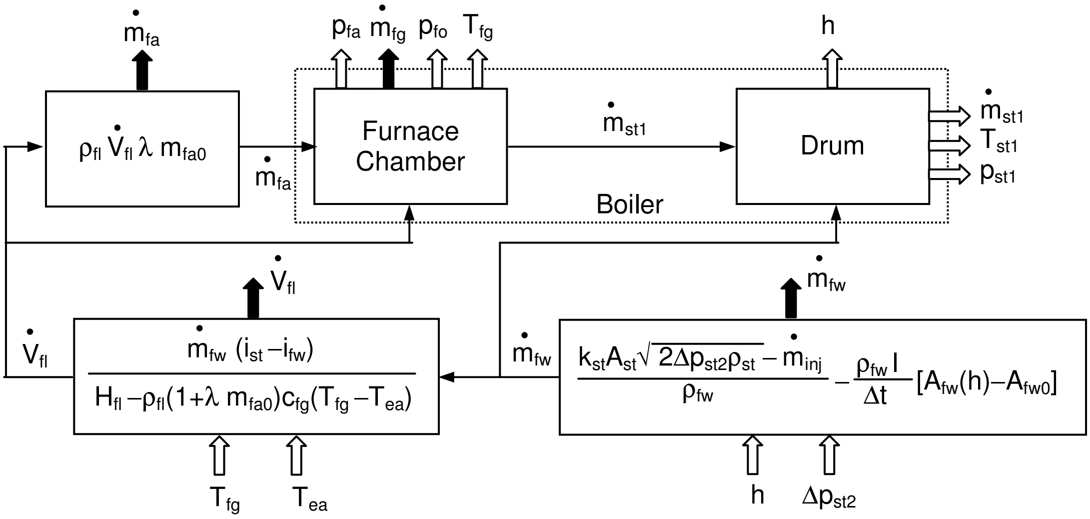
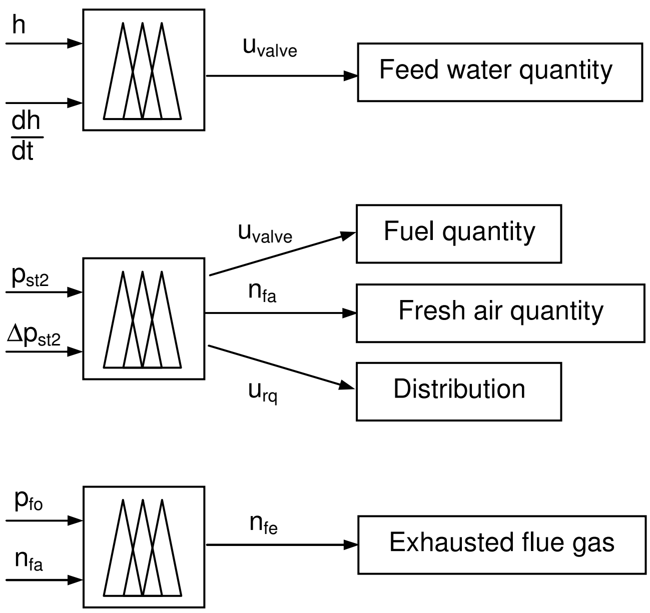


Figure 5.8. Control process of steam generator

Technological subsystem, the steam generator requires hierarchical control as it seems in Figure 5.8. All the controlled parameters signed with black colored arrows depend on each other, and the output data. Changing of outlet steam features, the steam load, and the temperature, and the pressure occur the changing of input settings. It seems, the control system requires a *multiple inputs/outputs fuzzy inference system.* MFIS applied for control the steam generator can be seen in Figure 5.9.



Figue 5.9. Structure of FIS for the control of steam generator

5.5.1. Fuzzy system for feed water level control in the steam drum

The control will start after the setup of the drum has been finished, i.e. the drum has been filled by water over the level *lower interlock*, at least. The water level in the steam drum is controlled by the measured values of actual water level height $\dot{m}_{st1}$ h and steam load in accordance with the following rules:

- **while the water level is inside the optimum range shown in Figure 3.8 discharge area of the feed water valve will not change;**
- **while the water level is out of the optimum range and the temporary value of water level is higher than h_{min}, and lower than h_{max} then the discharge area of feed water valve will be computed by equation (3.54) and it will be changed until the water level will be set in the optimum range;**
- **if the water level will be equal or under h_{min} and the water level will be equal or over h_{max}, then the valve will close fast and an alarm signal will be occurred.**

Description of FIS is shown in Figure 5.10 which has been developed with MATLAB fuzzy toolbox.. MFs of the FIS shown in Figure 5.11 are bell-shape ones at the inputs, and the output is constant value of voltage for setting the discharge area of feed water valve computed by Sugeno's rule. Groups of inputs are the following ones:

Input1 **consists of three MFs which are the followings:**

- ***low* means $h_{min}<h$ and h is out of the optimum range,**
- ***high* means $h<h_{max}$ h is out of the optimum range,**
- ***optimum* is set of appropriate values.**

Input2 **includes the direction of changing of water level:**

- ***negative* means the changing of water level has been decreased,**
- ***positive* means the changing of water level has been increased,**
- ***none* means the changing of water level is zero.**

```
[System]
Name='tanksg_ol1'
Type='sugeno'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=4
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='max'
DefuzzMethod='wtaver'

[Input1]
Name='level'
Range=[0.6 1]
NumMFs=3
MF1='low':'gbellmf',[0.119 18.6 0.6]
MF2='okay':'gbellmf',[0.0815 13.5 0.8]
MF3='high':'gbellmf',[0.119 18.6 1]

[Input2]
Name='rate'
Range=[-0.1 0.1]
NumMFs=3
MF1='negative':'gbellmf',[0.0624 23.5 -0.0987]
MF2='none':'gbellmf',[0.0353 12.3 -0.000529]
MF3='positive':'gbellmf',[0.0646 32.2 0.1]

[Output1]
Name='valve'
Range=[-1 1]
NumMFs=4
MF1='close_fast':'constant',0.9
MF2='close_slow':'constant',0.3
MF3='no_change':'constant',0
MF4='open_slow':'constant',-0.3

[Rules]
2 0, 3 (1) : 1
-2 0, 1 (1) : 1
2 3, 2 (1) : 1
2 1, 4 (1) : 1
```

Figure 5.10. Fuzzy inference system for level control of the steam drum

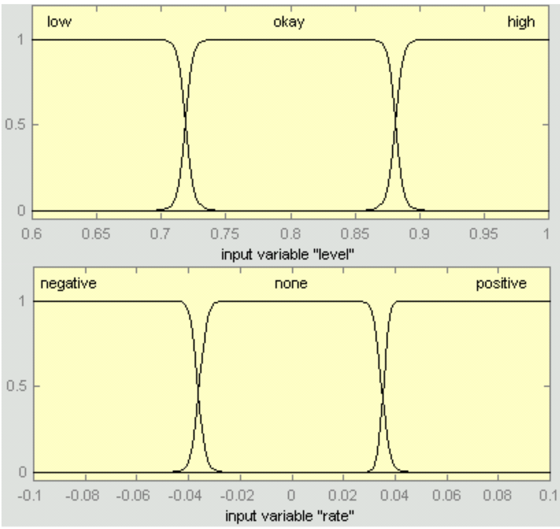


Figure 5.11. MFs of FIS for control of feed water level in the steam drum

Output1 **group of outputs is described by the followings which are voltage values for changing the discharge area of feed water valve:**

- ***close_fast*** **is maximum positive voltage for closing fast the feed water valve,**
- ***close_slow*** **is medium value of positive voltage for reduction slowly the discharge area of feed water valve,**
- ***open_slow*** **is a value of negative voltage for rising slowly the discharge area of feed water valve,**
- ***no_change*** **means the voltage is zero to keep the actual discharge area of feed water valve.**

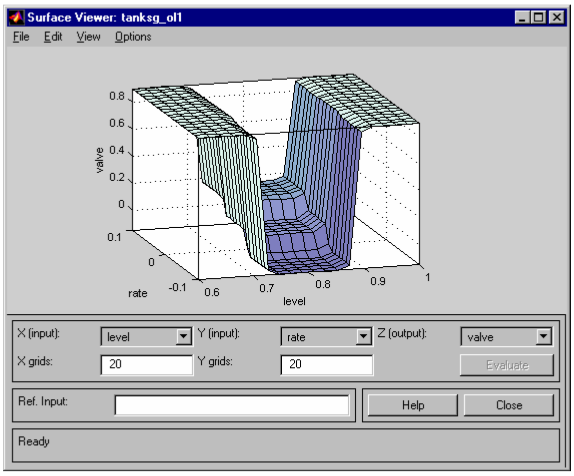


Figure 5.12. Function of level control in the steam drum

Figure 5.12 shows the function of operation. Three ramps inside the optimum range of level are meaning the activities of control system. When the working point is on the upper ramp the valve is closing slowly, when the working point is on the lower ramp the valve is opening slowly, and when the working point is on the medium ramp the valve does not change. Changing between ramps is staggered. Otherwise, when the level is equal or under the lower interlock or equal or over the upper interlock levels the valve will close fast and an alarm signal will be generated.

5.5.2. Fuzzy system for control the furnace chamber

Processes in the furnace chamber require control for the burner's power by changing the quantity of combusted fuel, and control for internal pressure of furnace chamber. The blasted fresh air quantity is set by changing the revolution number of blaster ventilator, and the quantity of exhausted flue gas is set by changing the revolution number of exhauster ventilator. The exhauster has to be produce the appropriate pressure to output the generated flue gas.

The required power of burners depend on the steam load and the output pressure. Since these parameters affect on each other, the fuzzy logic system is a *two-input three-output Sugeno FIS* described in Figure 5.13.

The control system is based on the following preconditions:

- if the steam load is smaller than the technical minimum value then the steam production will be stopped;

- if the steam load raises over the maximum then a request will be sent to the load distributor of supervisory system to change the load.

```
[System]
Name='furn_chamb'
Type='sugeno'
Version=2.0
NumInputs=2
NumOutputs=2
NumRules=7
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='max'
DefuzzMethod='wtaver'

[Input1]
Name='pressure'
Range=[10 60]
NumMFs=3
MF1='low':'gbellmf',[12.3 7 10]
MF2='good':'gbellmf',[12.6 7 35]
MF3='high':'gbellmf',[12.3 7 60]

[Input2]
Name='loading'
Range=[20 70]
NumMFs=3
MF1='low':'gbellmf',[12.3 5.62 20.1]
MF2='good':'gbellmf',[12.4 7.07 44.9]
MF3='high':'gbellmf',[12.3 6.74 69.9]
```

```
[Output1]
Name='fuel_valve'
Range=[-1 1]
NumMFs=5
MF1='close_fast':'constant',0.9
MF2='close_slow':'constant',0.5
MF3='no_change':'constant',0
MF4='open_slow':'constant',-0.5
MF5='open_fast':'constant',-0.9

[Output2]
Name='blaster'
Range=[-1 1]
NumMFs=3
MF1='reducing':'constant',1
MF2='no_change':'constant',0
MF3='raising':'constant',-1

[Output3]
Name='distribution'
Range=[0 1]
NumMFs=3
MF1='request':'constant',0
MF2='no_change':'constant',0.5
MF3='disconnect':'constant',1
```

```
[Rules]
  1 2, 4 3 2 (1) : 1
  2 2, 3 2 2 (1) : 1
  1 3, 5 3 1 (1) : 1
  2 3, 3 2 1 (1) : 1
  3 2, 2 1 2 (1) : 1
  0 1, 1 2 3 (1) : 1
  3 3, 2 1 3 (1) : 1
```

Figure 5.13. Fuzzy inference system for control processes of the furnace chamber

MFs shown in Figure 5.14 are bell-shape ones at the inputs, and the outputs are constant values of voltage for setting the discharge area of fuel valve and revolution numbers of blaster and exhauster ventilators computed by Sugeno's rule.

Groups of inputs are the following ones:

Input1 **'pressure' includes three MFs:**

- ***low*** **means the pressure of outlet steam is under the minimum value,**
- ***good*** **means the pressure of outlet steam is inside the limits,**
- ***high*** **means the pressure of outlet steam is over the maximum value.**

Input2 **'loading' has the following three MFs:**

- ***low*** **means the loading is under the technical minimum,**
- ***good*** **means the loading is between limits,**
- ***high*** **means the loading of boiler is equal or over the maximum value.**

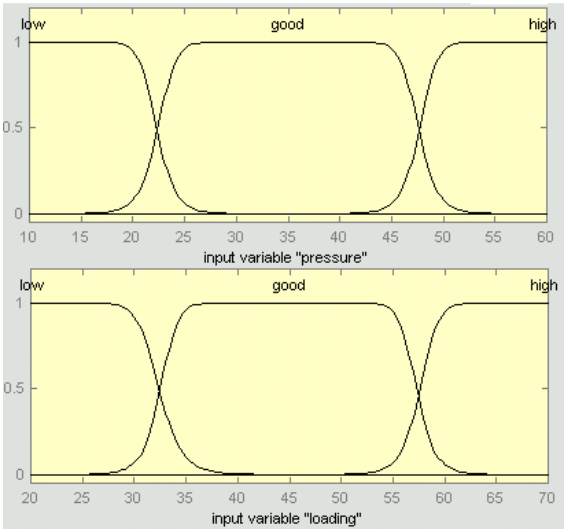


Figure 5.14. MFs of FIS for control of devices of furnace chamber

Groups of outputs are the following ones:

Output1 **'fuel_valve' group of outputs is described by the followings which outputs are voltage values for changing the discharge area of fuel valve of burner's:**

- ***close_fast*** **is the control voltage on the fuel valve drive being closed fast,**
- ***close_slow*** **is a control voltage on the fuel valve drive being reduced the discharge area of valve slowly,**
- ***no_change*** **means there are no voltage on the fuel valve drive, the discharge area does not change,**
- ***open_slow*** **is a control voltage on the fuel valve drive being increased the discharge area of valve slowly,**
- ***open_fast*** **means the voltage on the fuel valve drive which occurs opening the fuel valve fast.**

Output2 **'blaster' includes rules for setting the revolution number of blaster ventilator by the followings:**

- ***reducing*** **means the control voltage decreases the revolution number of blaster ventilator to reduce the inlet fresh air quantity,**
- ***no_change*** **means the fresh air quantity set by revolution number of blaster ventilator does not change,**
- ***rising*** **means the control voltage increases the revolution number of blaster ventilator to produce higher quantity of inlet fresh air.**

Output3 'distribution' includes rules for request of changing the load distribution among the steam generators by the followings:

- *disconnect* means the steam generator must be disconnect because of changing of steam parameters,
- *no_change* means there are no required changing in load distribution,
- *request* means the steam load must be modified.

The setting of fuel valve is shown in Figure 5.15. When the loading is under the technical minimum then the burner will switched off because the operating of steam generator would be no economic.

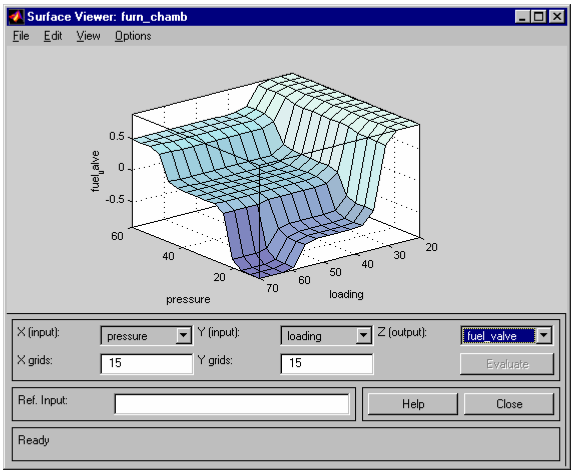


Figure 5.15. Fuzzy control of fuel valve by Sugeno's rule

Figure 5.16 shows how the revolution number of blaster ventilator is controlled by the pressure and outlet quantity of steam. It seems that the control process is also influenced by the steam load and pressure under the technical minimum and over the maximum capacity. When the limits are over and combustion is switched off, the blasted fresh air quantity will not change because the residual flue gas in the furnace chamber must flush out of the room by the blasted fresh air after combustion has been stopped. In the other case, when the power of burners might no be increased the quantity of inlet fresh air is setting on and held on the appropriate value.

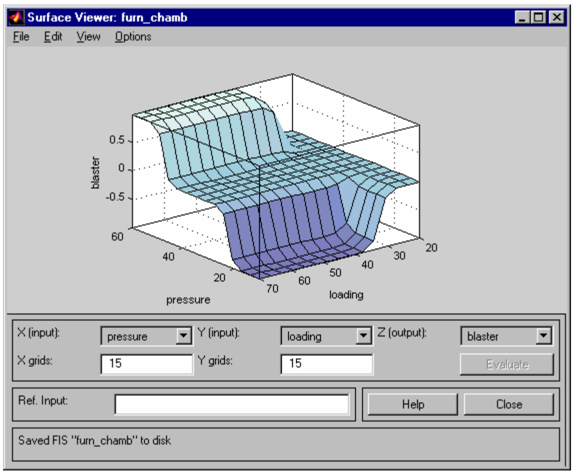


Figure 5.16. Fuzzy control for the blaster ventilator by Sugeno's rules

When output parameters of steam generator has changed sharp then those changings affects on the outlet steam quality. Therefore, load distribution among the boilers must be modified. Figure 5.17 shows the control of distribution request by single steam generator to the distribution system..

A controlled parameter of furnace chamber is the internal pressure. The produced internal pressure is set by the power of blaster ventilator and the power of exhauster ventilator. The speed of

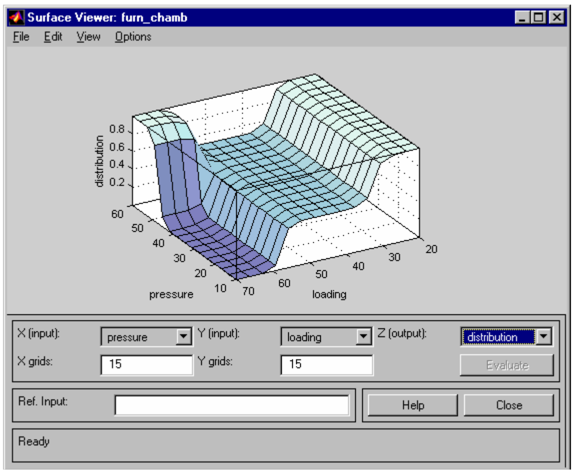


Figure 5.17. Fuzzy control for request changing of load distribution by Sugeno's rule

exhauster ventilator is controlled in accordance with the required value of internal pressure and revolution number of blaster ventilator. The FIS for control the revolution number of exhauster ventilator is a *two-inputs single-output Sugeno FIS* described in Figure 5.18.

```
[System]
Name='exhauster'
Type='sugeno'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=3
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='max'
DefuzzMethod='wtaver'

[Input1]
Name='fchamb_pressure'
Range=[-100 0]
NumMFs=3
MF1='high':'gbellmf',[24.6 7 -100]
MF2='good':'gbellmf',[25.2 7 -50]
MF3='low':'gbellmf',[24.6 7 0]

[Input2]
Name='blaster'
Range=[800 1500]
NumMFs=3
MF1='low':'gbellmf',[172.2 5.62 801.4]
MF2='good':'gbellmf',[174 7.07 1150]
MF3='high':'gbellmf',[176 6.74 1500]

[Output1]
Name='exhauster'
Range=[-1 1]
NumMFs=3
MF1='reducing':'constant',1
MF2='no_change':'constant',0
MF3='raising':'constant',-1

[Rules]
1 2, 1 (1) : 1
3 2, 3 (1) : 1
2 2, 2 (1) : 1
```

Figure 5.18. Fuzzy inference system for control the revolution number of exhauster

Membership functions of the FIS shown in Figure 5.19 are bell-shape ones at the inputs, and output is constant values of voltage for setting the revolution number control of exhauster ventilator computed by Sugeno's rule .

Groups of inputs are the following ones:

Input1 **'fchamb_pressure' has three MFs:**

- ***low*** **means the produced pressure of furnace chamber is under the required minimum,**
- ***good*** **means pressure of furnace chamber has an appropriate value,**

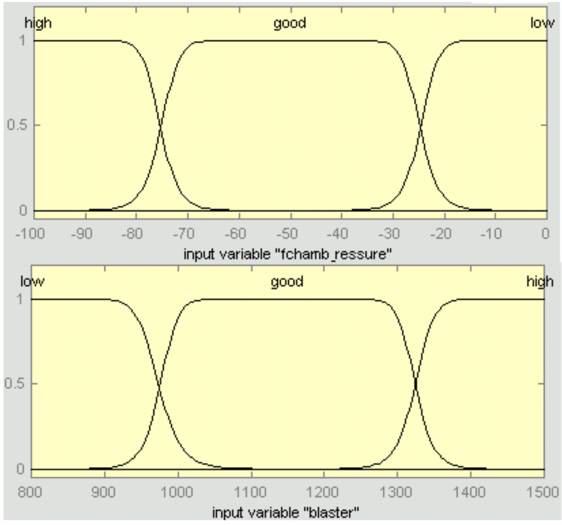


Figure 5.19. MFs of FIS for control of revolution number of exhauster ventilator

- ***high*** **means the pressure of furnace chamber is over the maximum value.**

Input2 **'blaster' means the appropriate revolution number of blaster ventilator which has been set in accordance with the required fresh air quantity for the combustion described above.**

Output1 **'exhauster' includes rules for setting the revolution number of exhauster ventilator by the followings:**

- ***reducing*** **means the control voltage decreases the revolution number of exhauster for decreasing the quantity of outlet flue gas,**
- ***no_change*** **means the revolution number of exhauster ventilator does not change,**
- ***raising*** **means the control voltage increases the revolution number of exhauster ventilator to produce higher quantity of outlet flue gas.**

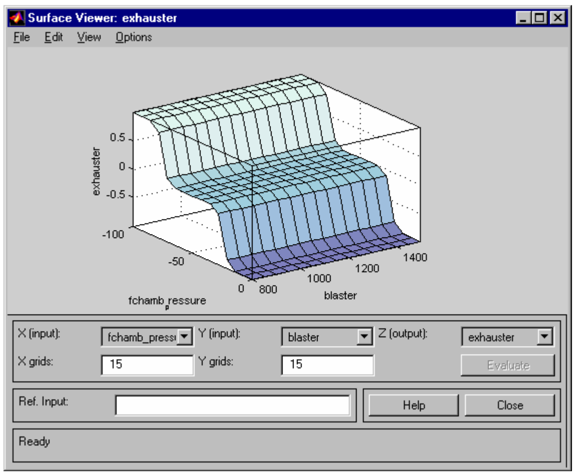


Figure 5.20. Fuzzy control for the exhauster ventilator by Sugeno's rules

Figure 5.20 shows the control of revolution number of exhauster ventilator which depends on the required chimney draught and the temporary revolution number of blaster ventilator.

5.6. Fuzzy system for control of outlet steam temperature

The outlet steam temperature is controlled by setting of injected water quantity which is changed by the setting of discharge area of injected water valve. The temperature of outlet steam is controlled by the temporary steam load measured by orifice differential and the measured temperature before the second superheater. Since the temperature T_{st2} is set by the second superheater, and the heat quantity given by the superheater is constant, the only controlled temperature is T_2 set by injected water. The scheme of control for water injection to set the temperature of outlet steam can be seen in Figure 5.21.

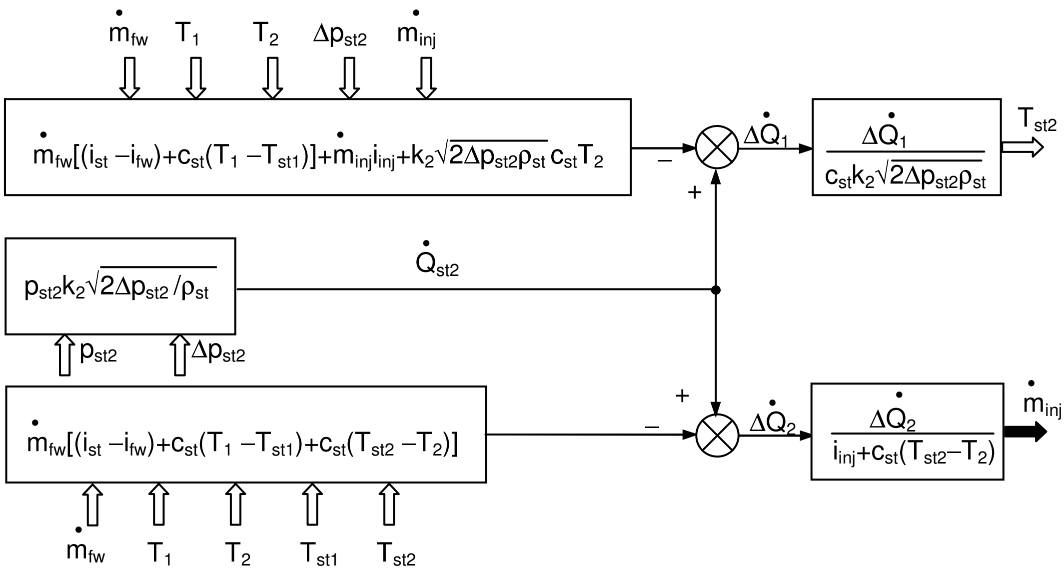


Figure 5.21. Scheme of output temperature control

As the temperature of outlet steam depends on the temperature of steam at the input of temperature control device and the injected water quantity, and the heat quantity transferred by superheater can be considered as a constant value, the required discharge area of injected water valve is computed by equations (3.57). It seems that the transferred heat to the steam depends on the temporary steam load, only.

The schematic structure of control for setting the discharge area of injected water valve is shown in Figure 5.22.

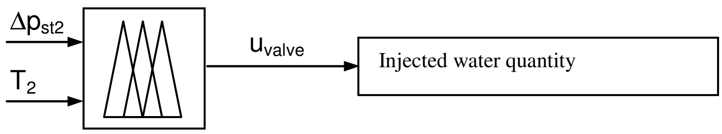


Figure 5.22. Structure of FIS for the control of outlet steam temperature

The inputs of temperature setting device are the temporary steam load computed from the orifice differential Δp_{st2} measured at the output, and the intermediate temperature T_2. Therefore, the FIS for control the outlet steam temperature is *two-inputs single-output Sugeno FIS* described in Figure 5.23.

MFs of the FIS shown in Figure 5.24 are bell-shape ones at the inputs, and output is constant values of voltage computed by Sugeno's rule for setting the discharge area of injected water valve.

```
[System]
Name='steam_temp7'
Type='sugeno'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=6
AndMethod='prod'
OrMethod='probor'
ImpMethod='prod'
AggMethod='max'
DefuzzMethod='wtaver'

[Input1]
Name='steam_temperature'
Range=[400 480]
NumMFs=3
MF1='low':'gbellmf',[21.2 7.79 400]
MF2='good':'gbellmf',[18.6 6.39 440]
MF3='high':'gbellmf',[21.4 6.33 480]

[Input2]
Name='steam_load'
Range=[20 70]
NumMFs=3
MF1='low':'gbellmf',[12.3 5.62 20.2]
MF2='good':'gbellmf',[12.4 7.07 44.9]
MF3='high':'gbellmf',[12.3 6.74 69.9]

[Output1]
Name='inj_valve'
Range=[-1 1]
NumMFs=5
MF1='open_fast':'constant',-0.9
MF2='open_slow':'constant',-0.5
MF3='no_change':'constant',0
MF4='close_slow':'constant',0.3
MF5='close_fast':'constant',0.9

[Rules]
3 1, 1 (1) : 1
3 -1, 2 (1) : 1
2 3, 4 (1) : 1
2 -3, 3 (1) : 1
1 3, 5 (1) : 1
1 -3, 4 (1) : 1
```

Figure 5.23. Fuzzy inference system for control the temperature of outlet steam

Group of inputs are the following:

Input1 includes the following MFs:

- *low* means the temperature before the second superheater is under the required value,
- *good* means the temperature is in the optimum range,
- *high* means the temperature of steam is over the required value.

Input2 consists of the following MFs:

- *low* means the steam load is lower than the required value,
- *good* means the steam load is in the appropriate range,
- *high* means the steam load is over the required value.

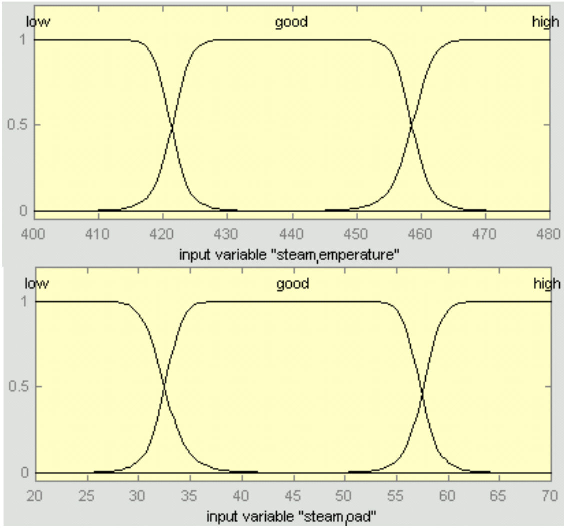


Figure 5.24. MFs of FIS for control of discharge area of injected water valve

Output1 'inj_valve' includes rules for setting discharge area of injected water valve by the followings:

- *open_fast* means the voltage on the injected water valve drive which occurs opening the injected water valve fast,
- *open_slow* is a control voltage on the injected water valve drive being increased the discharge area of valve slowly,
- *no_change* means there are no voltage on the injected water valve drive, the discharge area of valve does not change,
- *close_slow* is a control voltage on the injected water valve drive being reduced the discharge area of valve slowly,
- *close_fast* is the control voltage on the injected water valve drive being closed fast.

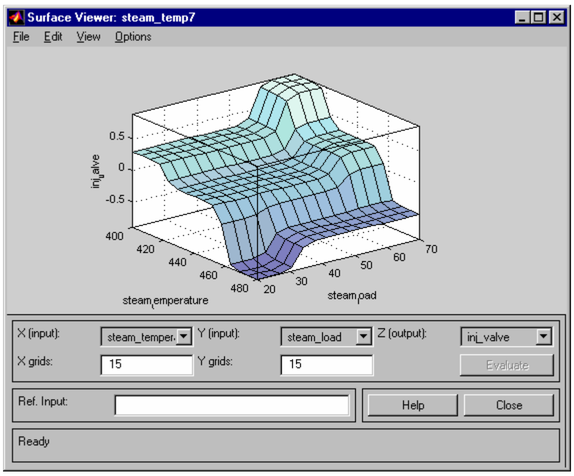


Figure 5.25. Fuzzy control for the injected water valve by Sugeno rules

. Figure 5.25 includes control function of discharge are of injected water valve where the discharge are is setting by the voltage switched on the motor of valve.

5.7. Large-scale system for control of individual boiler

The purpose of a fuzzy logic control is to mimic the behavior of a human operator able to control a complex plant satisfactorily (Mamdani and Assilian,1975). In this case, the complex plant is the technology of steam production. The technology plant consists of units shown in Figure 5.5 where those technological units belong to a network of technological operations. Since individual FCs have behaviors which are influenced by their related individual units, and the changing of any output belonged to any individual plant affects on outputs of other ones, that means all changes of output parameters of the system make other subsystems change their operational features, the *set of FCs can be seen as a neural network*. This neural network built of FCs belonged to the steam production system can be seen in Figure 5.26, where X_0 means the set of initial input data: the steam load, the temperature and the pressure of outlet steam and the level height of feed water in the drum.

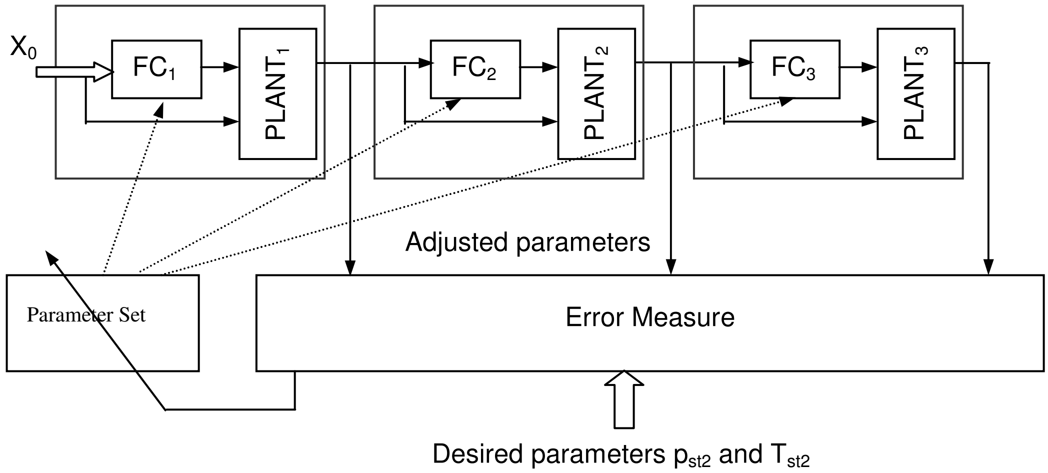


Figure 5.26. Adaptive network composed of individual FCs

FC_1 is the fuzzy control for setting the temperature of outlet steam PLANT1, FC2 means the fuzzy control for setting the pressure of outlet steam PLANT2, and FC3 is the fuzzy control for setting the level of feed water in the drum PLANT3. FC2 controls the operation of furnace chamber, the fuel quantity, and the fresh air quantity, and the pressure inside the furnace chamber.

The adjustable parameters all pertain to the FC block implemented as an ANFIS built of *fuzzy neurons*. Although there are *k* FCs, all of them refer to the same parameter set, the produced steam quantity, the steam temperature and the steam pressure which decide all the other internal parameters.

The corresponding error measure to be minimized is

$$E = \sum_{k=1}^{m} \| x(k) - x_d(k) \|^2, \tag{5.7}$$

where $x_d(k)$ is the desired state vector at time step *k*. If control efforts are taken into consideration, then a revised error measure would be

$$E = \sum_{k=1}^{m} \| x(k) - x_d(k) \|^2 + \lambda \sum_{k=0}^{m-1} \| \boldsymbol{u}(k) \|^2 \tag{5.8}$$

where $u(k)$ is the control action at time step *k*. By proper selection of λ, a compromise between trajectory error and control efforts can be obtained.

Let the input be consisted of set of data pairs $\{(x^{(k)}, d^{(k)})\ k=1,2,\ldots,p\}$, the algorithm provides a procedure for changing the weights in the network to classify the given input patterns correctly.

For a given input-output pairs *($x^{(k)}$,$d^{(k)}$)*, the backpropagation algorithm will perform two phases of data flow. The input pattern $x^{(k)}$ is propagated from the input layer to the output layer. As a result of this forward flow of data, it produces an actual output $y^{(k)}$. Then the error signals resulting from the difference between $d^{(k)}$ and $y^{(k)}$ are *propagated backwards* from them to update their weights (Lin and Lee,1996).

5.8. Supervisory control for the large-scale system of the heat power station

There are much boilers in the heat power station of Nyíregyháza, and the temporary steam load is distributed between the communal heating service, the local industrial consumers, and the electric energy production of the heat power station Nyíregyháza. In this chapter, the supervisory system of hierarchical composite subsystems will be described which has to have a proper economic control. The base of economy would be the optimal distribution of steam load. The distribution of steam load would be computed by the specific cost of steam production by individual boilers. The method of specific cost computation is based on the method developed by Tóth, Detzky, and Lövei (Tóth, 1988) (Tóth, 1998).

The goal of approach by supervisor system is to give proper stability for the steam production system whose load is changing periodically. The stability control must be focused on the stability of individual boilers by their steam load. The stability criteria would be analysed by the Lyapunov rules (Jamshidi, 1997)(Lin and Lee, 1996)(Jang et al., 1997), and by the structural stability of catastrophe events described by catastrophe functions (Thom, 1975)(Thom,1977)(Poston and Stewart, 1985).

The high dimensionalities, complexities of interconnection in large-scale systems provide computational and analytical difficulties not only in modeling, control, or optimization but also in the fundamental issues of stability, controllability, and observability (Bailey,1966)(Araki,1978)(Moylan and Hill,1978).

When the stability of large-scale system is of concern, one basic approach, consisting of three steps, has prevailed:

- decompose a given large-scale system into number of small-scale subsystems,
- analyze each subsystems using the classical stability theories and methods,
- combine the results leading to certain restrictive conditions with the interconnections and reduce them to the stability of the whole.

One of the earliest efforts regarding the stability of composite systems was the application of Lyapunov function for each subsystems. Then using the theory of the vector Lyapunov function, the stability of the composite system was checked.

In an other method, a scalar Lyapunov function has been constructed as a weighted sum of the Lyapunov functions of the individual subsystems. This line of work has given rise to the so-called "Lyapunov-methods".

An alternative approach, the "input-output method" describes each subsystem by a mathematical relation or an operator on functional space, and then functional analysis methods are employed (Michel and Porter,1972)(Cook,1974)(Moylan and Hill,1978).

A basic issue involved in interconnected systems stability is the question of how large was the interaction magnitude and strength before the stability of the composite system has been affected? In some systems a strong coupling exists between various subsystems which makes a major contribution to stability. Such issues lead to connective stability, which is essentially the extension of stability, in the sense of Lyapunov, to take into account the structural perturbations (Siljak,1978).

A system is said to be "completely state controllable" if it is possible to find an unconstrained control vector $u(t)$ that would transfer any initial state $x(t_0)$, for any t_0, to any final state $x(t)$, say origin, in a finite time interval $t_0 \leq t \leq t_f$. Observability is a concept related to the determination of the state from the measurement of output. A system is said to be "completely observable" at any time t_0 if it is possible to determine $x(t_0)$ by measuring $y(t)$ over the interval $t_0 \leq t \leq t_1$.

Let a linear time-invariant system described by the following equations:

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{5.9}$$

$$y(t) = Cx(t) + Du(t) \tag{5.10}$$

where x, u, and y are n-dimensional, m-dimensional, and r-dimensional state, control and output vectors, and A, B, C, and D are constant matrices of appropriate dimensions. The standard criteria for checking controllability and observability of this system are the following two rank conditions (Kalman,1960):

$$\text{rank } P = \text{rank}\{B \;\; AB \ldots A^{n-1}B\} = n \tag{5.11}$$

$$\text{rank } Q = \text{rank } \{C^T A^T C^T \ldots (C^T)^{N-1} C^T\} = n \tag{5.12}$$

where P and Q are the $n \times nm$ controllability and $n \times nr$ observability matrices. These conditions are useful and computationally simple if n is small enough. If the system is large in scale or has particular inherent properties which make these two conditions to check, alternative criteria are required.

The bulk of research in the controllability and observability of large-scale systems falls into four main problems: controllability and observability of composite systems, controllability (and observability) of decentralized systems, structural controllability, and controllability of singularly perturbed systems (Jamshidi, 1997).

The controllability and observability of composite systems was first considered by (Gilbert,1963) where the controllability and observability of the system were studied in term of those of the subsystems.

The *structural controllability* has been determined the controllability of pair (A,b) through the properties of system structure through the graph of (A,b). The graph theoretic concepts have also been used for composite systems (Lin,1974) (Davison,1976).

5.9. The determination of safety integrity by qualitative method

In this work I carried out a qualitative method made for single channel safety control. The goal of this method is to determine the value of *safety integrity level* in accordance with the number of applied *independent protection layers* in SIS by a knowledge base without the application of any historical data base. Soft computing applied for SIS is based on the hazardous event severity matrix in Figure 4.34 proposed by standard IEC 61508 part 5 and standard IEC 61511-3.

The principal method to determine the number of IPLs is a special event of Thom's catastrophe theory, the conditional catastrophe described in Chapter

4. In this case, the number of needed independent protection layers depend on the severity of hazardous events and the number of independent protection layers. The environmental condition is the event likelihood, and the output is the SIL value.

5.9.1. Fuzzy system to determine the value of SIL

The fuzzy system has two no-numerical input variables, the severity and the event likelihood which are linguistic variables, and one numeric variable the number of independent protection layers which is not determined by analytical function but consists of discrete values. The original output is the value of SIL, however the number of IPL can be used rather as output because this value is required to realize the required SIS, technically. Independent protection layers are protection circuits operated by shared or separated sensors. MFs of the FIS is shown in Figure 5.27.

Groups of inputs are the following ones:

Input1 **'Severity' has three MFs:**

- ***Minor* means hazardous events are less dangerous,**
- ***Serious* means the hazardous events can occur damage of the controlled device,**
- ***Extensive* means hazardous events occur total damage of the controlled system.**

Input2 **'Event-likelihood' is the "conditional switch" for conditional catastrophe which determines the changing of events on the catastrophe surface:**

- ***Low* means the probability of occurrence of hazardous event is low,**
- ***Medium* means the probability of occurrence of hazardous event is medium,**
- ***High* means the probability of occurrence of hazardous event is high.**

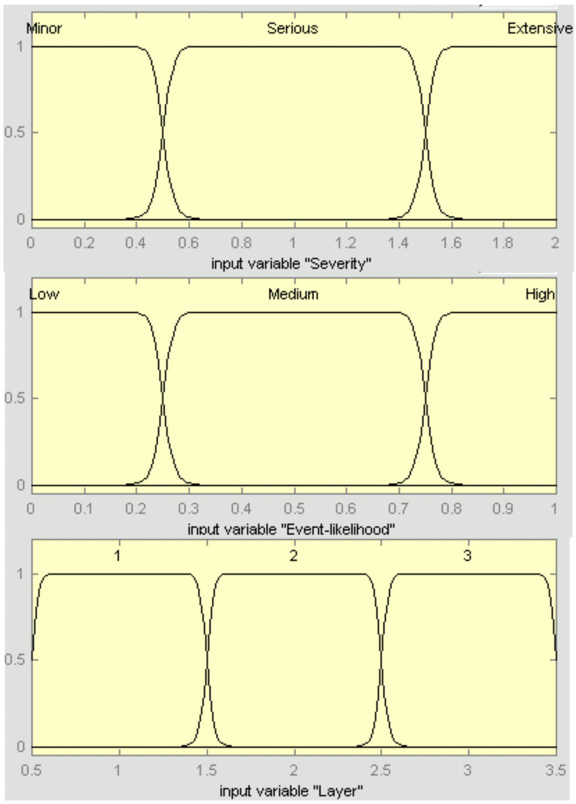


Figure 5.27. MFs of FIS for the determination of safety integrity

Input3 **'Layer' gives the number of used independent protection layers:**

- ***1* means single protection layer is applied in the SIS,**
- ***2* means two independent protection layers are in the SIS,**
- ***3* means three independent protection layers are in the SIS.**

Group of output includes single output, the value of SIL:

Output1 **'SIL' is the required value of safety integrity level:**

- ***0* means there is no required value,**

- *1* **means the value of SIL is 1,**
- *2* **means the value of SIL is 2,**
- *3* **means the value of SIL is 3.**

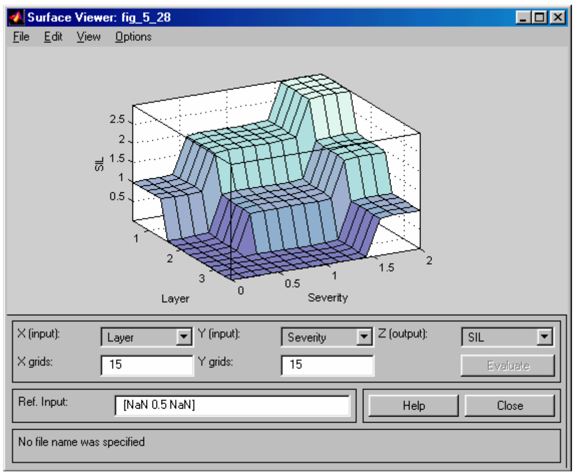


Figure 5.28. Fuzzy logic for determining the SIL

The relationship between the *Severity* and the *IPL,* and the *SIL* influenced by the condition *Event-likelihood* is shown in Figure 5.28. However, the goal of the safety development by soft computing system is rather the determination of the required number of IPLs. In this case, SIS has to have the determined number of IPLs by the fuzzy inference system in accordance with the value of SIL. The fuzzy inference system is a three-input single output FIS described in Figure 5.29.

```
[System]
Name='safe__SIL'
Type='sugeno'
Version=2.0
NumInputs=3
NumOutputs=1
NumRules=22
AndMethod='prod'
OrMethod='probor'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='wtaver'

[Input1]
Name='Severity'
Range=[0 2]
NumMFs=3
MF1='Minor':'gbellmf',[0.5 12.5 0]
MF2='Serious':'gbellmf',[0.5 12.5 1]
MF3='Extensive':'gbellmf',[0.5 12.5 2]

[Input2]
Name='Event-likelihood'
Range=[0 1]
NumMFs=3
MF1='Low':'gbellmf',[0.25 12.5 0]
MF2='Medium':'gbellmf',[0.25 12.5 0.5]
MF3='High':'gbellmf',[0.25 12.5 1]

[Input3]
Name='Layer'
Range=[0.5 3.5]
NumMFs=3
MF1='1':'gbellmf',[0.5 12.5 1]
MF2='2':'gbellmf',[0.5 12.5 2]
MF3='3':'gbellmf',[0.5 12.5 3]

[Output1]
Name='SIL'
Range=[0 3]
NumMFs=4
MF1='0':'constant',0
MF2='1':'constant',1
MF3='2':'constant',2
MF4='3':'constant',3
```


```
[Output1]
Name='SIL'
Range=[0 3]
NumMFs=4
MF1='0':'constant',0
MF2='1':'constant',1
MF3='2':'constant',2
MF4='3':'constant',3
```


```
[Rules]
1 1 1, 2 (1) : 1
1 2 1, 2 (1) : 1
1 3 1, 3 (1) : 1
1 3 2, 2 (1) : 1
2 1 1, 2 (1) : 1
2 2 1, 3 (1) : 1
2 2 2, 2 (1) : 1
2 3 1, 3 (1) : 1
2 3 3, 2 (1) : 1
3 1 1, 3 (1) : 1
3 1 3, 2 (1) : 1
3 2 1, 4 (1) : 1
3 2 2, 3 (1) : 1
3 2 3, 2 (1) : 1
3 3 1, 4 (1) : 1
3 3 3, 3 (1) : 1
3 3 3, 4 (1) : 1
1 0 3, 1 (1) : 1
1 -3 2, 1 (1) : 1
2 0 3, 1 (1) : 1
2 1 2, 1 (1) : 1
3 1 3, 1 (1) : 1
```

Figure 5.29. Fuzzy inference system for determination of SIL or number of IPL

5.9.2. SIL determination for the steam production system by qualitative method

The safety subsystems of steam production are introduced in the Appendix 1. SIL values in Appendix 1 are computed by quantitative method of standards IEC 61508 and IEC 61511.

In this session, the qualitative method based on soft computing method is used to determine SILs. Safety integrity level will be determined by the fuzzy logic system described in the previous session, shown the function in Figure 5.29.

It seems in Table 5.1 that the results of qualitative method have similar values for SIL as the quantitative method in Annex 1. There is difference in the *SIL* value of water injection system of temperature setting, only. The steam production system is not endangered by the malfunction of water injection system (*Severity* is minor) in accordance with the experiences in knowledge base. But if value of conditional variable *Event-likelihood* is changed to 'high' then *SIL*=2.

Subsystem	Severity	Layer	Event-likelihood	SIL
Furnace chamber	extensive	single	medium	3
Steam drum	serious	single	high	2
Temperature setting	minor	single	medium	1

Table 5.1. Determination of SIL by FIS in Figure 5.27

5.10. Control system for supervision of the group of boilers

The steam production system includes individual boilers which product steam for the customers and for electric energy production. The supervisory control system is connected to the local subsystems by the signals “distribution”, and measures the temporary steam load, and the temperature, and pressure of outlet steam. Since the customers need steam with different features there are collecting stations for all customers. All the collecting stations are connected to more boilers which produce steam with the same features, the temperature and the pressure.

The distribution of steam load among the boilers is done in accordance with the rate of heat power capacities of individual boilers. This distribution method results higher efficiency and lower costs.

Let the temporary steam load of the large-scale system consisted of individual subsystems, the boilers be

$$\dot{V}=\sum_{i=1}^{n}\dot{V}_i, \tag{5.13}$$

where the large-scale system has i subsystems.

Let the temporary quantity of outlet steam of the ith boiler be $\dot{V}_i$, and the technical minimum of outlet steam of the ith boiler be $\dot{V}_i^{min}$, and the maximum of outlet steam load of ith boiler be $\dot{V}_i^{max}$.

Then the computed ratio, the coefficient of steam load m_i of ith boiler can be computed by the following:

$$m_i = \frac{\dot{V}_i}{\dot{V}} = \frac{\dot{V}_i^{max}}{\dot{V}^{max}}, \tag{5.14}$$

where $\dot{V}$ is the temporary value of steam load and $\dot{V}^{max}$ is the maximum of steam load on the large-scale system. The rated steam load on a subsystem, the ith boiler is computed by the following function:

$$\dot{V}_i = m_i \dot{V}, \tag{5.15}$$

where $\dot{V}_i^{min} < \dot{V}_i \leq \dot{V}_i^{max}$ **, and the coefficient of temporary steam load** m_i **can be used as a control value for setting the steam load on the** ***i*****th boiler.**

The steam load $\dot{V}$ **of large-scale system can be computed by the following function, too:**

$$\dot{V} = \sum_{i=1}^{n} m_i \dot{V}, \tag{5.16}$$

that is,

$$\sum_{i=1}^{n} m_i = 1. \tag{5.17}$$

The cost K_i **of steam production is calculated for every boilers which is computed as**

$$K_i = k_i \dot{V}_i, \tag{8.18}$$

where k_i **is the specific cost of** ***i*****th boiler, and the total is**

$$K = \sum_{i=1}^{n} K_i = \sum_{i=1}^{n} k_i \dot{V}_i \tag{5.19}$$

When the distribution of temporary steam load is calculated then the specific cost k_i **must be taken into consideration.**

In case of reducing the steam load on the large-scale system the reduction will be executed in the sequence of specific costs. The reduction of steam load has to be executed by the application of linear programming, where the goal is the minimum cost of unity steam mass by resultant function.

The change of ratio m_i **of steam load on the** ***i*****th boiler will occur errors within the** ***i*****th subsystem, where the steam pressure and steam temperature will have to be changed. The correction of parameters of outlet steam will be produced by the FLC of the boiler. It seems, the errors will be flown from the output of large-scale system to the input FLCs of boilers, that is,** ***the large-scale system is a backpropagation neural network consisted of fuzzy neurons.***

The structure of supervisory control of heat power station is similar to the system in Figure 4.15. But, the applied system consists of hierarchical FLCs for control the large-scale subsystems, the boilers. The structure of subsystems can be seen in Figure 5.26. Those FLCs compose a quasi-neural system supervised by a central unit which has goals to realize the stable set of outputs and the economical operation.

5.10.1. The supervisory control as fuzzy neural network

The supervisory system is shown in Figure 5.30. It seems, the computation of m_i is made by the supervisory control, and the influences on fuzzy neurons, the control subsystems of individual boilers are propagated backwards. Input variables are the measured parameters on the output, but there are some secondary parameters measured in the individual subsystems described in Chapter 3.

The *Supervisory Control Device* consists of fuzzy neurons which calculate the proper multipliers m_i. All multipliers affect on their own control unit belonged to a boiler. Influences on the individual boilers are actions to change the discharge areas of outlet steam valves.

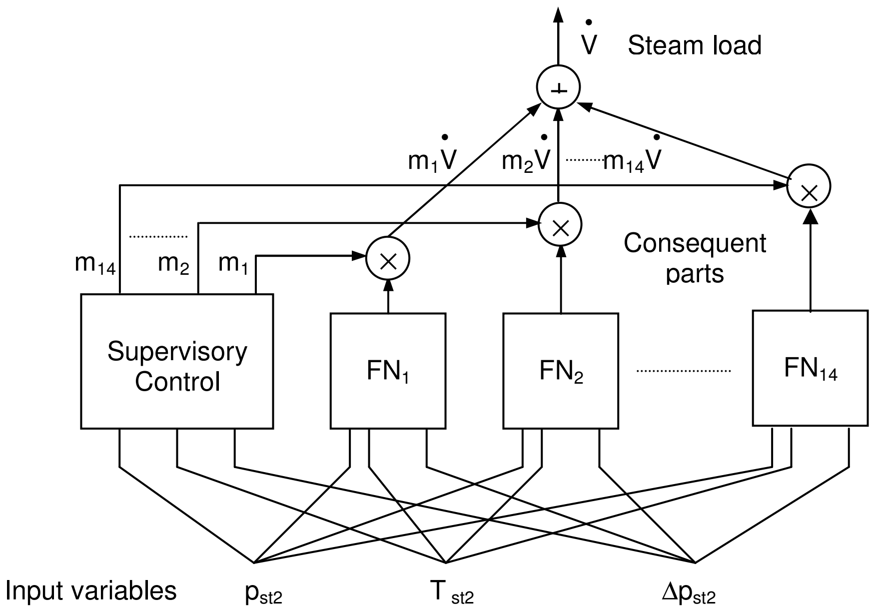


Figure 5.30. Block diagram of supervisor system for the heat power station

Membership functions of the FIS shown in Figure 5.31 are bell-shape ones at the inputs, and the output is constant value of multipliers m_i. Description of FIS is shown in Figure 5.32. The FLC is a *two-inputs single-output Sugeno FIS*.

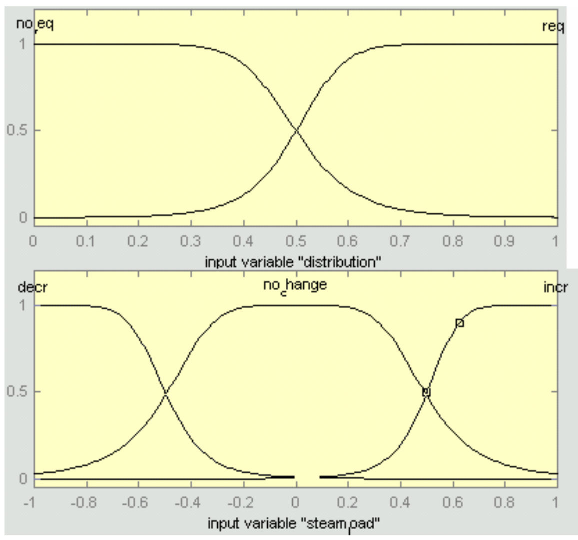


Figure 5.31. MFs of FIS for control of steam load distribution

Groups of inputs are the following ones:

Input1 **includes the following MFs:**

- ***no_req*** **means there is no subsystem having distribution request because of extreme volume of its steam load,**
- *req* means one or more subsystems require the change of individual steam load because of the too high or too low steam load.

Input2 includes the following MFs:

- *decr* means the steam load is decreasing, that is, the steam load is changing to the technical minimum,
- *no_change* means the steam load does not change,
- *incr* means the steam load is increasing which means the steam load is changing to the maximum.

Output1 **'multipl' includes values of multiplier m_i for computation the discharge area setting of injected water valve by the followings:**

- ***full_open*** **means the discharge area of steam valve of the identified boiler has to be set maximum,**

```
[System]
Name='load_distrib'
Type='sugeno'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=5
AndMethod='prod'
OrMethod='probor'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='wtaver'

[Input1]
Name='distribution'
Range=[0 1]
NumMFs=2
MF1='no_req':'gbellmf',[0.5 4.49 0]
MF2='req':'gbellmf',[0.5 5.2 1]

[Input2]
Name='steam_load'
Range=[-1 1]
NumMFs=3
MF1='decrease':'gbellmf',[0.5 3.34 -1]
MF2='no_change':'gbellmf',[0.492 2.49 0]
MF3='increase':'gbellmf',[0.5 3.84 1]

[Output1]
Name='multipl'
Range=[0 1]
NumMFs=5
MF1='full_close':'constant',0
MF2='close_slow':'constant',0.5
MF3='no_change':'constant',1
MF4='open_slow':'constant',1.5
MF5='full_open':'constant',2

[Rules]
1 2, 3 (1) : 1
2 1, 1 (1) : 1
2 3, 5 (1) : 1
1 3, 4 (1) : 1
1 1, 2 (1) : 1
```

Figure 5.32. FIS for distribution control of steam load

- *open_slow* **means the discharge area of steam valve belonged to the identified boiler has to be increasing slowly,**
- *no_change* **means the discharge area of steam valve of identified boiler need not be changed,**
- *close_slow* **means the discharge area of steam valve of identified boiler has to be decreasing slowly,**
- *full_close* **means the steam valve of identified boiler has to be closed full.**

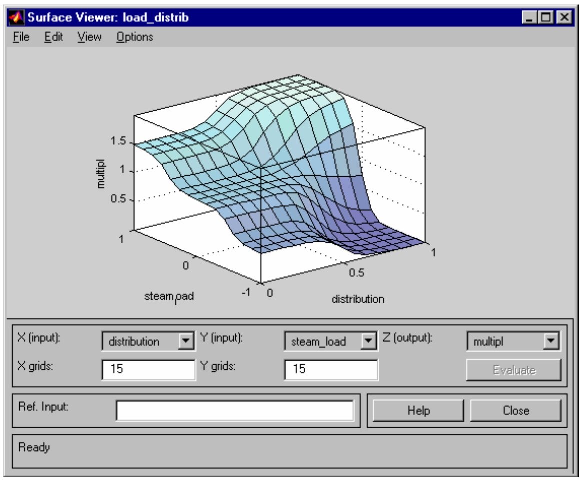


Figure 5.33. Fuzzy control for setting the distribution of steam load by Sugeno rules

. Figure 5.33 shows the control function for setting the discharge area of steam valve where the discharge area is computed by the product of temporary steam load and modifier coefficient m_i, the multiplier. The value of multiplier m_i is between 0 and 2, where 0 means the steam valve must be closing full, and 2 means the steam valve must be opening until maximum. When m_i=1 there are no change in the distribution of steam load. It seems in Figure 5.33 that if variable 'distribution' is over 0.5 then the output valves of boilers are opening or closing continuously. If there is no distribution request then the discharge area of output valves will change in according to the temporary steam load. The change of steam load on the outputs of large-scale subsystems, the individual boilers will occur changing of parameters of the produced outlet steam. Therefore the technological units of boilers will be operating in accordance with the temporary steam load.

5.10.2. The control of subsystem as fuzzy neuron

Let it be supposed that the steam parameters, the pressure, and the temperature are equal, and they are stable values at the outputs of all boilers, temporarily. Therefore, the produced steam originated from different boilers can be loaded into the distribution system which has a temporary capacity for output steam with pressure *p* and temperature *T*.

Assume we have the following rules:

$$R_r\text{: IF } X \text{ is } A_i \text{ AND } Y \text{ is } B_j \text{ THEN } Z \text{ is } C_p, \quad \text{for } 1 \le r \le n, \qquad (5.20)$$

where A_i, B_j, and C_p are fuzzy subsets of *R*.

Let all these fuzzy sets consist of fuzzy numbers specified by a_i, b_j, and c_p, respectively. Let $R_r(a_i, b_j, c_p)=M(A_i, B_j, C_p)$, which is a fuzzy relation in *R* for rule *r*, $1 \le r \le n$, and *M* is an implication operator that will produce a fuzzy relation R_r for each rule. Then, given $X=A'$ and $Y=B'$, each rule computes $C_r=(A',B') \circ R_r(a_i, b_j, c_p)$, **$1 \le r \le n$.**

C_r

The fuzzy expert system combines these results into one final conclusion *C'*, which is the rate *M* of steam load. This fuzzy expert system can be modeled by a fuzzy neural network built of *fuzzy neurons* of type III (Lin and Lee, 1996).

5.11. Conclusion

In this system, input data are the steam pressure, and the steam temperature, and the steam load, and the output data are the required setting of fuel valve, and the setting of valve of injected water to set the output temperature of steam, and the setting of feed water valve, and the speed of blaster and exhauster. Chapter 3 includes the descriptions of relationships between these inputs and outputs. It can bee seen that any change of steam load occurs changing the setting of actuators to produce the correct setting of steam temperature and steam pressure. The features of described control system built of fuzzy neurons are the followings:

- **the control process is based on Thom's catastrophe theory, therefore, the number of fuzzy rules could be decreased,**
- **the control system occurs the interruption of the controlled technology when the height of feed water level is under the lower interlock or over the upper interlock, and the steam load of the boiler is under the technical minimum,**
- **the control system generates a load distribution request signal for the supervisor system to modify the load of boiler when the local steam load would be near the maximum or to the minimum because *the distribution of steam load is optimum, when the temporary steam load is distributed by the rate of steam production capacities of individual boilers belonged to the supervisory system*,**
- **soft computing can be used to determine the safety integrity level of SIS, the technological subsystem,**
- **the needed number of protection layers also can be determined in accordance with the SIL and hazardous event severity,**
- **the applied tool is Thom's *conditional catastrophe* theory where the condition is the event likelihood,**
- the supervisor device is a fuzzy logic system to determine the value of multiplier m_i for the optimum distribution of steam load,
- the temporary steam load of an individual boiler is decided in the ratio of nominal loading of boilers,
- **the change of multiplier m_i will affect on the parameters of individual boilers,**
- **the error values flow from the output toward the input layer, that is, the large-scale system operates as a backpropagation neural network consisted of fuzzy neurons.**

New approach: fuzzy neurons composed of analogue circuits

6.1. Introduction

The human intelligence is product of the communicative collaboration between neurons in the brain. The speed of data processing and the number of answers depend on the number of neurons and the number of synaptic connections between neurons. The model of neural network is the human brain, which includes neural network used for perception and conversion inputs into stimulus, a neural network used for preparing the proper answers and activities, and neural network to make activities.

The operation and power of neural system is based on the reflex courses which are used as high-speed, real-time communicational devices (Ganong,1990). The operation of reflex course can be described by the application of formal description (Révész,1979)(Kuki et al., 1993).

Let the neural cell be considered as a finite-state machine (Vollmar,1982) which can be described by the application of formal description by Chomsky. Then the mathematical object for the description of the finite-state machines is the following:

$$M=\{Q, \Sigma, \delta, F\}, \tag{6.1}$$

where M is the symbol of the finite-state machine, Q is the set of states, Σ means the set of inputs, δ is the set of operational rules, and F is the set of finite-states.

6.2. Analog neural cells

Organic neural networks include a lot of neural cells with different functions. Artificial intelligence can be built of networks of artificial reflex courses. This simplification occurs that the number of neural units can be reduced. In accordance with the structure of organic reflex course, three basic types of neural cells has been designed; they are the *afferent neural cell*, the *moto-neuron*, and the *interim neural cell*. These neural cells can be used compose a fuzzy system.

6.2.1. Formal description of the afferent neural cell

The afferent neural cells percept stimuli originated from the environment. One an afferent neural cell can be connected to single receptor, only. The output of receptor is the generator potential. If the voltage of generator potential is high enough then an action potential will be generated on the axon of neural cell. The action potential may occur either excitation, or inhibition. In the first case it is called excitatory post synaptic potential *epsp*, in the second case it is inhibitory post synaptic potential *ipsp*. The model of afferent neural cell is shown in Figure 6.1.

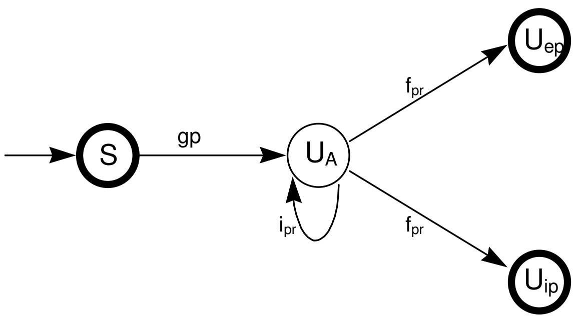


Figure 6.1. Finite-state machine of afferent neural cell

The finite-state machine of the afferent neural cell can be described by the following mathematical objects:

$$Q=\{S,\ U_a,\ U_{ep}, U_{ip}\}, \qquad (6.2)$$

where S means the symbol of initial state, U_a is the symbol of membrane potential on the afferent neural cell, U_{ep} is the symbol of excitatory potential on the post synaptic neural cell, and U_{ip} is the symbol of inhibitory potential on the post synaptic neural cell.

$$\Sigma=\{gp,\ i_{pr},\ f_{pr}\}, \qquad (6.3)$$

where gp means the generator potential on the output of receptor, i_{pr} is the symbol of inhibitory pre-synaptic potential, and is the symbol of pre-synaptic facility potential.

$$\delta=\{(S,\ gp)=U_a,\ (U_a,\ i_{pr})=U_a,\ (U_a, f_{pr})=U_{ep},\ (U_a, f_{pr})=U_{ip}\}, \quad (6.4)$$

and

It can be said by expressions (6.2)-(6.5) that the finite-state machine of the afferent neural cell is a non-determined, fully specified finite-state machine.

6.2.2. Formal description of the moto-neuron

Function of moto-neuron is to influence the operation of muscles, to generate activities. Action reflex is an uncontrolled activity of the muscles which may be occurred by the excitatory post-synaptic potential. If the excitatory post-synaptic potential is eliminated then the moto-neuron will go into initial state.

The model of finite-state machine of moto-neuron is described by the following expressions, and it is shown in Figure 6.2.

$$Q=\{S,\ U_{AC}\}, \qquad (6.6)$$

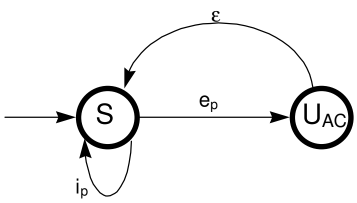


Figure 6.2. Finite-state machine of the moto-neuron

where S is the symbol of set of initial states, and U_{AC} is the symbol of action potential on the output of moto-neuron.

$$\Sigma=\{e_p,\ i_p,\ \varepsilon\}, \qquad (6.7)$$

where e_p is the symbol of excitatory post-synaptic potential, i_p is the symbol of inhibitory post-synaptic potential, and ε is an empty terminal.

$$\delta=\{(S,\ i_p)=S,\ (S,\ e_p)=U_{AC},\ (U_{AC},\ \varepsilon)=S\}, \qquad (6.8)$$

and

$$F=\{U_{AC}\}. \qquad (6.9)$$

It can be said, that the finite-state machine of moto-neuron described by mathematical objects (6.6)-(6.9) is determined, fully specified finite-state machine.

6.2.3. Formal description of the interim neural cell

The model of finite-state machine of the interim neural cell is shown in Figure 6.3. The function of this neural cell is the data processing to produce one or more reactions. Data are sensed internal and external signals. The finite-state machine of the interim neural cell can be described by the following mathematical objects.

$$Q=\{S,\ U_{e1},\ U_{e2},\ ...,\ U_{ex},\ U_{AC}\}, \qquad (6.10)$$

where S is the symbol of set of initial states, U_{e1}, U_{e2}, ..., U_{ex} are the symbols of membrane potentials, and U_{AC} is the action potential of the interim neural cell in its finite state.

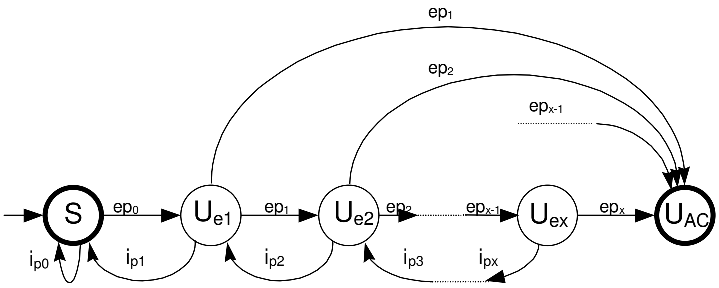


Figure 6.3. The finite-state machine of interim neural cell

$$\Sigma=\{ep_0,\ ep_1,\ ...,\ ep_x,\ ip_0,\ ip_1,\ ...,\ ip_x\}, \qquad (6.11)$$

where ep_0, ep_1, ..., ep_x are the symbols of excitatory post-synaptic potentials, and ip_0, ip_1, ..., ip_x are the symbols of inhibitory post-synaptic potentials.

$$\delta=\{(S,\ ep_0)=U_{e1},\ (S,\ ip_0)=S,\ (U_{e1},\ ip_1)=S,\ (U_{ej},\ ep_j)=U_{e(j+1)},\ (U_{ej},\ ep_j)=U_{AC},\ (U_{ex},ep_x)=U_{AC},\ (U_{ej},\ ip_j)=U_{e(j-1)}\}, \qquad (6.12)$$

where $j=1,\ 2,\ \dots,\ x$, and

$$F=\{U_{AC}\}, \qquad (6.13)$$

where U_{AC} is the symbol of action potential on the axon of interim neural cell.

It can be said that the model of finite-state machine of the interim neural cell described by mathematical objects (6.10)-(6.13) is non-determined, not fully specified finite-state machine.

6.3. The analogue fuzzy system

The neural cells described above are involved into a fuzzy system. This fuzzy system consists of all types of neural cells, the afferent neural cell, and the moto-neuron, and the interim neural cell, similarly to the human nervous system.

The fuzzy system composed of analogue circuits consists of circuits of reflex courses. The structure of the of catastrophe FIS are organized shown in Figure 6.4.

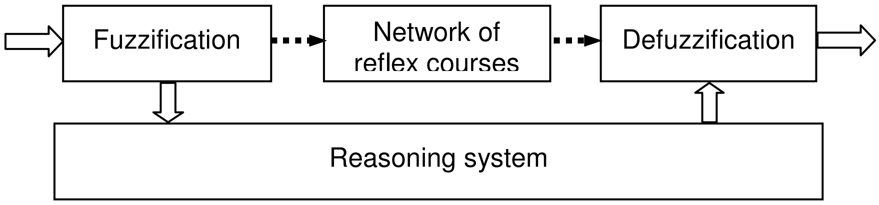


Figure 6.4. The scheme of catastrophe fuzzy inference system

The fuzzifier does not make computation to get fuzzy values, but it produces neural output signals, the membrane potentials which are answers to the stimuli. The fuzzy reasoning system is made by network of interim neural cells where the rules are set by the synaptic networks. All controlled functions require individual fuzzy reasoning network having the appropriate rules. The network of defuzzifier consists of interim neural cells and moto-neurons. Defuzzification means the generation of suitable output voltages.

The network for operating by Thom's catastrophe theory is completed with an additional unit which does not owned by digital fuzzy systems: a by-pass network of reflex courses. This by-pass network is active when the action potential is much more higher than in normal case. Then the output voltage occurred by network of reflex courses will be connected to the proper output device across the defuzzifier. In this case, the reasoning system will be shortcut by the reflex courses because fuzzy rules are invalid in operation. Then the controlled process will be constrained by the by-pass network to set the parameters of controlled process into the range of structurally stable operation.

The neural cells has been developed with the Development Kit TRAC20 of ZETEX, United Kingdom. The circuit of afferent neural cell and measuring data can be seen in Appendix 2, the circuit of interim neural cell and measuring data are shown in Appendix 3, and the circuit of moto-neuron and measuring data are shown in Appendix 4.

6.4. Conclusion

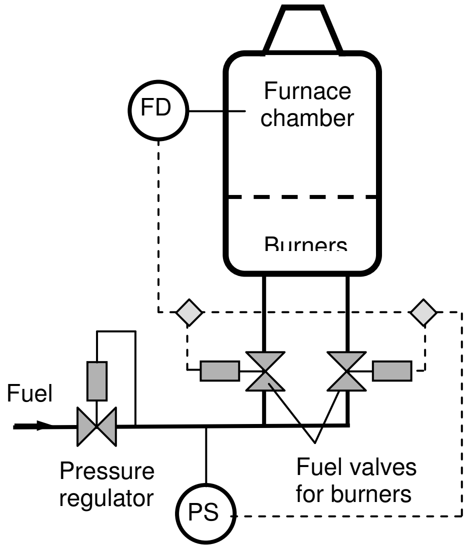
Analogue circuits applied for real-time operation give new opportunity for controlling extremely high speed or extremely low speed processes. That the new approach has the following features:

- an analogue neural network consists of three basic types of analogue neural cells: the afferent neural cell, the interim neural cell and the moto-neuron, which cells has similar architecture but different operations,
- the intelligence of analogue neural network is implemented by hardware synaptic connections, and this connections transfer the membrane potentials from one a neural cell to other neural cells,
- operation of analogue neurons in fuzzy neural networks is described with mathematical objects by Chomsky's rule, the formal description of regular languages,
- the catastrophe FIS includes the network of the *reflex courses* which are the circuit realization of Thom's theory.

Appendix 1

SIL determination by quantitative method

1. SIL for the furnace chamber



Simplified diagram of SIS for the furnace chamber

Symbols in the figure are the following: *FD* is the flame detector, *PS* is the fuel pressure sensor.

The estimated flame out frequency: *Ft=2/years*.

The probability of an explosion if the chance of an explosion is not greater than 1 in 4 per event: $Pe=1/4=0.25$.

The explosion rate: $Pc \leq$ *once per 5000 years*

1.1. Unprotected risk frequency

$$Fnp= Ft\ Pe=2 \cdot 0.25=0.5\ [1/year]$$

1.2. Protected risk frequency

$$Fp= \frac{1}{Pc} = \frac{1}{5000}=0.0002[1/year]$$

1.3. Risk reduction factor

$$\frac{Fnp}{Fp} \quad \frac{0.5}{0.0002}$$

1.4. Safety availability

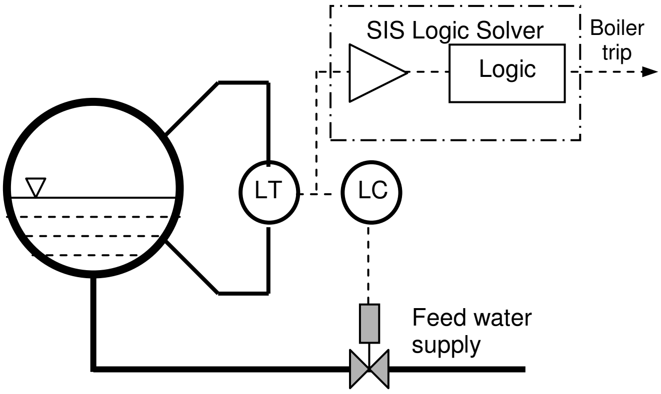
$$\frac{RRF-1}{RRF} \qquad \frac{2500-1}{2500}$$

1.5. Probability of failure on demand

$$\frac{1}{RRF} \quad \frac{1}{2500}$$

1.6. Safety integrity level SIL from the Table 4.1: ***SIL=3***

2. SIL for the steam drum



Shared sensor for level control of steam drum and trip

Symbols in the figure are the following: *LT* means the level tester, *LC* is the control for feed water valve.

The estimated water level error (under minimum) frequency: *Ft=1/years*.

The probability of malfunction if the probability of water level under minimum is not greater than 1 in 6 per event: $Pe=1/6=0.167$.

The malfunction rate: $Pc \leq$ *once per 5000 years*.

2.1. Unprotected risk frequency

$$Fnp = Ft\, Pe = 1 \cdot 0.167 = 0.167\ [1/year]$$

2.2. Protected risk frequency

$$Fp = \frac{1}{Pc} = \frac{1}{5000} = 0.0002 [1/year]$$

2.3. Risk reduction factor

$$\frac{Fnp}{Fp} \quad \frac{0.167}{0.0002}$$

2.4. Safety availability

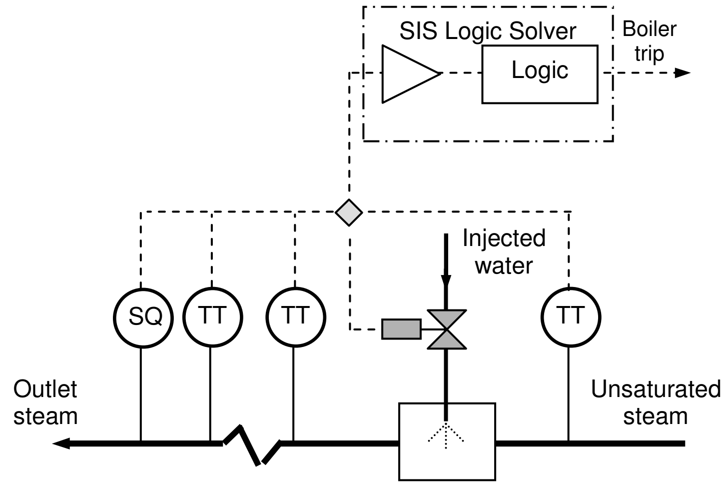
$$\frac{RRF-1}{RRF} \qquad \frac{835-1}{835}$$

2.5. Probability of failure on demand

$$\frac{1}{RRF} \quad \frac{1}{835}$$

2.6. Safety integrity level SIL from the Table 4.1: ***SIL=2***

3. SIL for the water injection for temperature setting



Simplified diagram of SIS for setting of outlet steam temperature

Symbols in the figure are the following: *SQ* is an orifice differential to measure the outlet quantity of steam, *TT*s are temperature transmitters to measure the temperature of steam before and after the water injection.

The estimated temperature setting error frequency: *Ft=1/years*.

The probability of malfunction if the probability of steam temperature under minimum is not greater than 1 in 10 per event: $Pe=1/10=0.1$.

The malfunction rate: $Pc \leq$ *once per 5000 years*.

3.1. Unprotected risk frequency

$$Fnp= Ft\, Pe=1\cdot 0.1=0.1\ [1/year]$$

3.2. Protected risk frequency

$$Fp = \frac{1}{Pc} = \frac{1}{5000} = 0.0002[1/year]$$

3.3. Risk reduction factor

$$\frac{Fnp}{Fp} \quad \frac{0.1}{0.0002}$$

3.4. Safety availability

$$\frac{RRF-1}{RRF} \qquad \frac{500-1}{500}$$

3.5. Probability of failure on demand

$$\frac{1}{RRF} \quad \frac{1}{500}$$

3.6. Safety integrity level SIL from the Table 4.1: ***SIL=2***

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