EXPERT CONTROL SYSTEMS

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Contents

Summary

This chapter provides some introductory material on expert control that complements the material presented in the related four chapters of the present Topic: *Expert Control Systems.* Section 2 gives the basic concepts of expert planning direct and expert control, and Section 3 presents the key features of the expert systems approach to control system development. Section 4 is concerned with the management of uncertainty, and Section 5 discusses a general functional architecture of supervised (indirect) expert control. Sections 6,7 and 8 present respectively a virtual expert control architecture, some more issues on supervisory expert control (based on a multilevel architecture), and an illustrative example of supervisory expert control. Finally, Section 9 gives a brief outline of the four related chapters of the present *Topic.*

1. Introduction

The design and application of knowledge-based expert systems for system control has received a good deal of attention by knowledge engineers and control engineers, due to the resulting improved efficiency, effectiveness and performance under uncertain and varying operational conditions. Expert systems are software programs, supplemented by man-machine interfaces, which use knowledge and symbolic reasoning to perform complex tasks at a performance level usually achieved by human experts. Process supervision and control are knowledge-intensive and experience-based tasks, which in complex processes can sometimes go beyond the capabilities of skilled operators and engineers. Expert systems can provide the critically required assistance for prompt detection and location of process malfunctions, as well as for real-time adaptive and predictive/anticipatory control. Actually, expert control is a paradigm for controllers of higher degree of automation than standard (ordinary) controllers. The system is composed of ordinary estimation and control algorithms which are combined with a knowledge-based system that captures the heuristics concerning the design and operational practice. Expert control can be viewed as a natural extension of conventional automation systems with knowledge-based controllers and relays for logic and sequencing. Many of the non-conventional controllers like fuzzy, neural and neuro-fuzzy controllers fit into this paradigm.

This chapter aims at providing some fundamental issues of expert control methodology which introduce the reader to the present *Topic* of Expert Control Systems that involves four particular related chapters. Sections 2 and 3 present the basic structures of expert control (direct expert control, expert planner-controller) and control system design using expert systems. Section 4 outlines how one can deal with uncertainty in expert control (probabilistic approach, certainty factors approach, Shafer- Dempster approach, fuzzy sets/logic approach). Sections 5 through 7 deal with supervisory expert control and describe a virtual general expert system architecture for expert process control. Section 8 gives a working example of supervisory control (based on the system developed at Lund University) which implements a flexible PID controller procedure involving four steps (operator inquiry, relay tuning, crude control design, final control design). Finally, Section 9 provides a link to all four related chapters of the present *Topic*.

2. Expert Control

In general, the knowledge-based approach to control can be classified in two categories; in the first, an expert system is used as a controller (expert control) and in the second, a knowledge-based planner is used as a controller. The general basic structure of expert control has the form shown in Figure 1.

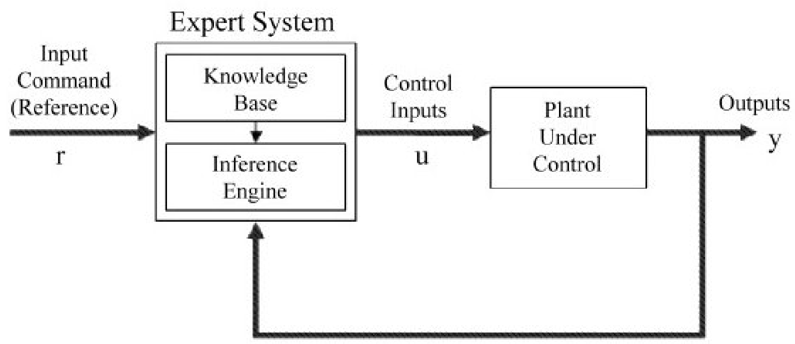

Figure 1: Basic structure of expert control.

Here, the expert system is used as a feedback controller with reference input r and feedback variable y. It employs the 'knowledge' contained in its knowledge base and the 'syllogism' residing in its inference engine to decide what control input u to generate for the plant. Conceptually, an expert controller is similar to a fuzzy controller but its knowledge base can use more general or sophisticated matching strategies to determine which rules should be allowed to fire. Its inference engine can use more elaborate reasoning strategies and priorities such as refraction (i.e. if a rule has fired recently it is not allowed to be considered again for firing) and recency (i.e. rules that were fired most recently are given priority to fire again), etc. The structure of Figure 1 shows a direct expert controller. But the expert system can also be used as a supervisor of conventional or fuzzy/ neuro-fuzzy controllers (the so-called *indirect expert control*). Additionally, expert systems themselves can also be used as a basis for general learning controllers.

Figure 2 shows how a knowledge-based planning system can be used as a typical control system. Here the 'plant' (problem domain) is the environment where the planner is acting.

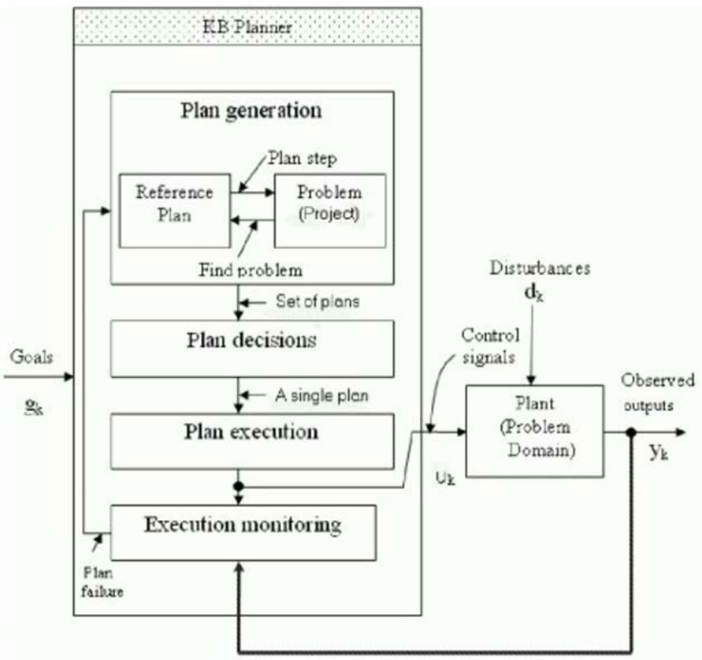

Figure 2: Knowledge-based feedback planner used as controller.

The variables of the problem domain that can be measured in real time are the observed outputs y_k of the plant under control. The disturbances d_k represent the random events which contaminate the outputs y_k. The system designer is given a set of closed- loop specifications which express in a qualified form the desired performance. The planner monitors the goals and observed outputs, and generates control signals (actions) which compensate the effect of the disturbances and ensure that the goals/closed-loop specifications are achieved. To this end, the planner generates a set of candidate plans for the future (usually using a model of the problem domain), which is then pruned to a single plan selected as the 'best' plan to apply at the current time (here the term 'best' can be interpreted in several ways, e.g. minimum energy and resource consumption). This plan is executed and the resulting system performance is monitored and evaluated. Frequently, the plans may fail to satisfy the goals and performance quality due to the existing disturbances. Thus the planner is called to generate a new set of candidate plans, select one, and then execute that one. Two popular ways to estimate and evaluate the problem domain (here the plant) are the use of **world modeling** and **situation assessment.** The planner design uses information from the world modeler and the situation assessment component to ensure that the right plans are made for the current status of the problem domain (the plant). One may note that this planner is actually a type of adaptive controller.

3. Expert System Approach to Control System Development

Using the expert system approach we are shifted from a procrustean design to model realism, i.e. instead of changing the world (problem domain) to fit our model we use system methodologies and information technology which enable the physical (natural) world to be modeled without distortion and destruction. This is achieved by, among others, modeling the existing uncertainty as part of the system and employing approximate and commonsense reasoning. Fuzzy logic seems to be the best approach for modeling and employing uncertainty for the purposes of control. If data is unavailable or inadequate we must not automate but leave the control to the hands of the human experts. In expert control we model the human expert as a decision-maker or controller. If neither a human nor an automatic system is alone adequate, the traditional (old) approach was to apply AdHoc system design, i.e., a mixture of automatic and human decision-making and control. In the expert system (new) approach we apply accountable integration, i.e., we integrate automatic and human activity, making the automation accountable (the decisions and control actions can be explained by the expert system via the replies to WHY questions).

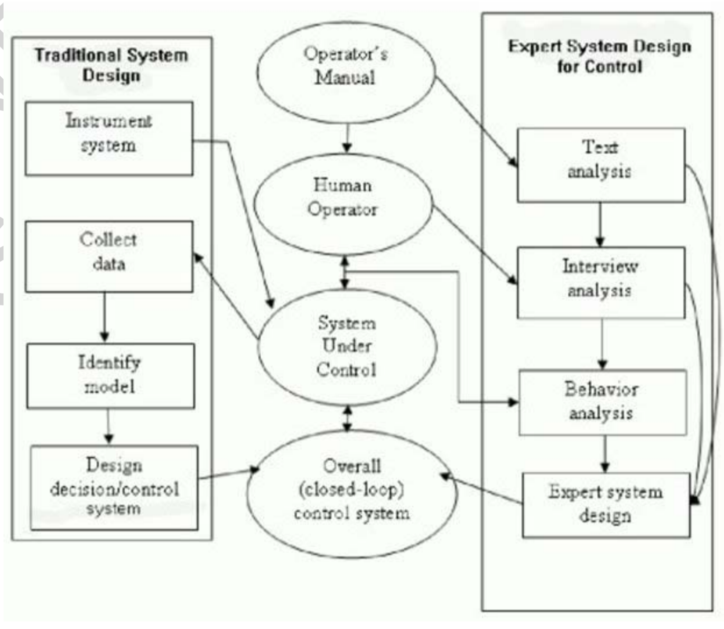

Figure 3: Control system design enhanced with expert system features.

Figure 3 shows the traditional system design paradigm enhanced with the knowledge-based /expert-system component combined with the human operator. The obvious approach to the design is interview analysis which is somehow extensively discussed in the next chapter. However, many times the operator cannot provide a full verbal description of his/her skill, or suggests an incorrect basis of it. In this case, behavior analysis via computer modeling of the operators input-output characteristics gives better results. Text analysis of the operators' manual is an additional source of knowledge about his/her intended behavior.

The knowledge acquisition (KA) tools used for automated KA should be: (i) domain independent, (ii) directly applicable by experts without intermediaries, (iii) able to access a variety of knowledge sources (interviews, texts, observations of expert behavior, etc), (iv) able to encompass a diversity of forms of knowledge and relationships between knowledge.

The users should be able to apply the knowledge in several domains familiar to them and easily experiment with its implications. The system must include facilities for algorithmic expression of knowledge where appropriate. As the overall knowledge acquisition develops it must converge to an integrated system.

4. Uncertainty Management in Expert Control

Uncertainty can be originated from several sources and appears to have many different forms, namely:

- *Random event*
- *Experimental error*
- *Computational error*
- *Uncertainty in judgment*
- *Lack of evidence*
- *Lack of certainty in evidence*

Reasoning under uncertainty is the process of drawing conclusions (and making decisions) in the presence of uncertainty with regard to the pertinent data, and knowledge is used to combat the uncertainty in arriving at the 'best conclusion' (decision, control action). The conclusion drawing/decision- making process can be defined as a set of applicable rules of the form:

IF D is D_x **THEN** A is A_x

where D are the data points in a certain *n*-dimensional data-space and A are the actions (conditions) in a 1-dimensional action space.

Thus $D = \{D_1, D_2, \ldots, D_n\}$ and $D_x = \{D_{x1}, D_{x2}, \ldots, D_{xn}\}$. In many cases the components D_{xi} of D_x involve uncertainty (instrumental errors, conceptual errors, etc) in which case A_x also involves uncertainty. *The problem is to assign the uncertainty value to* A_x

knowing the uncertainty values of D_{xi} $(i = 1, 2, ..., n)$ *expressed in some well defined way.*

The methods for dealing with uncertainty are distinguished in **non-numerical methods** (such as endorsements, high granularity symbol manipulation and nonmonotic logic) and various **numerical methods,** namely:

- *probabilistic approach*
- *certainty factors approach*
- *Shafer-Dempster approach*
- *fuzzy sets approach*

Probabilistic approach: Probability is associated with randomness—the estimation of the likelihood of a given event occurring out of a possible set of events which can be enumerated. Probabilistic techniques are used in stochastic control. The key concept is the concept of 'inverse probability', i.e. the likelihood of an event having a given cause, rather than a cause giving rise to a given event. Bayes' rule is used to compute the updated (posterior) probabilities using the available prior probabilities.

Certainty factors approach: This approach was developed by Shortliffe (1965) in the framework of developing the medical diagnostic expert system **MYCIN .** It is a good tool for diagnostic purposes but not for control.

Shafer-Dempster approach: This approach provides a rigorous basis for the use of certainty factors and other indicators (measures) of uncertainty. It uses the numbers of the interval [0,1] to represent the support of some hypothesis from a piece of evidence. For each hypothesis we assign the so-called evidential interval $\left[Cr, Pl\right]$ to express the uncertainty that exists in the validity of the hypothesis, where Cr is called credibility measure and Pl the plausibility measure. The Shafer-Dempster approach is very useful in signal (data) fusion.

Fuzzy sets approach: This approach was initiated by Zadeh (1965) and is extensively used in control, called *fuzzy logic control* or *fuzzy expert control*. Here, some or all of the rules of the expert system are fuzzy, .i.e. their premises and conclusions are fuzzy sets involving fuzzy (or linguistic)variables. The set A is said to be a fuzzy subset of a superset X if and only if

$$A = \left\{\left(x, \mu_A\left(x\right)\right) \middle| x \in X, \mu_A\left(x\right) : X \to [0,1]\right\}$$

where the function $\mu_A\left(x\right)$ is called the membership function of x. Clearly, in the special case where we have the two-valued set {0,1}, instead of the closed interval [0,1], the fuzzy subset A degenerates to the crisp (conventional) set A. The set operations: Union, Intersection and Complement are properly defined and the standard modus-ponens inference rule is generalized and expressed via Zadeh's max-min (or fuzzy composition) rule. Details on this approach can be found in the literature (e.g. the book of H.J. Zimmermann : Fuzzy Set Theory and Applications) and other chapters of this encyclopedia (e.g. the chapter of Albertos and Sala in the present topical group of chapters).

5. Supervisory Expert Control

A general structure of supervisory (or indirect) expert control has the form shown in Figure 4.

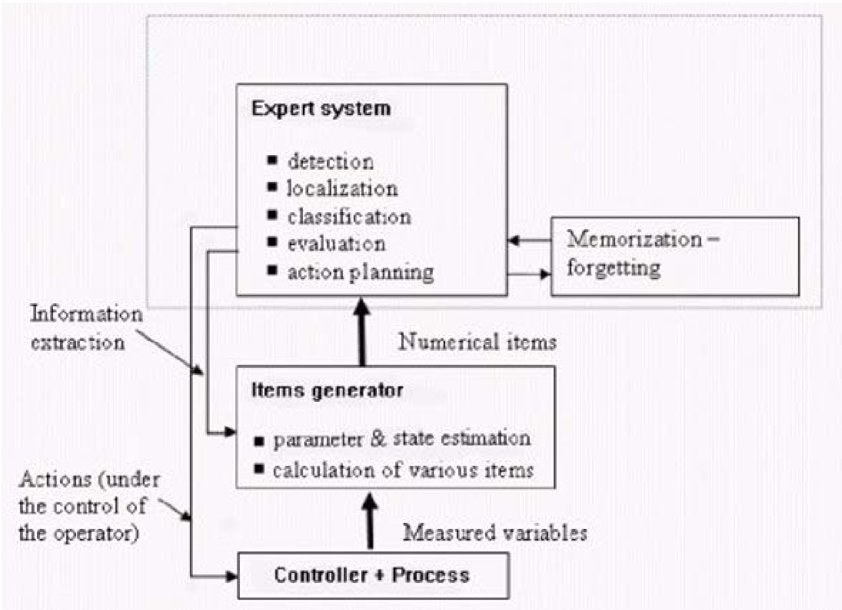

Figure 4: General functional structure of supervised expert control.

The supervision scheme must be able to face the case where the process under control is subject to both slow and fast changes at known or unknown instants, and also to environmental nonstationarities. System measurable inputs and outputs are used online to provide real-time estimation of the plant's model parameters. The identification of nonstationarities and the adaptation of the controller are performed under the control of a unique supervisory unit in three hierarchical levels, namely (in bottom-up direction): **contro**ller, perception (items generator) and decision (supervisor) levels. It is in the decision level that one can use an expert system tool for handling the quantitative and qualitative information about the process at hand. At the perception level, functions are continuously performing, but at the decision level, functions are discontinuous in time resembling (mimicking) the human operator actions. It should be remarked that the above expert supervisor is not intended to replace the process operator but to assist him/her by providing rapid useful real-time information about the process state. This is particularly important in large scale industrial processes, like a nuclear power plant or refinery, where the operator receives for handling thousands of measurements and alarms, while the plant status can change significantly within a few minutes. Exhaustive search is therefore not possible in real time. Thus the basic issues in designing an expert system for this purpose are:

- *Fast recognition of process conditions which are potentially significant*
- *Use of appropriate rule sets and focuses on these problem areas for diagnosis and control advice.*

Expressed in a different way, the three hierarchical functions of process management are:

- *Direct interaction with the process*
- *Supervision function*
- *Executive production scheduling and operational management.*

The first layer which is actually the interface between the process and the decision and control units involves three components, namely: data acquisition, event monitoring, and direct control function which implements the control policy selected by the supervisory layer. The supervisory unit supervises the operation of the first (lower) layer controller by renewing the parameters of the control law and of the monitoring functions. It also determines and imposes appropriate constraints wherever the process tends to fall in an emergency mode. Finally, the third layer involves high-level management activities such as production scheduling and operational management. The knowledge based approach is applicable to all hierarchical functions of process management mentioned above. The fault detection/diagnosis expert system module can be embedded to the lowest (i.e. the interface) layer as well as to the highest (the supervision) layer. In some cases, the event detection/localization, event analysis and reaction procedures are combined together in one component known as 'supervision loop'. Recently, supervisory expert control systems are enriched with proper learning, diagnosis, optimization and control units based on the capabilities of neural networks, neuro-fuzzy systems and genetic algorithms. A discussion of them is beyond the scope of the present chapter, but can be found in other chapters of this encyclopedia.

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