EXPERT CONTROL SYSTEMS: AN INTRODUCTION WITH CASE STUDIES

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Keywords*:* Expert control, knowledge representation, rule-based systems, knowledge acquisition, computer-aided control systems design, real-time expert systems, blackboard model.

Contents

Summary

This chapter gives a concise presentation of expert control on the basis of a generic architecture that involves the operator, the expert system, the control algorithm, auxiliary units (parameter estimator, state estimator, fault detector) and the plant under control.

Particular aspects covered are knowledge representation, knowledge acquisition, reasoning in expert control, real-time expert systems, expert system-based computer-aided control and anticipatory systems. Three case studies are briefly described to clarify many of the above concepts.

1. Introduction

Expert control or, more generally, knowledge-based control is a generic type of control possessing features of higher level than traditional controls. These features are usually achieved by involving human operator expertise or knowledge in the control loops. Expert control belongs to the more general class of intelligent control that aims at increasing the autonomy of technological systems such as process control systems, autonomous vehicles, robotic systems and manufacturing systems. Expert control can be used for both model-based and model-free control procedures although it fits more to the latter case.

Intelligent control has a hierarchical structure. At the lowest level, deterministic feedback control based on conventional control theory is employed for single linear plants. Kalman or other types of filters are used when the process stochastic noise and input disturbances are significant. Adaptive control techniques are used when the variations of plant parameters are large such that linear robust control theory is inappropriate. For still more complex plants, self-organizing or learning control may be necessary. At the highest level, plant complexity is so high and performance requirements so demanding, that intelligent control techniques (e.g. expert control) are necessary. The need to use intelligent autonomous control comes from the desire to have an increased level of autonomous decision making abilities in achieving/performing complex /sophisticated control tasks.

The three fundamental hierarchical levels of intelligent control are:

- **Organization level** (control executive): It performs upper management, learning and decision making functions (it issues commands to the managers and coordinates their actions),
- **Coordination level** (control manager): Middle and lower management, learning, decision making and supervision algorithms.
- **Execution level**: Decision and control algorithms in hardware and software.

Expert control is actually designed so as to possess a set of fundamental features which include (but are not restricted to) the following:

- ability to control a large repertory of systems (nonlinear, time varying, uncertain, etc)
- ability to use in an intelligent way the available *a priori* knowledge (which may be minimal)
- ability to work with qualitative specifications provided by the user (e.g. “small overshoot”, “fast response”)
- ability to enhance (via learning) its knowledge and improve its performance as the process operates
- ability to carry out fault detection/diagnosis procedures and accommodate faults (in the actuators and sensors) so as to assure an acceptable performance level (fault tolerance ability).
- Ability to communicate and interact with the user/system operator

– Ability to store transparently the underlying control knowledge and control heuristics in a way that allows their easy examination, modification and extension.

It is remarked that existing practical expert control systems have not necessarily all the above features, depending on the nature and particular goals of the plant under control.

2. Expert Control System Architecture

A generic architecture for expert control systems should include both the standard expert system's components and the control system's components in an integrated and cooperative way. In other words the expert system here should be part of a conventional feedback loop with a process, a controller, a parameter/state estimator, a fault detector/ isolator and a supervisor (Fig. 1). In actual practice very few systems exist that have embedded all the above components.

Over the years much effort was devoted for solving efficiently the analysis and design problems of controllers, parameter estimators, state estimators, fault detectors / diagnosers and supervisors using model based techniques. These efforts, together with the fuzzy logic, neural network and genetic algorithm techniques, have shown a significant impact on the practice of automatic control.

Our focus here will be on the issues of expert/knowledge-based control founded on the artificial intelligence methodologies. Thus we will start with the basis of expert control, i.e. the expert system component of Fig. 1.

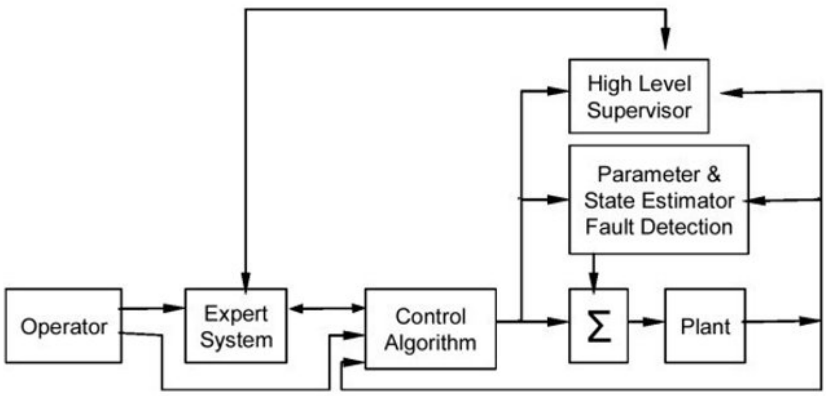

Figure 1: Generic architecture of expert control

An expert is a person, who, because of education and expertise, is capable of doing things the rest of us cannot. By expertise it is meant the solid body of operative knowledge each expert has about the problems of his/her domain. Thus, naturally, experts are the ones to ask when it is desired to represent the expertise that makes their behavior possible.

An expert (knowledge-based) system involves three main components: *knowledge of facts*, *knowledge of relations between the facts,* and a suitable technique for *acquiring*

and *storing* this information. An expert system is called to construct its solution selectively and efficiently from a space of alternatives. Since unavoidably the resources are limited, the expert system must search this space with as little unfruitful activity as possible. The expert's knowledge helps to draw useful data early, suggests suitable paths to exploit them, and helps to avoid low payoff efforts by rejecting blind paths as early as possible. The construction of an expert system is the subject of *knowledge engineering*. The job of the knowledge engineer is to extract the knowledge (i.e. rules, procedures, strategies, etc) out of human experts, and to embed it into a knowledge base. More on the knowledge acquisition process will be provided in section.
The architecture of an expert system is shown in Fig. 2.

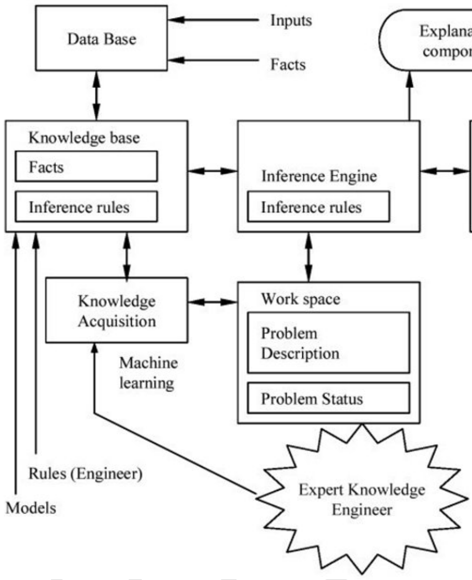

Figure 2: Expert system architecture

The components of this architecture are:

- Knowledge base (KB)
- Data base (DB)
- Inference engine
- Explanation component (EC)
- User interface (UI)
- Work space (WS)
- Knowledge acquisition (KA) component.

The KB contains the available symbolic knowledge about the problem, i.e. facts and rules. The DB contains the numeric information about the problem, i.e. input data. The inference engine involves methods for applying the general knowledge of the problem, e.g. a mechanism to match the left hand sides of the rules in order to succeed the goals or subgoals (i.e. the rules' actions). The explanation component serves to inform the user on how and why the conclusions are obtained. The user interface provides the means for the interaction of the user with the system. The WS is actually an area of memory for storing a description of the problem constructed from facts supplied by the user of inferred from the KB. Finally the KA component helps to extract the required knowledge from the expert.

A schematic view of the expert system building (construction) process is shown in Fig. 3.

The knowledge engineer extracts the knowledge from the expert and embeds it into the expert system tool used to construct the expert system in an interactive way that involves testing and tuning (refining) procedures.

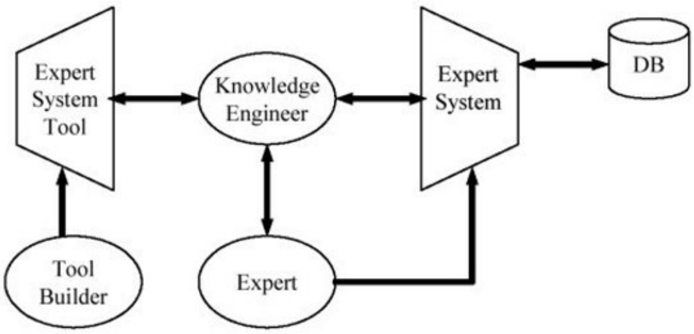

Figure 3: Expert System Building Process

The main advantages of using an expert system (artificial expertise) instead of an expert (human expertise) in control are the following.

Human Operator Expertise

- Perishable
- Difficult to transfer
- Difficult to document
- Unpredictable
- Expensive

Artificial Controller Expertise

- Permanent
- Easily transferable
- Easy to document
- Consistent
- Economically affordable

In many situations it is necessary or useful to keep a moderate human expertise inside the loop in order to fill up the holes and the imperfectness of the expert system. Clearly, the human experts have special features like: creativeness, adaptiveness, broad view, common sense and sensorial observation. It should also be remarked that symbolic inputs are inferior to sensorial observations since the latter starts from a global view that captures a priori mutual relations. The concept of common sense is difficult to describe exactly, but it is a kind of broad view of general knowledge about the system's world, its mechanisms and its relations. Actually, commonsense implies the awareness of some knowledge and the lack of awareness of other knowledge.

Regarding the control algorithm component in Fig. 1 it is noted that many different options for the same feedback control task may be used, for example PI, PID, PLC, self-tuning control, state or output feedback control, etc. Also there exist algorithms for generating perturbation signals to excite the process. The fault detection and diagnosis element serves to find faults that are local to the control loop whereby the expert controller belongs. This is different than the plant wide fault detection which needs separate specialized (model based or knowledge based) techniques.

A dominant reason for employing expert control is to reduce the engineering effort needed for realizing and exerting feedback control. This is due to that an expert controller supports many of the functions that are traditionally performed by operators, process specialists and control engineers and technicians. These functions are either computer supported or fully automated. Therefore, an expert controller helps to have a system with a higher degree of automation than a traditional control system. Of course, the use of expert controller design should be based on both the static and dynamic features required to be possessed by the overall closed-loop system. Static input-output features include signal ranges and static input-output relations. If the experimental data give a precise curve we have a *servo problem*, otherwise (i.e. when no definite relation between inputs and outputs can be established) we have a *regulation problem*. For a servo problem the variations in the static gain of the system must also be determined, which provides a good indication of whether gain scheduling is needed. The static gain curve can also be employed for diagnostic purposes.

The dynamic features include both *crude* (qualitative) and *detailed* (quantitative) features. Qualitative features are: stable / unstable, monotone / oscillatory, essential monotone, minimum phase, etc. These features can be determined by simple experimentation or by a properly trained operator or a neural network. The two principal techniques commonly applied are *step response* and *frequency response*. Quantitative features refer to both the amplitude and time characteristics. The amplitude can be described by mean, variance, maximum and minimum values. For a more detailed description the amplitude distribution is required. The time variations include: time constants, spectral distribution and cutoff frequencies. For a good assessment the disturbance levels below and above the bandwidth of the system (i.e. the time scale) must be known. In a PID controller the high-frequency measurement noise can be assessed by measuring the mean square value of the derivative part. Disturbances are key aspects of control systems design. The trade-off between rejection of load disturbances and measurement noise is a fundamental question, but no general methods exist (like Ziegler-Nichols method) to determine this trade-off. However, it helps a lot to know the origin of disturbances, i.e. if they are due to measurement noise, parameter variations, set-point changes or load variations. All the existing expert control systems in the process control and manufacturing industry employ proper static and dynamic design specifications.

3. Knowledge Representation in Expert Control

The way knowledge is represented, stored and extracted from the KB is a primary issue of expert systems and expert control. It affects the feasibility of the application, because no matter how nice an intelligent expert system / controller may be, it is useless if the time required to infer the answer is too long. This is particularly so in process and industrial / manufacturing control applications where the real-time aspect is a severe requirement. Before discussing the various knowledge representation schemes we briefly outline the type of control knowledge.

3.1. Control Knowledge

Domain (control) knowledge is a basic issue in expert control. Automation of control system design and operation involves the tasks of design, commissioning, normal operation, and treatment of emergencies. Control system design involves issues like modeling, control performance, and control law selection. Commissioning involves: initialization, tuning, troubleshooting and loop auditing. Normal operation involves supervision, diagnosis and fault detection.

To perform the above tasks knowledge about process dynamics, actuators' saturation, performance specifications and disturbances should be appropriately represented. It is essential to determine whether the performance is limited by the dynamics or other factors (e.g. the existence of oscillatory modes, the order of dynamics, time delays, etc). Time delays can be reduced by repositioning sensors and actuators. Dynamics can be improved by replacing sensors and actuators with faster ones.

Modeling uncertainty is another limiting factor. It can be reduced by having a high loop gain at the frequencies where the uncertainty is large. However special attention is needed for maintaining a high loop gain, since we need to know reasonably well the phase around the cross-over frequency. Uncertainties in the time delay, which result in very large phase uncertainties at high frequencies provide a severe limitation on the achievable bandwidth. The treatment of all the above issues is facilitated by proper knowledge acquisition, representation, and processing.

3.2. Rule-Based Systems

First-generation expert systems use the knowledge representation in the form of IF-THEN rules (the so-called production rules). Rules are also a natural way to describe much of the logic which is built around conventional controllers, but are not well suited for problems that have a strong sequential element, like the planning problem which needs the automatic generation of a sequence of actions that lead to a desired goal (e.g. bring an oscillatory system to a stable state, move a system from one operating condition to another in a smooth way, and so on). Planning has received much attention in AI research characterizing each action by preconditions and postconditions. Planning is outside the scope of this article, although many if the tasks in expert systems can be described as planning problems. For details on the planning problems the reader is referred to .

The basic form of a production rule is

Rule R_k

IF $c_1,\ c_2,\ \dots\ ,\ c_m$

THEN $h_1,\ h_2,\ \dots\ ,\ h_n$

where $c_i (i = 1, 2, \dots, m)$ are predicates known as conditions (antecedents, premises) and the h_i $(i = 1, 2, \dots, n)$ are referred to as consequents (conclusions, deductions, actions). The fundamental reasoning (syllogism) that applies here is: "IF A implies B and B implies C, then A implies C". When all $c_i (i = 1, 2, \dots, m)$ are true, rule R_k is said to be triggered. The set of triggered rules is called the conflict set. A rule is selected from the *conflict set* using a *conflict resolution strategy*. A triggered rule is said to be fired when its consequences are performed.

Some strategies for selecting the rule for firing from the conflict set are:

- Rule ordering (Rule appearing earliest has highest priority.)
- Data ordering (Rule with highest priority data-condition has highest priority.)
- Size ordering (Rule with longest list of constraining conditions has highest priority.)
- Context limiting (Activate or deactivate groups of rules at any time to reduce the occurrence of conflict.)
- Specificity ordering (Arrange rules whose conditions are a superset of another rule.)

The conflict resolution strategy is selected ad hoc. Most popular are specificity-ordering and context-limiting strategies.

The control (or interpretation) mechanism used by synthesis systems is:

1. Find rules whose IF parts are triggered, and select a rule using a certain conflict resolution strategy.
2. Fire the rule (i.e., do what the rule's THEN part says).

In analysis systems, the antecedents of rules can be either observed or derived facts, and the consequents are new facts that are deduced. The above mechanism is known as a *forward-chaining inference* mechanism. In analysis systems the control mechanism can be either of the forward or backward chaining type. In the backward-chaining mechanism, a particular hypothesis is selected, and the rules are searched to see if the hypothesis is a consequent. If yes, the antecedents of the rule constitute the next set of hypotheses. The process is continued until some hypothesis is not true or all hypotheses are true based on the data. Forward and backward inference chaining resemble the bottom-up and top-down control in general computer algorithms (compilers).

Rule-based systems have many advantages. For example:

- They provide a homogenous representation of knowledge.
- They allow incremental growth of knowledge through addition of new rules.
- They allow unplanned but useful interactions.

Rule-based systems can be efficiently implemented using various programming languages such as Pascal, C^{++}, Lisp, or Prolog or expert system tools (shells) which possess built-in inference mechanisms (including mechanisms for fuzzy reasoning).

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