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THE APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNIQUES FOR INTELLIGENT CONTROL OF DYNAMICAL PHYSICAL SYSTEMS

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SUMMARY

There is an increasing concern among the scientific community and industrialists over the safe and reliable operation of control systems in industries. Although several adaptive control techniques have been introduced, they are not robust enough for many real-world problem domains where the degree of uncertainty is high and therefore classical methods of mathematical modelling and control fail. Computer technology has reached a point where *machine intelligence* can be incorporated in many of the systems that we use daily. Changes in environments, unmeasurable disturbances, changing reference models and performance criteria and component failures are some of the characteristics which necessitate intelligent control. The developments in the field of artificial intelligence have reached a stage which will help to reduce these control complexities by incorporating *intelligence* into the control systems. In this paper we explain various artificial intelligence techniques that can be used to control dynamical physical systems.

KEY WORDS Artificial intelligence Intelligent control Neural networks Machine learning Fuzzy logic Expert systems

1. INTRODUCTION

In recent times there has been a growing concern over the safe operation of control systems in industries after the accidents at Bhopal, Windscale, Chernobyl, Three Mile Island, Seveso and Flixborough. Most of these accidents have been caused or exacerbated through human error in controlling the process systems. This has led to increasing concern among the scientific community and industrialists over the safe and reliable operation of control systems in industries. Such control systems should be able to withstand sudden changes in environments, unmeasurable disturbances, changing reference models and performance criteria, component failures, etc. in order to prevent industrial disaster.

Advances in the theory and practice of automatic control provide better control quality and the opportunity to meet the needs of more applications. As a result of such advancement, a substantial change in process automation has occurred in recent years and has led to the

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development of the so-called 'higher autonomous functions' such as[1]

(1) operation guidance
(2) process optimization
(3) production management
(4) emergency/security control
(5) emergency management.

The application of the above autonomous tasks to complex systems creates many problems such as[1]

(1) markedly incomplete information on the system and the running process
(2) fuzzy and/or confusing information
(3) important characteristics of the system cannot be fully formalized by classical methods
(4) multi-objective decision making
(5) disturbances are characterized by high amplitudes
(6) large volume of data
(7) the set of admissible control actions cannot be overlooked.

On the other hand, as social and technological systems are becoming increasingly complex and highly coupled, the demand for more powerful systems with strong control theory is growing rapidly. Although several adaptive methods have been introduced to solve the above complexities, they are not robust enough for many real-world problems where the degree of uncertainty is high and the computational complexity grows rapidly with the number of unknown parameters. Hence these methods fail to control. Today the development in artificial intelligence (AI) has reached a stage which will help to reduce these complexities.

The purpose of this paper is to provide an insight to the various artificial intelligence techniques that can be used to control dynamical physical systems.

2. THE CONTROL PROBLEM

The vast majority of processes in nature and in our man-made world exhibit dynamic behaviour, i.e. they change over time. Some examples are process control in industry, weather, gas pipelines, etc.[2] Control of the dynamic behaviour has been a challenge to the research community for years. All control problems involve manipulating a dynamical system input so that its behaviour meets a collection of specifications constituting the control objectives. A control system is called upon to satisfy various requirements, namely (i) suppressing the influence of external disturbances, (ii) ensuring the stability of the process and (iii) optimizing the performance of the process. Rational design of control systems requires both steady state and dynamic information about the process. The single most difficult problem is generally understanding the process. The processes are in general characterized by large dimensionality, strong interaction among process variables and very strong non-linear behaviour. Moreover, the control system that has to be built incorporating all these factors should also be able to withstand sudden changes in environments, unmeasurable disturbances, changing reference models and performance criteria, component failures, etc. in order to prevent industrial disaster.

The control of uncertain systems is difficult for a number of reasons.[3] First, it is not easy to find a suitable model structure from the non-linear dynamics, unlike linear systems where a standard form of transfer function is available for unknown systems of given order. The most appropriate control actions are unknown for non-linear systems. Secondly, there is no standard way of generating adaptation laws for non-linear systems. Thirdly, when a model is constructed, one must perform a set of experimental model validation tests to understand the conditions under which the model is accurate. Therefore the difficulties that arise in the control problem can be broadly classified into three categories. The first is complexity, the second is the presence of non-linearities and the third is uncertainty.[4]

3. INTELLIGENT CONTROL APPROACH TO THE CONTROL PROBLEM

One of the challenges for future research in the field of control is to develop robust, adaptive and fault-tolerant controls.[5] Over the years significant progress has been made in the theory and applications of adaptive control;[6] it has become a promising approach to achieve high performance of advanced control systems. However, the current adaptive control approach has its limitation: it makes use of a structured type of uncertainty in which the plant model has a known form but unknown parameters; the uncertainty is reduced by on-line parameter estimation in the adaptive feedback loop. Moreover, adaptive control systems designed according to the existing theory could become unstable owing to the excitation of the inevitable unmodelled dynamics and in the presence of unmeasurable output disturbances. Adaptive controllers do not have long-term memory and hence do not remember the optimal control parameters corresponding to different configurations of the plant. With an environment which is only partially known it is therefore necessary that the system be able to learn the characteristics of the environment so as to improve its control strategy. Hence there is a need for systems which possess some form of *intelligence* to be robust and adaptive in nature.

Changes in environments, unmeasurable disturbances, changing reference models and performance criteria and component failures are some of the characteristics which necessitate intelligent control.[4] The system should be able to learn from its experience in order to achieve some form of *intelligence*. Computer technology has reached a point where *machine intelligence* can be incorporated in many of the systems that we use daily. 'Intelligent control' has been used in a variety of ways and means different things to different people. Yet it is fairly clear that optimal control, adaptive control, robust control and so on depend heavily on the deterministic or stochastic features of the system of interest and rely on modelling, functional representation and logic as related to fixed goals. Intelligent control includes one feature that distinguishes it from other types of control, namely the capability of learning. Qualitatively, a system which includes the ability to sense its environment, process the information to reduce uncertainty and plan, generate and execute control action for several situations constitutes an intelligent control system. The greater the ability with the above difficulties, the more intelligent is the control system.

The challenge for any intelligent control system lies in two stages.[7] First, combining the readings for various sensors into a coherent and accurate picture of the world — a process called sensor fusion — is often difficult. Secondly, evaluating actions typically requires predicting their consequences to determine their suitability for the current situation. Intelligent control systems have two unique features that differentiate them from conventional control systems,[8] namely 'ability to make decision' and 'learning capability'. It is not possible to apply the well-known mathematical tools and techniques to achieve these characteristics. Intelligent control systems can be classified into two broad categories, namely (i) direct intelligent control and (ii) indirect intelligent control.[9] Figure 1 shows what a direct intelligent control system looks like. For this method the intelligent control component is included directly in the control loop. Figure 2 shows a typical indirect intelligent control system. In this system a controller

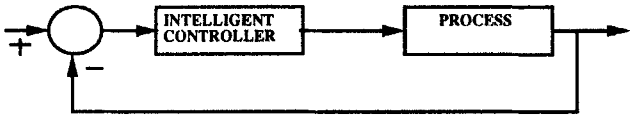

Figure 1. Direct intelligent control system

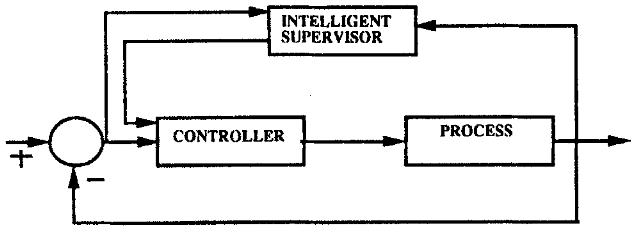

Figure 2. Indirect intelligent control system

is supervised by an intelligent supervisor. The controller can be a conventional controller or an intelligent controller.

Intelligent control strategies can be classified for purposes of understanding and analysis by several approaches. However, the underlying control technique is always based on a relationship between the measured output from a plant and the control input. This relationship is used to compute the control input, which is then used to control the plant. The relationship itself is often termed the *'control surface'*[10] and can take several forms. The paradigm used in synthesizing this control surface can be termed the *'control strategy'*.

4. ARTIFICIAL INTELLIGENCE FOR INTELLIGENT CONTROL

Artificial intelligence (AI) is roughly 36 years old.[11] In 36 years AI has made a huge impact in diverse scientific fields with a number of notable achievements. Artificial intelligence techniques have made significant impacts in the area of control in recent years.[9] The necessity for applying artificial intelligence to control problems originates from the growing complexity of modern control systems as well as from the traditional expense, time constraints and limited availability of human expertise. Classical control methods identify locally optimal control actions based on mathematical models of monitored processes. By contrast, artificial intelligence methods identify control actions that are locally and globally desirable based on knowledge and reasoning about monitored processes. AI technology offers the tools that enable us to[12–14]

(1) capture and retain expertise gained over many years of engineering
(2) amplify expertise needed to successfully deploy new methods and applications
(3) design systems that reason intelligently about necessary actions to take in real time, thus assisting operational staff.

AI systems should approach the control problem as a real-time planning problem.[15] The system should operationalize the intelligent control problem solving by achieving (at least) the following behavioural goals:

(1) make explicit control decisions that solve the control problem
(2) decide what actions to perform by reconciling independent decisions about what actions are desirable and what actions are feasible
(3) adopt various grain size control heuristics
(4) adopt control heuristics that focus on whatever action attributes are useful in the current problem-solving situation
(5) adopt, retain and discard individual control heuristics in response to the dynamic problem-solving situation
(6) decide how to control multiple heuristics of varying importance
(7) dynamically plan a strategic sequence of actions
(8) reason about relative priorities of domain and control actions.

AI control methods in general use symbolic reasoning with knowledge of the physical process and goals to detect anomalous trends, predict equipment failures and schedule appropriate maintenance before failures occu.. By applying more knowledge and various reasoning methods, an AI approach can respond to situations where classical control assumptions are not satisfied. An AI control system uses a global perspective of the process, looking at many different parameters to choose actions appropriate to the process goals. Classical control and AI control complement each other in the way each uses data, the decisions made and the time scale of responses. A closed-loop controller responds immediately to every value it receives for each of the few parameters it senses by adjusting the input to some effector. On the other hand, an AI system might look at values from many sensors, focusing on parameters relevant to current reasoning tasks and filtering or abstracting the data appropriately to preserve its computing resources. The selected data streams and type of filtering change as the environment and the needs of the reasoning system change. An AI control system can also use the behaviour of the real-time controllers as data. An AI system uses more knowledge and executes more complex computations to reason about abnormalities when the underlying assumptions of classical control are no longer met or when operating limits are exceeded.

On the basis of both the many professional publications and observations of industrial practice, it can be seen that three artificial-intelligence-based approaches seem to have significant impacts in the area of control, namely

(1) knowledge-based expert systems
(2) fuzzy logic
(3) machine learning.

These three approaches, all of which can be classified as falling into what has now become known as 'intelligent control', seem to offer much potential.

5. KNOWLEDGE-BASED EXPERT SYSTEMS FOR INTELLIGENT CONTROL

Expert systems or the so-called knowledge-based systems that emerged from applied artificial intelligence in the 1970s have demonstrated their ability to solve difficult problems of a specific domain.[16] Following the initial success of few expert systems, there is an increasing desire to apply expert system methodologies in a variety of areas.[17] The application of expert system techniques to process control has given rise to the term 'expert control'.[18] Expert system techniques offer considerable advantage in control applications compared with traditional numerical approaches. Two distinct approaches to utilizing expert systems in the design of control systems are currently being investigated. One approach attempts to automate the knowledge and skills of the control engineer, while the other attempts to represent the skilled operator's understanding of the process. These are fundamentally different approaches. The former attempts to select, modify or adjust a conventional control scheme if and when a deterioration of the performance is detected; it is a form of heuristic logic, switching in various control designs in an attempt to maintain control over a wide range of operating conditions. The latter approach replaces conventional analytic methods in favour of domain-specific knowledge of the behaviour of the process. The problem-solving power of any knowledge-based system comes from the knowledge it possesses and not just from the formalisms and inference scheme it employs.[19] Therefore, to make a knowledge-based system intelligent, it should be provided with lots of high-quality data about the problem domain. This applies to both the above approaches. Moore[20,21] believes that expert system technology offers a completely new way of augmenting the expertise of operators and can also offer cost benefits in the area of process optimization and scheduling.

There are advantages in using a knowledge-based system approach in control. Firstly, this approach allows us to tackle problems which have proved difficult for the more conventional techniques — either through the complexity of the task or through the task being too ill understood. Secondly, the knowledge-based approach can lead to more flexible and robust systems. In making the underlying knowledge more explicit, knowledge-based techniques make it possible to reuse that knowledge in different circumstances. Thirdly, the knowledge-based approach can lead to improved performance. The knowledge-based approach can use a wider range of data sources, including qualitative and uncertain data, by exploiting AI-based techniques for data fusion and reasoning under uncertainty. Fourthly, the knowledge-based approach helps to work closely with the users by providing them with alternative solutions and explanations about the processes rather than just giving out the results. It will provide a clear picture of what is happening and does not simply deluge the users with data. Finally, even if none of the above benefits was relevant and all applications could be handled completely satisfactorily by current algorithmic methods, there would still be the question of economics. A well-designed knowledge-based system should be easier to maintain and easier to reuse in new circumstances than a conventional programme. Given the soaring costs of software

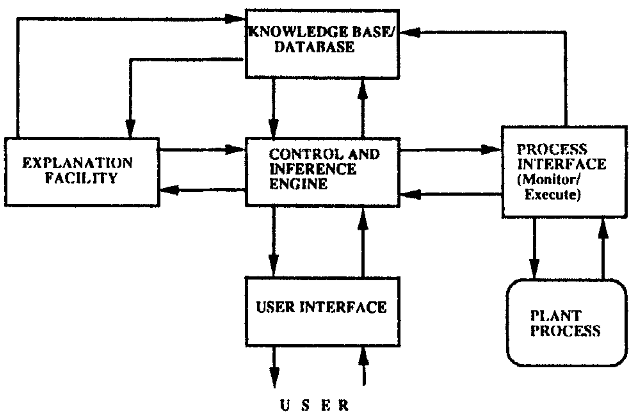

Figure 3. Conceptual view of a knowledge-based system for control operations

production, it may be that the economics of software ownership will eventually be the strongest force behind the move to knowledge-based approaches. In Figure 3 we present a conceptual view of a knowledge-based system for control operations.

6. MACHINE LEARNING FOR INTELLIGENT CONTROL

Machine learning, a branch of AI, has evolved through several stages. There have been several attempts to define machine learning and there is no standard definition yet. Machine learning is a very general term denoting the way in which computers increase their knowledge and improve their skills.[22] More precisely, machine learning refers to the ability of a computer to learn from the experience of repetitively performing a task, thus giving it the ability or knowledge to do better the next time around.[23] Manual methods of acquiring domain-specific knowledge from experts have a number of problems.[24] One can view machine learning as an alternative to knowledge engineering that replaces the interview process and manual entry of knowledge with automated methods.[24] Machine learning covers widely disparate techniques. There are almost as many paradigms for machine learning as there are systems.[26] Methods have been reported with claim to learn by analogy, abduction, being told, cases, debugging, discovery, doing, examples, experimentation, explanation, exploration, initiation, instruction, observation, rote and taking advice.

Machine-learning research spans almost for four decades and much of the research has been to define various paradigms, establish relationships among them and elaborate the algorithms that characterize them. Much less effort has been devoted to bringing machine learning to bear on real applications. Recently researchers have focused more on applying machine-learning techniques to real-world problems.[27] Machine-learning techniques have been successfully applied to real-world problems in the areas of classification and prediction, understanding events, configuration and design, planning and scheduling, and execution and control.[25] The success in applying machine learning to real-world problems in recent years has attracted considerable attention in the control community. When unpredictable effects exist while controlling a physical process, it might be expected that a controller capable of learning could be in use. Machine learning of control systems may lead to a better understanding of subcognitive skills which are inaccessible to introspection.[28] Control systems using learning techniques and often called intelligent control systems have two unique features that differentiate them from conventional control systems, namely 'ability to make decisions' and 'learning capability'.[8] It is not possible to apply the well-known mathematical tools and techniques to achieve these characteristics.

6.1. The connectionist learning approach

Among various machine-learning techniques the neural network has emerged as the most successful and has been applied widely to a variety of real-world problems.[64] Neural computing is one of the fastest-growing areas of artificial intelligence.[29] Kohonen[30] gave the following definition of a neural network.

> 'The neural networks are massively parallel interconnected networks of simple (usually) adaptive elements and their hierarchical organizations which are intended to interact with the objects of the real world in the same way as the biological nervous systems do'.

Neural networks have several properties that make them attractive as a robust, fault-tolerant, adaptive control strategy for non-linear and/or poorly understood typical control processes. They can be used to obtain a mathematical model of the real system to be controlled and to design a controller once a model of the system is available.[31] The neural network controller is expected to have the following capabilities.[32]

1. *Flexible structure to express non-linear systems.* This characteristic enhances the robustness of the controller.
2. *Learning capability due to the flexible structure.* This characteristic may give rise to a new control scheme.

The inherently parallel nature of the signal processing performed by these models and the commensurate increase in the speed with which this processing can be performed would alone merit attention from control engineers. Moreover, the additional properties exhibited by the distributed mappings implemented by these neural networks, such as noise rejection, fault tolerance and graceful degradation, as well as the adaptive manner in which the mappings are originally formed suggest that these techniques could be profitably employed as the starting point for a variety new control algorithms.

There are really only five generic designs now used to build neural networks to directly control actuators or effectors of some kind.[33] These are as follows.

1. *Supervised control.* A neural network learns the mapping from sensor inputs to desired actions by adapting to a training set of examples of what it should have done.
2. *Direct inverse control.* A neural network learns the inverse dynamics of a system so that it can make the system follow a desired trajectory.
3. *Neural adaptive control.* The linear mappings used in standard designs such as model reference adaptive control are replaced by neural nets, resulting in greater robustness and ability to handle non-linearity.
4. *Back-propagation utility.* This adapts an optimal controller essentially by solving a calculus of variation problems. As with calculus variations, this method requires a model of the system (which may itself be a neural network) and does not allow for noise. It has proven successful in a wide variety of problems and in its ability to model non-linear relationships.
5. *Adaptive critic methods.* The underlying idea is to approximate the Bellman equation of dynamic programming.

There are several learning techniques in neural networks, such as back-propagation, cascade correlation, competitive learning, generalized delta rule, Hebbian learning, minimax learning, principal component learning, probabilistic learning, reinforcement learning and stochastics, etc.[34,35] Problems concerning the application of neural networks to control, including the stability problem, have been surveyed by Zbikowski and Gawthorp.[36]

Regardless of the method or algorithms used for training the neural network for control actions, however, applications of neural networks as elements of real-time control systems will be very limited without special-purpose hardware designed to implement neural topologies and emulate their operation. Only with these can the real advantages of the connectionist designs be realized for control systems. Until such devices are readily available, neural networks of complexity sufficient to be useful for large-scale practical applications will remain laboratory curiosities, requiring weeks of computer time to train and evaluate, but impossible to implement physically.

6.2. *Genetic algorithms*

Apart from the neural-network-learning approach, several other approaches have been defined as mentioned earlier. Genetic algorithms are adaptive methods of searching a solution space by applying operators modelled after natural genetic inheritance, based on the Darwinian, neo-Darwinian and Lamarckian theories of the struggle for survival. They belong to a class of probabilistic algorithms and yet are distinguished by their distinct approach to searching and relative robustness of local traps.[37] As opposed to conventional optimizing solutions, they are goal-'sacrificing' in the sense that in practice we are not only interested in a truly optimum solution but in one that is satisfactory in achieving the goals and objectives of the closed-loop system. Golberg[38] gives a detailed analysis of the concepts of search and optimization using genetic algorithms. SAMUEL[39] is a successful system that learns control strategies using genetic algorithms.

6.3. *Rule-based learning*

Rule-based learning is another approach used in control. The main feature of this approach is learning by experience. This technique generally implies inductive learning and uses the ideas of generalization in some way. The controller's action can be represented by a control surface. The controller surface is defined by a set of situation–action rules and these rules are implemented by one of several reasoning techniques such as forward chaining, backward chaining, etc. The learning is based on trial and error. The trials are evaluated using a fitness function. The primary objective in the learning phase is to establish a complete set of situation–action rules by forming a generalized concept based on trial and error. A good example of this approach is Michie's boxes algorithm.[40] Sammut *et al.*[41] describe an autopilot using rule-based learning and argue that it is the most complex control system constructed by machine-learning methods. Learning control rules by induction provides a new way of building complex control systems quickly and easily.[41] The knowledge learnt by this technique can be expressed in an understandable and symbolic form.

6.4. *Hybrid learning techniques*

A hybrid or synergistic class of techniques for machine learning is evolving. The emergence of such synergistic techniques means that a number of cognitive features can be implemented in control systems. Hybrid techniques are based on a combination of induction, reinforcement learning, genetic algorithms, neural networks and/or fuzzy logic. DLS is a distributed learning system[42] for learning control strategies. It combines rule-based learning, namely induction and genetic algorithms. The use of genetic methods to improve the speed of learning in rule-based or connectionist-type neural-net-based methods is fast gaining popularity. Recently an increasing number of researchers have become involved in the area of fuzzy neural networks.[43] Several researchers have explored artificial neural networks and fuzzy sets as complementary techniques for information processing.[44] Kosko[3] has developed a hybrid technique which combines fuzzy logic with neural networks. The interest in this combination is motivated by the increasing recognition of the potential of fuzzy logic, some successful examples and the belief that fuzzy logic and neural networks are two of the most promising approaches for exploring the functioning of human brains. Kosko also presents an approach to intelligent self-organization based on differential competitive Hebbian learning applied to the fuzzy neural activation element. Thrift[45] and Karr[46] present hybrid techniques combining genetic algorithms with fuzzy logic. Sammut[47] proposes a hybrid learning system which combines reinforcement learning and rule-based learning for learning control strategies. ARIC[48,49] (approximate reasoning-based intelligent controller) combines approximate reasoning with reinforcement learning to develop a controller which can learn control strategies from experience.

7. FUZZY LOGIC FOR INTELLIGENT CONTROL

Fuzzy logic is a superset of conventional (boolean) logic that has been extended to handle the concept of partial truth — truth values between 'completely true' and 'completely false'. The application of fuzzy set theory[50] in control is gaining more and more attention in industry. The theory of fuzzy logic embodies the human-like logic, the soft logic, and seems to be a suitable mathematical tool for both modelling and control problems of complex systems. In the modelling of a complex control process the parameters in a model that are considered as random variables refer only to the way of coping with uncertainty (non-uniqueness) which arises from the ignorance of many physical variables and forces acting on the system. Therefore the notion of a fuzzy system should be understood as a concise denotation of a physical system depending upon an individual's level of perception of its dynamic behaviour. The task of the control engineer is, in addition to this modelling of the system, to design a controller based on this uncertain (fuzzy) model. Hence the concept of a fuzzy logic controller[51,52] has been introduced so as to formalize and implement the strategy which an expert human operator uses for controlling an ill-defined complex system. Fuzzy controllers can be viewed as consisting of two distinct parts. The variables and the linguistic terms essentially constitute the control structure, whereas the description of the fuzzy sets representing the linguistic terms is the basis of the quantitative relationship characterized by the control surface. Such a partitioning of fuzzy controllers is completely consistent with classical control.[23] A fuzzy algorithm can be used to represent essential relationships between inputs and outputs of a controller in the form of a set of situation–action pairs between a fuzzy input variable and the corresponding fuzzy output variable defined over disparate universes of discourse.

The basic principle of a fuzzy logic controller is illustrated in Figure 4.[23] Improvements to the basic fuzzy logic controller led to the introduction of self-organizing fuzzy logic controllers which provide the controlled plant with a strategy-learning feature.[53]

The basic principle of a self-organizing fuzzy logic controller is illustrated in Figure 5.[23] Improvements to the basic self-organizing fuzzy logic controller algorithm are presented by Yamazaki and Mamdani.[54] The stability analysis of such controllers is discussed by Aracil *et al.*[55] Two recent typical applications of self-organizing fuzzy logic control are described by Dote[56] and Linkens and Hasnain.[57] Nowe[58] discussed and improved fuzzy learning algorithms where the control strategy is based on maximizing 'safety'. Safety is interpreted as the availability of alternative control actions and can therefore be considered as an index of controllability. Safety is evaluated and updated in real time. Thus the control strategy is dynamic in nature.

The use of fuzzy control in a cement kiln, for example, was probably one of the first large-scale applications of fuzzy control, but over the past few years many new applications have been reported.[9] These applications are reported to be functioning well under the fuzzy logic controllers, with improved efficiency, reliability and operating response. Harris and Moore[59] give an overview of fuzzy logic applied to motion control. Fuzzy logic has worked effectively by combining it with other type of techniques, namely rule-based systems, neural networks, genetic algorithms, etc.

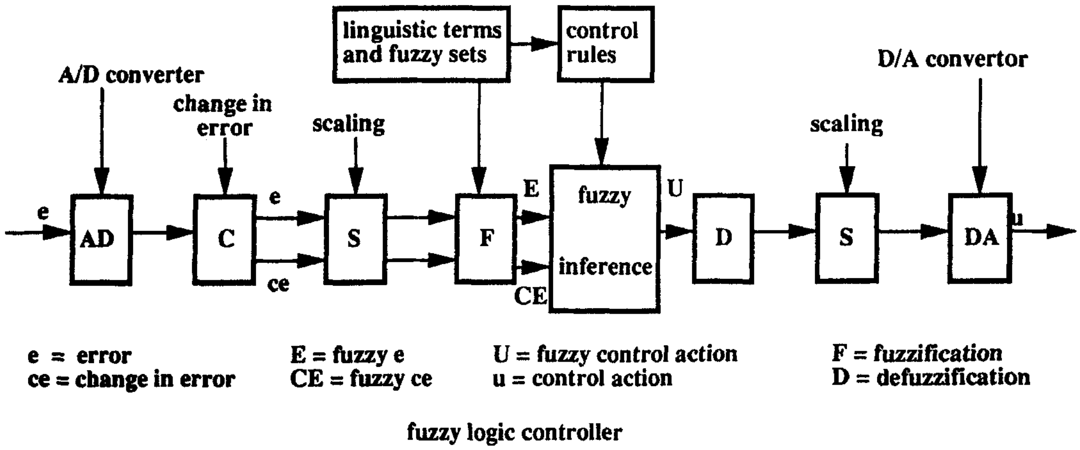

Figure 4. A simple fuzzy logic controller

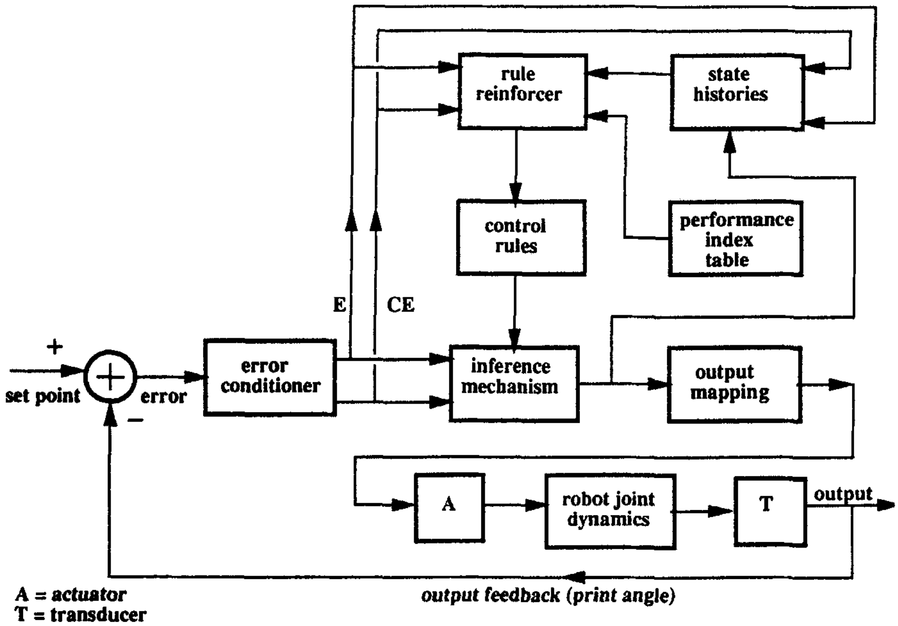

Figure 5. A self-organizing fuzzy logic controller

8. CONCLUSIONS

The purpose of this paper is to provide an insight to the emerging techniques in artificial intelligence that can be used to control dynamical physical systems. The design of intelligent control systems using these artificial intelligence techniques thus provides new dimensions beyond those of the conventional control systems with the ability to handle uncertain systems, which may involve fuzzy representation and/or symbolically described operations combined with learning and decision making. These intelligent control systems will play a very crucial role in preventing industrial disasters.

Although it is clear that major advances are taking place in the field of control systems, we are still at an early stage in completely understanding the power of artificial intelligence techniques and being able to utilize them fully in our control operations. There are some new and important ideas currently being researched that will change the very nature of control engineering in the next few years.[23] We can expect to see controllers capable of handling difficult processes which have proved impossible to model with the classical control techniques: condition-monitoring systems which integrate a much richer set of data sources than current systems, fault-diagnostic systems which can handle complex evolving fault situations without overloading the operator with irrelevant data, etc. Many of the techniques which will make such applications possible are still at the research level. Much work needs to be done in refining these techniques with sound and consistent theories, evaluating and classifying where they are applicable so that the process of designing intelligent controllers can be placed on a firm engineering footing. Despite the fact that extensive research is being carried out in this area, there are practically no intelligent control systems in real industrial use.[60,61] There are several reasons for this. Two of the most important reasons are:[62] (i) there is no mature methodology to design and verify an intelligent control system for a variety of processes; (ii) there is no sound implementation environment. If these issues are addressed, then one will see the emergence of a number of intelligent control systems for complex process systems in the near future. The authors are optimistic that intelligent control systems are likely to receive a warmer reception in the future from a control community that is dedicated to rigorous system analysis and proofs of stability.

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