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Hypothetical Studies for Devising a Real Time Expert Control System towards Process Automation

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Abstract

Real-time domain presents a novel and demanding environment for the application of knowledge-based techniques to find a suitable solution. Real-time systems encompass multiple goals and factors that contribute to decision making and in this context a knowledge based expert system finds application for process control in real time. A real time system should be predictably fast enough adhering to strict time limit within which the system need to respond, regardless of the algorithm employed.

This paper focuses on the constraints and criteria's in generating Real Time Expert Control Systems (RTECS) for a process control. The proposed system shall suit dynamic and changing environment, acquire sensor data, interface to external events, recognize and compensate for missing or uncertain data, handle scheduled or asynchronous events based on priority within the guaranteed response time along with reasoning about past, present, and future events.

The mathematical approaches for classification, characterization and mathematical modelling are discussed. Also a survey of few existing expert systems used in similar application and standard tools for real time system development are summarized

Keywords; *Mathematical modelling, Neural Networks, Fuzzy Logic, Control System, Expert System, Knowledge Base, Inference Engine, ANFIS, RTES*

I. INTRODUCTION

A real-time system with dynamic variational factors demand better knowledge based and obtaining information at the right time is equally important as the logical correctness. A real-time system is the choice where stimuli from the environment must be reacted within time intervals referred as deadline, else the process can literally go out of control [1].

Based on the constraints satisfying the timing, real time systems can be further classified as Hard real-time, Soft real-time and Firm real-time systems. Hard real time system is the most imperative to meet the deadline with high levels of predictability and availability. Missing the deadline is tolerable in soft real-time systems and the timing constraints are less critical compared to hard systems. In a firm real-time system the result delivered late neither impacts nor results in any serious failure, but the instance of such task missing its deadline should be discarded as early as possible.

The complexity of a real-time system involves the count of functions and the rate at which the functions must be ruled, apart from the number of factors for decision making. It is in this context that an Expert System suits a real-time application [2] A real time process control system performs the fundamental tasks of sensing, analysing, decision making and executing remedial actions for which an expert system aids in making the system intelligent. Whereas conventional computer program are procedural, dealing with equations and numerical values, an expert system encompasses the cognitive aspects of human knowledge as a collection of rules, databases and associated logical operation that are inferred by the Inference engine

II. EXPERT SYSTEMS

Expert systems (ES) are knowledge intensive programs developed from artificial Intelligence that can mimic human experts with control decisions for any complex system. Expert systems can simulate human reasoning along with mathematical computations and data collection [2]. Problems are expounded through heuristics, approximation, probabilityand algorithmic solutions.

ES has a domain *Knowledge Base, A Working Memory, An Inference Engine, System Analysis, and User Interface.*

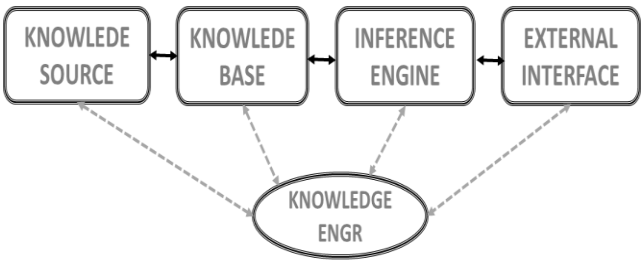

Fig 1 Expert System

Fig 1 shows the architecture of an expert system. The Knowledge *Acquisition* component facilitates knowledge or expertise entry into the expert system, Knowledge *Representation is* in a form that the inference engine can process, and the *User Interface* to interact with the user.

Identifying the nature and characteristics of the problem, Conceptualization, Formalization of a structure to organize the knowledge, Formulation and validation of rules for the inference engine are the crucial stages in the process of Knowledge Acquisition along with refinement to build an apt system. The Knowledge acquired in may be *Domain Knowledge* normally taken in the form of rules and *Case Knowledge* that specifies facts about a particular case and can be appended to the system during execution. Here knowledge will be described through real data and conditions.

The inference engine *Matches* the hypothesis patterns of the conditions against those factors in a working memory and deploys a *Conflict Resolution* strategy to favor one of the alternate rules, if more than one rule exists and activates the chosen rule.

Prominent contents of an Expert System include

- ❖ Goal Driven Reasoning (Backward chaining) : If-Then rules to subdivide the sequence of the problem into smaller units
- ❖ Data Driven Reasoning (Forward chaining) : If-Then rules to deduce a solution for the problem from initial data
- ❖ Dealing with uncertainty when the data and rules are not precise
- ❖ Data Representation using If Then Rules , Semantic Networks and Frames
- ❖ Search algorithms based on Depth first and Breadth first Algorithms

III. REAL TIME EXPERT SYSTEMS

Knowledge-based problem-solving techniques can be used only when the data are not dynamic, and no time-series related critical responses are needed [3]. The need of a real time expert control system can be felt when the traditional systems do not have the capacity to arrive at any optimal solution, when there are conflicting constraints and when it is not able to perform all the manipulation in quick and effective manner. Hence, the real-time expert system intends to drastically bring down the cognitive load of the user and thereby induce productivity increase. [4]

A Real-Time Expert System needs to be integrated and compatible with the conventional software. While the conventional code will perform functions such as application-specific I/O operations, data compression, signal processing, feature extraction etc., the expert system does the task of real time decision making.

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3.1 Survey of Real Time Expert Control Systems(RTECS)

i. *Automated Load Forecasting Assistant* (ALFA) developed in LISP predicts electric load well in advance. The rule base are extracted from the proficient load forecasters and a real-time pattern matching algorithm searches the database based on the predicted weather pattern [1].

ii. *Computerized Emergency Action Level Monitor* (CEALMON) is a real time expert system in a nuclear power plant that adopts a condition based problem-solving criterion using the logic of forward-chaining [1].

iii. COOKER is a real-time process supervising and assisting system for manufacturing processes with four subsystems viz*Data Frames, Data Gatherer, Operator Interface, and Inference Engine.* While the data collector intermediates data from the microcomputer, the inference engine handles unbuffered data, receives replies from the operator, recognizes the goals and provides solution for the goals. The system uses a expertise portrayal procedure called Goal/Sub goal (GSG).

iv. *Expert System for Complex Operations in Real Time* (ESCORT) aids process operators in control rooms with advice on plant crisis in advance thereby reducing the cognitive load [1].

v. *Fault AnaLysisCONsultant*(FALCON) examines alarm prompt in a chemical process plant. Falcon has five modules viz*Supervisor, Simulator, Monitor, Fault Analyzer, Human-Machine Interface*. The monitor module continuously examines process data and determines whether a disturbance occurred and frame work-based approach find the cause of the disturbances[1].

vi. *Logic Machine Architecture* (LMA) developed in Pascal used to stabilise the inlet temperature of the reactor constant at the observational breeder reactor in a nuclear power plant encapsulates functions required to perform reasoning with four software levels viz*Abstract Data Types, Database Support Functions, Inference Mechanisms, Theorem Prover* [1].

vii. *Materials Composition Management* (MCM) developed in LISP combines heuristic and analytic process control for a chemical manufacturing. The system consists of the *Heuristic Control Virtual Machine* (HCVM) and an *Application Shell*. HCVM is a generic "Event-driven Object-oriented computational framework" for developing on-line trial and error control applications. The application layer provides a mechanism for *Monitoring, Examining* and *Dynamically Controlling Module Activity* [1].

viii. *REACTOR* is an expert system that observes and controls a nuclear reactor facility in which the intelligent base contains incident based knowledge and activity based knowledge. The incident based knowledge, is displayed as if-then rules, describes expected output when the conditions are known. When an incident occurs that does not match with a known pattern, the activity based knowledge is used. The activity based knowledge displays the reactor system's configuration and uses forward and backward chaining for reasoning

ix. Supervisor is an expert system for process control in cement manufacturing that makes use of both the long and short-term memory. The long-term memory contains conditions or rules, and the short-term memory contains data relevant to the state at that point of time. The operating mechanism uses the present data by calling appropriate rules from the knowledge base and also has the potentiality to find new goals and pathways under different environmental conditions.

x. The Hybrid Expert System Controller (Hexscon) integrates traditional logic and arithmetic programming with expert system in which the expert system segment runs a discrete operation under the real-time operating system and issues to be taken care by the expert system are given a priority.

xi. The Process Intelligent Control (PICON) PICON is a real time expert system mechanism for developing process control applications. The knowledge base is organized as a hierarchical framework and supports parallel processing.

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3.2 Salient Features of an RTECS

- Priority based handling of scheduled or asynchronous events
- Interrupt handling
- Maintain guaranteed response time
- Capable of handle dynamic sensor data and external events ,
- Integration with procedural components
- Recognize and compensate for missing or uncertain data
- Handle noisy and rapidly changing data within strict time limits

In addition to the above features an RTECS need to ensure fail safe operation and reason about past, present, and future events along with garbage collection.

IV. KNOWLEDGE BASE MODELLING TECHNIQUES

Modelling is an activity that aims to understand, define visualize a system that is essential where experiment is a challenge. Models that are generated based on assumptions and evaluated by empirical data can also explain the past and predict the future using time series forecasting based on previous values. Conceptual model for better understanding, Operational model, Mathematical model for quantification and Graphical modelling for visualization are few prevailing modelling techniques.

An Expert System may be high level modelled based on algorithms where the knowledge is embodied in *if-then* rules or low level modelled with the knowledge embodied as parameters that is based on machine learning algorithm.

4.1 Mathematical Modelling

Mathematical model is a set of functions that brings out the relation among variables. In a mathematical model independent variables are described in terms of dependent variables as a relationship along with assumptions and constraints. Mathematical models can also be associated with subjective information using theoretical frameworks, experience, expert opinion etc. suitable for for analysis, optimization and control.

A mathematical model is classified as *linear* when the objective functions and constraints can be represented by a *linear* equation or *nonlinear* if the process is chaos and irreversible, *Static* (time-invariant) or *dynamic* (time dependent), Explicit if the output parameters can be calculated by a finite series of computation using known parameters or Implicit if the input parameters are estimated by iterative procedures , Discrete or continuous, Deductive (theoretical), Inductive based on empirical findings and generalization, black box or white box models based on the priori information.

4.2 Generalized Linear Models

Generalized linear modelling is a framework for modeling response variables that are bounded or discrete. Linear regression models the relationship between variables using linear predictor functions where the model parameters are found from the data. Linear regression models are fitted using least square estimation or using cost function. Whereas simple linear regression comprises single scalar predictor and response variable, multiple linear regression being its extension has vector valued multiple predictor variables.

4.3 Artificial Neural Network Modelling

An Artificial Neural Network (ANN) is a framework for learning algorithms that combine to process complex data and learns by identifying characteristics from examples rather than task specific rule. Neural network models are black box models defining a function or associated with a learning rule with opaque approximation. The model being defined with certain parameters need be trained, optimized and evaluated using data set denoted as cross validation.

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In a neural network, interconnected group of artificial neurons model the input output relationship and process information by a collective and parallel approach. The main architecture features three neuron layers viz*Input layer, Hidden layers, and Output layer* . In feed-forward networks, the signal flow is directed from input to output layers and the data is distributed across multiple hidden layers. Back propagation algorithm aids training of multi-layer network efficiently by distributing the error term back through the layers and modifying the weights at each node using gradient descent to compute the actual gradient method by changing the network parameters in response to the cost function.

Synapses in an artificial neuron are denoted by connection weights that modulates the input signals while the non-linearity is represented using Sigmoid, Gaussian, and Trigonometric functions . While impulse of each neuron is calculated as the weighted sum of the input signals, the learning process is accomplished by adjusting the weights using learning algorithm. Each neuron has an activation state, an output value, and a set of input connections, bias value and finally a set of output connections that can be described mathematically by real values. Thus, each connection owns a synaptic weight that defines the influence of the input on the unit activation limit.

The adaptive nature of ANN alters its structure according to the information flow through the network during the learning phase. The robustness of the network depends on the correct choice of the model, cost function and learning algorithm. ANNs can reproduce and model nonlinear processes and apt for System Identification, Control, Decision making , pattern recognition deploying mathematical techniques like Function approximation, Regression analysis, Time series forecasting and Modelling.

V. CONTROL STRATEGIES FOR A REAL TIME APPLICATIONS

Control systems are deployed to take control of constant process conditions by manipulating certain process variables at the set value in the midst of disturbances, while changing the level of the process variable. Feedback is used to reject the effect of the disturbance on the controlled variable and the variation of this controlled variable due to disturbances acts on the overall control process. The term Process Identification refers to the experimental technique of the dynamic behaviour of the process. The nature of the process can be identified using a step response (Process Reaction Curve) or using a sinusoidal input (Frequency Response) and by a pulse input (Pulse Response). The dynamics of the system can be understood from the input output relation associated with various experiments in closed and open loop conditions.

5.1 PID Control

PID control is the most common form of closed loop control used in Industrial application. In a PID loop the control signal is the sum of the three terms : P term - proportional to the error, I term - integral of the error and the D term - derivative of the error along with the controller parameters, proportional gain K, integral time T_i, and derivative time T_d. While the integral component defines the control action based on past, the proportional component determines the present and derivative, the future. A steady-state error exists in the control loop that decreases with increased proportional gain and induces oscillation in the system. When the integral time is increased the steady state error and the oscillations get suppressed. Damping increases with increased derivative time.

The advantage of PID controller is its adaptability and easy on process deployment. PID gains may be created based on the system variables when they are estimated precisely. But PID control being a mathematical model cannot adapt to higher order systems and is not fit for processes that are too much

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oscillatory. Since the PID controller needs to optimize these gains comprising the transient responses. Again PID controller is not robust to multiple challenges of the system.

5.2 Advanced Control Strategies

While PID controllers use single closed loop, advanced control strategies like *Cascade Control, Feed Forward Control, Ratio Control, and Smith Predictor Control* deploy multiloops with single or multiple variables. *Cascade Control* deploys a primary and a secondary controller for disturbance rejection where the primary provides the set point for the secondary. In a *Feed Forward Control* the model predicts the effect of a disturbance in advance and the controller initiates action to nullify the effect. *Ratio Control* blends two components with specified ratio. A *Smith Predictor Control* counteracts the ill-effects of dead time on process control where a process model predicts and negates the effect of dead time.

5.3 Adaptive Control

Adaptive control along with Lyapunov stability criteria, estimates parameter online for process plants with unknown or sporadic parameters. Based on the parameter estimator and the control law different adaptive control schemes can be derived. Adaptive control are opt when the dynamic model of the plant change unpredictably over a period of time either due to environmental conditions or due to load changes. An adaptive controller applies to systems with parameters which vary, or are initially uncertain and does not consider the bounds on the uncertain or time-varying parameters.

While a conventional control system aims to minimize and nullify the disturbance on controlled variables, adaptive control aims to achieve and maintain the desired performance of the control system with an Index factor. The desired performance index is measured using inputs , states, output and the known disturbances and the adaptation mechanism adjusts the parameters and maintains the performance index of the system to desired level. In an adaptive control the estimation becomes challenging when the unknown parameter enters the process model. The design of adaptive controller is based on specialized techniques and depends on trial and error. Again adaptive control may be classified as feed forward or feedback with direct, indirect and hybrid parameter estimation techniques. Using an estimation procedure the unknown process model is estimated at each instant.

5.4 Fuzzy Based Control

The concept of fuzzy logic formulated by Zadeh [5] that can represent vagueness in linguistics and express human knowledge in a natural way aids to overcome uncertainties. The constituents of a Fuzzy logic are a *Fuzzy Set* that contain elements with a membership defined by a membership function, Fuzzy*Operators* , Fuzzy intersection (T-norm), Fuzzy union (S-norm), and Fuzzy complement (NOT).

Fuzzy based control approach is optimum for complex and ill-defined problems and high level process control application. Unlike closed loop error based control strategies , Fuzzy based control is a knowledge based approach that utilizes expert knowledge and experience of a human operator for building a control application based on input output relation established by a collection of fuzzy rules using linguistic variables instead of a dynamic model.

A fuzzy logic system comprises Fuzzification strategies, Fuzzy Knowledge-Base, Fuzzy Rule-Base, Decision making logic and Defuzzification strategies. The fuzzy rule base is a collection of if-*then* rules and linguistic variables of the form ‘If x is A then y is B’ where A and B are linguistic values, the ‘if’ part is the *premise* and the ‘then’ part is the *consequence* that can be interpreted by fuzzification of the input, application of fuzzy operators and defuzzification.

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Fuzzy based system suffers from drawbacks as to defining the rules and need to get enough rules, accuracy, inter dependability of parameters and multi parameter optimization. Here a change in the member ship function calls for a change in rule and vice versa.

5.5 Hybrid Intelligent Control

Hybrid Intelligent Control Systems are frameworks comprising different knowledge based schemes, decision- modules, and learning strategies aimed for a particular computational application. Intelligent systems combine knowledge, techniques and methodologies and mimic human expertise within a specific domain while adjusting them to learn and adapt to changing environments.

The integration of soft-computing paradigms Artificial *Neural Networks (ANN), Genetic Algorithms (GA) and Fuzzy Inference Systems* (FIS) overcomes the individual constraints and a combinatorial approach i.e. Neuro-Genetic, Neuro-Fuzzy benefit aids the deployment of hybrid intelligent systems that benefits from both paradigms. While Neural networks are systems with built in adaptive heuristics having a defined architecture for learning by virtue of its internal structure, Priori knowledge cannot be inducted into a neural network. Fuzzy inference systems is an effective framework for reasoning as it attempts to cognitive modelling, Incorporates expertise in the form of if-then rules and apply the rules along with interpolation and extrapolation , but suffers with respect to adaptation and learning. Genetic Algorithm optimizes neural networks and Fuzzy inference systems and Evolutionary Computing aids in converging a solution to a global optimum instead of a local optima.

VI. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

Neuro-Fuzzy networks are models that are designed using expert knowledge and learned from data. Artificial neural networks and adaptive fuzzy systems are apt solutions that can characterize and model unknown systems, by approximating and smooth nonlinear function with hidden neurons, training data, self-learning and fuzzy sets.

ANFIS (Adaptive Neuro Fuzzy Inference System) is a data driven procedure introduced by Jang [6] that represent a *Neural Network* approach that approximates sets of numerical samples of the unknown function, and a TSK (Takagi, Sugeno and Kang) *Fuzzy Inference System* for creation of fuzzy rules using the data set, whereas the parameter identification deploys a hybrid learning rule comprising Back-propagation, Gradient descent and a Least-squares method.

Ideally ANFIS is a graphical network with nodes in each layers representing neurons with specific functions while neurons in each layer execute same function [7].

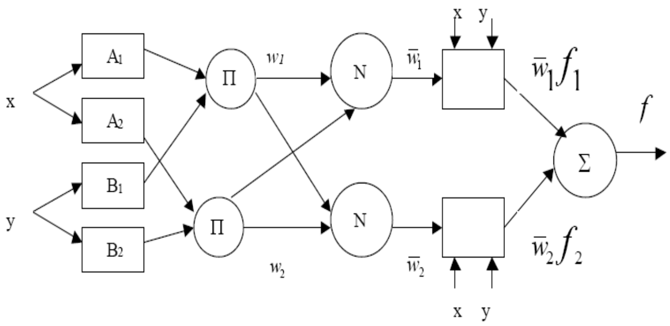

Fig 2 ANFIS Architecture

Fig 2 represents an Two input ANFIS network with 5 layers and Sugeno fuzzy system having the following rule base:0

1. If x is $A1$and y is $B1$, then $f_1= c_{11}x+c_{12}y+c_{10}$

2. If x is $A2$and y is $B2$, then $f_2= c_{21}x+c_{22}y+c_{20}$

Layer 1 (L1): The nodes in L1 are adaptive nodes that generates the membership grades for the linguistic label. For example as shown below the generalised*bell function* with the premise parameters (a,b,c) varies its shapes according to the chosen parameters.

$$\mu(x) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}}$$

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$O_{1,i} = \mu_A(x_1)$, where i = 1 & 2 or $O_{1,i} = \mu_{B-2}(x_2)$, where i = 3 & 4

Here x_1 and x_2 - inputs;

A_i and B_i - linguistic labels

$O_{1,i}$ - membership grade for fuzzy set A

μ_{Ai}, μ_{Bi} - membership functions for fuzzy sets *Ai, Bi*, *i*=1, 2

Layer 2 (L2): The nodes in L2 are fixed node for calculating the firing strength of each rule using the *t- norm* or s- norm operator. The output of each node is the dot product of the input that determines the firing power of that rule .

$O_{2,i} = w_i = \mu_A(x_1)\ \mu_B(x_2)$ for i = 1,2

Layer 3 (L3): The nodes in L3 are fixed nodes that normalises the firing strength by computing the ratios of the rule's firing strength to the sum of all the rules firing strength.

$O_{3,i} = w_i = w_i / (w_1 + w_2)$ for i = 1,2

Layer 4 (L4): The nodes in L4 are adaptive nodes that computes a parameter function for the L3 output using the *consequent parameters*.

$O_{4,i} = w_i f_i = w_i(p_i x_1 + q_i x_2 + r_i)$

Layer 5 (L5): L5 has a fixed node for summation of the L4 signals

$O_{5,i} = \sum w_i f_i = \sum w_i f_i / \sum w_i$

For a given set of fixed premise parameters , the overall output *f* can be written as

$$f = (w_1 x)c_{11} + (w_1 y)c_{12} + w_1 c_{10} + (w_2 x)c_{21} + (w_2 y)c_{22} + w_2 c_{20}$$

which is a linear combination of the consequent parameters. Here c_{ij} (i = 1,2, j = 0,1,2) are the consequent parameters and $\{a_i, b_i, c_i\}$ are the premise parameters. The consequent parameters are adjusted in the forward pass by least square method and the premise parameters are adjusted in the backward pass using gradient descent.

6.1 Choice of Hardware Implementation

Though Hybrid Neuro-fuzzy system has many favourable features like adaptability, self-learning mechanisms and linguistic rule base for ideal control , the complexity of the system lies on the choice of the number of premise parameters and for real time operation the algorithm requires complex operations to be executed within dead line. With the advent of high speed computing devices that exploit parallelism real time embedded controllers will be the right choice [8,9]

Whereas a prototype can be realised using the IO flexibility of a Field Programmable Gate Array (FPGA) device that can be logically programmed using Hardware Description Languages or High Level Synthesis tool, this FPGA designs suffer from the drawback of higher power consumptions and cost for scaling.

Cortex ARM embedded processor with Graphic Processing Units (GPU) is the apt and best choice for a real time controller design that can be programmed to suit the requirement using CMSIS (Cortex Microcontroller Software Interface Standard). CMSIS is a vendor-independent hardware abstraction layer that provides a common approach to interface to peripherals, real-time operating systems, neural network kernels, DSP libraries and middleware components. CMSIS components are compatible with a range of C and C++ language standards and licensed under Apache 2.0. CMSIS has software layers and device support for a wide range of hardware and also aids portability and re-usability. Software development will be faster through these easy-to-use, standard software interfaces for data exchange with external devices apart from synchronisation to a common time frame. [11]

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VII. CONCLUSION

Process Control refers to the methods controlling the complex system parameters against disturbance. PID controller is a basic process control approach that suits linear and constant control. The dynamic behavior arising in these type of complex system can be characterized as higher order nonlinear time variant system that needs an adaptive control approach for process prediction and adaptation. For optimizing the performance advanced process control techniques are deployed along with conventional control that executes in parallel and generates supervisory control instruction for execution by the conventional controller and it is at this juncture that the choice and design of a Real Time Expert Control System fits in. The emergence of high performance processors and GPUs for vector processing along with powerful software frameworks can realize the dynamic criteria's, optimized search and decision execution of the RTECS.

VIII. ACKNOWLEDGEMENT

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