ABSTRACT
A new iterative fuzzy clustering algorithm has been proposed that incorporates a supervisory schema into an unsupervised manner by using fuzzy c-means clustering and a cluster validity criterion. Meaningful fuzzy partitions can be gradually constructed over the input space. The proposed algorithm scores points as compared with the approach of lateral tuning as the need for implementing the 2-tuples representation can be eliminated. Chemical Recovery Boiler optimization in terms of achieving increased productivity had been taken up as a case study to demonstrate application of the newly proposed algorithm.

KEYWORDS Fuzzy rule-based systems, genetic algorithms, Interpretability, linguistic 2-tuples representation, rule selection, Type 2 models, Tuning, Particle Swarm Optimization, Chemical Recovery Boiler Productivity.

I. INTRODUCTION
Research over the past few years has proved time and again the need for development of a linguistic fuzzy model which is reasonably accurate. The existing system deals with the modelling of systems which is clearly interpretable by human beings. However, since the accuracy and the interpretability of the obtained model are contradictory properties, the necessity of improving the accuracy of the linguistic model arises when complex systems are modelled. In order to eliminate these problems and to deal with data patterns with linguistic ambiguity and with probabilistic uncertainty in a single framework, it is proposed to construct an interpretable probabilistic fuzzy rule-based system. A new iterative fuzzy clustering algorithm has been proposed that incorporates a supervisory schema into an unsupervised manner by using fuzzy c-means clustering and a cluster validity criterion. Meaningful fuzzy partitions can be gradually constructed over the input space. The proposed algorithm scores points as compared with the approach of lateral tuning as the need for implementing the 2-tuples representation can be eliminated.

II. TYPE 2 FUZZY MODELS
It has been found that over the past few years, Fuzzy type 1 models have been used where precise values may not be available. These models have met with considerable degree of success. The very fact that results are obtained within a very short span of time speaks volumes. However, with problems involving a large number of uncertainties, Fuzzy type 1 models have their own set of fallacies. With introduction of optimization in the picture, there exists a dire necessity to go in for Fuzzy Type 2 Models. A Type-2 Fuzzy Ontology is a knowledge representation model to describe the domain knowledge with uncertainty. It is an extension of domain ontology and consists of six layers, including a domain layer, a category layer, a fuzzy-concept layer, a fuzzy variable layer, a T1FS layer, and a T2FS layer. The T2FO has three relationships, namely, “generalization,” “aggregation,” and “association.” The domain layer deals with the possible areas where the problem under study could be taken up. The relationship between the domain layer and the category layer talks about the generalization.”. The category layer defines several categories, namely, “Category 1,” “Category 2,” . . . , “Category k.” The relationship between each category in the category layer and its corresponding concepts in the fuzzy-concept layer deals with the aggregation. : The fuzzy concepts, “fuzzy concept1,” “fuzzy concept 2,” . . . , “fuzzy concept i,” exist in this layer. The relationship between the fuzzy-concept layer and the fuzzy-variable layer deals with the association. There are many fuzzy variables in the fuzzy-variable layer, which are defined for the fuzzy concept in the fuzzy-concept layer. The
association relationship also exists between two fuzzy variables in the fuzzy-variable layer. T1FS and T2FS talk about the fuzzy system layers where T2FS is an extension of T1FS. The structure of Type 2 Fuzzy model is shown in Fig.1.

![Fig.1. Structure of Type 2 Fuzzy system](image)

The Type 2 FLS can in turn be modeled as a combination of large number of Type – 1 FLS. This is shown in Fig.2.

![Fig.2. Type 2 FLS as a collection of set of type – 1 FLS](image)

In a type-1 FLS, the inference engine combines rules and gives a mapping from input type-1 fuzzy sets to output type-1 fuzzy sets. Multiple antecedents in rules are connected by the norm (corresponding to intersection of sets). The membership grades in the input sets are combined with those in the output sets using the sup-star composition. Multiple rules may be combined using the conorm operation (corresponding to union of sets) or during defuzzification by weighted summation.

In the type-2 case, the inference process is very similar. The inference engine combines rules and gives a mapping from input type-2 fuzzy sets to output type-2 fuzzy sets. To do this, one needs to find unions and intersections of type-2 sets, as well as compositions of type-2 relations. In a type-1 FLS, the defuzzifier produces a crisp output from the fuzzy set that is the output of the inference engine, i.e., (crisp) output is obtained from a type-1 set. In the type-2 case, the output of the inference engine is a type-2 set. Hence, extended mechanisms are needed to give a type-1 fuzzy set. First, type reduction is carried out (for conversion of Type 2 fuzzy sets to Type 1 Fuzzy sets) followed by defuzzification for conversion of Type 1 fuzzy sets to crisp values.

The chief parameters to be considered as Fuzzy Type 2 variable include Boiler Liquor Solids flow and its gross heating value.

III. FUZZY RULE BASED SYSTEM LEARNING

In general, a learning system structure and its learning algorithm are selected based on analysis of the learning target in consideration of the target environment. It can be observed that determination of a learning system becomes painstaking when human behavior is the subject of the learning target. In fact, human physical, logical, and/or emotional behavior are known to be complex and quite involved for mathematical modeling because of various attributes of human-related data such as ambiguity, apparent inconsistency, high dimensionality, time-variance, and high susceptibility to the environment. The choice of application also plays a major role. In this case, since the behavior of the model is unknown at the time of the application, a degree of reinforcement learning needs to be carried out. Reinforcement learning is learning to map situations to actions so as to maximize a numerical reward signal. The learner is not aware of the actions to be taken but instead must discover which actions yield the most reward by trying them.

A model of the reinforcement learning network is shown in Fig. 3.
One of the challenges that arise in reinforcement learning and not in other kinds of learning is the trade-off between exploration and exploitation. Another key feature of reinforcement learning is that it explicitly considers the whole problem of a goal-directed agent interacting with an uncertain environment.

IV. FUZZY C-MEANS CLUSTERING

The characteristics of cluster separability and pureness are the two major factors to be considered in the problem. The detailed set of operations has been shown in Fig.4.

Fig.4. Schematic Model

The basic notion of separability leads to another kind of validation of a cluster. The detailed clustering algorithm is shown in Fig.5.

Fig.5. Detailed Clustering model

With fuzzy c-means, the centroid of a cluster is the mean of all points, weighted by their degree of belonging to the cluster.

$$\text{center}_k = \frac{\sum_{i=1}^{n} u_{ik}(x)^m x_i}{\sum_{i=1}^{n} u_{ik}(x)^m}$$

The degree of belonging is related to the inverse of the distance to the cluster center:

$$u_{ik}(x) = \frac{1}{d(\text{center}_k, x)}$$

With a large amount of uncertainty being present, fuzzy models fit better. A degree of concurrent learning has also been exhibited wherein a behavior of number of parameters like Boiler Liquor solids flow, Concentration, Primary and Secondary Air flows and their temperatures, excess air etc. are learned at the same time. This results in a large number of fuzzy states being activated concurrently. By this fuzzy methodology, lesser number of fuzzy states will be defined for learning which may even avoid the curse of dimension for reinforcement learning.

V. DESIGN OF A FUZZY EXPERT SYSTEM

A fuzzy expert system is an expert system that uses fuzzy logic instead of Boolean logic. In other words, a fuzzy expert system is a collection of membership functions and rules that are used to reason about data. Unlike conventional expert systems, which are mainly symbolic reasoning engines, fuzzy expert systems are oriented toward numerical processing. The model of a Fuzzy Expert system is shown in Fig.6.

Fig.6. Model of a Fuzzy expert system

The rules in a fuzzy expert system are usually of a form similar to the following:

if Concentration is low and Primary Air Temperature is high then Steam flow rate is medium. Here, Concentration and Primary air temperature are input variables while steam flow rate is an output variable to be computed. Low, Medium and High correspond to defined membership functions. Most tools for working with fuzzy expert systems allow more than one conclusion per rule.

VI. PARTICLE SWARM OPTIMIZATION (PSO)

Birds and fish adjust their physical movement to avoid predators, seek food and mates, optimize environmental parameters such as temperature,
etc. Humans adjust not only physical movement but cognitive or experiential variables as well. We do not usually walk in step and turn in unison. Human beliefs and attitudes conform with those of our social peers. This is a major distinction in terms of contriving a computer simulation, for at least one obvious reason: collision. Two individuals can hold identical attitudes and beliefs without banging together, but two birds cannot occupy the same position in space without colliding. Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. PSO is easy to implement and there are few parameters to adjust. Each rule in a rule base is considered to be a particle. PSO has proved to be effective in optimizing complex multidimensional discontinuous problems. Optimization of performance of Chemical Recovery Boiler has been considered in this work. PSO in conjunction with type 2 fuzzy logic models has also been used in nonlinear identification techniques. The chief advantage of PSO is that each particle has inbuilt memory.

VII. PSO ALGORITHMIC APPROACH

Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called lbest. when a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest.

The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its pbest and lbest locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and lbest locations. After finding the two best values, the particle updates its velocity and positions with following equations:

\[ v[i] = v[i] + c1 * \text{rand}() * (pbest[i] - \text{present}[i]) + c2 * \text{rand}() * (gbest[i] - \text{present}[i]) \]  
\[ \text{present}[i] = \text{present}[i] + v[i] \]

V is the particle velocity, pbest[i] – Fitness value, gbest[i] – Global best value.

\text{rand}() is a random number between (0, 1). c1, c2 are Learning Rate.

The pseudo code of the procedure is as follows:

For each particle
  Initialize particle
END

Do
  For each particle
    Calculate fitness value
    If the fitness value is better than the best fitness value (pBest) in history
      set current value as the new pBest
  End
  Choose the particle with the best fitness value of all the particles as the gBest
  For each particle
    Calculate particle velocity according equation
    Update particle position according equation
  End
  This procedure is repeated until error has been minimized to an acceptable value or if number of iterations has reached a threshold value.

Each particle's value can then be changed from one to zero or vice versa. In binary PSO, the velocity of a particle defined as the probability that a particle might change its state to one. Particles velocities on each dimension are clamped to a maximum velocity Vmax. If the sum of accelerations would cause the velocity on that dimension to exceed Vmax, which is a parameter specified by the user, then the velocity on that dimension is limited to Vmax.

VII. APPLICATION

Typical case study taken up is one that Fuzzy Interpretation of Boiler Heating surface
cleanliness. Refer Fig.7 and Table-1 in conjunction for the interpretation.

![Steam Output Prediction](image)

**Fig.7. Steam temperature profile with little/no spray attemperation**

<table>
<thead>
<tr>
<th>CF Degree</th>
<th>State</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>Best</td>
<td>Totally clean surface</td>
</tr>
<tr>
<td>4</td>
<td>Good</td>
<td>Just a thin layer</td>
</tr>
<tr>
<td>3</td>
<td>Average</td>
<td>Soot blowing once a shift</td>
</tr>
<tr>
<td>2</td>
<td>Poor</td>
<td>Repeated Soot blowing</td>
</tr>
<tr>
<td>1</td>
<td>Extremely Poor/Worst</td>
<td>Totally Fouled –soot blowing</td>
</tr>
</tbody>
</table>

*It means that the Recovery Boiler should be stopped & washing has to be done to remove the deposits from superheater surface.

When a control system has been defined, performance criteria must be specified. It has been mentioned earlier that a larger amount of deposits on the super heater coils could be present not removed inspite of regular time bound soot blowing. This leads to a decision wherein soot blowing frequency needs to be increased at selected locations, thereby ensuring uniform attemperation and improved performance. Besides, the air distribution may also need to be adjusted. It has been observed that a wide variety of parameters play a significant influence in ensuring that steam flow is maximized besides ensuring that steam temperature is maintained constant at 465ºC. Fuzzy constraints are designed for several variables present in the system. Besides, existing stochastic non-fuzzy models have rarely matched the ontological criteria. There arises a definite need for optimizing the choice of parameters and their precise values which would ensure enhanced steam output. Particle Swarm Optimization has been tried out for the same where each rule framed is considered as a particle. Particles which do not know the precise path to be followed try to follow other particles thereby increasing their chances of reaching the goal.

In a complex system such as combustion system of a boiler, the need to design and implement a suitable controller which has a fast response of time and one that can control the nonlinear behavior of a complex system has become a focal point in the Fuzzy sets and fuzzy logic were developed as a means for representing, manipulating, and utilizing uncertain information and to provide a framework for handling uncertainties and imprecision in real-world applications.

**VIII. DIAGNOSTIC OPERATIONS**

A fuzzy expert system has been designed which considers the role of various parameters used in the work and performs sensitivity analysis. C-means algorithm has been used where similarity features are built into a cluster and then the entire cluster is tested. It is clear that the given model could optimize simple two dimensional linear functions. It has been observed that the optimization actually occurs faster when nearest neighbor velocity is removed.

**IX. CONCLUSIONS AND RECOMMENDATIONS**

Fuzzy logic operators provide wide variety of possibilities for deduction using fuzzy rules. The knowledge entering fuzzy controllers is structurally shallow, both statistically and dynamically and hence no run time chaining of inferences is needed. The knowledge stored in the knowledge base typically reflects immediate correlations between the inputs and outputs of the system to be controlled. The numerical parameters of their rules and of their qualitative input and output modules are tuned in a learning process.

They take less time to develop, when compared with traditional expert systems. Collaborative fuzzy expert systems support the design of distributed decision making. Fuzzy expert system combined with Particle swarm optimization has yielded real time results.
Particle Swarm Optimization is found to be more effective with stochastic aspects of the boiler. The tendency of the system to move towards the results faster is one of the chief advantages of this work. The stochastic factors allow thorough search of spaces between regions that have been found to be relatively good and the effect caused by modifying the velocities rather than replacing them results in overshooting, or exploration of unknown regions of the problem domain. The case study taken up relating to the Boiler is just the beginning for trying out the newly developed algorithm. Utilizing the available operating data bank, the model has to be pruned and trimmed further to yield the desired results. Although it has been found that the simulation yields interesting results, one feature that has been found wanting is the feature of abstractness. Incorporation of this feature into the work would provide a more realistic picture.

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