5. CONCLUSION

An adaptive system based on Hierarchical Censored Production Rules (HCPRs) system has been presented that relies on development of some ties between a combined approach of Genetic-Based Machine Learning (Michigan's approach and Pitt's approach) and symbolic machine learning. Several genetic operators are suggested that suit the proposed system including extension of genetic operators as defined in [73] to HCPRs system and advanced genetic operators, namely, Fusion and Fission. The problem of distinguishing a major contributor from a minor contributor in a problem solving process is also addressed and a partial solution is suggested for the system by partitioning the problem into subproblems and assigning weights to each subproblem according to its importance such that contribution of each HCPR-tree involved in the solution path of a subproblem is proportional to the weight of the corresponding subproblem. An appropriate credit apportionment scheme is developed that takes care of forward as well as backward chaining of reasoning process.

A Lisp based prototype implementation of the proposed system is presented and the performance of the system has been demonstrated through experimental results. The system has been tested under two different examples (Equipment selection and Student-Department choice). It is shown how the structure of the initial knowledge base affects the performance of the system and the results confirm that better is the structure of the initial knowledge base, a fewer number of generations are required. It is also observed during
experimentation that the system adapts to improve its performance in a relatively consistent manner. As expected, the results show that the system performs well even in learning the problems corresponding to the lower level nodes.

Naturally, in HCPR-trees, the problems corresponding to the upper level nodes are learned faster as compared to the more specific problems corresponding to the lower level nodes. Certainly, the number of generations would be proportional to the size of the working set of HCPR-trees as well as the size of the individual HCPR-trees in the working set. One proposal to expedite the learning of the lower level nodes is that, when the system is capable of solving most of the problems, the HCPR-trees which have not yet participated in solution paths may be taken out from their working set and transferred into another set. Then applying genetic operators on this new set. This strategy will expedite the process of solving the remaining unsolved problems because the genetic operators will be applied on a much smaller search space and that would discover the necessary rules much faster than applying genetic operators on the entire working set. As and when any HCPR-tree in the new set of HCPR-trees works well, it will be merged into its corresponding working set.

It may be noticed that the proposed scheme of credit assignment which is based on the assigned weight would work well. That is, the upper level nodes which fire more frequently (contributes more to solution paths) than the lower level nodes have higher credit compared to that of the lower level nodes. It is further observed that, the more complex is the HCPR, the higher is its credit.
This is also true for HCPR-trees, that is, the more is the complexity of the HCPR-tree, the higher is its credit.

An overview of bucket brigade algorithm, its suitability to rule-based systems (production systems), and some of the attempts to modify it are presented. A modified bucket brigade algorithm suitable for Censored Production Rules and Hierarchical Censored Production Rules system is proposed. The rule accuracy involved in the bid formula is computed in terms of $\delta_{\text{max}}$ (the maximum certainty value for the $i$th rule which can be achieved if all its censor conditions are checked) and $\delta_i$ (the certainty value of the $i$th rule considering only some of the censor conditions). A rule-status was introduced in the proposed algorithm to solve the problem of weakening correct rules that are initiated by incorrect rules. This is done by deciding the status of the rule in terms of correctness. Rule-status is also useful in eliminating such incorrect rules by decreasing their strength until they become ineligible to enter the conflict set and thereby not activating any rule. The main difference between the modified algorithm and the standard bucket brigade algorithm is that a scheme has been proposed that modify the rule-status according to the rule performance. Examples have been presented to show the weaknesses of the standard bucket brigade and how the modified version could overcome these weaknesses. It is to be noticed that the modified version also suffers from the problem of long action sequence mentioned in [42], [66], [81]. One solution to this problem could be an approach that combines our modified version and the hierarchical bucket brigade algorithm proposed by Wilson [81].
Some directions for future research could be:

- Exploring capability of the system for handling other problem domains.
- Incorporating the proposed solution for the problem of distinguishing a major contributor from a minor contributor in problem solving process into the system.
- Implementing the proposed modified version of the bucket brigade algorithm and testing it under different domains.
- Incorporating the proposed solution to expedite the learning of the lower level nodes in HCPR-trees.
- Exploring the possibilities of combining the proposed modified bucket brigade algorithm and Wilson's hierarchical bucket brigade algorithm.
- Investigating the connections between GBML, connectionism, and symbolic machine learning.
- Developing mathematical foundation for the validation of the system.