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# An Improved Artificial Immune System for Solving Loading Problems in Flexible Manufacturing Systems

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## Introduction

According to Stecke [1], an FMS is characterized as an integrated, computer-controlled complex arrangement of automated material-handling devices and numerically controlled (NC) machine tools that can simultaneously process medium-sized volumes of a variety of part types.

The highly integrated FMS offers the opportunity to combine the efficiency of a transfer line and the flexibility of a job shop to best suit the batch production of mid-volume and mid-variety of products.

However, flexibility has a cost, and the capital investment sustained by firms to acquire such systems is generally very high. Therefore, particular attention must be paid to the proper planning of an FMS during its development phase in order to evaluate the performance of the system and justify the investment incurred. Prior to production, careful operational planning is essential to establish how well the system interacts with the operations over time.

The decisions related to FMS operations can be broadly divided into pre-release and post-release decisions.

Pre- release decisions include the FMS operational planning problem that deals with the pre-arrangement of jobs and tools before the processing begins whereas post-release decisions deal with the scheduling problems.

Pre-release decisions, e.g. machine grouping, part type selection, production ratio determination, resource allocation, and loading problems must be solved while setting up an FMS.

Amongst pre-release decisions, machine loading is considered as one of the most vital production planning problems because the performance of the FMS largely depends on it.

Loading problems, in particular, deal with the allocation of jobs to various machines under technological constraints, with the objective of meeting certain performance measures; hence, it is considered as a combinatorial optimization problem and happens to be NP-hard in nature.

Numerous methods based on mathematical, heuristics, meta-heuristics, and simulation have been suggested by researchers in the pursuit of obtaining quality solutions to loading problems and reduce computational burden [1-10].

But these approaches are barely capable of producing optimal/near-optimal solutions or require excessive computational efforts to arrive at quality solutions.

In order to alleviate these difficulties, an attempt has been made in this work to propose an algorithm based on Artificial Immune Systems (AIS) to solve the machine-loading problem of a random FMS with the objective of the minimization of system unbalance while satisfying the constraints related to the available machining time and tool slots. The novelty of the approach lies in the fact of applying chaotic search as it has nice capability of hill-climbing and escaping from local optima, and is more efficient than random search

## Logistic Function

Logistic function is represented as

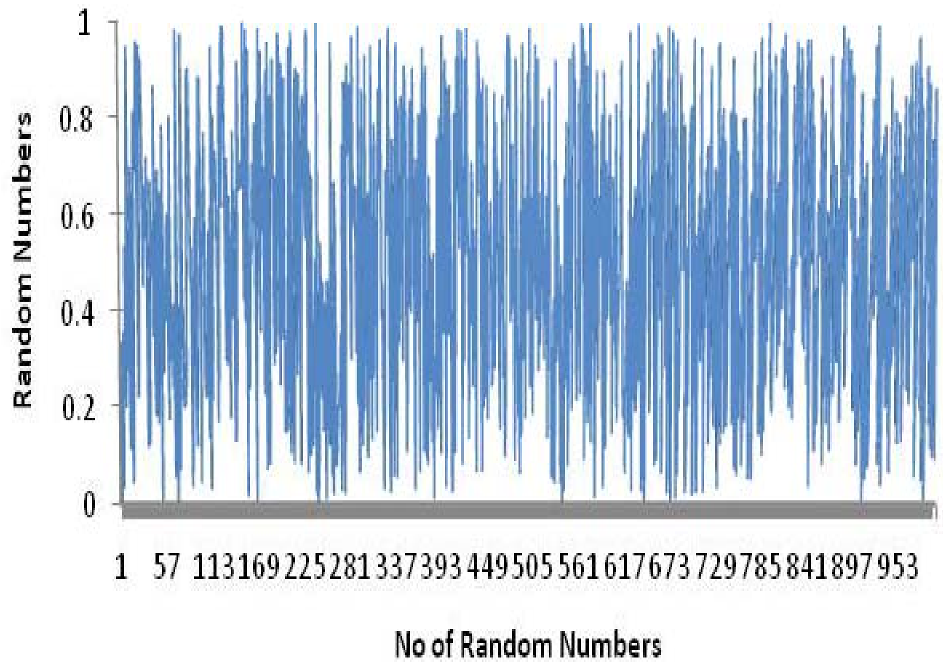
$$N(t+1)=R\times N(t)\times(1-N(t))$$

where, N(t) is the value of chaotic variable in $t^{th}$ iteration and R shows the bifurcation parameter of the system.

The reason behind opting the chaotic sequences is due to their ability to converge fast toward optimal solution while retaining a proper balance between exploitation and exploration.

The logistic map shows one of the simplest dynamic systems evidencing chaotic behaviour.

The graphical representation of one-dimensional logistic chaotic function is illustrated below (for 400 generations with initial value of N(0)=0.1 and R=4). From this figure, it is evident that the spread spectrum characteristic of logistic mapping enables it to be utilized in place of RNGs



## The Algorithm

**Initialization:** Initially a population of size 'n' is generated and each individual represents a job sequence for loading problem in FMS.

. **For a five job problem, the string length equals 5**.

| | | | | |
|---|---|---|---|---|
| **0.52** | **0.32** | **0.09** | **0.95** | **0.41** |

**Arrange the above string in ascending order**

| | | | | |
|---|---|---|---|---|
| **0.09** | **0.32** | **0.41** | **0.52** | **0.95** |

**Generated string is**

| | | | | |
|---|---|---|---|---|
| **3** | **2** | **5** | **1** | **4** |

**So permutation coding creates the string of antibodies**.

**Selection of Antibodies:** The initial population is exposed to the threats posed the antigens and antigenic affinity ($f_k$) is evaluated for each antibodies present in population. Based on their affinity, the antibodies are selected to proliferate and to produce clones (greater the affinity of the antibodies, greater will be there chance of cloning). A roulette wheel selection rule is adopted for the selection of antibodies for proliferation.

**Proliferation:** Here highest affinity antibodies are selected and proliferated by duplication known as Cloning. This process is called clonal expansion where each antibody produces clones independently and proportionally to their antigenic affinity. Higher the fitness value, then higher the number of clones generated for each antibody.

**Hyper mutation:** It is usually used in Immune Algorithms to introduce random changes in to the individuals. The higher affinity antibodies selected in the previous step are submitted to the process of hyper mutation.

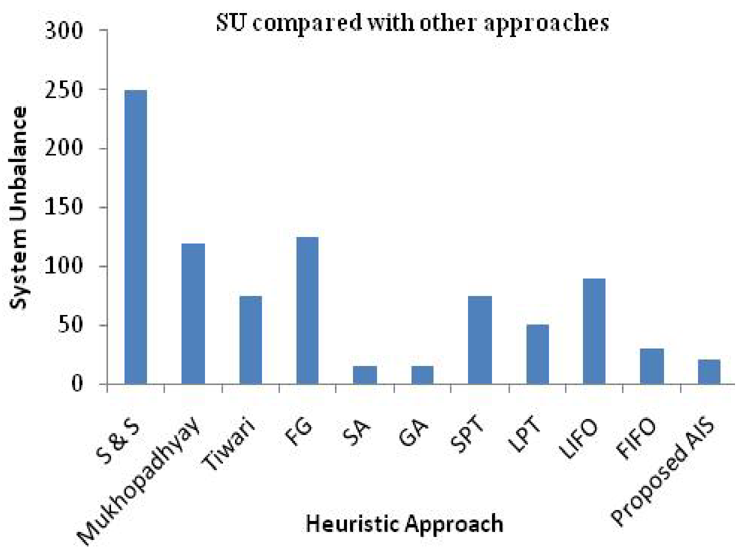
**Receptor editing:** Receptor editing can prevent the immune system from becoming “premature” and also increase the affinity. Receptor is editing to provide an additional mean of introducing diversity in immune cells during the process of affinity maturation. It works as replacing B% of lower affinity clones.

**Termination criteria:** The termination criteria are considered when the number of generations reaches the maximum specified value or no further improvement is possible.

## Result and discussions

Two benchmark problems are taken from open literature [2,18].

| Reference | B | Solution by [2] | | Solution by [18] | | Proposed AIS | |
|---|---|---|---|---|---|---|---|
| | | S U | Th | SU | Th | SU | Th |
| 18 | 6 | 388 | 51 | 202 | 63 | 11 | 73 |
| 2 | 8 | 253 | 39 | 122 | 42 | 18 | 46 |


SU compared with other approaches
System Unbalance
0
50
100
150
200
250
300
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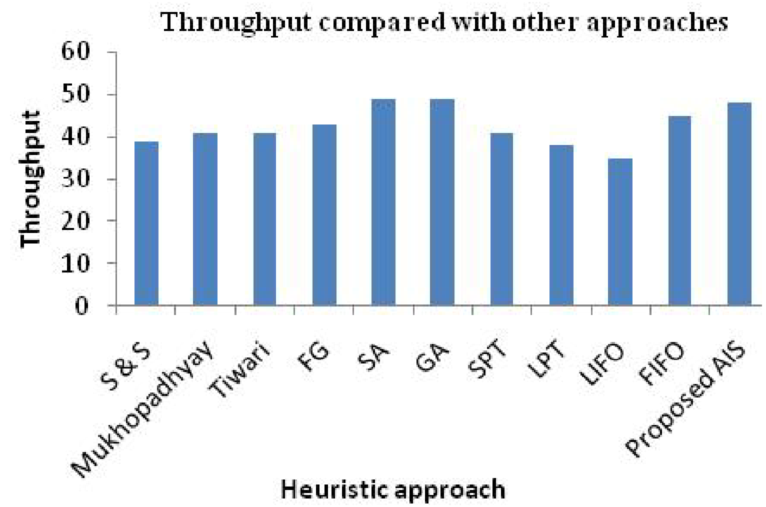
Mukhopadhyay
Tiwari
FG
SA
GA
SPT
LPT
LIFO
FIFO
Proposed AIS
Heuristic Approach


Throughput compared with other approaches
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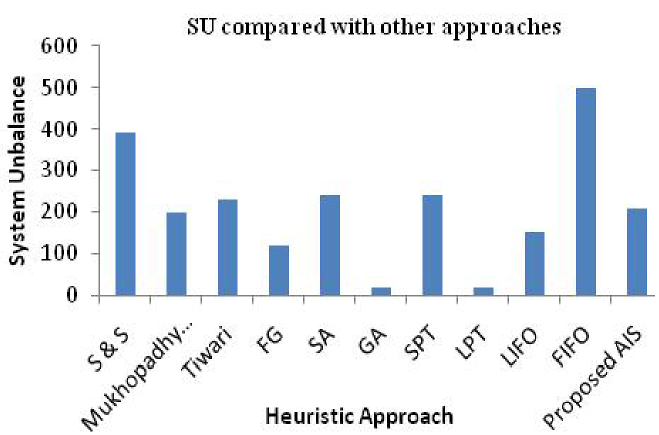
Proposed AIS
Heuristic approach

(2)


SU compared with other approaches
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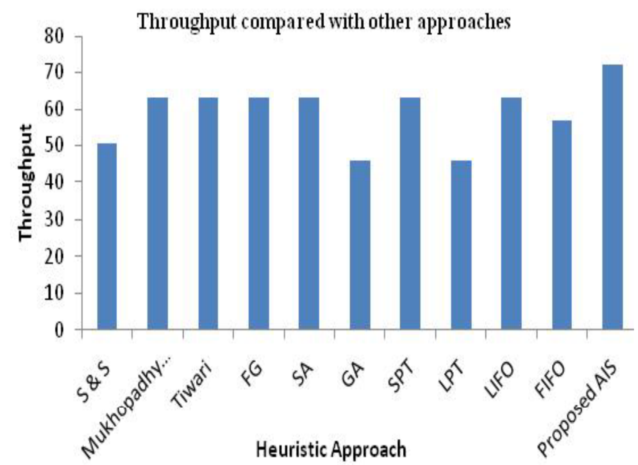
(18)


Throughput compared with other approaches
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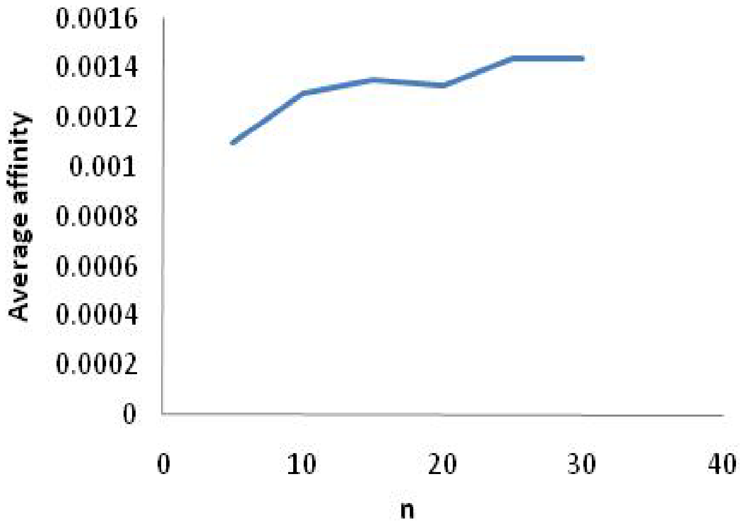
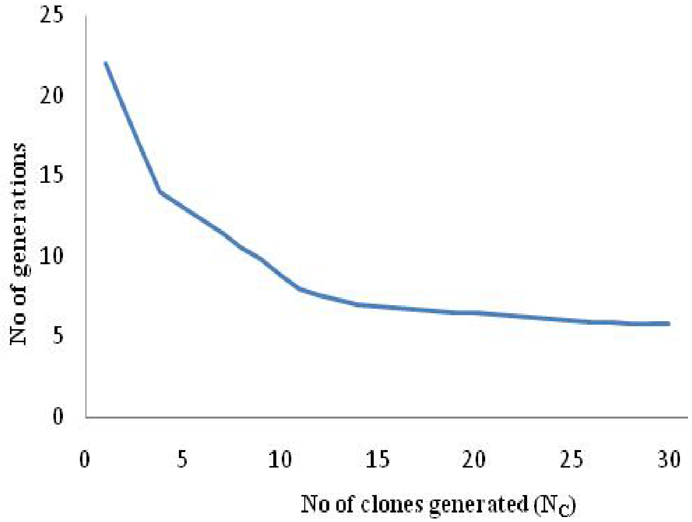
FIFO
Proposed AIS
Heuristic Approach

| Different FMS Scenarios | Different Heuristic Approaches | | | |
|---|---|---|---|---|
| | GA based sequence rule | | Proposed Algorithm | |
| | SU | Th | SU | Th |
| Problem 1 | 63 | 48 | 14 | 55 |
| Problem 2 | 276 | 61 | 228 | 61 |
| Problem 3 | 819 | 51 | 619 | 55 |
| Problem 4 | 536 | 137 | 1182 | 137 |
| Problem 5 | 168 | 120 | 108 | 120 |
| Problem 6 | 356 | 107 | 176 | 117 |
| Problem 7 | 20 | 122 | 59 | 125 |
| Problem 8 | 9 | 167 | 1 | 145 |
| Problem 9 | 619 | 128 | 569 | 128 |
| Problem 10 | 0 | 146 | 2028 | 241 |




The average population affinity increases with an increase in n. This can be attributed to the fact that the higher the value of n, the larger the number of antibodies, which will be located at maximum.

While, evaluating the effect of $N_C$, n was set to 10. It can be seen that higher the value of $N_C$, the faster the convergence occurs in terms of number of generations. However, the computational time per generation increases reasonably linearly with $N_C$.

## Conclusions

The proposed Artificial Immune System enhances the applicability of traditional Clonal algorithm by making some modifications in the operators.

The chaotic representation gives better results compared to other computing meta-heuristics for machine loading problem.

The main focus of present work is to find a more versatile and efficient methodology, which is capable of maintaining good memory and can give better quality results with fast convergence rate,

## References

[1] K. Stecke, “Formulation and solution of non-linear production planning problems for flexible manufacturing system,” *Management Science*, vol. 29, no. 3, pp. 273–288, 1983.

[2]K. Shanker, and A. Srinivasulu, “Some solution methodologies for a loading problem in random FMS,” *International Journal of Production Research*, vol. 27, no. 6, pp. 1019–1034, 1989.

[3]T. Sawik, “Modelling and scheduling of flexible manufacturing systems,” *European Journal of Operational Research*, vol. 45, no. 2–3, pp. 177–190, 1990.

[4] M. Liang, and S. P. Dutta, “Combined part-selection, tool sharing and machine loading problem in flexible manufacturing system,” *International Journal of Production Research*, vol. 30, no. 10, pp. 2335–2349, 1992.

[5]M. Berrada, and K. E. Stecke, “A branch and bound approach for machine load balancing in flexible manufacturing systems,” *Management Science*, vol. 16, no. 10, pp. 1316–1335, 1986.

[6]M. K. Tiwari, and N. K. Vidyarthi, “Solving machine loading problem in flexible manufacturing system using genetic algorithm based heuristic*, International Journal of Production Research*,” vol. 38, no. 14, pp. 3357–3384, 2000.

[7]M. K. Tiwari, Sanjeev, Kumar, Shashi, Kumar, Prakash, and R. Shankar, “Solving part type selection and operation allocation problems in a FMS: an approach using constraint based fast simulated annealing algorithm,” *IEEE Transactions on Systems*, *Man and Cybernetics, Part A*, vol. 36, no. 6, pp. 1170–1184, 2004.

[8]F. T. S. Chan, R. Swarnkar, and M. K. Tiwari, “Fuzzy goal-programming model with an artificial immune system (AIS) approach for a machine tool selection and operation allocation problem in a flexible manufacturing system,” *International Journal of Production Research*, vol. 43, no. 19, pp. 4147–4163, 2005.

[9]N. Kumar, and K. Shanker, “A genetic algorithm for FMS part type selection and machine loading,” *International Journal of Production Research*, vol. 16, no. 38, pp. 3861–3887, 2000.

[10]U. M. B. S. Sarma, S. Kant, R. Rai, and M. K. Tiwari, “A solution to machine loading problem in FMS using tabu search based algorithm,” *International Journal of Computer-Integrated Manufacturing*, vol. 15, no. 4, pp. 285–295, 2002.

[11] R. Argawal, M. K. Tiwari, and S. K. Mukherjee, “Artificial Immune System Based Approach for Solving Resource Constraint Project Scheduling Problem,” *International Journal of Advanced Manufacturing Technology*, vol. 34, no. 5-6, pp. 584-593, 2007.

[12]M. Chandrasekaran, P. Asokan, S. Kumanan, T. Balamurugan, and S. Nickolas, “Solving job shop scheduling problems using artificial immune system,” *International Journal of Advanced Manufacturing Technology*, vol. 31, no. 5-6, pp. 580–593, 2006.

[13] O. Engin, and A. Doyen, “A new approach to solve hybrid flow shop scheduling problems by artificial immune system,” *Future Generation Computer Systems*, vol. 20, no. 6, pp. 1083–1095, 2004.

[14] B. Naderi, M. Khalili, and R. T. Moghaddam, “A hybrid artificial immune algorithm for a realistic variant of job shops to minimize the total completion time,” *Computers and Industrial Engineering*, vol. 56, no. 4, pp. 1494-1501, 2009.

[15] H. Gao, and X. Liu, “Improved Artificial Immune Algorithm and its application on the Permutation Flow Shop Sequencing Problems,” *Information Technology Journal*, vol. 6, no. 6, pp. 929-933, 2007.

[16] B. Li, and W. Jiang, Optimizing Complex Functions by Chaos Search*, International Journal of Cybernetics and Systems*, vol. 29, no. 4, pp. 409-419, 1998.

[17]C. Zhou, and T. Chen, Chaotic Annealing for Optimization, *Physical Review E*, vol. 55, no. 3, pp. 2580-2587, 1997.

[18]S. K. Mukhopadhyay, S. Midha, and V. M. Krishna, A heuristic procedure for loading problems in flexible manufacturing systems, *International Journal of Production Research*, vol. 30, no. 9, pp. 2213–2228, 1992.

[19] L. N. De Castero, and F. J. Von Zuben, Learning and optimization using the clonal selection principle, *IEEE Trans Evolutionary computation*, Special issue on Artificial immune systems, vol. 6, no. 3, pp. 239-251, 2002.

[20] J. Determan, and A. J. Foster, Using chaos in genetic algorithm, *In: Proceedings of the 1999 Congress on Evolutionary Computation*, vol. 3, IEEE Press, Piscataway, NJ, pp. 2094-2101, 1999.

[21] R. Caponetto, and M. G. Xibilia, Chaotic Sequences to Improve the Performance of Evolutionary Algorithms, *IEEE transactions on evolutionary computation*, vol. 7, no. 3, pp. 289-304, 2003.

[22] L. Chen, and K. Aihara, Chaotic simulated annealing by a neural network model with transient chaos, *Neural Networks*, vol. 8, no. 6, pp. 915-930, 1995.

[23]Luo and Shao, Evolutionary algorithms with chaotic perturbations, *Control Decision*, vol. 15, pp. 557-560, 2003.

[24] M. K. Tiwari, Prakash, A. Kumar, and A. R. Mileham, Determination of an optimal assembly sequence using the Psycho Clonal Algorithm, *Journal of Engineering Manufacture*, vol. 219, pp. 137-149, 2005.

[25] L. N. DeCastro, and F. J. V. Zuben, Learning and optimization using the clonal selection principle, *IEEE Transaction on Evolutionary Computation, special issue on Artificial Immune System (AIS)*, vol. 6, no. 3, pp. 239-351, 2002.

**Thanks**