Scientia Iranica B (2014) 21(5), 1726–1731

SCIENTIA IRANICA

Sharif University of Technology

Scientia Iranica

Transactions B: Mechanical Engineering

www.scientiairanica.com

Research Note

Intelligent pheromone up gradation mechanism through Neural augmented Ant Colony Optimization (NaACO) meta heuristic in machine scheduling

M. Umer*, **R. Ahmad and Sh. Ikramullah Butt**

School of Manufacturing and Mechanical Engineering (SMME), National University of Science and Technology (NUST), Sector H-11, Islamabad, Pakistan.

Received 5 May 2013; received in revised form 10 October 2013; accepted 4 January 2014

KEYWORDS
Pheromone update;
Neural augmented Ant Colony Optimization (NaACO);
Artificial Neural Networks (ANN).

Abstract. The pheromone update phase in Ant Colony Optimization (ACO) has been addressed by various researchers in the context of scheduling problems. Various Artificial Intelligence (AI) techniques have also been used to investigate and improve the pheromone trail in worker assignment issues at the workshop floor level. This paper proposes a novel way of investigating and analyzing the issue of pheromone assignment through the Neural augmented Ant Colony Optimization (NaACO) technique. The technique thus developed has its roots in combining the strengths of Artificial Neural Networks (ANN) and the extra ordinary convergence capabilities of Ant Colony Optimization (ACO), thus, formulating NaACO (Neural Augmented ACO). A set of one hundred problems has been taken and an extensive methodology has been formulated to address the issue of pheromone updates in worker assignments on these problems. The results have been formulated and areas of future research have also been indicated.

© 2014 Sharif University of Technology. All rights reserved.

1. Literature review

Job shop scheduling problems are, most probably, some of the hardest optimization problems, which are NP-complete [1]. Mozdgir et al. [2] proposed efficient heuristic algorithms to solve no-wait two-stage assembly flow shop scheduling problems with comparatively low computational effort. The basic idea of the systems approach is to "divide" the problem into more realistic and manageable domains, and then "conquer" the problem through amalgamation of achieved results for the parts [3]. Wilkerson and Irwin [4] developed one of the earliest neighborhood search methods. The concept of these methods correlates to the notion of "hill climbing".

ACO has proven to be competitive in terms of its performance, while searching for an optimal solution, when seen in the contest of wide variants of optimization problem. The advent of this technique is related to development of the theory of stigmergy presented by the French scientist, Grasse (see [5]). The first algorithm was proposed by Dorigo [6] and its initial application was on the Travelling Salesman Problem (TSP). Many variants of the basic algorithm were then introduced by Dorigo & Thomas [7], e.g. Ant System (AS), ATNS-OAP, MAX-MIN Ant System (MMAS), etc. The successful application of ACO on scheduling problems was showcased for a single machine weighted tardiness problem [8]. Similarly, successful applications were also seen for flow shop scheduling problems [9]. The constrained problems, in terms of resources, were

*. *Corresponding author. Tel.: +92 51 90851201; Fax: +92-51-90851202*
E-mail address: muhammad.umer@smme.nust.edu (M. Umer)

undertaken by Merkle et al. (see [10]). Blum and Sampels [11] proposed a non-delay scheduling sequence and performed the optimization through local search. Naurali and Imanipour [12] presented a Particle Swarm Based (PSO) algorithm for FJSSP. In another piece of research, Niknam et al. [13] proposed a new hybrid evolutionary algorithm, named HFAPSO, to solve the Distribution Feeder. Reconfiguration (DFR), which is a combination of Fuzzy Adaptive Particle Swarm Optimization (FAPSO) and Ant Colony Optimization (ACO). A software system, leaning towards development of an intelligent manufacturing system, was proposed through software by Rossi and Dini [14], for solution of Flexible Job Shop Problems (FJSP). ACO has constantly been known to outperformed Genetic Algorithms (GA) in local search and convergence rates. The evidence comes from development of the MMAS based heuristic algorithm proposed by Girish & Jawahar [15]. The approach was used to address various benchmark problem sets.

Neural networks can perform two basic functions. They can be used to remember some information about the problem [16], and can also be used to perform optimization and satisfy the conditions of the given constraints [17,18]. The later form of neural network handles job shop scheduling problems. Numerous approaches have been formulated to solve the scheduling problems through neural networks [19]. Two of the most popular approaches are the branch and bound method and that of simulated annealing. Sastri and Malave [20] applied a Bayesian classifier and a BEP network in the calculation of expected cost per time period and, thus, in determining the overall optimal control policy. Neural networks have also joined hands with ACO to put forth yet another dimension for the solution of scheduling problems. Evidence of the combined strength of ANN and ACO is evident from the work of Huawang and Wanqing [21]. Irani and Nasimi [22] developed a technique to use ACO with ANN for permeability estimation of a reservoir. The combination of ACO with ANN for tackling scheduling problems poses a novel paradigm to solve combinatorial optimization problems.

2. Description of this paper

This paper focuses on combining the strengths of ANN with that of ACO and, thus, tries to formulate a unified technique, coined as Neural augmented ACO (NaACO). We have endeavored to interface the strengths of ANN in the pheromone up gradation phase of conventional ACO. The supervised ANN methodology has been used in the evaporation or the consolidation phase of ACO, once the initial "first sweep" has been carried out by conventional ACO. So, this paper is organized as follows:

- Section 2.1 describes the problem formulation;
- Section 2.2 describes formulation of the Neural Augmented ACO methodology;
- Section 3 represents the results of our research once applied on a set of problems;
- Section 4 represents the conclusion;
- Section 5 represents areas of future research.

2.1. Problem formulation

n jobs and W workers must be scheduled to m parallel machines, based on the following given conditions:

a. The jobs in our problem are pre-assigned;

b. The processing time for each machine is represented by three variables, A, B and E;

c. The jobs are not to be divided within the machines;

d. The workers are to be assigned to the machines;

e. The selected objective is to allocate W workers through ACO and, then, reallocate additional resources (in the form of man hours available) through ANN;

f. The set up delays in machines are neglected;

g. The machines perform continuous operations once the workers have been assigned;

h. The time and motion component and related analysis are negligible;

i. The capabilities of the workforce shall remain the same during allocation of additional man hours;

j. At the start of the problem, all workers are available from $t = 0$;

k. It is assumed that the processing time function has the simplified form of:

$$p_{i(\omega_i)} = A_i + \frac{B_i}{E_i}. \tag{1}$$

In essence, the problem formulation can be best explained by Figure 1.

The pseudo code for this problem is as follows:

Part-I (scheduling of jobs)
Initialize ACO through a heuristic function.

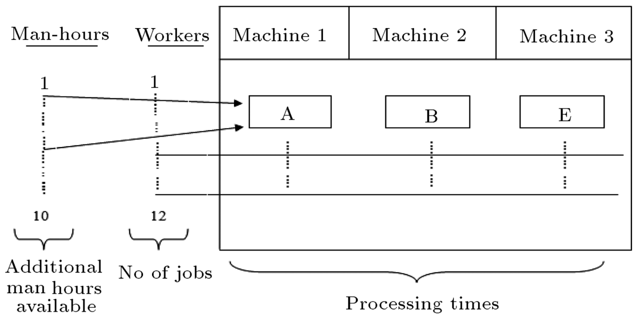

Figure 1. The problem formulation.

a) Set n as the set of scheduled workers for m machines.

b) The workers are assigned through local search.

c) Each worker is assigned to a particular machine.

d) Identify all schedulable jobs and include them in the partial solution.

e) end for.

Apply the global updating rule through Neural Supervised learning and generate an intelligent pheromone interface.

Part-II (assigning additional man hours)
Once all jobs have been assigned, globally constructed solutions are further improved by assigning the remaining 10 man hours, so as to cater for additional resources.

2.2. Neural augmented ACO formulation

Step 1: In this formulation, the reciprocal of the heuristic function is η_{ij}. In our case, on each machine, the triggering heuristic is the processing time, i.e., the less the processing time, the more workers are required, so that the "artificial ant" directs towards the "food source" (in our case, the machine) through the shortest processing time.

$$P_{i,j,k} = \frac{\sum[\tau_{i,j}]^{\alpha}[\eta_{i,j}]^{\beta}}{\sum[\tau_{i,k}]^{\alpha}[\eta_{i,k}]^{\beta}}. \tag{2}$$

Figure 2 demonstrates the heuristic based methodology, through which the workers have been assigned to various machines. This also prepares the groundwork for us to present a pheromone update to assign additional man-hours with the Neural Augmented ACO.

Step 2: The pheromone update is undertaken by incorporating supervised learning artificial neural networks. In that novel arrangement, additional man-hour assignments are accompanied by the amount of pheromone calculated in which the additional man-hours may be assigned to the most committed machine, as the maximum assistance will be required. Figure 3 explains the process of additional workforce assignment.

Step 3: The NaACO is a logic based (Yes/No) artificial neural network model, which aggregates the combination of the three-machine times and the initial workers assigned, and combines these entities with the amount of additional man-hour availibility (pheromone updates). If the overall combination is correct, the answer would be "Yes", which indicates that the overall compatibility of all the variables is "recognized" and the value can be "*combinatorially used*".

3. Results of the applied technique

Figure 4 represents the training of ANN on the given set of 100 problems. The trained network provides the NaACO approach to cater for additional resources.

The trained ANN is then executed to test the various combinations. These include the processing time of the machines, the allocated workers on the

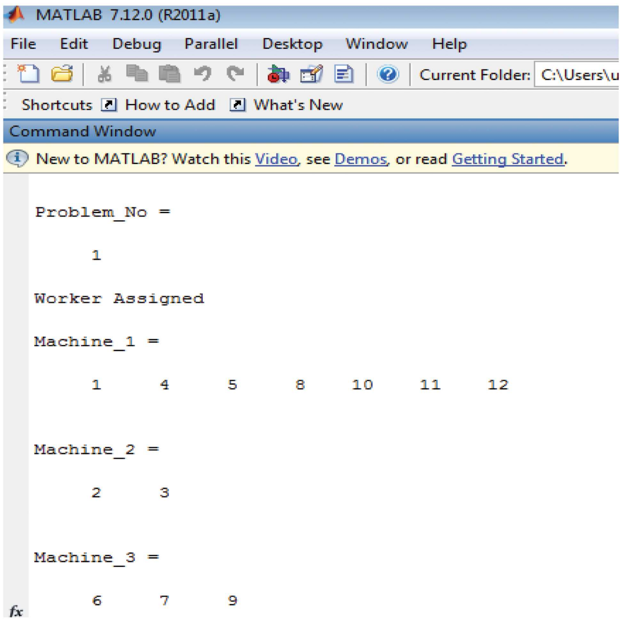

Figure 2. The worker assignment to the machines through ACO.

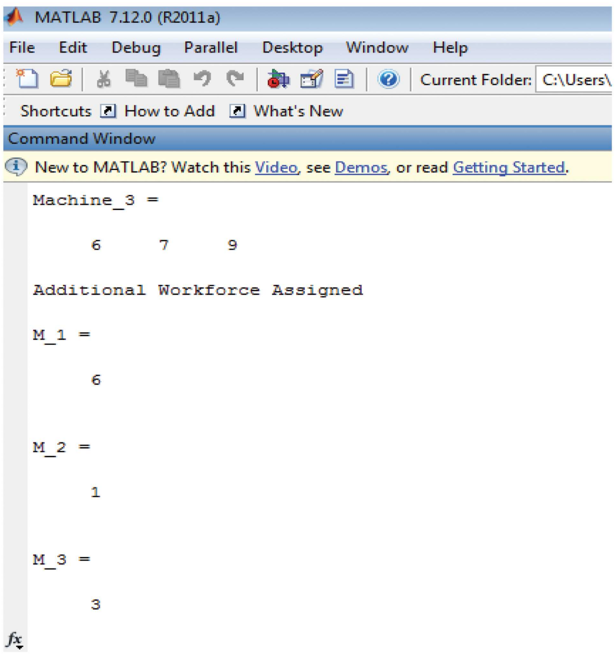

Figure 3. The additional man-hours (in the figure referred to as *workforce*) assigned to the machines.

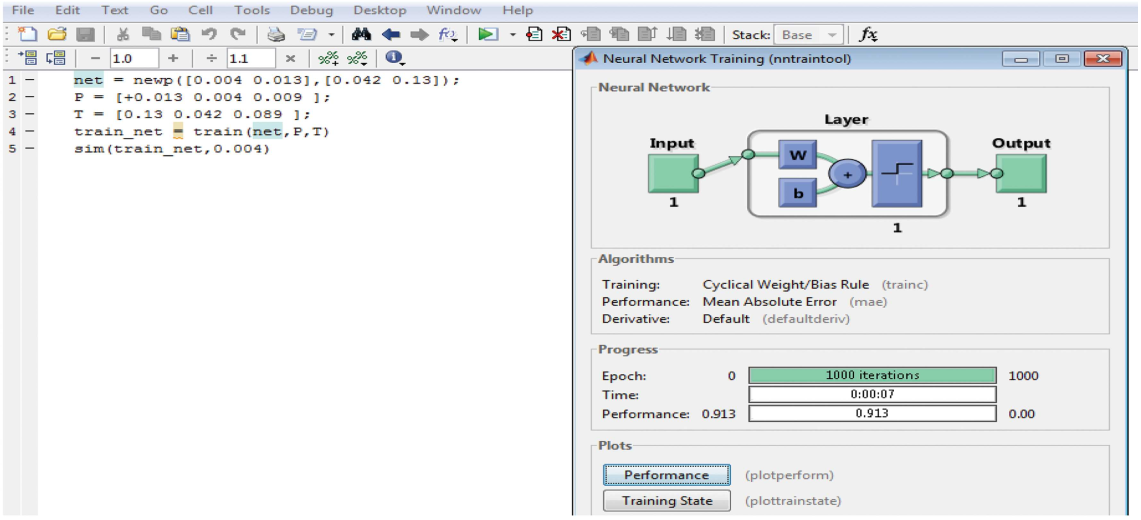

Figure 4. The NaACO setup being trained on a set of 100 problems through supervised ANN at the pheromone up gradation phase.

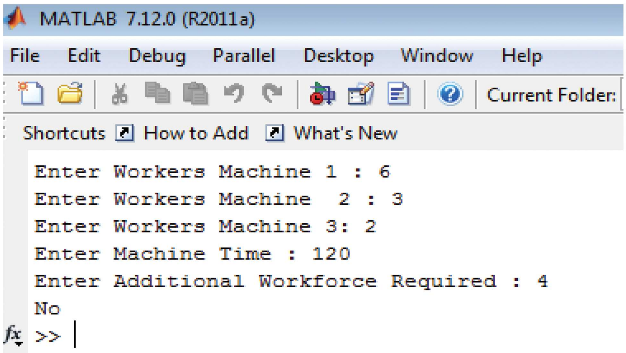

Figure 5. The NaACO interface that can handle various input argumentations and generate results.

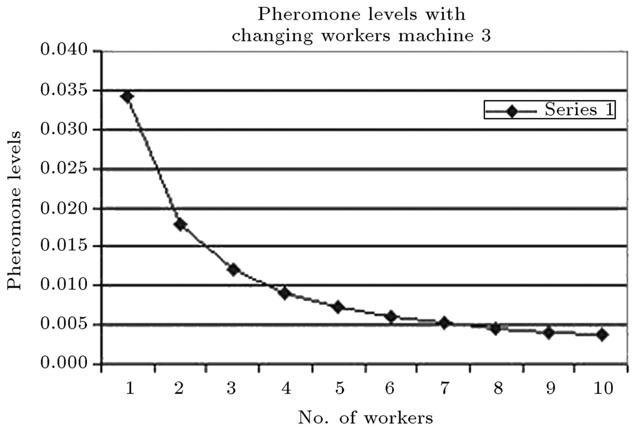

Figure 6. The pheromone levels which are used to train the NaACO model for correct recognition of the combinations which are feasible, and response is generated after the model has been trained on these levels.

machines and the additional workforce requirement to extensively check the complete feasibility of the total combination. This approach introduces a novel approach in which the correction or pheromone update is *Combinatorially* tested, rather than done separately, as shown in Figure 5.

The significance of the additional workforce allocation is also assessed by its effects on the overall pheromone level of the problem. Figure 6 demonstrate the effects of pheromone levels, with the changing number of additional workers, representing the variation patterns for machine 3 as a specimen.

4. Conclusion

This paper represents a novel procedure for combining the strengths of ACO and ANN by illustrating an intelligent technique to give ACO the necessary potential at the pheromone up gradation phase. In conventional ACO, the pheromone up gradation phase is used merely to consolidate or evaporate the initial solution, but has never been used to generate a combinatorial characteristic. This paper demonstrates the potential of using supervised ANN at the subsequent loops of ACO, thus, enabling this meta heuristic to evaluate and reconsider, whilst overlooking the whole environment of the problem set and all the variables involved. A very useful and suitable set of combinatorial problems are presented using the worker assignment perspective of various scheduling problems which is of enormous interest to many industries and services.

5. Areas of future research

Finally, we propose the following areas of future research/improvement:

- To test and evaluate the potential of the proposed technique, it can be implemented on various similar problems ranging from manufacturing to services sectors.

- The NaACO technique can be used on other benchmark problems with the combined dimension of man-hour assignment, and the concluded results can be congregated with the optimal solutions. In this technique, the ANN augments the conventional ACO (in the domain of pheromone calculation and combined assignments).
- This technique can also be considered to formulate an unsupervised ANN methodology which can incorporate SOM topology (Self Organizing Maps) to train the networks prior to pheromone consolidation or evaporation.
- Furthermore, this paper introduces a system that can be designated as a broad category of the meta-heuristic problem formulation technique, formed for "intelligent ACO (iACO)".
- This technique can also be used to tackle Dynamic Scheduling problems, which have a greater difficulty level and require more holistic analysis of the situation.

References

1. Garey, M.R. and Johson, D.S., *Computer and Intractability: A Guide to the Theory of NP-Completeness* (1979).
2. Mozdgir, A., Fatemi Ghomi, S.M.T., Jolai, F. and Navaei, J. "Three meta-heuristics to solve the no-wait two-stage assembly flow shop scheduling problem" *Scientia Iranica: Transactions on Industrial Engineering*, **E20(6)**, pp. 2275-2283 (2013).
3. Zhang, J., Hu, X., Tan, X., Zhong, J.H. and Huang, Q. "Implementation of an ant colony optimization technique for job shop scheduling problem", *Transactions of the Institute of Measurement and Control*, **28**(1), pp. 93-108 (2006).
4. Wilkerson, L. and Irwin, J. "An improved algorithm for scheduling independent tasks", *AIIE Transactions*, **3**, pp. 239-245 (1971).
5. Grassé, P.P. "Rebuilding the nest and interpersonal coordination among *Bellicositermes natalensis Cubitermes* and the theory of *stigmergy*. Possible interpretation of the behavior of termite as manufacturers", *Insectes Sociaux*, **6**(1), pp. 41-80 (1959)
6. Dorigo, M. "Optimization, learning and natural algorithms", PhD Thesis, Politecnico di Milano, Dipartimento di Eletronica, Milan (1992).
7. Dorigo, M. and Thomas, S, *Ant Colony Optimization*, The MIT Press, London (2004).
8. den Besten, M.L., Stutzle, T. and Dorigo, M. "Ant colony optimization for the total weighted tardiness problem", In *Proceedings of PPSN-VI, Sixth International Conference on Parallel Problem Solving from Nature*, Springer-Verlag, Berlin, pp. 611-620 (2000).
9. Rajendran, C. and Ziegler, H. "Ant-colony algorithms for permutation flowshop scheduling to minimize makespan/total flowtime of jobs", *European Journal of Operational Research*, **155**(2), pp. 426-438 (2004)
10. Merkle, D., Midderdorf, M. and Schmeck, H. "Ant colony optimization for resource-constrained project scheduling", *IEEE Transactions on Evolutionary Computation*, **6**(4), pp. 333-346 (2002).
11. Blum, C. and Sampels, M. "Ant colony optimization for FOP shop scheduling: A case study on different pheromone representations", In *Proceedings of the 2002 Congress on Evolutionary Computation (CEC-02)*, IEEE Press, Piscataway, NJ. pp. 1558-1563 (2002a).
12. Nourali, S. and Imanipour, N. "A particle swarm optimization-based algorithm for flexible assembly job shop scheduling problem with sequence dependent setup times", *Scientia Iranica*, **21**(3), pp. 1021-1033 (2014)
13. Niknam, T., Khorshidi, R. and Firouzi, B.B. "A hybrid evolutionary algorithm for distribution feeder reconfiguration", *Sādhanā*, **35**(2), pp. 139-162 (2010).
14. Rossi, A., Dini, G. "Flexible job-shop scheduling with routing flexibility and separable setup times using ant colony optimization method", *Robotics and Computer-Integrated Manufacturing*, **23**(5), pp. 503-516 (2007)
15. Girish, B.S. and Jawahar, N. "Scheduling job shop associated with multiple routings with genetic and ant colony heuristics", *International Journal of Production Research*, **47**(14), pp. 3891-3917 (2009)
16. Rumelhart, D.E. and McClelland, J.L., *Parallel Distributed Processing*, MIT Press, Cambridge, MA. (1986).
17. Hopfield, J.J. and Tank, D.W. "Neural computation of decisions in optimization problems", *Biological Cybernetics*, **52**(3), pp. 141-152 (1095).
18. Poliac, M.O., Lee, E.B., Slagle, J.R. and Wick, M.R. "A crew scheduling problem", In *Proceedings of IEEE International Conference on Neural Networks*, pp. 779-786 (1987).
19. Di Caro, G. "Ant colony optimization and its application to adaptive routing in telecommunication networks", Thesis, Universite Libre De Bruxelles, Faculte Des Sciences Appliques, Bruxelles (2004).
20. Sastri, T. and Malave, C.O. "Identification of the optimal control policy for the Markov decision process by back propagation", *Intelligent Engineering Systems Through Artificial Neural Network*, C.H. Dagli, S.R. Kumara, Y.C. Shin, Eds., New York, ASME, pp. 873-881 (1991).
21. Huawang, S. and Wanqing, L. "Artificial neural network with ant colony optimization for assessing performance of residential buildings", *International Conference on Future Bio Medical Information Engineering*, pp. 379-382 (2009).

22. Irani, R. and Nasimi, R. "An evolving neural network using an ant colony algorithm for a permeability estimation of the reservoir", *Petroleum Science and Technology*, **30**(4), pp. 375-384 (2012).

Biographies

Muhammad Umer obtained his MS degree in Engineering Management from CASE in 2006, and also has a "Certificate in Nanotechnology" (2006-2007) from Stanford University, USA. Following industrial work experience, he obtained a second MS degree from LSE (London School of Economics) in "Operations Research", in 2009, and is currently a PhD degree candidate at NUST, with Ant Colony Optimization as his main field of research. Since 2009, he has contributed to Pakistani Academia and Industry in various areas and has almost ten years of National and International experience in manufacturing and supply chains with multinational companies, such as Eurocopter, Bell Helicopters, Textron Lycoming, Rolls Royce, etc.

His consultancy in Pakistan also encompasses corporate training all over the country in areas of supply chain (both basic and advanced versions) to clients from the Pharmaceutical, Glass Fabrication, and Textile Industries, Pakistan Air Force and Army, KRL, Logistics Service Providers, KSB Pumps, Shifa Hospital, and Academia, etc. He has also been nominated by Harvard University as their "External Proctor" for distance learning students for the Asian Region.

Riaz Ahmad obtained a BS degree in Aerospace Engineering in 1984, and MS and PhD degrees in Computer Aided Process Planning and Product Lifecycle Management, respectively, from Beijing University of Aeronautics and Astronautics, China. He has over 27 years of experience in industry and academia, including middle and senior management posts. He is currently supervising research, and teaching undergraduate and post graduate courses at the National University of Sciences and Technology, Pakistan. He has also published a number of research papers in international journals and conferences in the field of mechanical/aeronautical manufacturing.

Shahid Ikramullah Butt obtained his BS degree in Mechanical Engineering from the University of Engineering and Technology, Lahore, Pakistan, and his MS degree in Engineering from Mississippi State University, USA. Following industrial work experience, he obtained a PhD degree in Industrial and Manufacturing Engineering from Beijing Institute of Technology, China. Dr Shahid is currently Head of the Mechanical Engineering Department at NUST School of Mechanical and Manufacturing Engineering, Islamabad, Pakistan.

He has authored more than 30 research papers, and supervised many MS and PhD degree theses.