Unsupervised Artificial Neural Networks (ANNs) For Intelligent Pheromone up Gradation. Further Evolution of Neural Augmented Ant Colony Optimization (NaACO)

Muhammad Umer[1], Dr. Riaz Ahmad[2], Dr. Imran Chaudhry[3]

All with School of Mechanical and Manufacturing Engineering (SMME), National University of Science and Technology (NUST), Islamabad, Pakistan
muhammad.umer@smme.nust.edu.pk[1], drresearch@nust.edu.pk[2],
imranchaudhry-cae@nust.edu.pk[3]

Abstract: The pheromone up gradation potential of Ant Colony Optimization (ACO) provides this meta-heuristic ability to reconsider, revaluate and revamp the already derived conclusions and results. In the recent path various attempts have been made to come up with novel implementation plans in which this facet of ACO has been addressed extensively. This research paper takes Pheromone Up gradation as a construct and hence tries to inculcate an intelligent aspect into the basic technique. The unsupervised Artificial Neural Network (ANN) has been incorporated to give intelligence to pheromone up gradation phase. 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). This paper applies the newly formulated technique on a set of hundred problems related to worker assignment in scheduling environments...The results have been formulated and areas of future research have also been indicated.
[Muhammad Umer, Riaz Ahmad, Imran Chaudhry. **Unsupervised Artificial Neural Networks (ANNs) For Intelligent Pheromone up Gradation. Further Evolution of Neural Augmented Ant Colony Optimization (NaACO).** *Life Sci J* 2013;10(3):318-327] (ISSN:1097-8135). http://www.lifesciencesite.com. 50

Keywords: Pheromone update; Neural Augmented Ant Colony Optimization (NaACO); Unsupervised Artificial Neural Networks (ANN).

1. Literature Review

NP-Complete set of solutions has been researched on to its utmost depths with the help of the scheduling problems specifically tailored within job shop environments. In the start operations research techniques were used to solve the scheduling problems e.g. via dynamic programming, Branch and Bound method and many more. To ensure that the problems give out optimized results the use of very efficient operation research techniques and tools were availed so that they may adopt to the localized nature of the problems. Authors, including Mathirajan et al. (2007) are of the view that to solve any large size real-life examples can be solved using efficient heuristics algorithms with relatively minimal computational effort. Furthermore, due to the emergence of Artificial Intelligence (AI) systems most of the new heuristics search algorithms for scheduling problems. The main attraction in using these heuristics algorithms is that they give out the optimal solution relatively quicker than other algorithms, hence significantly reducing processing time, but the issue occurs when it need to justify the quality of the solutions and the ultimate capacity of the resulting algorithm, that is also an area which needs to be broadly evaluated.

The gap between heuristics and optimization approaches was narrowed with the use of single machine sequencing and their optimization through heuristics approaches. Lagrange method provides a more real-life and practical way for machine scheduling, in this process an optimal solution is evolved by the use of Lagrangian multiplier, and an updation loop was incorporated to be used for the recurrent nature of the problems.

A single processing step, performed on a single or multiple resources can help resolve the scheduling problems which are single stage single processor and single stage multiprocessor. Optimization is need in the multistage flow shop and job shop problems, as they possess an innate complex nature and most often require allocation of multiple resources. Additionally, the problems are said to be static if the number of jobs and their ready time available are considered, and the problems are said to be dynamic if the number of jobs and their characteristics are ever changing.

“Intelligent scheduling” from “systems approach” can be generated in a more better and compact way through the artificial intelligence approach to scheduling problems. The basic notion of the systems approach is “Divide and Conquer”, as it “conquers” the problem through amalgamation of achieved results for parts by “dividing” the problem into more realistic and manageable domains. The whole idea of implementing the AI approach to any scheduling problem is to identify the agents that are “adaptive” yet “intelligent”. For the AI techniques to take affect and present a feasible solution, these agents are the basic ingredients and enablers. It cannot be made sure of that a perfect solution may be achieved by the developed systems approach, but it does ensures that the systems can be formulated that are self-adjusting. The solution of a very popular scheduling problem known as “neighborhood search methods” can now be easily catered for due to the development of “systems approach”. One of the earliest neighborhood search methods were developed by Wilkerson & Irwin, these methods associate to the idea of “hill climbing”, as it suggests while solving any problem it is advised to take incremental and continual steps should be taken so that each result can be recorded easily and if there is no visible improvement in the objective function, terminate. The most popular of the “neighborhood search methods” include techniques like simulated annealing, taboo search, and genetic algorithms, each of these techniques present their own agitation technique, various methods to avoid the agents going into local optima’s, and termination points.

ACO – Ant Colony Optimization techniques are the newest addition to these methods. Like many other problem solving methods as Genetic Algorithms (GA), and many other methods, ACO is inspired by the scavenging behaviors of ants and how they make their ways towards a food source. The core of this method revolves around convergence capability of “real” ants and how can their ways be adapted and how these “real” ants can be converted into “artificial” ants which then can be worked upon as “agents”.

While searching for an optimal solution ACO has proven to be very competitive in terms of its working and performance. The dawn of this techniques is related to the theory development of stigmergy, presented by Grasse, a French scientist. This theory focuses on the concept of a non-centralized and indirect mechanism of coordination between the “agents” and their “environments”. The basic notion of the concept was that the actions taken by the initiating “agents” resulted for the consequent “following agents” actions through the traces left by the early initiators. Dorigo (1992), was the pioneer in presenting the first ever algorithm in this field and its initial presentation was in the working of TSP – Travelling Salesman Problem. After that many of the applications were presented bt Dorigo & Thomas (2004), like Ant Systems (AS), MAX-MIN Ant Systems (MMAS), ATNS-OAP, etc. The first ever ACO on scheduling problems successful application was presented for a single machine weight tardiness problem, and the successful applications were also seen for flow shop scheduling problems. Merkle et al. (2002), was responsible for the introduction of constrained problems in terms of resources. Many authors after that have presented their work in the like of Merkle et al. (2002), and one of them are Blum & Sampels (2002) who proposed that a non-delay scheduling sequence can be optimized through local search. From the emergence and early usage of these algorithms it was suspected that the hybridization with the combination of ACO and some other local procedures, will present a new area of research. The combinations of ACO and taboo search for the application of JSP was first presented by Huang & Liao (2008). While in another research, Niknam et al. (2010) presents a new evolutionary hybrid algorithm to solve Distrubuiton Feeder Configuration (DFR) named as HFAPSO, which is the collection of fuzzy adaptive particle swarm optimization (FAPSO) and ACO. Rossi & Dini (2007) proposed a solution software system which focused on building an intelligent manufacturing system, for the solution of flexible job shop problem (FJSP). In convergence rates and local search ACO has positioned itself in outperforming genetic algorithms constantly, which is proved by Girish & Jawahar (2008), from the development of MMAS based algorithms. This approach was used to solve various standardized problem sets. To sum it up, ACO has proven its ability in providing an efficient method to solve the scheduling problems, and it has made its mark in proving that it is completely able to tackle complex, yet ever evolving FJS formulations and problems.

Neural networks conventionally refers to presentation of a circuit or network of biological neurons, the biological neural networks (BNN) primary function is to maintain the working of the nervous system. The artificial neural network (ANN) are thus composed of artificial interconnected neurons, which are given a set of inputs and values and then are trained to develop a relationship that might help in forecasting futuristic values, given a definite new input, this type of learning is referred to as “unsupervised learning” of the artificial neural networks. Feed forward neural network (FFNN) is amongst the simplest forms of the neural networks in which the flow of information is one way; that is the information moves from the inputs to the hidden nodes, if present, and finally to the outputs, the feedback mechanism is not present in this type of neural system. The feedback mechanism is present in the back propagated (BP) neural network, in this mode the information flow from the neurons move in a loop, as it goes forward and comes back too, in the form of feedback. Neural networks can perform two of the basic functions:

- Neural networks can be embedded to remember information about the problems, and
- They can also be used to satisfy the conditions of the given constraints by performing optimization.

The advanced form of neural networks can now handle the JSSP, as numerous neural network techniques have been formulated to provide solutions to various scheduling algorithm problems. Two of the most popular are that of Simulated Annealing and Branch & Bound methods. To solve scheduling problems with the help of neural networks, the shifting bottleneck procedure also provides sufficient evidence. To determine the overall optimal control policy, Sastri & Malave (1991) have applied a Bayesian classifier and a BEP network to calculate the expected cost per time period. The collaboration of neural networks and ACO have brought forward quite many dimensions for the solution of scheduling problems.

For the assessment of the performance of residential building employing the back propagated algorithm can be used with the combination of ANN and ACO, the evidence of their strength can be seen from the works of Huawang & Wanqing (2009). For the permeability estimation of a reservoir, Irani & Nasimi (2012) have developed their techniques to make use of both the ANN with ACO methods. In the medical diagnostic field through ACO, another piece of research is available in which the researcher has trained a feed forward neural network. Furthermore, researchers have also found a brand new neuron model which has a relativel less number of interconnections among their neurons which improves the computing time of training, decreasing inefficiencies, known as Compensatory Neural Network Architecture (CNNA).

To solve combinatorial optimization problems, an innovative way can be to tackle the scheduling problems with the combination of artificial neural networks and ant colony optimization techniques. To be more specific in any work environment the ANN can be optimally utilized to handle the "worker" variable in the scheduling process, so that by the use of supervised learning of ANN, the pheromone levels are obtained and updated. This paper is designed to present such techniques that will answer to various standardization and benchmarking problems and the results of those will be communicated and for the future researchers a course of action is also suggested.

2.1 Unsupervised Learning

The term actually refers to a mode of "unofficial learning" or one can say "learning without a teacher", it is generally associated with the process of collecting observations from a sampled form of distribution to the properties of any group. The term unsupervised learning can be declared as meaningless, as it needs be appropriately regarded as a way that is not aptly qualified. In its totality unsupervised learning can be summarized by describing two methods i.e. Clustering and Mixture Decomposition.

2.2 Clustering

Clustering generally refers to "grouping" of data from the raw information. Just like "unsupervised learning", "clustering" is a poorly defined term. In the literature the following definitions are common:

- The process of finding the datasets.
- The process of dividing the datasets into groups that are similar to each other.
- The process of dividing the datasets into groups, where the points in each group are relatively close (or similar) to one another.
- The process of dividing the datasets into groups, where the points in each group are close (or similar) to each other, and where different sets of points are still far (or different) from each other.
- The process of dividing an area of advantage in areas with high density of points, separated by regions with a low density of points.

Also, the definitions are generic: they do not specify what the terms "datasets" is, what "similar", "close", "far", "high density", "low density", etc., actually notify. This can actually be a good thing and a bad thing at the same time. It is not a good thing in terms of that in generality we have no clue that what the clustering method might result in until we see its algorithmic specification. It is a good thing because just by changing the original meanings of these terms no one can make up an endless variety of clustering algorithms. This has put many researchers to advantage as the existing variety of clustering algorithms is awe-inspiring, and the new algorithms are continuously patented and published from different platforms. And since, new problems are solved by new algorithms, they give the more effective In conclusion, we can spell out that the general populous these days is extremely good at recognizing and interpreting 2- and 3-dimensional data plots and spatial patterns whilst picking out clusters. The issue occurs when we anticipate out intuition at figuring out the higher-dimensional spaces. One side of this demon of dimensionality is the fact that the geometry of high-dimensional Euclidean spaces does not coincide with the innate human ability to project and visualize data in 2 or 3 dimensions and which can cause for the weak minded get frustrated. As a solution to project data in more than just 2 or 3 dimensions and to actually see the results, help of the algorithm software like Matlab can be of undertaken.

2.3 Mixture Decomposition:

In practicality it is used in a very specific class of methods that operate as in following steps:

- For a separate cluster assign each sample;
- Start grouping clusters with the lowest the lowest similarity criteria;
- Assign value to the merged cluster between the grouped clusters;
- Repeat the above two steps until all of the data is grouped and all of it is in a single cluster

It is to be noted that that these processes are agglomerative in nature. This process can be represented by using a tree, known as a dendrogram, it different from a normal tree in the direction from the leaves to the roots, is interpreted as a similarity axis, and onto that merges are drawn at the coordinate corresponding to the attached similarity value. The biggest advantage of dendrogram is that you can cut the tree at the desired similarity value, and keep the only nodes that are needed. Therefore, it can be said that a whole new variety of trees can be constructed with your desired values just by cutting down the full dendrogram to the desired size. By doing so a wide variety of clusters can be built from the ground up, with respect to the similarity indexes if the clusters. Some of the most commonly used indexes are as follows:

- Nearest-neighbor or Single-Link. It refers to the (dis) similarity between two clusters, is the minimum distance between the elements of the two clusters. This method produces lengthy, stingy clusters and can facilitate the creation of bridges among clusters that the human element cannot select.
- Furthest-neighbor or Complete-Link. It refers to the (dis) similarity between two clusters, is the maximum distances between the elements of the two clusters. This method produces tight, compact clusters unlike single-link – it fails to recognize the lengthy and stingy clusters in the begging of the computing process.
- Group Average. It refers to the (dis) similarity between two clusters, is the average of all the distances between the elements of two clusters. Group average somewhat comes in-between the complete-link and the single-link methods.
- Centroid, or Mean. It refers to the (dis) similarity between two clusters, is the distance between the centroids or the arithmetic means of the two clusters.
- Median. It refers to the (dis)similarity between two clusters, is the distance between the medians in between the two clusters.
- Ward's method. It refers to the (dis)similarity between two clusters, due to cluster merging it intensifies of the scattering of the points around the centroids of their clusters. The scattering of the points is measured by the sum of distances squared between the scatter points and the centroid. One can measure the dispersion of the points of the first cluster around the centroid of that cluster, before the merging has taken place and same can be done for the second cluster. But as the merging process is done the measurements can be done by computing the centroid of the cluster that has been merged, and then sums the squared distances of all the points of the two clusters, from the newly formed centroid. It is to be noted that this same procedure is used in computing divisive approach. Just like the complete-link methods, this method also fails to favor length clusters.

If the data results to be as it was planned; that is a tight and roundish data are not remotely close to each other and are well separated, all the above mentioned results will produce the same results. Here is a mention from a group of authors included in Hastie, et al., (p. 475) (2000), who present a more precise statement in a more objective way to judge the representation of data by a hierarchical algorithm. It starts with following assumptions:

- N, being the number of samples;
- Choosing a metric; after selecting pair-wise distances between the clusters, that being $N(N - 1)/2$.
- For points (i, j), cophenetic dis-similarity can be define by looking at the dendrogram and finding the nodes ni,j, at this point in a cluster to points will be merged;
- The value of the similarity index of the nodes ni,j will be the cophenetic distance between the two points i and j;
- A 2-dimensional scatter plot can now be created with the pair-wise distance $N(N - 1)/2$ and the co-ordinates of pi,j;
- The cophenetic dis-similarity and the original dis-similarity between the points i and j will be derived from the co-ordinates of pi,j;

Now we can compute from the set of points, that are pi,j, the co-relation coefficient between the two co-ordinates, which will be then called the cophenetic correlation coefficient. To judge how well the original distances between points are captured by the cluster hierarchy.

3. 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 are 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 form of man hours available) through ANN.
f. The set up delays in machines are neglected
g. The machines shall perform continuous operations once the workers have been assigned
h. The time and motion component and related analysis is 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. Assume processing time function has simplified form of $P_{i\,(W_i)}= A_i + \frac{B_i}{E_i}$

In essence the problem formulation can be bes (1) ned by the following figure.

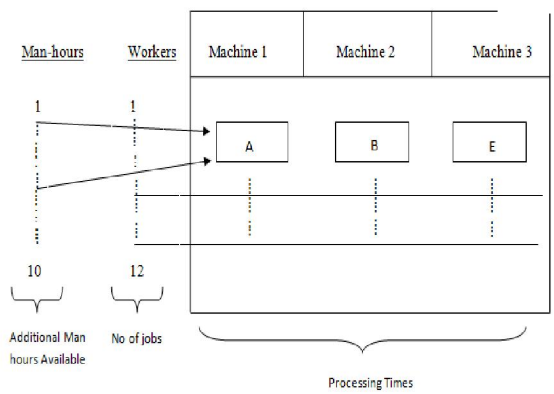

Figure 1: Schematic view of our problem
The pseudo code for this problem is as under:

Part-I (Scheduling of Jobs)
Initialize ACO through Heuristic function.
Set n as the set of scheduled workers for m machines.
The workers are assigned through first local search.
Each worker is to be assigned to a particular machine.
Identify all schedulable jobs and include them in the partial solution.
end for
Apply 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, and then further improve the globally constructed solutions by assigning remaining 10 man hours so as to cater for the additional resources.

3.1 Neural Augmented ACO Formulation through Unsupervised ANN and Results

Step 1: In this formulation, the reciprocal of the heuristic function is $\eta_{i,j}$. 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 toward the "food source" (in our case the machine) through the shortest processing time.

$$P_{i,j,k} = \frac{[T_{i,j}]^{\alpha}\,[\eta_{i,j}]^{\beta}}{\Sigma\,[T_{i,k}]^{\alpha}\,[\eta_{i,k}]^{\beta}} \qquad (2) \qquad\qquad (1)$$

The subsequent figure demonstrates heuristic based methodology, through which the worker have been assigned to the various machines. This also prepares ground for us to present pheromone update, to assign additional man-hours with the Neural Augmented ACO through unsupervised ANN.

Table 1: The sample problem sets

Workers	Machine 1			Machine 2			Machine 3		
	A_i	B_i	E_i	A_i	B_i	E_i	A_i	B_i	E_i
1	7	556	8	8	227	1	4	328	3
2	5	784	4	7	36	5	2	330	9
3	5	195	3	3	236	9	6	570	1
4	2	427	9	9	305	4	6	260	4
5	3	85	6	8	240	7	2	506	4
6	7	799	6	0	758	5	2	166	5
7	0	540	4	9	783	5	8	148	2
8	7	12	1	3	321	5	8	466	5
9	8	460	6	5	222	4	5	64	3
10	7	80	7	7	128	4	9	366	6
11	0	82	9	0	130	3	9	724	5
12	4	639	8	5	517	1	2	209	2

Workers	Machine 1			Machine 2			Machine 3		
	A_i	B_i	E_i	A_i	B_i	E_i	A_i	B_i	E_i
1	7	521	6	6	655	1	5	659	5
2	9	646	8	0	175	6	3	575	2
3	3	333	6	6	147	9	4	716	3
4	6	637	4	9	189	4	5	178	1
5	7	576	2	0	740	2	7	284	9
6	0	554	5	9	206	4	4	442	3
7	7	584	9	0	204	7	3	284	6
8	4	153	7	2	571	4	0	163	3
9	2	618	4	5	531	4	4	463	8
10	6	55	5	8	618	7	5	503	3
11	9	198	5	0	607	4	7	111	8
12	9	760	7	0	246	7	5	48	2

Workers	Machine 1			Machine 2			Machine 3		
	A_i	B_i	E_i	A_i	B_i	E_i	A_i	B_i	E_i
1	9	263	9	0	205	5	4	164	4
2	6	76	6	1	71	4	3	691	5
3	5	471	4	3	24	8	1	470	8
4	3	135	2	1	258	8	7	603	5
5	1	742	5	0	632	7	9	742	4
6	7	78	2	5	237	7	5	264	5
7	4	355	9	6	188	9	0	434	3
8	7	218	2	5	384	4	7	64	6
9	5	698	1	8	203	5	4	507	5
10	8	600	4	0	272	4	4	328	7
11	0	218	5	1	35	7	4	768	8
12	2	538	9	6	385	2	2	91	4

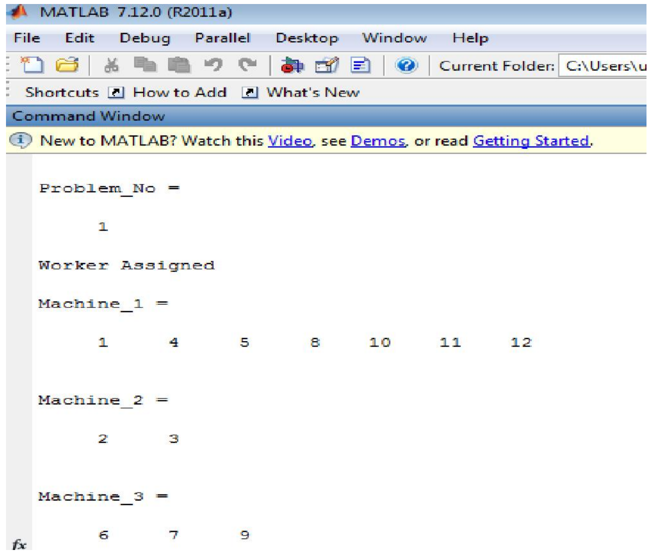

Figure 2: The worker assignment to the machines through ACO. The basic form of ACO has been triggered and the results have been formulated.

Step 2: The pheromone update is done by incorporating the unsupervised learning artificial neural networks. In that novel arrangment, additional man-hours assignment is companied with the amount of pheromone calculated in which the additional mah-hours may be assigned to the most committed machine as it will need the maximum assitance. The Unsupervised ANN is then trained based on generating random inputs of Pheromone levels for this problem. Subsequent training of this ANN has also been carried out and subsequent SOM topology with weights concentration is also shown in the following figures.

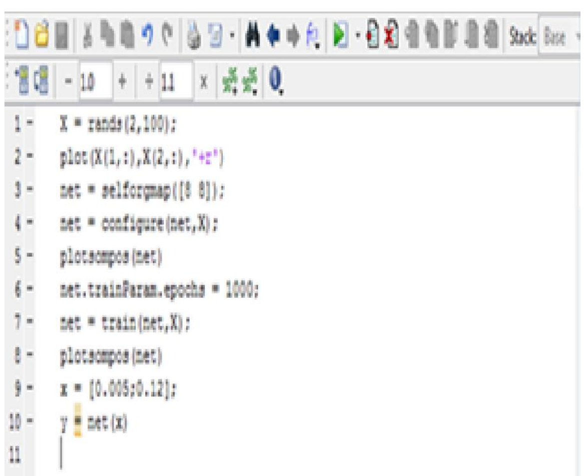

Figure 3: ANN Topology

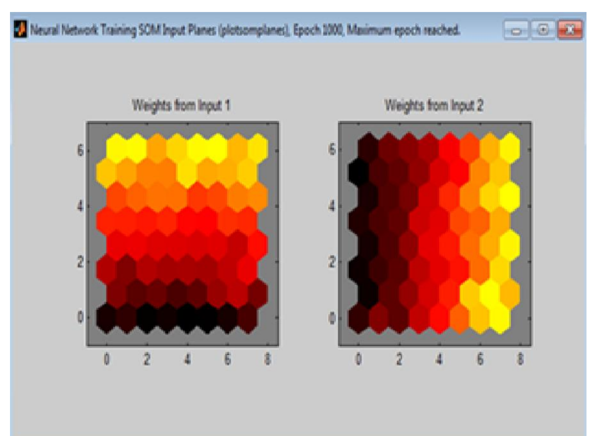

Figure 4: SOM Topology

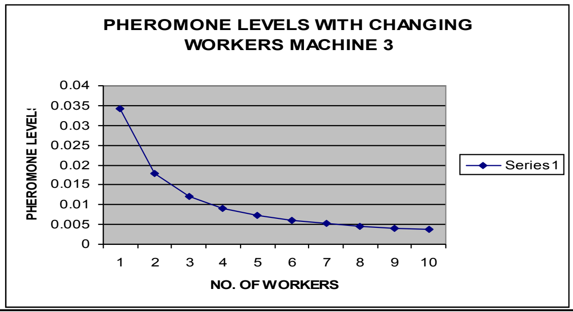

Figure 5: The SOM weight positions depict the concentration of points towards the pheromone level values between 0.3 and 0.8

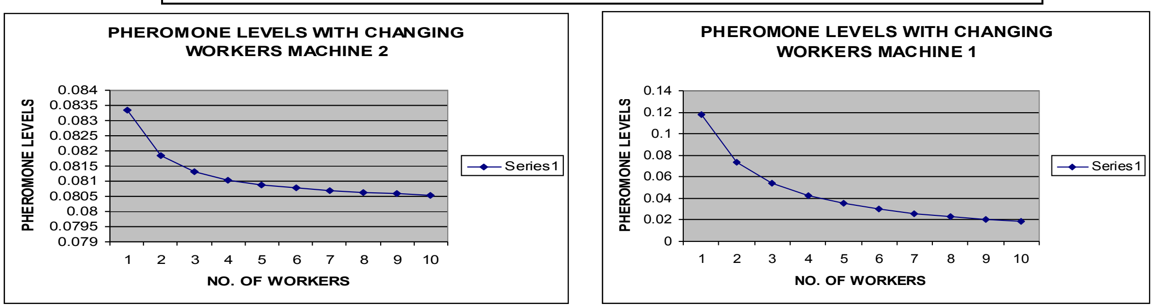

Figure 6: The Pheromone levels with changing worker levels is shown in this figure. This result was obtained by knowing the inputs and outputs and the same result is also obtained by our unsupervised approach as discussed earlier, thus proving the validity of our approach.

Step 3: The resultant NaACO is a logic based (Yes/No) artificial neural network model which aggregates the combination of the three-machine times, initial workers assigned and combines these entities with the amount of additional man-hours 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***". The trained ANN is then executed to test the various combinations which include the processing time of a machine, the allocated workers on the 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 separately.

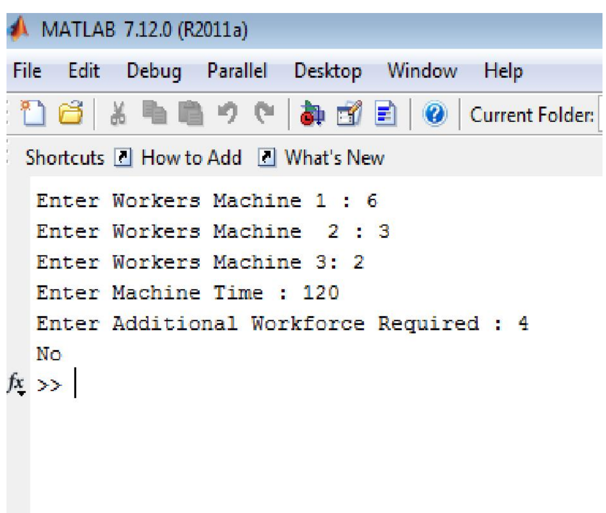

Figure 7: The results of NaACO

3. Conclusion and Areas of Future Research

We have proposed a novel technique of making ACO's pheromone update an intelligent form of up gradation mechanism. We have adopted unsupervised ANN for the evaluation of Pheromone levels which can give the best optimal results. It is different from our previous research as previously we have used supervised learning on the same problem sets whereas in this contribution we have adopted unsupervised learning methodology. This methodology can be further adopted for use in other benchmark problems related to scheduling and worker assignment. The unsupervised ANN in itself is a vast field with its various sub techniques. These individual sub techniques can also be used in isolation to compare and improve the results. The application of ACO should be made intelligent and NaACO should be tried and tested in conjunction with the unsupervised ANN methodology.

Corresponding Author:
Muhammad Umer
School of Mechanical and Manufacturing Engineering (SMME),
National University of Science and Technology (NUST),
Islamabad, Pakistan
Email: muhammad.umer@smme.nust.edu.pk

References

1. Aftab T, Muhammad U, Ahmed R Year 2012 Ant colony optimization for jobs scheduling and workers assignment problem to minimize total makespan. In International Conference on World Academy of Science, Engineering and Technology, Bangkok, Thailand.
2. Ahn, Joyup. “Nonstandard Work in Japan and Korea-the Origin of Wage Differentials”. In Nonstandard Work-Draft, March 1, 2006.
3. Blum C, Sampels M 2002 Ant colony optimization for FOP shop scheduling: A case study on different pheromone representations. Proceedings of the 2002 Congress on Evolutionary Computation (CEC-02), D B Fogel, M A ElSharkawi, X Yao, G Greenwood, H Iba, P Marrow, M Shackleton (eds), Piscataway, NJ, IEEE Press, pp.1558-1563.
4. Den Besten M L, Stutzle T, Dorigo M 2000 Ant colony optimization for the total weighted tardiness problem. Proceedings of PPSN-VI, Sixth International Conference on Parallel Problem Solving from Nature, M Schoenauer, K Deb, G Rudolph, X Yao, E Lutton, J J Merelo, H P Schwefel (eds), Berlin, Springer-Verlag, pp. 611-620.
5. Di Caro G 2004 Ant colony Optimization and its Application to Adaptive Routing in Telecommunication Networks. Thesis, Universite Libre De Bruxelles, Faculte Des Sciences Appliques, Bruxelles
6. Dorigo M 1992 Optimization, Learning and Natural Algorithms. PhD thesis, Politecnico di Milano, Dipartimento di Eletronica, Milan
7. Dorigo M, Thomas S 2004 Ant Colony Optimization. London, The MIT press.
8. Fisher M L 1973 Optimal Solution of Scheduling Problems Using Lagrange Multipliers: Part I. Operations Research, 21(5): 1114-1127.
9. Garey M. R, Johson D S 1979 Computer and Intractability. A Guide to the theory of NP-Completness.
10. Girish B S, Jawahar N 2008. Scheduling job shops associated with multiple routings with genetic and ant colony heuristics. International journal of production research in DOI: 10.1080/00207540701824845.
11. Grasse P P 1959 La reconstruction du nid et les coordinations interindividuelles lles chez. bellicositermes natalensis et cubitermes sp, 6: 41-81
12. Hopfield J, Tank D W 1985 Neural computation of decisions in optimization problems. Biological Cybernetics, 52.
13. Hu P-C 2004. Minimizing total tardiness for the worker assignment scheduling problem in identical parallel-machine models. International Journal of Advanced Manufacturing Technology, 23(5–6): 383-388.
14. Hu P-C 2005 Minimizing total flow time for the worker assignment scheduling problem in the identical parallel-machine model. International Journal of Advanced Manufacturing Technology, 25(9–10): 1046-1052.
15. Hu P-C 2006 Further study of minimizing total flow time for the worker assignment scheduling problem in the identical parallel machine models. International Journal of Advanced Manufacturing Technology, 29(7–8): 753-757
16. Hu P-C 2006 Further study of minimizing total tardiness for the worker assignment scheduling problem in the identical parallel machine model. International Journal of Advanced Manufacturing Technology, 29: 165-169.
17. Huang K, Liao C 2008 Ant colony optimization combined with taboo search for the job shop scheduling problem. Computers and Operations Research, 35: 1030-1046.

18. Huawang S, Wanqing L 2009 Artificial Neural Network with Ant Colony Optimization for Assessing Performance of Residential Buildings. International Conference on Future BioMedical Information Engineering, pp. 379-382.
19. Irani R, Nasimi R 2012 An Evolving Neural Network Using an Ant Colony Algorithm for a Permeability Estimation of the Reservoir. Petroleum science and Technology, 30(4): 375-384
20. K. Alam, A.V. Mitrofanov, V.V. Silberschmidt, 2010 Experimental investigations of forces and torque in conventional and ultrasonically-assisted drilling of cortical bone. In Medical Engineering & Physics - March 2011 (Vol. 33, Issue 2, Pages 234-239, DOI: 10.1016/j.medengphy.2010.10.003)
21. Martin P D 1996 A Time-Oriented Approach to Computing Optimal Schedules for the Job-Shop Scheduling Problem. PhD Thesis, Cornell University, School of Operations Research & Industrial Engineering, Ithaca, New York
22. Mathirajan M, Chandru V, Sivakumar A I 2007 Heuristic algorithms for scheduling heat-treatment furnaces of steel casting industries. Sādhanā, 32(5): 479-500
23. Merkle D, Midderdorf M, Schmeck H 2002 Ant colony optimization for resource-constrained project scheduling. IEEE Transactions on Evolutionary Computation, 6(4): 333-346
24. Niknam T, Khorshidi R, Firouzi B B 2010 A hybrid evolutionary algorithm for distribution feeder reconfiguration. Sādhanā 35(2): 139-162
25. Pinedo M 1995 Scheduling - Theory, Algorithms, and Systems, Second edition, Prentice Hall.
26. Poliac M O, Lee E B, Slagle J R, Wick M R 1987 A Crew Scheduling Problem. Proceedings IEEE International Conference on Neural Networks, pp. 779-786.
27. Rabanimotlagh, Ahmad. "An Efficient Ant Colony Optimization Algorithm for Multiobjective Flow Shop Scheduling Problem". In World Academy of Science, Engi.
28. Rajendra C, Ziegler H 2003 Ant-colony algorithms for permutation flowshop scheduling to mini-mize makespan/total flowtime of jobs. European journal of Operational Reseacrh
29. Rossi A, Dini G 2007 Flexible job-shop scheduling with routing flexibility and separable setup times using ant colony optimization method. Robotics and Computer-Integrated Manufacturing, 23(5): 503-516.
30. Rumelhart D E, McClelland J L 1986 Parallel Distributed Processing. D E Rumelhart, J L McClelland, P R Group (eds), Cambridge, MA, MIT Press.
31. Sastri T, Malave C O 1991 Identification of the optimal control policy for the Markov decision process by bavk propagation. Intelligent Engineering Systems Through Artificial Neural Network, C H Dagli, S R Kumara, Y C Shin (eds), New York, ASME, pp. 873-881.
32. Sinha M, Kalra P K, Kumar K 2000 Parameter estimation using compensatory neural networks. Sādhanā 25(2): 193-203.
33. T. Hastie, Tibshirani, and J. Friedman. The Elements of Statistical Learning. Springer Series in Statistics, 2000.
34. Zhang J, Hu X, Tan X, Zhong H J, Huang Q 2006 Implementation of an Ant Colony Optimization technique for job shop scheduling problem. Transactions of the Institute of Measurement and Control, 28(1): 93-108.

6/2/2013