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Research Article

Resource Optimization in Job-shop Scheduling using Ant-Colony-Optimization Metaheuristic

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Abstract: Present study elucidates the probity of ant colony optimization metaheuristic in minimizing the makespan by efficiently allocating jobs to workstations in general aviation maintenance. The metaheuristic technique is applied to real workplace problems in general aviation sector of Pakistan to resolve scheduling quandaries of XT-10 helicopters inspection in Burq Air Services (Pseudo names of organization and helicopter to keep anonymity). Secondary data for processing times of jobs at workstations was obtained from job cards and process sheets. Matlab codes were developed for reaching the optimal scheduling. Results indicated almost 25% improvement in efficiency, and proffered a customized yet efficient solution to scheduling problem in real aviation maintenance setup. The study posited that with the slight adjustment, the present model could be applied to other variants of job-shop, service industry, and similar areas of social sciences.

Keywords: Ant-colony-optimization, heuristic, job-shop, scheduling problem, makespan, aviation, helicopter

1. INTRODUCTION

One of the means to achieve competitive advantage is resource optimization, i.e., judicious and efficient utilization of available resources. Scheduling is one of the most effective tools for achieving resource optimization. Its main objective is to minimize makespan, i.e., completing all the jobs in shortest time span. It aims at finding most efficient mix of machines, jobs (tasks) and workers so that human resource and machines are utilized optimally. It entails allocating shared resources over time to mutually competing activities. One of the main purposes of scheduling is to increase efficiency. In other words, scheduling is the optimization of multiple jobs and limited resources for efficiency, and is an important area of research [12].

Allocation of jobs to workstations is a basic yet intricate scheduling problem for two reasons. Firstly, scheduling possibilities increase as factorial of number of jobs. For example, scheduling problem involving 4 jobs presents 4! or 24 scheduling possibilities, while a problem involving 25 jobs present 25! or 15,511,210,043,330,985, 984,000,000 scheduling possibilities. Secondly, various assumptions are to be met in order to solve scheduling problems. Nonetheless, in majority of cases all these assumptions do not correspond to the actual problems, resultantly the quality of model and solution is compromised. Conventionally, experienced managers are employed for job-shop scheduling using manual methods to deal with various uncertainties and intricacies. With increase in the number of scheduling possibilities, manual technique becomes increasingly complex. Hence, seeking the best possible way to complete the required work in the quickest possible manner becomes a challenge. To address this issue, initially various calculus and exact techniques were presented, e.g., Fibonacci method, enumerative techniques etc. But these techniques have various limitations i.e. calculus techniques have tendency to stick to local optima, while the enumerative techniques demand considerable computational effort and long times to reach at optimal solution [30]. Alternatively, various heuristic techniques were developed.

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Heuristic techniques provide good results in shorter times with nominal computational resources but the optimal solution is not guaranteed i.e. guaranteed optimal solution is traded off with less computational effort and time. Heuristics are basically approximation algorithms, which are employed in cases where exact solution is either not available or where exact methods take too long to reach a solution. Job scheduling problem and time constraints have been studied extensively and several heuristic approaches have been developed for its solution [16]. Metaheuristics and the proposed algorithms evaluated under different scenarios demonstrated that these strategies outperform other available methods [7, 16, 35]. These techniques are being increasingly employed for optimization problems. Each heuristic technique has its own advantages and limitations. Ant-Colony-Optimization (ACO) is one of the heuristic based techniques that have been used extensively to solve complex problems. It is claimed that this technique provides the best solution in a very short time with nominal computation resources [31, 33]. It uses artificial intelligence (AI) and is metaheuristic in nature, and can be applied to different optimization problems with few job specific modifications [12]. Prior researchers have extensively tested ACO metaheuristic to resolve variety of complex problems [e.g., 10, 13, 20, 23, 27] but it has never been applied to job-shop scheduling problem in aviation maintenance.

This study endeavors to address job-shop scheduling problem (JSSP) in aviation maintenance setup utilizing ACO technique, and formulates workable model to significantly minimize the makespan. In so doing, it seeks to answer two main queries: a) How to formulate problem and develop an algorithmic tool based on ACO metaheuristic that minimizes the makespan? b) How to apply ACO metaheuristic to a real practical problem? The answer to these queries addressed in this study will contribute to the existing body of knowledge on applied optimization and metaheuristic in aviation maintenance.

1.1 Theoretical Foundation

This study is conceptually inspired by prior work of Umer et al. [34] and Aftab et al. [4]. Theoretically, it approaches JSSP through ontological premise of determinism i.e. all events (e.g., job-shop maintenance scheduling) have causes, and one events (e.g., inspection) can be linked to another event through general laws [2]. Epistemologically, the trade-offs between theory development and applying it for resolving job-shop scheduling problems in aviation sector is dealt with by foundationalism, and espousing a positivist methodology [29]. A concise outline of basic features presented herein provided foundation for model development.

1.2 Ant-Colony-Optimization

Ant-Colony-Optimization (ACO) algorithm is a probabilistic technique employed for solving computational problems. Its application enables finding good or good enough solutions to optimization problems by determining paths through graphs. It has been developed based upon Evolutionary Algorithm, which utilizes guided random search techniques. ACO can be traced back to theory of 'stigmergy' presented by Pierre-Paul Grassé in the year 1959 [14]. Stigmergy means communication and coordination between agents through indirect means like pheromone level in ant's system. In 1980s research was conducted on the ants' colonies, their behavior and social aspects. In 1991, Dorigo in his PhD thesis first presented the concept of ant colony for solving optimization problems [11]. In mid 80s and late 90s other researchers like Stutzle, Hoos, and Binachietc worked on the development of ACO concept on variety of problems and applications. Subsequent developments in ACO framework have enabled its application to diverse problems [10, 13, 20, 23, 27]. Resultantly ACO has emerged as one of the preferred application tools and promising area of research [12]. JSSP using ACO metaheuristic was first attempted in 1994. However, with the passage of time ACO metaheuristic was applied to various other variants of job-shopissues [12].

Recent literature published on ACO metaheuristic envisages its growing popularity. Jing and Tomohiro [21] presented hybrid approach using two optimization techniques, ACO and Tabu search. It was applied toflexible job-shop scheduling problem (FJSSP) with multi objectives, the primary objective being makespan minimization. Many researchers claim that proposed hybrid approach provide far superior results than the other optimization algorithm [e.g., 10, 13, 20, 21, 23, 27, 32, 37]. Remarkable improvements were achieved with regard to time required to solve the problems while maintaining good accuracy closer to genetic algorithm and exhaustive search [4]. Huang et al. [19] came up with new method named 2PH-ACO (two pheromone Ant-Colony-Optimization), a variant of ACO metaheuristic. It was applied to FJSSP, and results obtained were better than the traditional ACO. More recently, the concept of Neural Augmented ACO (NaACO) was coined to address worker assignment problem besides JSSP by combining Artificial Neural Network (ANN) and ACO [33, 34]. Application of ACO on various types of JSSP and FJSSP validated its application [26].

1.3 Job-Shop Scheduling Problems and Makespan

Job-shop is characterized by low volume of production and high customization. A job-shop entails various operations to be performed in a definite sequence. The machine sequence of jobs (also called process plan) is fixed, however, the problematic is to find a particular sequence on machines "m" in such a way that all "n" number of jobs are completed most efficiently. This is called 'Job-shop Scheduling Problem' (JSSP). The main objective is most optimal utilization of resources aiming at efficiency and elimination of all sorts of wastes [25, 36]. It is done by allocating resources like machines and workers to jobs in such a way that idle time of machines and workers are minimized and jobs are completed in minimum possible time. In Job-shop, machines are arranged according to functions or processes, and this arrangement is termed as process layout [17]. Conventionally scheduling has been carried out manually for simple scenarios. However with the increase in scheduling possibilities, the scheduling become increasing complex where manual working does not remain a feasible option and require solution through advanced techniques like heuristics or calculus based techniques.

The reported history of JSSP spans over 5 decades. Fisher and Thomson introduced famous 10 x 10 problem (ten jobs and ten machines). This particular instance of 10-job 10-machine problem remained unresolved for over 25 years [8]. The most commonly used measure of efficiency in JSSP is makespan (time required to complete all the jobs). Makespan is dependent upon the sequence in which jobs are fed to machines. The other measures of efficiency include job lateness, job tardiness, job flow time etc. Job-shop scenario of 'n' jobs and 'm' machines presents $(n!)^m$ scheduling possibilities. If we consider single sequence of processing through all the machines than scheduling possibilities reduce to n! Thus scheduling of 3 jobs on 2 machines in a single sequence presents six scheduling possibilities (a simple manual method i.e. Johnson's rule).

With increase in number of scheduling possibilities, manual methods like Johnson's rule do not remain a workable option, and various exact techniques were presented. However, these techniques require a lot of computation effort and unrealistically long times to reach to an optimal solution. Another issue is that there are many problems for which exact solutions are not possible. Thus scheduling problems presents hardest optimization problems which are NP-complete [6]. In the similar vein, various heuristic based techniques were presented. These techniques provide good results in shorter times with nominal computation resources however best results are not guaranteed. Flexible Job-shop Scheduling Problem (FJSSP) is an extension of JSSP that incorporates flexibility of route, and provides decision point for assignment to more than one machine. Likewise, non-deterministic polynomial times i.e. 'NP complete problem' is a problem in which there is no efficient way to reach the solution directly and no fast solution to such problem is known. If any of the currently known algorithms is used, time required to solve the problem increases remarkably with increase in solution space. In other words best solution for these problems is not possible within polynomial bounded computation time [12]. Solutions of such problems are obtained through methods like heuristic or approximation algorithms.

1.4 Optimization

Optimization simply means achieving the best solution of a problem under given set of constraints. When best solution is not possible due to nature of problem, limited computation ability and longer times involved, then good or good-enough solutions are searched. Optimization problems are maximization or minimization problems. An objective function and set of constraints are defined for the problem. Solutions that satisfy the constraints form a set of feasible solutions from which best or good solution is selected. The easiest way is to find out all the possible solutions (exhaustive search) and select the best one. But, number of possible solutions becomes too large for slightly complex problem that exhaustive search becomes inappropriate. Resultantly, the approximation algorithms are the wise option. At European based airports, Ravizza et al. [28] found optimization approach more convincing for settling ground movement of aircrafts. Optimization problem in which the feasible solution consists of discrete members is termed as combinatorial optimization. On a broader level, JSSP can be classified as static combinatorial problem as variables like number of machines and number of jobs are discrete and fixed.

NP hard problems can be solved by calculus methods or through application of algorithms. The algorithms can be exact or approximate. Exact algorithms provide best solutions. However, their usage is constrained due to two factors. First is their inability to solve beyond certain number of dimension, and second is that even nominally complex problems require long times to reach solution. That is why their usage for optimization problem after certain level becomes inappropriate. On the other hand, approximate or partial algorithms provide solution to optimization problems in reasonable time frame. They are also known as heuristic [12, 30].

An optimization problem has many possible solutions called solution space. Each individual possible solution is called a candidate solution. In algorithm based optimization methods working principle the solution is searched in the solution space and results with desired accuracy are obtained. Method of search progression and criteria for results is defined pre hand. In the exhaustive search methods, all the possible ways are explored and investigated, thus best solutions are guaranteed. However, these methods become infeasible for sizably voluminous solution space. In comparison, the local search methods apply metaheuristic method that iteratively seeks neighboring solution candidates only starting from an initial one. The termination may be according to lapse of defined time or non-improvement in results after certain iterations. This method has limitation that at times solution may only be locally optimum, but not globally. Global optimum means that the solution obtained is the best one amongst the entire solution space, while local optimum means solution obtained is the best one only amongst the neighboring solution candidates, which may or may not be best in the entire solution space. An example is shown in Fig. 1.

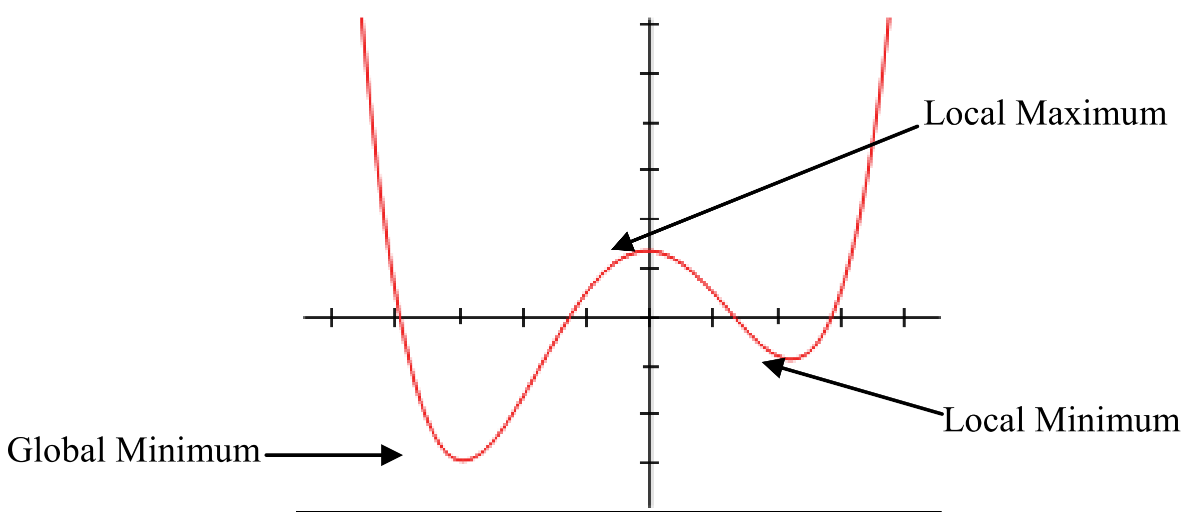

Fig. 1. Global and local optimum [15].

1.5 Metaheuristics

Heuristics are basically approximation algorithms which are employed in cases where exact solution is either not available or where classical methods take too long to reach solution. It has been applied to a wide range of disciplines [1, 7, 22, 24, 31]. It aims at finding solution of problem in hand in a reasonable timeframe that is good or good enough but may not be the best. Thus, guaranteed optimal solution is traded off with less computational effort and time to reach the solution. Heuristics have its limitation: a) Problem specific information is required for working of heuristic; b) Single run algorithms provide limited solutions and terminates search on reaching local optima. The problem has not been addressed despite incorporating the improvement that runs the heuristic various times [12]. In order to address limitations of heuristics, concept of metaheuristic has been introduced. A metaheuristic is a set of algorithmic concepts that can be used to define heuristic methods applicable to a wide set of different problems [12]. Thus, specific problem would require incorporation of only few modifications. Alternatively, it can be said that a metaheuristic is basically higher-level heuristic built upon lower level heuristic. Metaheuristics also tend to bypass the problem of entrapment in local optima. It provides good or good enough solution to optimization problems in a quick time frame with limited computation capacity. Thus, these can be referred to as soft computing techniques capable of solving hard problems. In metaheuristic, first a set of solutions is sampled. This set of solutions is searched to find feasible solution and ultimately the good solutions. In certain cases, few assumptions are made especially where information is not perfect or complete. This flexible property enhances utilization domain of metaheuristic for diverse categories of problems [9]. Available metaheuristics differ in two aspects, the way in which they avoid entrapment in local optima and the way in which solution space is searched [12].

1.6 Conceptual Framework

ACO employed in this study is metaheuristic-based and has ability to converge to global optima. ACO algorithm refers to ‘swarm intelligence’: a concept used in artificial intelligence inspired from natural systems. Swarm means collection of agents. These agents demonstrate alike behavioral traits, and mostly adhere to certain rules on collective level. Their interplay results in collective intelligence that would not be possible individually or at non-group level. Examples include honey bee, ant colonies, etc. [5, 13, 23].

The ACO heuristic has been developed based on behavioral pattern of ants foraging for food. The ants search for food more or less follows a certain pattern [3]. Initially ants roam randomly looking for food source. Once food source is found, ants return to their colony. On their way back, these ants lay a chemical called ‘pheromone’. Consequently a pheromone trail is formed, which can be sensed by other ants. Once other ants wandering for food sense a pheromone trail, they no longer move randomly rather follow the pheromone trail. While returning from the food source, these ants reinforce the pheromone trail. However, pheromone trail also evaporates with time resulting in decrease of attractive strength, and on a longer path pheromones strength decrease due to evaporation. If a shorter path is detected, then more ants follow this shorter path. This results in increase of pheromone level on this shorter path. This positive feedback eventually leads to following a single short path. Advantage of pheromone evaporation is that longer paths are avoided due to decreased pheromone level. In the absence of evaporation phenomenon, new shorter paths would not have been possible [3]. In ACO algorithm, the artificial ants replicate the real ants. “Simulated ants" imitate natural ants behavior in search of optimal solution. Its working is based on the principle of indirect communication between ants (stigmergy) through pheromone. The artificial ants deposit pheromone, which is taken as numerical information. Based on this information, probabilities are calculated which directs the artificial ants to shortest paths. The pheromone trails are reinforced or evaporated as per the experience of the artificial ants.

In ACO, metaheuristic delineates: a) Problem in general terms; b) Objective function and behavior of the ants in relation to the objective function and solution construction procedure i.e. rules for solution built up; c) Pheromone Update i.e. rules for pheromone updating; and d) Daemon actions i.e. actions prohibited for single ant. The simulated ants move asynchronously at same time and solution is built up incrementally. Better solutions are given higher pheromone level thus probability of artificial ants to converge to better solutions increase iteratively. This knowledge is updated for entire community and is used in solution building. Desired preferences are heuristically defined, which adds remaining components to the solution [23]. Thus, provision of correct heuristic information is pivotal in reaching solution of excellent quality. The algorithm follows three basic steps i.e. construct ant's solutions, update pheromones and daemon actions. Updating the pheromones describes how pheromone levels will be increased (reinforced) or decreased (evaporated). Daemon actions are related to collective wisdom of colony, which is not possible individually. The three procedures are managed through schedule activities construct; however scheduling is left on the discretion of designer to specify as per the requirements of problem [12].

2. METHODS

2.1 Sample and Data

The data included in this study presents a real workplace JSSPs that are encountered in Burq Air Services (Pseudo name for general aviation organization) that owns a large fleet of XT-10 Helicopters (Pseudo name), which has an elaborative maintenance setup is in place. Purposive sampling technique i.e. total population sampling was espoused, and entire fleet of 60 XT-10 helicopters was included in the study. These helicopters have to undergo season change inspection on three workstations. As a standard, each inspection takes 120 man-hours however it fluctuate towards upper side due various factors, major one being unscheduled tasks detected during inspection. The helicopters were divided into five batches of 12 helicopters, which is a multiple of number of workstations (3 workstations) as well as a factor of total population (60 helicopters). This way inspection of the complete population can be completed in 5 steps with the critical advantage that synchronous loading of the three workstations remains a candidate solution. An additional advantage that can be accrued from this number is that once inspection of a batch is completed, its data can be incorporated as past data for the next set of jobs. In order to have substantial amount of data for comparison and testing of algorithm, secondary data for period covering last six seasons was selected. Data set for each season was taken as separate problem set. Data was collected using job

Table 1. Data for problem set 1.

Workstation 1				Workstation 2				Workstation 3			
Helicopter	Airframe	Engine	Avionics	Helicopter	Airframe	Engine	Avionics	Helicopter	Airframe	Engine	Avionics
	Hours	Hours	Hours		Hours	Hours	Hours		Hours	Hours	Hours
1	103	22	4	1	100	23	5	1	99	22	4
2	100	23	4	2	100	22	4	2	110	20	5
3	101	25	4	3	105	25	4	3	106	21	4
4	103	21	5	4	115	22	6	4	96	22	6
5	96	25	4	5	96	28	4	5	107	20	4
6	100	22	4	6	115	21	5	6	99	20	4
7	104	28	5	7	100	22	4	7	109	21	5
8	99	21	4	8	103	20	6	8	96	22	4
9	96	22	7	9	110	20	4	9	101	22	4
10	103	24	4	10	96	21	5	10	103	24	6
11	96	23	5	11	96	22	4	11	120	20	6
12	110	20	4	12	96	21	4	12	96	27	4

Note: Hours means man-hours

cards and process sheets for analysis as well as for comparison and validation of results.

In Burq Air Services, a job card is a controlled document used for every work order. It records all the materials / spares used during the job, details of the technicians & inspectors who have worked on the job and the time taken besides other auxiliary details. Similarly, the process sheet is another controlled document, which includes all inspection steps, reference for the technical manual, names & signatures of technicians and inspectors, standard time allowed against each step, time actually taken at each step and various other auxiliary details. Data set for each season was considered a separate problem set thus presenting total of six problems. A sample data set is shown in Table 1.

2.2 Problem and Constraints

Various inspections mandated by the OEM (Original Equipment Manufacturer) of the helicopter are carried out to ensure safe operations. This study focused on the season change inspection of XT-10 helicopters. This inspection is performed at the onset of every season i.e. summer and winter. Thus all 60 helicopters become due for inspection at the same time. This context exactly matches the generic assumption of JSSP thus enabling true modeling of the actual scenario. To undertake these inspections three maintenance setups are available i.e. workstation 1, workstation 2 and workstation 3. Each inspection comprises three trade examinations called Airframe, Engine and Avionics, and every workstation is capable to undertake the complete inspection and all three workstations work in parallel.

All the scheduling solutions are based on certain assumptions/constraints:

- There are n jobs that are required to be assigned to workstations. Number of these jobs remains fixed and does not vary for the problem under consideration.
- At the start, say (time zero) all the n jobs are ready to be assigned to the workstations, and very individual job consists of one operation as a whole.
- There are w workstations and all are ready to take jobs. Number of these workstations remains fixed and does not vary for the problem being considered. Handling capacity of any of the workstation is limited to one job at one time. In other words one workstation cannot undertake two or more jobs simultaneously.
- Each workstation has known benchmark-processing times that are fixed. There are no breakdowns and setup time for any of the workstation and any job can be assigned to any of the workstation initially and subsequently.
- There is no transportation time between workstations.
- Enough workers are available at each of the workstation to undertake the job, and all workers are equally proficient to undertake the job.
- Splitting any job and retrieving any job incomplete and assigning to other workstation is prohibited.

2.3 Instruments

The complete scenario was modeled mathematically based on the generic assumptions of JSSP in the form of equations, expressions and inequalities that presented constraints for the model. Objective function was set as makespan minimization. It is important to highlight that all the generic assumptions of JSSP were consistent with the problem considered except: a) zero set up time; and b) fixed processing times. The former was addressed by adding set up times in the processing times while the latter inconsistency was addressed by deriving processing times from past data instead of minimum standard bench mark time of 120 hours. Processing time at each workstation was worked out according to PC Hu rule [18]:

$$t_k = X_k + \frac{Y_k}{Z_k} \qquad \text{(a)}$$

For makespan minimization, the ant (job) should be assigned to nearest food source (workstation) based upon the shortest path (processing time). The probability of an ant j to converge to a food source k was expressed as under:

$$P_{j,k} = \frac{[T_{k,j}]^{\alpha}[\eta_{k,j}]^{\beta}}{\Sigma[T_{k\prime,j}]^{\alpha}[\eta_{k\prime,j}]^{\beta}}$$ (Dorigo & Stutzle [12], pp. 171-172 (b)

Where:

$k'j$ represented job not assigned to workstation k

$T_{k,j}$ represented desirability of assigning job j to workstation k based on probability

Here it is the pheromone value or pheromone level. It is given by the expression: -

$T_{k,j} = T + \Delta T$

Whereas T= Present pheromone level and

$\Delta T =$ Evaporation or reinforcement

$\eta_{k,j}$ is the reciprocal of the heuristic function defined in equation (a). So it can be written as: -

$\eta_{k,j}$ = 1/ heuristic function =

$$\frac{1}{t_{kj}} = 1/(X_{kj} + \frac{Y_{kj}}{Z_{kj}}) \qquad \text{(c)}$$

The α and β are sensitivity factors that represent the boundary level condition for this probability.

Initial triggering is independent of the evaporation or reinforcement so

$$[T_{k,j}]^{\alpha} = 1 \ \& \ [T_{k\prime,j}]^{\alpha} = 1$$

The jobs are assigned to workstations as per heuristic function of minimum processing times as per equation (b). Total flow time at workstation k (k = 1, 2 or 3) is the sum of processing times of all the assigned jobs to workstation k while makespan is the maximum of the total flow time at workstation k.

Based on above, algorithm was defined in Matlab seeking for output schedule of the jobs with minimum makespan. The problem data sets were analyzed using this ACO based algorithm, which provided output schedules of jobs with minimum makespan.

2.4 Construct Validity and Reliability

Aftab et al. [4] applied the similar technique to well-known set of 100 problems and validated it through comparison of results with exhaustive search and genetic algorithm. The standard for the comparison was average deviation from the best solution through exhaustive search and time taken to solve these problems [4]. Moreover, the method has also been tested and validated by prior researchers, and as compared with others this method produced better solutions [e.g., 1, 34]. Umer et al. [34] validated neural augmented ACO technique (NaACO) through application on set of 100 problems. The heuristic information in both the cases was same as in this study i.e. processing times from past data although the applications scenarios were different. Thus defined ACO metaheuristic and its Matlab code are validated. Likewise, both the documents (Job card and process sheet) used for data collection are controlled documents of Burq Air Services. These documents form the basis for all the planning and control mechanism of the organization. Job cards, in addition, have information on materials used and thus have

Table 2. Summary of results.

Problem #	Jobs Assigned to Workstations			Makespan (Hours)
	WS 1	WS 2	WS 3	
Problem 1	4 (3,5,9,11)	4 (2,7,10,12)	4 (1,4,6,8)	412.4500
Problem 2	4 (2,7,10,12)	4 (1,4,6,8)	4 (3,5,9,11)	411.4500
Problem 3	4 (1,4,9,11)	4 (3,5,7,10)	4 (2,6,8,12)	412.9167
Problem 4	4 (2,5,8,11)	5 (1,4,7,10,12)	3 (3,6,9)	512.5000
Problem 5	4 (1,6,8,12)	4 (3,5,7,10)	4 (2,4,9,11)	428.7429
Problem 6	4 (3,5,8,12)	4 (1,4,7,10)	4 (2,6,9,11)	419.0833

Note: Time taken to solve the problem = 0.017800seconds financial aspects, which add to the accuracy of the document. In other words, these two are the most authentic documents for man-hours data collection. Therefore, data collected for this study is considered reliable and accurate.

3. RESULTS

ACO metaheuristic has been applied for scheduling of jobs (helicopters) to workstations and calculations of makespan. Each data table concerns a separate problem, thus presenting a total of six separate problem sets requires scheduling. These have been labeled as problem 1 to 6. Summary of study results is presented in Table 2.

Table 2 elucidated that workstations have been loaded with equal number of jobs for all the problem sets except for problem set 4 where workstation 2 has been assigned 5 jobs, while workstation 3 has been assigned 3 jobs. Analysis of data for problem set 4 revealed that workstation 2 was taking times close to the minimum benchmark time while workstation 3 was taking times much more than the minimum benchmark time. Thus workstation 2 was able to complete the 4th job prior to the end of 3rd job by the workstation 3, and 4th job by workstation 1. Therefore workstation 2 was loaded with the 5th job as shown graphically in Fig. 2. Investigation revealed two major factors were attributable to lower efficiency of workstation 3 at that time. First, severe deficiency of manpower at workstation 3 at that point of time, and second was breakdown of specific equipment required for the inspection at that point of time. It can be inferred from the results that scheduling is not only confined to the efficient utilization of the resources, rather it also signals some underlying problems demanding investigations and subsequent corrective measures in such like scenarios. It is worth mentioning that all these loading are probabilistic in nature derived from the past data. However, in practice variations are expected due to factors attributable to jobs and/or workstations. Job related factors might include some unscheduled works required on specific jobs. Workstation factors may include non-availability of required equipment, workers availability, workers proficiency, etc. Minimum makespan for all the problem sets are shown in Table 2 indicating that jobs would be completed in this time if matching assignment of jobs to workstations were adopted.

Amongst all possible scheduling possibilities, the projected sequence presented minimum time to complete all the jobs. In other words this sequence enables minimum makespan. Assuming uniform loading of the workstations, i.e., 4 jobs each to all the 3 workstations and calculation of corresponding makespan would enable uniform comparison. Based on past data, the makespan has been worked out by calculating average time taken to complete 4 jobs at each workstation, and choosing the maximum one. This comparison is shown in Table 3. Results indicated improvements up to 25% through application of ACO technique.

4. DISCUSSION

The study presents 1,714,233,849 scheduling possibilities if simple exhaustive search is applied.

Table 3. Comparison of results with empirical data.

Problem#	Average Time to Complete 4 Jobs			Makespan*	Results Achieved through ACO	% Improvement
	WS1	WS2	WS3			
1	514	518	520	520	412	21
2	518	520	510	520	411	21
3	517	533	547	547	413	24
4	553	556	580	580	513	12
5	574	574	571	574	429	25
6	536	538	540	540	419	22

*Makespan for the empirical data is the maximum of the time to complete 4 jobs by WS1, WS2 and WS3.

However, the proposed model established that the number of jobs 'n' assigned to a workstation 'w' matters and not their sequence. It means that processing jobs assigned to workstations in any order would not result in change of flow times and makespan. For example, if 4 jobs (say job # 1, 5, 7 and 9) are assigned to workstation 1, the processing of these jobs in any sequence would result in same flow time and makespan. This would hold true even for the scenarios where all the jobs are not available at time zero provided they are made available before completion of the preceding job. It reduces the possibilities to 91 for each problem set, thus presenting a total of 546 possibilities for all the six problem sets under consideration. These possibilities are explored heuristically for optimal solutions to bring a single optimal schedule. A worth mentioning achievement of this work is that all the constraints and limitations posed by the problem have been well catered for while formulating the problem. No unnecessary and unreal simplifications have been made to the problem in hand. Thus, the developed model encompasses the problem in its real form. In line with prior researchers [e.g., 1, 10, 13, 20, 22, 23, 24, 27], this work has come up with a customized yet efficient way to optimize the scheduling problem in a real workplace setup.

4.1 Practical Application

Aviation maintenance is not only critical from safety point of view but also equally important from financial perspective due to intense competition. Careful application of the metaheuristic technique presented in this study can provide scheduling efficiencies, which has direct implications for financial gains, and indirect implications for safety enhancement. Being the first attempt, this study has addressed the scheduling problem that is encountered in an aviation maintenance setup to schedule upcoming inspections using artificial intelligence through ACO metaheuristic. It has provided a scheduling technique, which is not merely based upon theory or standard times, but provided its practical application based on the actual past data. The findings are important for systems where processing times are not fixed rather varies due to various factors like unscheduled works, different proficiencies of workers, breakdowns etc. These scenarios are normally encountered in aviation setups and pose serious challenges to optimization researchers. Though this work addressed scheduling problem in job-shop setting, with little modification it can be easily extended to various other variants like open shop scheduling problem (OSSP), group shop scheduling problem (GSSP) etc. This effort addresses scheduling problem of twelve jobs assignments to three workstations. With minor changes, it can be tailored to any number of workstations and jobs. An important aspect is that this work can be applied in service setup as well as workstations and jobs. This work can be applied in other allied areas of social and medical sciences for solving optimization problems with little or no modification. This study enabled futuristic loading of workstations based on past data as a forecasting tool. With these results in hand, it can be posited that the proposed ACO algorithm will help in better forecasting based on past data in variety of situations. The Burq Air Services and similar setups can accrue various advantages from this research for improved efficiency through better loading of workstations, better forecasting of future scenarios and indication of low efficiency workstations warranting investigations and subsequent corrective actions.

4.2 Limitations

This research attempted to cover all major facades of JSSP; however, there are certain limitations. First, the presented algorithm is not a generic tool; rather it is specific to the problem discussed in this study. It implies that the algorithm presented in this study requires customization to match other problems. Second, the developed tool is not simple, and its application is adjunct to method that alters work dynamics with technical arbitration [38]. It requires basic understanding of the working of algorithm and certain aspects of the problem in hand. Therefore, training is required prior to the application of the presented technique. Third, the technique does not incorporate pheromone up gradation because the problems set were small. The developed technique faces problem in assigning jobs to workstations when heuristic information (minimum processing time) is the same for two or more workstation. The simulated ants (jobs)

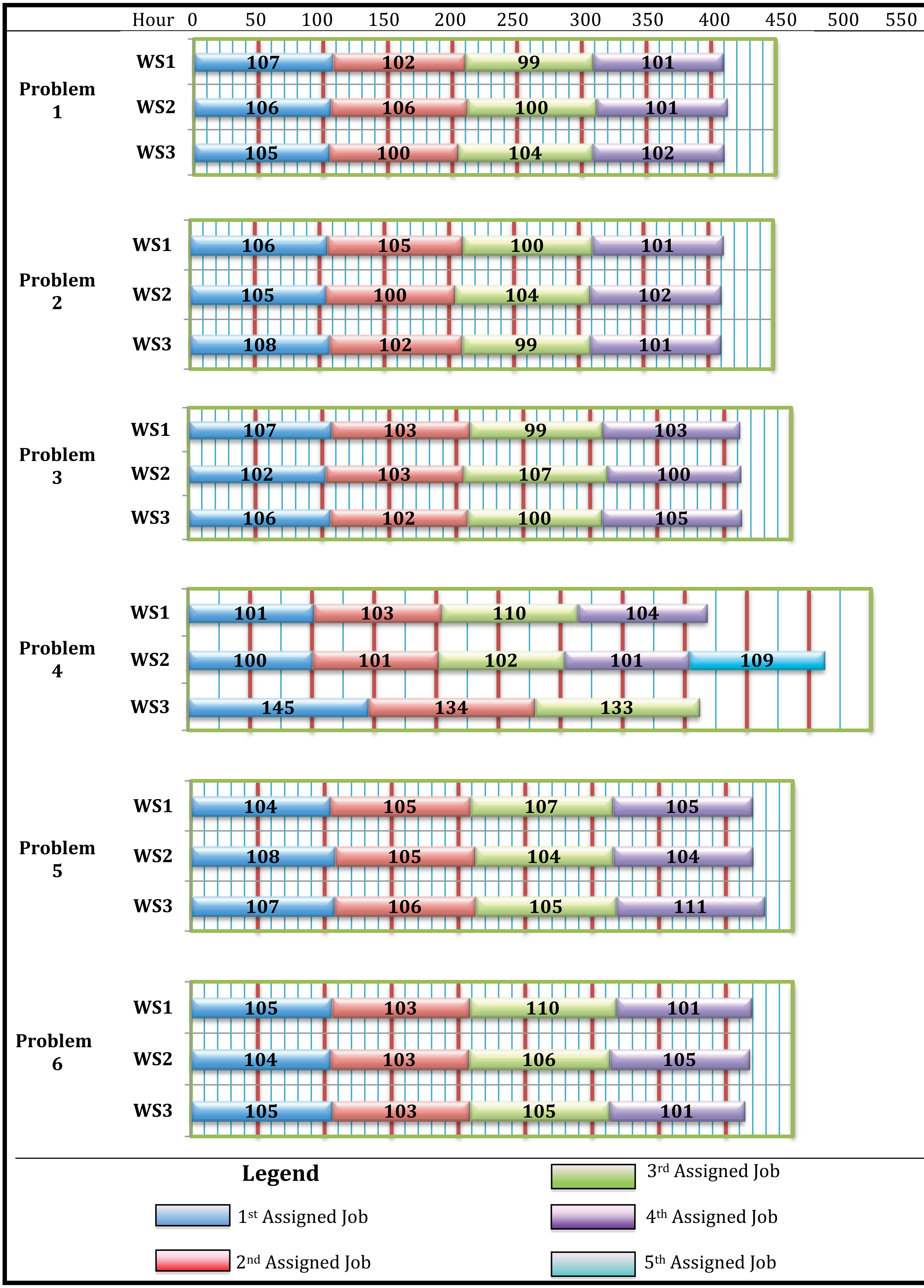

Fig. 2. Jobs assignment and Makespan of all six problems.

get confused in deciding which food source (workstation) to choose, as the probabilities are equal. However, it is a rare possibility as heuristic information is checked till the last decimal place. Fourth, the algorithm may present deviated results in cases where past data has huge dispersion with regards to the processing times. In such scenarios data should first be adjusted manually. Last, the work does not address worker's assignment of the problem, which can further reduce the makespan.

4.3 Future Prospects

Although this study extended the existing body of research on the topic, it has remained confined to the specific problem. Various avenues are opened for the future researchers in the form of extension and modification of the proposed technique. Firstly, formulation of generic tool capable of addressing wide variety of scheduling problems using ACO is an important area for future research. Secondly, improvement of technique through incorporation of pheromone up gradation functions is a promising area for future research. Thirdly, the study addressed problem sets involving only three machines or workstations and twelve jobs only. Problems with more workstations and jobs would pose interesting scenarios for future researches. Fourthly, improvement of the proposed technique to overcome equal probability problem is possible through EAS (Elitist Ant System). Besides, the improvement of the proposed technique various other problems can be modeled and solved through this variant of ACO. Thus, it is another favorable area for future researchers. Fifthly, the proposed algorithm does not address workers assignment problem. Incorporation of the same in the proposed technique using ACO is a potential area of research. Sixthly, present study focused only one particular type of inspection for XT-10 helicopter. Nonetheless, there are various other forms of inspections that are performed on XT-10 helicopters. Formulation of tool capable of addressing scheduling as well worker assignment problems for all sorts of inspections of XT-10 helicopters would be a challenging domain for the future researches. Similarly, domain of such optimization problems is strictly restricted to a certain setup without taking into account the upstream and downstream players i.e. suppliers and customers. Scenarios requiring optimization of complete supply chain would require intricate programming from optimization researchers. Lastly, application of this technique in service industry would be fascinating and challenging. Its application in hospital, food and transportation disciplines is strongly recommended for future studies in this field.

5. CONCLUSIONS

This study adds to the existing body of knowledge in the realm of optimization. It covered both the theoretical and practical application of optimization. All the constraints and limitations posed by the problems were catered for, and no unrealistic simplification was made. This work has come up with a customized yet efficient way of optimizing the scheduling problem in a real aviation maintenance job-shop setup to schedule the upcoming inspections using artificial intelligence through ACO metaheuristic which has not been attempted earlier. Application of presented ACO algorithm can help in better forecasting based on past data in a variety of situations. Aviation organizations can accrue various advantages from this research aimed at improving efficiency through better loading of workstations, forecasting the future scenarios, detecting the underperforming workstations, and taking the corrective actions. This work can also be taken as a reference source in future research to extend its application in other fields with requisite modifications.

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