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Fixed Task Scheduling of Industrial Robot using Genetic Algorithm Based Travelling Salesman Problem

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Abstract: The task scheduling of any industrial robots is a prior requirement to effectively use the capability by obtaining shortest path with optimum completion time. In this article, we have presented Travelling Salesman Problem (TSP) with Genetic Algorithm (GA) search technique based task scheduling technique for obtaining optimum shortest path of the task.TSP finds an optimal solution to search for the shortest route by considering every location for completing the required tasks by setting up GA. This article embrace the adaption and implementation of the Genetic Algorithm search strategy for the task scheduling problem in the cooperative control of multiple resources for getting shortest path with minimize the completion time for two zone specific task allocation problem. It can be inferred from the simulation results that the Genetic Algorithm search technique can be considered as a viable solution for the task scheduling problem.

Keywords: Genetic algorithm (GA), Travelling Salesman Problem (TSP), Robot, Task scheduling, Cooperative control.

I. INTRODUCTION

Static scheduling algorithms involves assigning the tasks to processors and positioning these tasks to minimize the completion time and in other words minimize the distance (or find the shortest path) of the application. If homogeneous processor networks are considered, then most of static scheduling algorithms fit in this space, whereas heterogeneous processor networks specific for robot task scheduling require different scheduling algorithms. Existing finest heterogeneous scheduling algorithms [1, 2] generate sub-optimal schedules and there is ample space for development of alternate scheduling algorithms for heterogeneous processor networks. Our research objective is to develop a technique that generates schedules with lesser completion time (or shorter distance) as compared to the schedules produced by the finest static scheduling techniques. Here we are selecting a single robot but multi-variety task. Ideally the method for calculating shortest path which will minimize the completion time for a single robot can be extended easily for multi robot system with multi task. In our proposed work, we have solved the complete task with eight numbers of task targets by finding out the optimum root of the overall problem using genetic algorithm for travelling salesman problem. In this article, we are considering Genetic algorithms for solving the travelling salesman problem, one of the most famous NP-hard problems, because Genetic algorithms(GA) are a relatively good optimization technique which does not guarantee an optimal solution, but usually gives good approximations in a reasonable amount of time. Genetic algorithms use a “survival of the fittest” technique as part of theory on natural evolution, where the best solutions survive and are varied until we get acceptable result. This article presents genetic algorithms and methods of encoding, crossover, mutation and evaluation in detail along with the operations used for the travelling salesman problem.

A real time scheduler is dependent on the underlying dispatching mechanism and is required in a multi-robot system. Dispatching mechanism is based on priority-driven or time-driven. Algorithms based on priority-driven, dispatch task based on priority. Priority assignment can be static or dynamic [7]. Scheduler schedule tasks based on priority assignments and can be preemptive or non-preemptive. Time-driven dispatching algorithm assign a start time to each task.

There are many scheduling algorithms widely used for scheduling requirements [10, 11, 12, and 13] and Branch and bound search is commonly used in optimal scheduling for time-driven scheduling and static priority scheduling. Examples include Round- Robin (RR), First-In-First-Out (FIFO), Earliest-Deadline-First (EDF), and Minimum-Laxity- First (MLF), Least-Slack-Time-First (LST), etc [13].

In case of multi-level chain of tasks, relative constraints are considered [14] and a parametric scheduling method has been developed. Unfortunately, in case of multi-robot systems, neither time-driven nor priority-driven schemes provide enough sustenance for relative task constraints and time constraints. Another approach is Design-to-time which is applicable to real-time problems when multiple methods make tradeoffs in execution time and solution quality are available for many tasks [9]. Hence this is an AI approach that uses all available resources to maximize the solution quality within the available time. Similar results have been obtained for tasks with relative separation constraints [8].

Design-to-time approach although guarantee task execution constraints, but does not consider task interdependencies which is a critical factor in scheduling in a multi-robot system.

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There are three main categories in static scheduling algorithms: *guided random algorithms, heuristic algorithms*, and *hybrid algorithms*.

Guided Random search techniques are utilized arbitrarily in the path connected with directing instruction to investigate the quest space of the problem. The knowledge acquired from earlier investigation results is utilized to lead the quest process in these techniques. Heuristic scheduling algorithms moves in the quest space from one point to other point rendering a specific transition order. These methods are capable as they find close optimal solutions in little polynomial time but, control some ways in the quest space, and avoid rest [3].Heuristic algorithms can be grouped into three categories: *clustering heuristics*, *list-based heuristics and duplication heuristics* [2, 3, 4]. List-based scheduling heuristics starts with assigning a given priority to each task which is enclosed in a list of wait tasking in a manner that allows over head priorities task placed in advance inferior priorities task. Following three steps: task selection, processor selection and status update are repeated until all the tasks in the list are scheduled. During scheduling the topmost-priority ready-assigned work is scheduled and detached from the list. Next, Choose the assigned work is given to the processor that decreases a predefined distance measure. Finally, the condition of the system is revised. Lastly we get optimum valid result. [2, 3, 5, 4].

The typical heuristic scheduling techniques change from one point in the quest space to other using a specific transition order. This point-to-point transit may misdirect the inquire process in multimodal scheduling problems. To beat this issue Hybrid-based Algorithms scheduling techniques can be used as these works on a mass of stage in equal. This decreases the chances of confluent to a local optimum [3]. On the contrary, a weak representation of the scheduling problem may lead to struggle in recommending good results within a sensible period of time. Hybrid-based Algorithms are the most commonly used forms of Guided Random techniques for the task scheduling problem [2]. Hybrid scheduling algorithms can be good alternative to heuristic scheduling technique as the former one act on individuals that encode achievable candidate schedules as opposed to heuristic ways which need direct information about the DAG and processors to decide next scheduling step. Hybrid scheduling algorithms combine both heuristic scheduling algorithms and GA.

This article discusses the proposed scheduling technique and the analysis based on travelling salesman problem (TSP) with genetic algorithm, it is structured as follows: Section 3 depicts the incitement for proposed scheduling algorithms; Section 4 discourses analysis results acquired during performing travelling Salesman Problem (TSP) with Genetic algorithm search technique.

II. PROBLEM DESCRIPTION

Task scheduling problem is a major concern in most of the industrial robot applications. In this work, we have taken a problem of an industrial automatic drilling and hot gun packing at eleven numbers of task locations as depicted in the figure 1 (a). The complete task is divided into two zone specific task locations for finding the optimum route using our proposed TSP-GA approach. Here we have taken a SCARA type robot to complete the tasks. The robot is a SCARA type robotic arm which is capable of moving x-y-z directions. The control unit of the robotic arm is interfaced with a computer for recording data. The complete x-y-z coordinate recording is performed using a control unit with data acquisition system connected with a computer. Complete setup is shown in the figure 1 (b). The optimum distance of travel and completion of the tasks is achieved using TSP-GA based approach. Following sections describe the solution of the task scheduling problem.

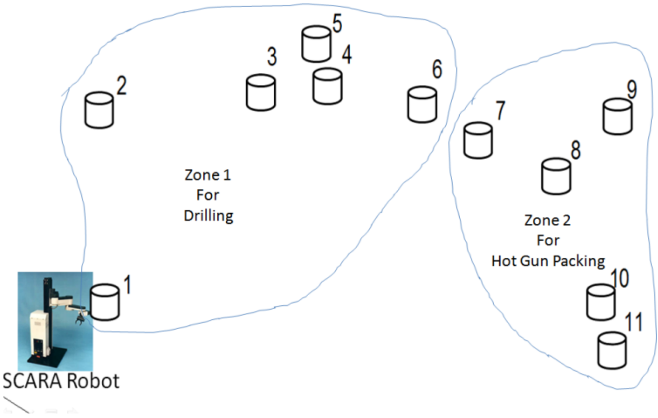

Figure 1 (a). Pick and place sequence and fixture requirements

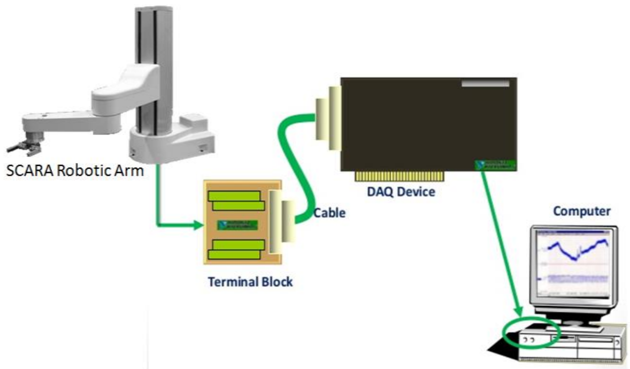

Figure 1 (b). Pick and place sequence and fixture requirements

III. THE PROPOSED METHODOLOGY

The new task scheduling algorithm that is based on zone specific task route optimization using TSP with GA search technique for robot task scheduling is detailed in this section. The proposed method runs a hybrid scheduling algorithm to create its initial population. The new location of schedule produced by the heuristic scheduling algorithm is at an approximate area in the search space around the optimal schedule. The operation of the Hybrid scheduling base algorithm is outlined in figure 2. The robot task locations are listed in the table 1.

Table 1. Locations for robot task scheduling

Sl. No	X-AXIS	Y-AXIS	Z-AXIS	Task Zone
1	0	952.806	469.878	Zone 1
2	4.8367	1000	706.805	Zone 1
3	523.106	808.735	706.805	Zone 1
4	369.361	788.861	706.805	Zone 1
5	630.423	539.699	766.426	Zone 1
6	785.629	101.451	742.386	Zone 1

7	373.23	-93.01	356.25	Zone 2
8	451.2	-182.83	338.46	Zone 2
9	524.96	-223.7	365.39	Zone 2
10	480.72	-260.36	277.91	Zone 2
11	500.39	-271.06	255.24	Zone 2

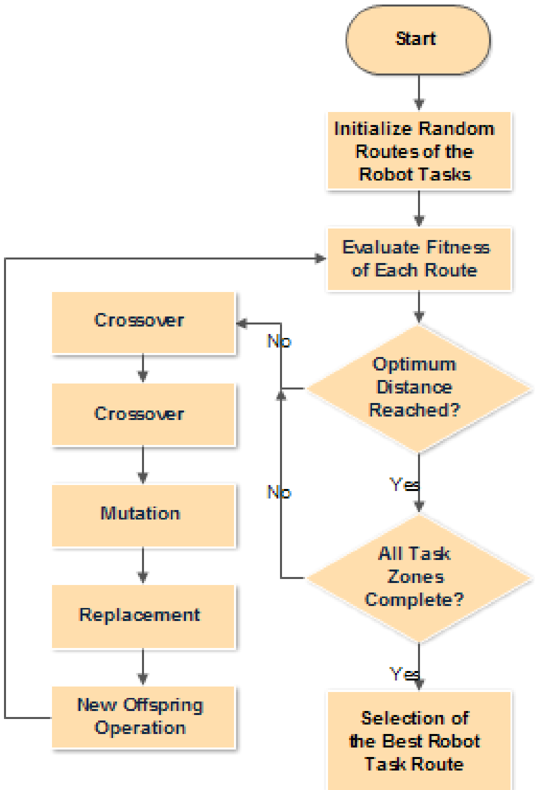

Figure 2. Outlined of genetic algorithm for solving TSP

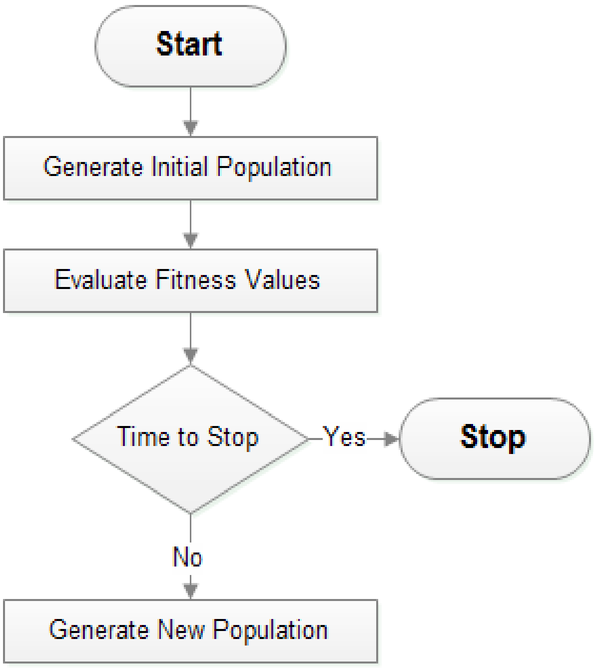

Figure 3 (a). Broad steps of genetic algorithm

Figure 3 (a) depicts the major steps associated in genetic algorithm. There are four basic steps working inside a genetic algorithm, namely: encoding, evaluation, crossover and mutation. The first step i.e. encoding process in genetic algorithms is often the most difficult aspect of solving a problem. When applying encoding to a specific problem it is often difficult to find an appropriate representation of the solution that will be easy to use in the crossover process [14]. The evaluation mechanism performs a major role in genetic algorithm. Here the evaluation function is used to find the good chromosome. The evaluation function finds the optimal solution to the TSP by setting the genetic algorithm for the shortest route for two task zones as depicted in the section 2 of the article.

In this article, the specifications of the GA adapted in our hybrid approach to minimize the distance covered by TSP throughout the entire process. Here we summarize the short record regarding algorithm plan:

Population size: 80;

Number of iteration: 5000 without any fitness improvement

Minimum Tour: 1

Number of salesman: 5

Crossover and mutation functions on the genetic material in the pairing pool. In crossover two offspring genetic materials are produced from two genetic materials having chromosomes from both parents. For each parent, exchange crossover arbitrarily selects one substring to use the crossover on it. Similarly, mutations conserve the difference of the community by arbitrarily selecting two tasks from a genetic material and exchange them. Interchange mutation is used with probability of 0.5.

After using the swap crossover and interchange mutation operators, the genetic materials in the pairing pool are combined with the chromosomes in the selectivity set to generate the new population [14].

IV. FLOW DIAGRAM OF THE PROPOSED MODEL

The solution of the above problem is implemented successfully using the above configurations mentioned in the section 3. The complete flow model for the implementation of our proposed hybrid TSP-GA model is shown in the figure 3 (b). The optimum task location for the problem mentioned in the section 2 is found out using our proposed TSP-GA model.

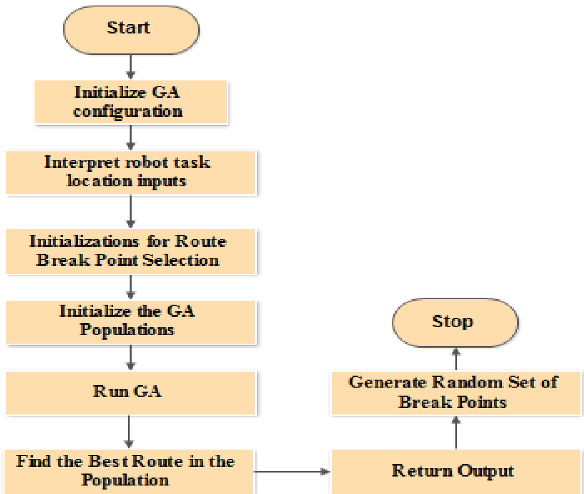

Figure 3 (b).Complete flow model for the implementation of hybrid TSP-GA model

V. RESULTS AND DISCUSSIONS

The proposed model consists of eleven number of task locations separated into two specific task zones where two task locations are considered as starting and ending locations for travelling salesman problem with optimization using genetic algorithm. Figure 4 shows all the task locations in x-y-z directions. The proposed shortest path algorithm produces same sets of optimum path in every run. The overall path of the task locations for zone 1 is shown in the figure 5 (a). Whereas figure 5 (b) shows the every route to accomplish the task for zone 1.

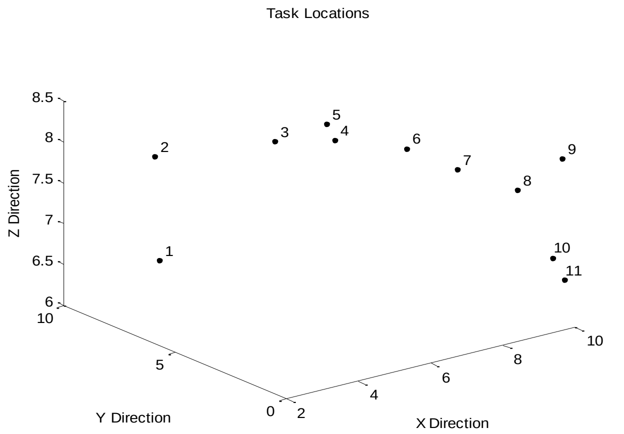

Figure 4.Task locations in x-y-z directions.

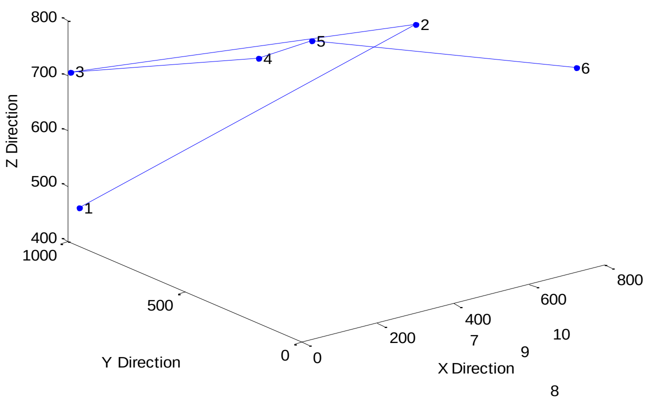

Figure 5 (a).Optimum path of the task locations for zone 1 using TSP-GA.

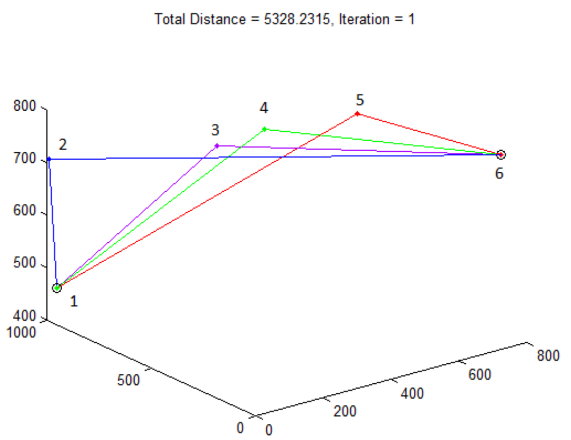

Figure 5 (b). All paths of the task locations for zone 1.

Similarly the problem depicted in the section 2 is solved for zone 2 using our proposed TSP-GA model. The optimum task locations and overall path is also shown in the figure 5(c) and 5(d) respectively.

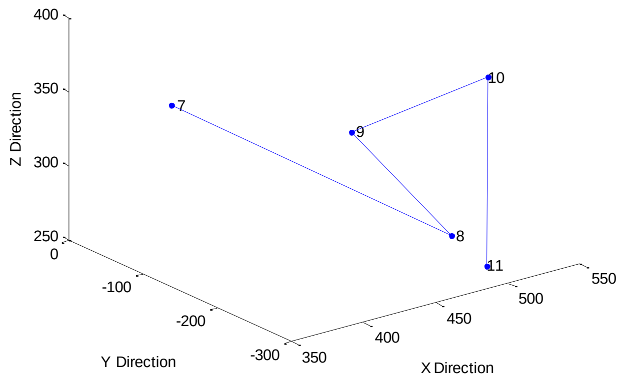

Figure 5 (c).Optimum path of the task locations for zone 2 using TSP-GA.

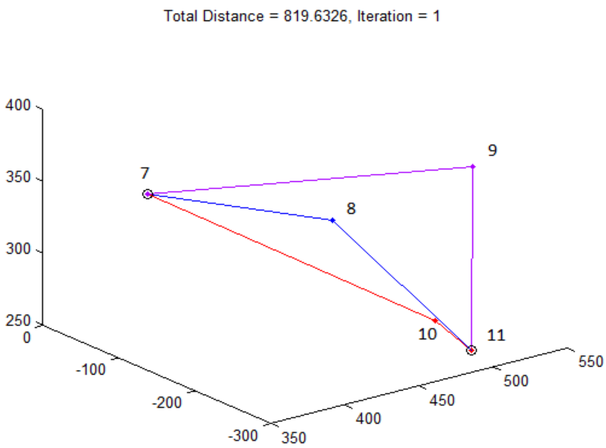

Figure 5 (d). All paths of the task locations for zone 2.

Finally the overall optimum task locations obtained using our proposed TSP-GA model is shown in the figure 6.

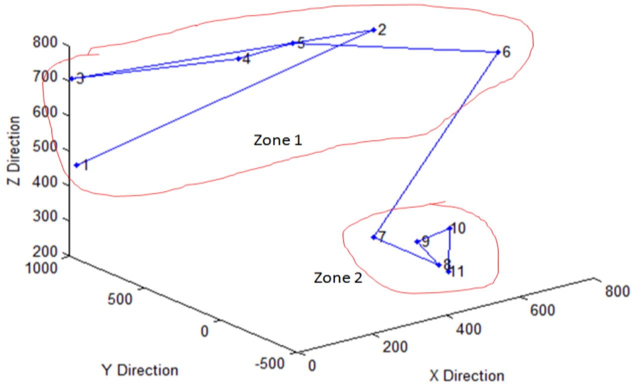

Figure 6.Optimum path of the task locations for zone 1 and zone 2 using TSP-GA.

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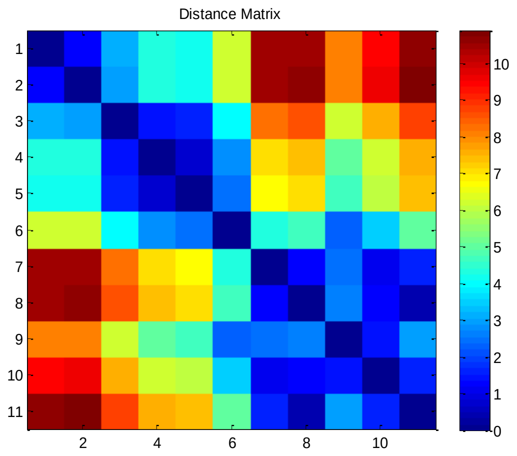

Figure 7.Plot of the distance matrix.

The distance matrix obtained during each running of the algorithm is shown in the figure 7.Here the distance matrix signifies the distances, taken pair wise between every element the task locations. From the distance matrix plot, it can be observed that the distances are symmetrically distributed over the entire region.

The shortest path obtained during each time running of the algorithm are listed in the table 2.

Table 2. List of location index during each running of the TSP-GA algorithm

Sl. No.	Index of each locations	Distance	
1.	[1 5 2 4 3 6 7 4 2 3 11]	6147.8641	With TSP-GA
2.	[1 2 3 4 5 6 7 8 9 10 11]	11987.5632	Without TSP-GA

It is observed from the table 2 that the minimum distance obtained during each time is same and the algorithm provides best root of the robot tasks to perform the complete task.

VI. CONCLUSION

The hybrid task scheduling algorithm based on TSP with GA is successfully implemented and tested. The GA optimizes tasks with starting and ending locations efficiently by optimizing TSP. The GA algorithm employs a set of genetic operators that are specifically designed for the task scheduling problem. These operators search the search space efficiently. The optimum distance is obtained about 6147.8641 during each running of the algorithm. Whereas by calculating the overall Euclidian distance of the complete task locations is about 11987.5632. The optimum route is also obtained successfully using TSP with GA search technique. Hence we have seen that the conventional methods for finding the optimum task are not best suitable for a large task allocation problem. Whereas the TSP with GA performs less scheduling time for obtaining optimum task locations in a complex application.

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