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The scheduling of automatic guided vehicles for the workload balancing and travel time minimization in the flexible manufacturing system by the nature-inspired algorithm

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The real-time scheduling of automatic guided vehicles (AGVs) in flexible manufacturing system (FMS) is observed to be highly critical and complex due to the dynamic variations of production requirements such as an imbalance of AGVs loading, the high travel time of AGVs, variation in jobs, and AGV routes to name a few. The output from FMS considerably depends on the efficient scheduling of AGVs in the FMS. The multi-objective scheduling decisions for AGVs by nature inspired algorithms yield a considerable reduction throughput time in the FMS. In this paper, investigations are carried out for the multi-objective scheduling of AGVs to simultaneously balance the workload of AGVs and to minimize the travel time of AGVs in the FMS. The multi-objective scheduling is carried out by the application of nature-inspired grey wolf optimization algorithm (GWO) to yield a balanced work-load for AGVs and also to minimize the travel time of AGVs simultaneously in the FMS. The output yield of the GWO algorithm is compared with the results of benchmark problems from the literature. The resulting yield of the proposed algorithm for the multi-objective scheduling of AGVs is observed to outperform the existing algorithms for scheduling of AGVs.

1. Introduction

In this era of rapidly varying demands for product and production outputs, maintaining high production outputs for customized products from the programmable production centers operating in a flexible manufacturing system (FMS) is indeed one of the most challenging tasks. The FMS consists of programmable production systems which comprise machining centers, automatic inspection centers, automated material handling systems and automated storage and retrieval systems (Singh & Singh, 2012). Scheduling in the FMS can be defined as a procedure to prioritize and to take decisions for allocation of different jobs to different FMS resources under some set of constraints. The selection and application of appropriate scheduling decisions are equally significant for scheduling of material handling systems as well as for the scheduling of programmable production centers in the FMS. A multifold increase in productivity of FMS can be observed with appropriate coordination and scheduling between programmable production systems and automated material handling systems. The automatic guided vehicles (AGVs) are commonly deployed in the FMS facility to cater the material transfer re-

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quirements from one production center to another. The real-time FMS operations are significantly susceptible to the dynamic change of manufacturing system variables due to which, the development of AGVs schedule also becomes complex and critical. The simultaneous multi-objective scheduling decisions to transfer jobs by more than one AGV in the FMS facility can reduce throughput time and also lower down the makespan significantly (Kashyap & Thakkar, 2012). Therefore in the present study, an attempt is carried out for the development of a muti-objective schedule of two AGVs serving in FMS under different scenarios of production centers so as to balance the workload of AGVs and simultaneously minimize the AGVs total travel time by application of a nature-inspired grey wolf optimization (GWO) algorithm. This leads to improve the utilization of AGVs and also increase the productivity of the FMS.

2. Literature Review

The AGV scheduling system assigns job transfer task from one production center to another by the moving AGVs. The AGVs according to the schedule performs pick and drop-off action for parts to and from the required workstation, after fulfilling certain conditions. The sustainable profits in business operations can be achieved through optimum utilization of resources (Chawla et al., 2018c). Optimum AGV scheduling assures optimum utilization of the resources along with no adverse effect on the system makespan. An optimum schedule also assures minimum travel time for AGVs in the FMS (Akturk & Yilmaz, 1996). An agent-based scheduling system for the FMS was proposed by the Saad et al. (1997a, 1997b). Authors developed a bidding production reservation scheme (BPRS) on a contract net protocol so as to yield the production schedule for each part. The percentage tardy of jobs was minimized by the rescheduling scheme. Authors found that the BPRS backward scheduling increases the percentage tardy of jobs in comparison to BPRS forward scheduling. Qiu et al. (2002) reported some drawbacks of improper scheduling of AGVs in FMS namely AGVs collisions – when one or more AGV cruise on the same track at the same time then a collision between AGVs may happen. Congestion – when too many AGVs cruise on same track then chances of congestion rise up further lowering the throughput of the system. Livelocks – at the intersection point sometimes higher priority are given to one AGV to cruise on a layout in comparison to other AGV which cause livelocks. Deadlocks – when more than one AGVs on the same path wait for the release of work assignment then situation of deadlock arises. The profit from the manufacturing systems can be maximized with a reduction in time spent in manufacturing and material handling activities. This objective can only be achieved by generation of optimum schedules for material handling operations and manufacturing operations. The material handling time of AGVs can be reduced by performing dynamic scheduling so that AGV idle time, total travel time can be reduced. Several researchers have done significant research in this area. Nayyar and Khator (1993) evaluated the effect of different dispatching rules for multi-load AGVs, on the overall throughput of the AGV system. Authors compared the performance of unit load AGVs and multi-load AGVs. Levitin and Abezgaouz (2003) developed an algorithm for finding the shortest route out of available routes and further validated the performance of the algorithm by solving benchmark problems from the literature. Yang et al. (2004) considered real-time manufacturing conditions and applied time window constraint for online scheduling of AGVs and further generated feasible scheduling solutions. Authors found that time window constraint every time generate a new service request along with new assignment schedule for AGVs. Beam search algorithm for dynamic scheduling of AGVs serving in FMS was proposed by Meersmans (2002). It was found that scheduling depends on the length of the planning horizon and after completion of the planning horizon, rescheduling is carried out. Authors mentioned that results from beam search algorithm found to be good for longer planning horizons and frequent rescheduling. Similar directions of research on AGV scheduling were also presented by the Powell et al. (2000) and Fleischmann et al. (2004). A new flexibility priority rule along with MILP approach for locating idle vehicles was presented by Grunow et al. (2005) Authors considered total lateness of the AGVs before application of the newly developed approach. Jerald et al. (2006) addressed the simultaneous scheduling problem of AGVs and machining centers. Authors tried to minimize penalty cost and machine idle time by introducing an application of an adaptive genetic algorithm (AGA) and validated the performance of the AGA algorithm by comparing its results with the results of the conventional genetic algorithm and it was observed that the AGA outperforms the conventional genetic algorithm. Regression-based metamodels in an FMS to simulate discrete event models was developed by Kumar and Sridharan (2010), Authors applied seven scheduling rules on the AGVs. For the applied algorithms and scheduling rules, authors found that fewest number of operations (FNOP), and earliest modified due-date (EMDD) and Koulamas algorithm yield better results for various factors such as mean tardiness, percentage tardy and mean flow time for the work transfer by AGVs in the FMS. Udhayakumar and Kumanan (2010) performed multi-objective task scheduling of AGVs in the FMS. Authors applied and compared the performance of the genetic algorithm and ant colony optimization algorithm (ACO) for the multi-objective task scheduling of AGVs. In their findings, the authors observed the performance of ACO algorithm better than the genetic algorithm. A vehicle routing issue with uncertain demands and distributions was resolved by the Moghadam et al. (2010, 2012). Authors introduced an advanced particle swarm optimization algorithm for solving uncertainty in the vehicle routing problem and results of the applied algorithm were validated by comparing them with the resulting yield of existing algorithms. In order to address the production planning problems statically and dynamically, Sadjadi and Makui (2002) introduced a novel method. Sadrabadi and Sadjadi (2009) introduced an interactive algorithm and solved multi-objective problems. The algorithm solved nonlinear utility effectively and also developed solutions towards the feasible area. Sadaghiani et al. (2014) applied an efficient integrated heuristic algorithm and solved a multi-objective optimization problem for maximizing the workload of jobs, makespan minimization, and total system load. A multi-agent criterion for scheduling of vehicles by applying bidding criteria was developed by Erol et al. (2012) further, authors applied to bid criteria on real-time manufacturing agents and validated the methodology on benchmark problems from the literature. In their research real-time schedules found to be comparable with the schedules developed from the application of other optimization algorithms. An integrated hybrid genetic algorithm for optimization of various variables such as AGV travel time, makespan, penalty cost due to tardiness and delay due to conflict avoidance was introduced by Umar et al. (2015). Authors integrated FMS resources namely scheduling rules, dispatch rules, machine centers, and AGVs and applied fuzzy logic to control the overall performance of the algorithm. Authors observed that integrated scheduling of jobs, machine centers, and AGVs scheduling, in the FMS can yield impressive utilization. Komaki and Kayvanfar (2015) applied a grey wolf optimization algorithm for two-stage assembly flow shop scheduling problem considering the release time of fabrication jobs and assembly jobs. Similarly, Lu et al. (2017) solved a multi-objective dynamic scheduling problem by application of grey wolf optimization algorithm for the welding operations. In order to address real-time dynamic scheduling problem for welding operations and to minimize the makespan, the authors considered job quality, machine reliability and job delay along with controlling process time, sequence-dependent time and job transport time in the formulated scheduling problem. The loading and unloading problems for the FMS was solved by Singh and Khan (2016). Authors developed an efficient analytical method for the solution of loading and unloading problems. The appropriate selection and application of the material handling system's equipment is a strategic decision (Sen et al., 2017). Chanda et al. (2018) and Chawla et al. (2018a, 2018b, 2018d, 2018e) applied the modified memetic particle swarm optimization (MMPSO) algorithm, clonal selection (CS) algorithm and grey wolf optimization (GWO) algorithm for the simultaneous scheduling of AGVs and optimization of AGVs fleet size in the FMS. Angra et al. (2018) evaluated the performance of different priority dispatching rules when applied to multi-load AGVs in variable sized FMS configurations.

From the literature review, a potential research gap is observed to fill for the simultaneous multi-objective job scheduling of AGVs by the application of a grey wolf optimization algorithm for different sizes of FMS layouts. In light of the aforesaid research gap, in the present study, an attempt is made to develop simultaneous multi-objective schedules for two AGVs operating in three different sizes of FMS layouts so as to simultaneously balance job transfer work-load between the AGVs and minimize the AGVs travel time by using grey wolf optimization algorithm.

3. Problem Definition

3.1 Assumptions and limitations

The following assumptions are considered in the present study.

i. The AGVs fleet size is considered to be of two.
ii. The AGV can deliver and pick upload to/from the production center for a certain number of times only.
iii. The AGV will prioritize the jobs and will complete one job at a time. After completion of a job request, the AGV will take another job request.
iv. In case both AGV's receive a request to serve the same production center, then AGV at least distance from the production center will be permitted first. In case both AGVs are at the same distance then AGV having the higher priority according to the priority dispatching rule will be allowed first to serve production center in the FMS facility.
v. The loading and unloading of jobs on production center will be carried out by the AGVs only.
vi. The AGVs are reliable and free from any kind of the failure in service.

3.2 Problem Statement

Two AGVs are serving in three different FMS, a multi-objective simultaneous scheduling has to be carried out for AGVs job balancing and for AGVs minimum travel time by application of the grey wolf optimization algorithm. The analytical combined weighted objective function for the problem is mentioned in equation 1.

$$\min\ Z = p_1\left(\sum T_1 - \sum T_2\right) + p_2\left(\sum T_1 + \sum T_2\right) \tag{1}$$

where,

$\sum T_1$ = Gross traveling times for AGV_1

$\sum T_2$ = Gross traveling times for AGV_2

$\sum T_1 - \sum T_2$ = Work balance of both AGVs

$\sum T_1 + \sum T_2$ = Total travel time of both AGVs

$p_1 = 0.6$, normalized weight applied for AGVs work load balancing.

$p_2 = 0.4$, normalized weight applied for AGVs minimum travel time schedule.

The selection of weight value for the premultiplication with the formulated objective problem of a multi-objective problem significantly depends on the comparative importance of the unit objective among all the objectives which are formulated in a multi-objective problem. The AGVs in FMS facility are used for material transfer operations, the workload balance of AGVs also reflects the FMS balance up to some extent. Therefore the work balance of AGVs must be given more relative significance in terms of the applied weights in comparison to the total travel time. In view of this, the $p_1 = 0.6$ (higher weight) is applied for multiplication with $\left(\sum T_1 - \sum T_2\right)$ *i.e.* work balance of the AGVs and $p_2 = 0.4$ (lower weight) is applied for multiplication with $\sum T_1 + \sum T_2$ *i.e.* a total travel time of both AGVs.

4. Algorithms Overview

3.1 Grey Wolf Optimization Algorithm

The grey wolf optimization (GWO) algorithm is a nature-inspired meta-heuristic algorithm which works on the basis of the leadership hierarchy and the intelligent hunting process of the grey wolves. The grey wolfs has a natural tendency to carry out hunting of a prey in a group. In the algorithm, the group of wolfs is considered in which the leader wolf also referred as α wolf has the highest hierarchy and takes decisions about the actions and behavior of other wolfs in the group. In a group of wolfs, only α wolf is allowed to perform a mating action in the group of wolfs. It is not necessary for alpha (α) wolf to be the strongest wolf in the group but the α wolf posses the best management capabilities within the group. The beta (β) wolf has the second best command in the group. The β wolf assists the α wolf and also act as middle manager between the α wolf and another wolf in the group. The other decreasing authority level in the group is maintained by the delta (Δ) and omega (ω) wolf respectively. The Δ wolf act as assistant to α and β wolf and also maintain third best command in the group of the wolfs. The ω wolf has the lowest level of hierarchy in the group and ω wolf follows orders and instructions of a Δ, β and α wolf. In the GWO algorithm four types of grey wolves, representing the four fitness functions and also called α, β, Δ, and ω are applied for the simulation. The main steps of the algorithm are as follows (Mirzalili et al., 2014; Mirzalili et al., 2016),

i) a search of prey
ii) encircle the prey
iii) attack the prey and then
iv) hunt the prey

During the iteration of the algorithm, a number of wolves and their positions are initially generated. The survival of the best fitness function is known as alpha (α) thereafter, the second and the third best fitness function are known as beta (β) and delta (Δ), respectively. The rest of the solution is known as omega (ω) (Mirzalili et al., 2014; Mirzalili et al., 2016; Bozorg-Haddad, 2017). If $\vec{X}p(t)$ and $\vec{X}(t)$ represents the position of prey and wolf respectively at the current iteration of the GWO algorithm then the encircling behavior of grey wolf algorithm can be modeled in the following equation:

$$\vec{D}=\left|\vec{C}\,.\,\vec{X}p\;(t)\;-\;\vec{X}(t)\right|, \tag{2}$$

$$\vec{X}(t+1)=\vec{X}p(t)\,-\,\vec{A}.\vec{D}\,, \tag{3}$$

where,

t = number of iteration,

$\vec{A}$ and $\vec{C}$ = coefficient vectors of the bootstrap program,

$\vec{X}p(t)$ = position vector of prey.

$\vec{X}$ = position vector of the grey wolf.

$\vec{D}$ = Calculation of vector, to specify the new position of the grey wolf.

$$\vec{A}=2\vec{a}\;.\;\vec{r}_1\;-\;\vec{a}, \tag{4}$$

$$\vec{C}=2\vec{r}_2, \tag{5}$$

$\vec{a}$ = The linear decrease of vector set from 2 to 0 during the iteration.

$\vec{r}_1$ and $\vec{r}_2$ = The random vectors in [0, 1].

The grey wolf at (x, y) location move and update its location according to the prey location (x', y'). In the algorithm, the position of the best agent is defined according to the position of the grey wolf and prey by controlling $\vec{A}$ and $\vec{C}$. Furthermore, the hunting behavior of grey wolves is iterated considering that the wolves will not quit the attacking phenomena until the prey stops its movement. The value of $\vec{a}$ reduces during the simulation of the algorithm and the fluctuation rate $\vec{A}$ also reduced during the simulation. The alpha (α, best agent), beta (β) and delta (Δ) have the information about the location of the prey and accordingly the algorithm stores the three best solutions and thereafter, it starts the omega (ω), as the fourth agent to update its position in the algorithm to achieve the best location within the search space. The alpha (α), beta (β) and delta (Δ) estimate the prey's location and location update of wolves around the prey are carried out by the omega (ω). The process of grey wolf optimizing algorithm is portrayed as flowchart and pseudo-code in Fig. 1 and Fig. 2, respectively.
The GWO algorithm is modeled in following equations.

$$\vec{D}_\alpha=\left|\vec{C}_1.\vec{X}_\alpha\;-\;\vec{X}\right| \tag{6}$$

$$\vec{D}_\beta=\left|\vec{C}_2.\vec{X}_\beta\;-\;\vec{X}\right| \tag{7}$$

$$\vec{D}_\Delta=\left|\vec{C}_3.\vec{X}_\Delta\;-\;\vec{X}\right| \tag{8}$$

$$\vec{X}_1 = \vec{X}_\alpha - A_1.(\vec{D}_\alpha) \quad (9)$$

$$\vec{X}_2 = \vec{X}_\beta - A_2.(\vec{D}_\beta) \quad (10)$$

$$\vec{X}_3 = \vec{X}_\Delta - A_3.(\vec{D}_\Delta) \quad (11)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (12)$$

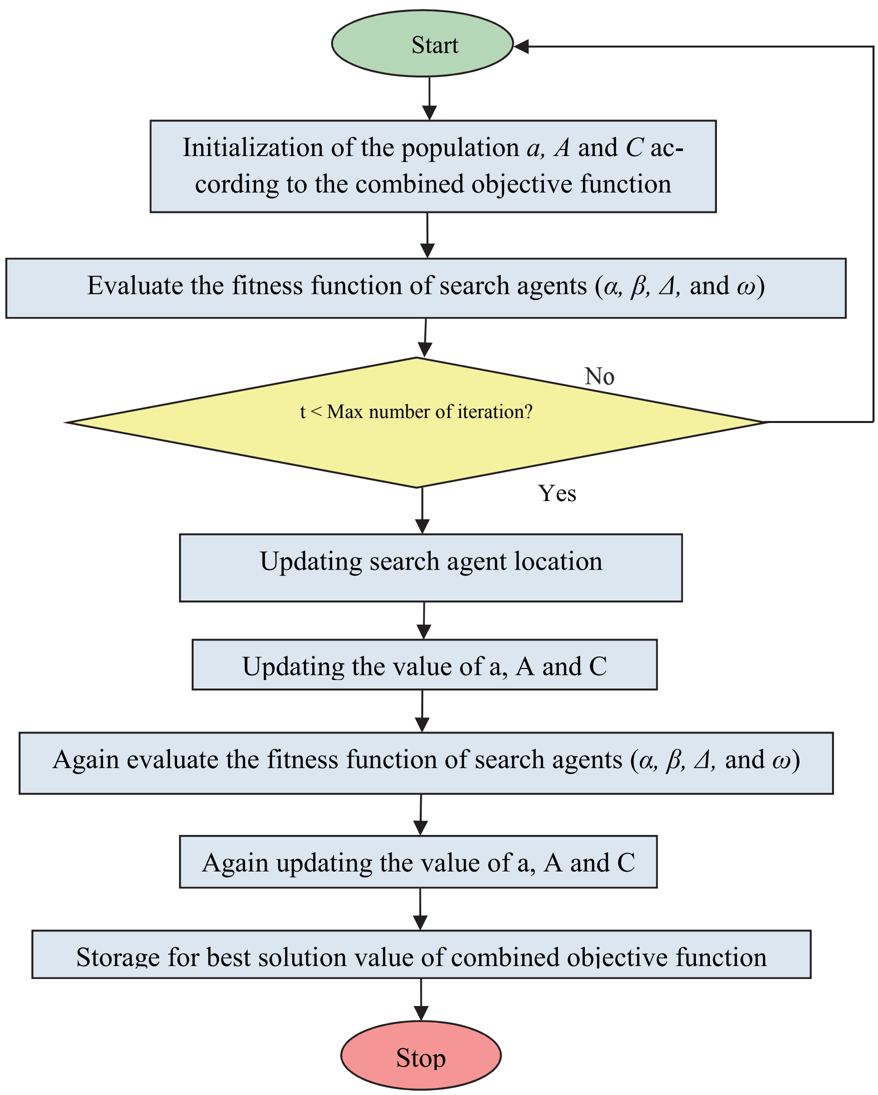

Fig. 1. Flowchart of grey wolf optimization algorithm

```
Input:  Problem Size, Population size
Output: P_g_best
Start
      Initialize the population of grey wolves Xi (i = 1, 2, ... , n)
      Initialize a, A, and C according to combined objective function
      Calculate the fitness values of search agents and grade the agents.
      (Xα = the best solution within the search agent, Xβ = the second best solution
      within the search agent, and Xδ = the third best solution within the search
      agent) t = 0
      While (t < maximum number of iterations)
            For each search agent
                  Update the position of the current search according to the equation
            End for
      Update value of a, A, and C  according to combined objective function
      Again Calculate the fitness values of all search agents and grade them
      Again update the position of  Xα, Xβ, and Xδ
      t = t+1
      Store the best solution value.
      End while
End
```

Fig. 2. Pseudo-code of grey wolf optimization algorithm

3.2 The GWO algorithm application on the AGVs jobs scheduling

In order to apply the GWO algorithm in scheduling problem, some changes are carried out in the algorithms as mentioned below.

Step 1: Population initialization.

Let K_{max} is the number of wolves in the group and $Xp_{(t)}$ and $Xi_{(t)}$ shows the position of the grey wolf "i" and prey "p" and, i=1, 2,3,4…., K_{max}, at "t" iteration in the algorithm. In this paper, the wolf represents the AGVs jobs scheduling. Initially, the AGVs jobs scheduling is calculated randomly by assignment of some random value between 0 to 1 and after that to find the job schedule the highest position magnitude (HPM) rule is applied. For example, if there are six jobs for AGVs each job is assigned with a random value as also shown in figure 3. The AGVs job schedule based on HPM can be considered as ψ = (2, 4, 3, 1, 6, and 5). In the proposed procedure the wolf represents the AGVs job schedule and both terms can be used interchangeably.

AGV job *j*	1	2	3	4	5	6
Randomized value	0.51	0.85	0.68	0.73	0.31	0.4

Fig. 3. The randomized AGVs job schedule

Step 2: Sequencing of wolfs.

The performance of any metaheuristic approach for a yield of good quality of output solutions significantly depends upon the quality of the initial solutions, considering this fact, in order to improve quality of the randomly generated initial solutions the Nawaz-Enscore-Ham algorithm (Nawaz et al. 1983) is applied. The jobs permutation yield from Nawaz-Enscore-Ham algorithm is converted by assigning 1 to the first job in AGV job schedule, 1-1/n to the second job in AGV job schedule, 1− 2/n to the third job in the AGV job schedule and similarly it follows till assignment of the last job.

Step 3: Evaluation of fitness of α, β, and Δ wolf.

The fitness of solutions (job schedule) is found by equation (13 and 1):

$$F(Xi) = \mu - Z(Xi) \text{ for } i = 1, 2, \ldots, K_{max} \tag{13}$$

Where μ is the highest positive value and the value of Z (Xi) can be found from equation (1).

Step 4: Sorting α, β, and Δ wolf.

Arrange the schedule of jobs according to their fitness value yield, the first job schedule is considered to be X_{α}, the second job schedule will be X_{β} and the third job schedule will be X_{Δ} respectively. The X_{α}, $X_{\beta,}$ and X_{Δ} have a significant effect on the convergence rate and quality of solution yield from the algorithm. In order to yield better and improved quality of solutions after arranging the order of jobs schedule a local search algorithm was applied to the X_{α}, $X_{\beta,}$ and X_{Δ}. If the solution yield of applied algorithm remains same and does not improve for the ten numbers of repetitive iterations of the algorithm then the local search algorithm will select an appropriate job schedule from the available jobs schedule and reinsert it in all possible position to finally select the best possible job schedule. The same procedure will be carried out for all the jobs. The pseudo-code for the local search for the solutions is also portrayed in figure 4. After iterating the local search algorithm for X_{α}, $X_{\beta,}$ and X_{Δ} their fitness values is calculated. If some deviation is observed in previous fitness values in comparison to new fitness of solutions from the application of local search for then update the order of X_{α}, $X_{\beta,}$ and X_{Δ}.

Step 5: Position update of wolfs.
Apply the equation (12) to update ω wolf position.
Step 6: Evaluation of the fitness of wolfs.
Apply step 2 to calculate the fitness of each wolf after the movement of wolves.

Step 7: Updating the α, β and Δ wolfs in the group.
The performance and role of wolfs are decided by their fitness value in their group. The wolf with the highest fitness value has the highest order in the group. The wolf order is maintained in form of α, β, and Δ respectively according to the fitness values of the wolves. During the update of the fitness values of wolves, the wolves' position also changes leading to change in the role of wolves in the group. Hence after the update, in order to find the best solution values, the new values of α, β, and Δ should be calculated and updated accordingly. The steps 5-7 are repeated until the termination criterion is achieved.

```
Input ψ_present,
Output ψ *
ψ* = ψ present
For i = 1: n
   ψ^(i) = ψ present
   Remove the job i form ψ^(i)
   For j=1: n and j≠i
      Insert the job i in position j of ψ^(i) to get ψ^(i)-(j)
      If Z min (ψ^(i) - (j)) < Zmin(ψ^(i))
            ψ^(i) = ψ^(i) - (j)
      end
   end
   ψ present = ψ^(i)
end
If Z min (ψ present) < Z min(ψ*)
   ψ* = ψ present
end
return ψ*
```

Fig. 4. Pseudocode for the local search for solutions

4. Numerical Example and Results

Three different sizes of FMS as a benchmark problem from literature (Udhayakumar and Kumanan, 2010) are considered in this study for the investigations. The three sizes of FMS layouts constitutes of 3, 4 and 5 production centers along with one load and unload center each. All three sizes of FMS layouts are served by the two AGVs to transfer and load–unload jobs to the production centers. If an AGV is transferring a job from one production center to another then the travel time spent on job transfer is to be considered as AGV job time and the two AGVs are scheduled to balance job transfer workload in between them and also to minimize the AGVs job transfer times simultaneously. Two objectives should be accomplished in develop schedule such that the AGVs job transfer time should be equal for both the AGVs on the basis of their travel time and also the AGVs job transfer time in the optimum schedule should be minimum. This multi-objective simultaneous schedule is optimized by the application of a grey wolf optimization algorithm. The AGV has to transfer job 5 times in each FMS facility, the AGV-production center travel-time matrix for FMS layout 1, 2 and 3 are presented in table 1, 2 and 3 respectively (Udhayakumar & Kumanan, 2010). The normalized weight is considered to be $p_1 = 0.6$, $p_2 = 0.4$ for balancing the job transfer load on both the AGVs and minimizing the job transfer travel time by the AGVs in the FMS layouts respectively.

The optimum yield of grey wolf optimization algorithm depends on several factors such as grey wolves' size, iteration run, and parameter setting applied in the algorithm. For the present study, the GWO algorithm is iterated on a computer with Intel(R) Core(TM) i5 processor specifications. The algorithm was simulated for 50 iterations thereafter cooled off. The population size of the grey wolves was considered to be 50. The parameter setting of the algorithm is carried out with two random vectors $\vec{r}_1$ and $\vec{r}_2$ in range of (0, 1) and the controlling parameter $\vec{a}$ had a linearly reducing value from 2 to 0 in the iteration process. The resulting yield of GWO algorithm is compared with the resulting yield of other algorithms namely GA and ACO, from the literature (Udhayakumar & Kumanan, 2010) and also presented in table 4. After the completion of iterations of algorithm the GWO reduces the combined objective function by 2.7% and 2.1% in comparison to the GA and ACO respectively for the FMS facility working with 3 production centers and the combined objective function is reduced by 5.7% and 2.9% in comparison to the GA and ACO respectively for the FMS facility functioning with 4 production centers. Furthermore, the combined objective function yield from GWO is also reduced for FMS layout operating with 5 production centers by 5.3% and 3.7% in comparison to GA and ACO respectively. The output results clearly cast a light on the better performance of the GWO algorithm for the multi-level simultaneous scheduling decisions for AGVs in the FMS resources.

Table 1
AGV- Production center travel-time matrix for FMS layout 1

AGV	Production centers		
	PC 1	PC 2	PC 3
1	20	25	40
2	25	30	45

Table 2
AGV-Production center travel-time matrix for FMS layout 2

AGV	Production centers			
	PC 1	PC 2	PC 3	PC 4
1	18	21	43	48
2	15	16	42	50

Table 3
AGV-Production center travel-time matrix for FMS layout 3

AGV	Production centers				
	PC 1	PC 2	PC 3	PC 4	PC 5
1	20	25	35	42	54
2	25	40	45	50	55

Table 4
Comparison of the combined objective function yield for the three sizes of FMS layout

S. No.	Number of production center in FMS layout	Genetic algorithm (Udhayakumar & Kumanan, 2010)	Ant colony optimization (Udhayakumar & Kumanan, 2010)	GWO algorithm (Proposed)
1	3	185	184	180
2	4	210	204	198
3	5	242	238	229

5. Conclusion

This paper presents the multi-objective scheduling of two AGVs serving in FMS under three different scenarios of production centers to balance the workload among the two AGVs and to minimize the AGVs travel-time simultaneously. The multi-objective scheduling is performed by the application of nature-inspired grey wolf optimization algorithm (GWO) while transferring the jobs to the different number of production centers within the FMS. The output yield of combined objective function by the nature-inspired GWO algorithm is compared and validated with the output yield of benchmark problems from the literature. The output yield of nature-inspired GWO in form of the combined objective function is observed to be better than the resulting yield of genetic algorithm (GA) and ant colony optimization (ACO) algorithm available in the literature. The proposed procedure is observed to reduce the combined objective function and accordingly a significant improvement in the overall utilization of AGVs and increase in the FMS productivity can be yield. The proposed scheduling procedure can also be applied to optimize the different scheduling objectives separately or in combination with the different FMS configurations operating with same or different resources.

6. The scope of future work

In future, the research work can be carried out for multi-objective integrated scheduling decisions for the multi-load AGVs and other FMS resources. Furthermore, for scheduling bio-inspired algorithm, hybrid algorithms, artificial intelligence algorithms such as modified memetic particle swarm optimization algorithm or clonal selection algorithm etc. can also be attempted.

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