Mathematical modelling and solving the Car Resequencing Problem considering remaining in PBS buffer as a new objective

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Abstract

One of the most important problems in managing the final assembly line of the car manufacturing factories is Car Sequencing Problem (CSP). By solving this problem, the optimal permutation of car models launched down in a mixed-model assembly line is determined. In a realistic circumstance, unforeseen occurrence of disturbances like shortage or delay in feeding required parts to the assembly line, caused to stir up an initially planned sequence. In this situation, another challenging problem should be solved that is car resequencing. This study treats the car resequencing problem where there is an intermediate buffer before final assembly line to rearrange a given initial sequence. Two objective functions are considered: (1) minimizing the ratio constraint violations (classic objective of car sequencing problem), and (2) minimizing work in process that remained in PBS buffer. For this problem, an integer linear programming mathematical model is developed. Since this problem has been proved to be strongly NP-hard, a new hybrid algorithm is proposed based on NSGAII+VNS in order to solve the problem in medium and large scales. The numerical experiments are used according to sample problems in CSPLib to run the mathematical model and evaluate the performance of the proposed algorithm in comparison to NSGAII. The computational results show that the hybrid proposed algorithm has a good effect on minimizing two .objective functions in solving the medium and large-sized problems

Keywords: car sequencing problem ; supply disturbance ; PBS buffer

Introduction

Car sequencing problem (CSP), a very particular job-shop scheduling problem, is one of the most interesting issues in the field of optimization of mixed-model assembly lines in car manufactories. This problem was first introduced by Parello et al. in 1986[1].Car sequencing problem aims to create a daily production plan in which a set of cars entering to a final assembly line should be sequenced. In this problem also various options such as air-conditioning, sun-roof, air bag, anti-lock breaking system, and so on can be installed on the cars without over-burdening the predefined restrictions of different work stations throughout the assembly line. These restrictions are modelled by defining a ratio constraint for each option cp as Ncp / Qcp means that for any production sequencing section of length Qcpof the cars (i.e. window) assembled in the line, at most Ncp cars can encompass the respective option cp. It is clear that, the smaller the ratio, will make the constraint easier [2].

Kis (2004) discussed the complexity of the car sequencing problem by giving an easier proof of the known result that the car sequencing problem was NP-hard in the strong sense [3]. Gagne, Gravel, and Price (2006) proposed an Ant Colony Optimization (ACO) algorithm for scheduling the paint and assembly shops in single objective and multi objective formulation [4]. Riberio, Aloise, and Noronha (2008a, 2008b) proposed hybrid heuristic algorithms for solving a real-world car sequencing problem with the objectives of minimizing the number of violations of assembly constraints and the number of paint colour changes [5],[6]. Solnon (2008) described the ACO algorithm and introduced two different pheromone structures based on this algorithm for car sequencing problem [7]. They showed that the combination of two pheromone structures obtain very competitive results on the car sequencing problem, being able to solve many instances much quicker than others. Joly and Frein (2008) also studied this problem considering the assembly shop and paint shop objectives by proposing heuristic models [8]. To compare these models, computation time is an important decisive factor especially in industrial cases. Other search algorithms were proposed and compared by Cordeau, Laporte, Pasin (2008), Gavranovic (2008), Fliedner, Boysen (2008), and Estellon, et al (2008).[9,10,11,12]

Same as any other planning, production sequences that have been prepared by solving the car sequencing problem may be encounter by unforeseen perturbations such as material shortages or material defects (supply disturbances). In such cases, in a reactive approach, some orders should be taken out of the primary production sequence and re-located in secondary production sequence. The procedure of placing these orders into new positions in the production sequence is called resequencing [13]. A framework of strategies, policies and methods based on different approaches that have been proposed by researchers in rescheduling literature are given by Vieira, Herrmann, and Lin [14]. Boysen, Golle, and Rothlauf (2011) and Boysen and Zenker (2013) analyse the final assembly lines based on the car-sequencing approach for different types of buffer. [15,16]

Gujjula and Günther (2009a, 2009b) pursue the mixed-model sequencing approach for resequencing the orders before they enter the final assembly line by considering stability of sequence and minimizing utility workers in the proposed models [17,18]. Franza, Hällgrena&Kobersteinb (2014) and Franza, Kobersteinb and Suhlc (2014) investigate resequencing of mixed model assembly line aiming to minimize number of deployments of utility workers in two static and dynamic versions and propose solution methods for [these problems.[19,20

The rest of this paper is organized as follows: Problem description and the mathematical model with needed parameters and variables are presented in Section 2. In Section 3, solution approaches are described. Analysing the results and performance evaluation is presented in Section 4. Finally, the main findings and the recommendation for future .research are provided in Section 5

Problem description .۲

The basics production process of a car making factory configured as three successive shops: First, body shop in which that the metal panels are welded by robots and operators to form the car body structure. Second, paint shop in which that the car body is painted by robots with spray guns, and finally, in the assembly shop various processes take place and power train, interior and option parts are added to painted body. Typically, buffer systems named as painted body storage (PBS) are installed between the paint shop and assembly shop, which allow for a limited resequencing of the jobs. .Figure 1 shows a schematic view of basics production process of a car making factory

Figure 1. A schematic view of the considered problem

This paper considers the car resequencing problem according some unexpected supply disturbances in the assembly shop, focusing on the question of in which sequence the painted bodies should be taken out of the painted body storage and be sent to assembly shop. To better understanding, suppose that a few days before the start of the production, the daily production plan is determined, and then in the next step, the orders are sequenced day by day. According there is some unexpected supply disturbances, we have to resequence the cars to minimizing the buffered in painted body storage (PBS) .considering the constraint violations as the classic objective of car sequencing problem

If all production processes worked perfectly, then the planned sequence would be achieved at the assembly shop. However, many disturbances can occur, in practice. For example, difficulties at earlier production stages can delay the production of certain car bodies, or suppliers might not be able to deliver the required parts in time. If the car body or an important part of an order is missing, then the order is blocked and eventually deferred from the planned sequence. When the missing part arrives and the order is ready for assembling, it is unblocked. Unblocked orders must be put into new positions in the planned sequence. The decision about the orders that are actually assembled is made within the operative control process. To reduce the number of changes to the planned sequence, only reactive optimization methods are considered, which means that only unblocked orders are placed into new positions and that all of the other orders preserve their precedence relations. This process of creating a new planned .sequence is called resequencing, and it is addressed in this paper

When orders are unblocked, they must be resequenced, i.e. they must be placed into new positions within the planned sequence. To account for the information delivery times and the additional human decisions, the calculation time for a resequencing algorithm is limited to a fraction of the cycle time. This limiting factor is a crucial .[condition for any solution method [20

This study aims to treat above conditions in the classic car sequencing problem. In previous papers, work overload minimization has been investigated. In this paper, a new objective function is considered to deal with minimizing work in process that is .(buffered in painted body storage (PBS

Notations .۲.۱

:The following notations are used in this paper

.N: total number of cars that their sequence should be determined

.i: position index of cars in the sequence, .i=1…Imax

. j: cars index, j=1,…, N

. cp: parts index , cp=1,…,NCp

Imax: maximum time that latest car can be remained in PBS buffer according to stock .policy

.aj: lower limit for availability of car j

.bj: upper limit for availability of car j

.NConf: number of cars configuration

.Ncp / Qcp: ratio constraint for part cp

.δk : demand for car configuration k

APcp,j: is a binary matrix that determines whether car configuration j requires part cp .or not

EPcp,m : is a binary matrix that determines whether mthcar from previous planning .period has part cp or not

.dcp: number of times that part cp is required

.xj,i: 0-1decision variable that indicates that whether car j assigned to position i or not

.rcp,i: variable that indicates usage of part cp up to position i

$g_{cp,i}$: variable that indicates the number of violations on part cp for the window ending at position i.

Z1: objective function corresponds to ratio constraint violations.

Z2: objective function corresponds to remaining time of cars in PBS buffer.

۲.۲. Assumption

Main assumptions of this study is as bellow:

In this paper, only supply disturbances that occur unexpectedly in the final assembly shop have been treated. Due to such disturbances, producing of disturbed car will be stopped.

After occurrence of supply disturbance for any car, that car will be blocked and cannot be sent to the final assembly shop.

Blocked cars after resolving the reason of blocking will be unblocked and can be sent to final assembly shop. Therefore, these unblocked cars should be resequenced.

۲.۳. Matematical modelling

In this section, mathematical model of the classic car sequencing problem that was introduced by Prandtstetter et al. (2008) is developed for the considered problem of this study [21]. Accordingly, some new variables and constraints added to that model. The proposed formulation of the problem is presented as follows:

Minimize (Z1) = $\sum_{cp=1}^{Ncp}\sum_{i=1}^{Imax} g_{cp,i}$ (۱)

Minimize (Z2) = $\sum_{j=1}^{N} PBS_j$ (۲)

Subject to:

$\sum_{i=1}^{Imax} x_{j,i} = 1$ j=1,…, N (۳)

$\sum_{j=1}^{N} x_{j,i} \le 1$ i=1,…,Imax (۴)

$\sum_{i=1}^{Imax}\sum_{j=1}^{N} AP_{cp,j} \times x_{j,i} = d_{cp}$ cp=1,…,NCp (۵)

$r_{cp,i} \ge 0$ cp=1,…,NCp ; i=1,…,Imax (۶)

$r_{cp,1} = \sum_{j=1}^{N} AP_{cp,j} . x_{j,1}$ cp=1,…,NCp (۷)

$r_{cp,i} = r_{cp,i-1} + \sum_{j=1}^{N} AP_{cp,j} . x_{j,i}$ cp=1,…,NCp ; i=2,…,Imax (۸)

$g_{cp,i} \ge 0$ cp=1,…,NCp ; i=1,…, Imax (۹)

$g_{cp,i} \ge r_{cp,i} + \sum_{m=1}^{Q_{cp}-1} EP_{cp,m} - N_{cp}$ cp=1,…,NCp ; i=1,…,Qcp - 1 (۱۰)

$g_{cp,i} \ge r_{cp,i} - r_{cp,(i-Q_{cp})} - N_{cp}$ cp=1,…,NCp ; i=Qcp,…, Imax (۱۱)

$a_j \le \sum_{i=1}^{Imax} x_{j,i} . i \le b_j$ j=1,…, N (۱۲)

$\sum_{i=1}^{Imax} x_{j,i} . i + 1 \le \sum_{i=1}^{Imax} x_{j+1,i} . i$ j∈fixedcars (۱۳)

Y_j=∑_(i=1)^Imax▒x_(j,i) .i   j=1,…, N   (۱۴)
(〖PBS〗_j=Max(Y_j-j ,0   j=1,…, N   (۱۵)

i ,j ∀   (۱۶)
(x_ij∈(0 ,1

Objective function (1) corresponds to minimize the ratio constraint violations (classic objective of car sequencing problem). Objective function (2) aims to minimize work in process that remained in PBS buffer. Constraint (3) ensures that each of N cars should assign to one of the positions from 1 to I_max. Constraint (4) ensures that in each position, only one car assign. Constraint (5) ensures that in total dcp cars requiring component cp are produced. To count number of occurring constraint violations, number of part cp that has been used up to position i should be counted. Accordingly constraints (6), (7) and (8) have been added to the model. To ensure that the number of occurring constraint violations is correctly counted, constraints (10), (11) and (9) are added. Inequalities (12) ensure that assigned position to j^thcar should be between upper and lower limit. Constraint (13) ensures that order of fixed cars in primary sequence should be unchanged in the secondary sequence after resequencing in according to guarantee the stability. Constraint (14) determines the position assigned to j^thcar. Constraint (15) calculates remaining time of car j in PBS buffer. Constraint (16) .specifies the domain of the decision variable x_ij

The proposed solving approach .۳

As mentioned before, the car sequencing problem is known as NP-Hard problem in classic format, so it is clear that this problem additional a new objective function is NP-Hard too. Therefore, due to the complexity of the considered problem and the limited decision time, exact approaches can address with only small-sized instances. In order to solve this problem in medium and large-sized scales, applying approximation methods could be useful. Therefore, a hybrid meta- heuristic algorithm named NSGAII+VNS is introduced to solve the considered problem in medium and large-sized scales. These .two powerful algorithms are widely used in multi-objective optimization problems

Multi-objective optimization algorithms usually concerned with optimization problems involving more than one objective function to be optimized simultaneously. This problem has been applied in many fields of science, including engineering, economics and logistics where optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives. The objective functions of this problem are said to be conflicting, and there exists a possibly infinite number of Pareto optimal solutions. A solution is called Pareto optimal, nondominated, Pareto efficient or non inferior, if none of the objective functions can be improved in value without degrading some of the other objective values [22]. In the following, first two multi-objective optimization algorithms NSGAII and VNS are introduced and then, the hybrid meta-heuristic algorithm NSGAII+VNS is developed.

۳.۱. Non-dominated Sorting Genetic Algorithm (NSGA)

The idea behind non-dominated sorting approach is to select the better points according ranking the points based on amount of domination. Since this method is based on non-dominated sorting approach, and also applies the genetic algorithm procedure, so it is called as the Non-dominated Sorting Genetic Algorithm (NSGA). Because of some weakness in the first version of NSGA, such as lack of elitism and complexity of calculations, the new version that is called Non-dominated Sorting Genetic Algorithm revision II (NSGA-II) was developed by Deb [23]. This algorithm is a well-known algorithm for solving multi-objective optimization problems using a non-dominated approach. Like other population-based meta-heuristic algorithms, the NSGA-II begins by generating some preliminary solution as the first populations. This algorithm also ranks and sorts each individual according to non-domination level. Evolutionary Operations (EVOPs) contains of crossover and mutation are applied to create new pool of offspring, and then combines the parents and offspring before partitioning the new combined pool into fronts. During this procedure (search and modification of solutions), the Pareto fronts are formed. The NSGA-II then conducts niching by adding a crowding distance to each member. As solutions become more diverse and better, ones can be more efficiently used by genetic operators.

In order to evaluating the solutions and calculating fitness of each solution, another ranking criterion called “crowding distance between non-dominated solutions” is used. This index shows that how near a member of the front is to other members in its neighbourhood. Larger average value of this factor for each point distance indicates more diversity of it. Figure 2 shows Flow diagram of work procedure in NSGA-II.

Figure 2. A schematic view of the NSGA-II works

In this figure, P_Tisthe parents’ population and Q_Tis the offspring population at generation t. F_1 indicate the best solutions from the combined populations (parents and offspring),F_2 shows the second best solutions and so on.

۳.۲. Variable Neighbourhood Search (VNS)

Variable neighborhood search (VNS) is a well-known metaheuristic local search that works based upon systematic changes of neighborhoods both in descent phase, to find a local minimum, and in perturbation phase to emerge from the corresponding valley.

This algorithm is also very easy to use in solving combinatorial optimization problems. :Procedure of the basic VNS is as bellow

Initialization
Select a set of neighbourhood structures N_k (k=1,2,…,k_max) that will be used in searching
Find an initial solution x
Choose a stopping condition
Set k=1
Repeat the following steps until k=k_max
.((Shaking (generate a point x^' from k^thneighbourhood of x (x^'∈N_k (x

Local search (application of some local search method with x^'as initial solution; .(denote by x^"the obtained local optimum

Mover not (If this local optimum x^"is better than the incumbent, move there .(x=x^") and continue search with N_k , otherwise set:k=k+1

Based on this procedure, the VNS algorithm starts with an initial solution, x ∈ S, where S is the whole set of search space. This algorithm manipulates initial solution through a two-nested loop, in which the core one alters and explores via two main functions so-called ‘shake’ and ‘local search’. Local search explores for an improved solution within the local neighborhood, while shake diversifies the solution by switching to another local neighborhood. The inner loop iterates as long as it keeps improving the solutions, where an integer, k, controls the length of the loop. Once an inner loop is completed, the outer loop reiterates until the termination condition is met. Since the complementariness of neighborhood functions is the key idea behind VNS, the neighborhood search (NS) should be chosen very rigorously so as to achieve an efficient VNS. The pseudo code shows that the systematic search of expanding neighborhoods for a local optimum is .abandoned when a global improvement is achieved

Hybrid NSGAII+VNS algorithm .۳.۳

Research in metaheuristics for optimization problems has lately experienced a noteworthy shift towards the hybridization of metaheuristics to each other and or with other optimization techniques. The combination of components from different algorithms is currently one of the most successful trends in optimization. The hybridization of metaheuristics such as ant colony optimization, evolutionary algorithms, and variable neighborhood search with techniques from operations research and artificial intelligence plays hereby an important role. The construction of hybrid metaheuristics is motivated by the need to achieve a good trade-off between the capabilities of a heuristic to explore the search space and the possibility to exploit the .experience accumulated during the search

According to the Characteristics of the considered problem and various reviews that have been done in metaheuristics, a hybrid algorithm from combination of NSGA-II and

VNS has been proposed to solve the considered problem as its procedure is shown in .[figure 3. This proposed hybrid algorithm in this paper is based on Asefi et.al [22

.[Figure 3. Hybrid NSGAII+VNS procedure [22

In this hybrid algorithm, first the input parameters of the algorithm including population size (N), probability of crossover (Pc), probability of mutation (Pm) and the highest iteration of the algorithm (Max−Gen)are determined. Then preliminary random populations (P_0) are generated randomly and their fitness at the target functions is calculated. The pseudo code of the proposed hybrid algorithm is as figure 4. Also the main steps of the proposed algorithm is shown in fig. 4. Also the main steps of the .proposed algorithm is shown in fig. 5

;Input: N, Pc, Pm, Max_Gen, kmax, tmax
;Generate Initial Pop
;Evaluate fitness values of the Initial Pop
;Assign rank base on pareto dominance sort

For i=1 to Max_Gen do
;[For j=1 to round [(Pc*N)/2
;(Select two individuals: (X1, X2
Apply Single Point Crossover and repairing procedure in addition delete of ;duplicate individuals
End for
[For j=1 to round [(Pm*N)/2
;Select an individual X
;Consider X as a first solution of VNS
;Time =0
While time<= tmax
While k <= kmax
Generate a point x′ at random from the kthneighborhood of x
;Apply some local search method with x′ as initial solution
Denote with x″ the so obtained local optimum
;″Move or not: If this local optimum is better than the incumbent; then x=x
Continue the search with Nl
Otherwise
K=k+1
End if
End while
Update time
End while

End for
{Combine offspring and parents {P∪Q
;Assign rank based on pareto dominance sorting algorithm
;Calculate the crowed distance of individuals in each front
Select the best N individual base on rank, crowed distance and possibility of production ;in available range
End for
;Output: Extract the best pareto front
End
[Figure 4. General structure proposed NSGA-II+VNS [22

Figure 5. NSGA II +VNS flowchart

The best value of the parameters for the hybrid proposed algorithm is obtained using Taguchi settings considering plan of L_27 in three levels. In order to determine the best combination of these parameters, three levels of each parameter was examined as table .((1

Table 1. The values of the parameters of hybrid proposed algorithm

Test values	Number of level	parameter
۳۵ , ۳۰ , ۲۵	۳	Max_Gen
۵۵ , ۵۰ , ۴۵	۳	N
۰.۸ , ۰.۷ , ۰.۶	۳	Pc
۰.۴ , ۰.۳ , ۰.۲	۳	Pm
E-08 , 1E-07 , 1E-06۱	۳	tmax

Due to the considered problem is a two-objective problem, the MID index is used to .(determine better solution as equation (17

$$MID = \left(\sum_{i=1}^{n} c_i\right)/n \quad (۱۷)$$

$$\forall i = 1.2.\ldots.n \quad \text{When } c_i = \sqrt{f_{i1}^2 + f_{i2}^2}$$

This index is calculated for each set of pareto solution. So, for each 27 cases of Taguchi plan a number will be obtained. Based on this number, comparison the Relative Percentage Deviation (RPD) will be possible. Figure (6) and (7) presented the main effect of RPD values and the average Signal/Noise ratio (S/N) respectively. Also the .(analysis of variance is shown in table (2

Figure 6. The main effect of RPD

Figure 7. The average of S/N ratio

Table 2. ANOVA table for S/N ratio

P-Value	F	Adj MS	Adj SS	Seqss	DF	source
۰.۰۰۸	۶.۹	۱۰۸.۸	۲۱۷.۶	۲۱۵.۴	۲	Max_Gen
۰.۴۷۶	۰.۷	۱۲.۳	۲۴.۶	۲۶.۴	۲	N
۰.۳۲۰	۱.۲	۱۹.۴	۳۸.۹	۴۵.۱	۲	Pc
۰.۰۳۷	۴.۲	۶۶.۵	۱۳۳.۱	۱۳۱.۹	۲	Pm
۰.۵۷۰	۰.۵	۹.۲	۱۸.۴	۱۸.۴	۲	Tmax
		۱۵.۷	۲۲.۴	۲۲۰.۴	۱۴	Eror
				۶۵۷.۸	۲۴	Total

Finally, after doing experiments, the best combination of the parameters for the hybrid proposed algorithm (NSGA II+VNS) was determined as below:

Max_Gen: 35
N: 50
Pc: 0.8
Pm: 0.4
Tmax: 1E-07

Also these experiments was done for the algorithm NSGA II and the need parameters was determined as below:

I: 20
N: 40
Pc: 0.95
Pm: 0.3

For running the crossover, single point crossover is implemented over the selected values. Offspring values are then added to the pool of offsprings. Based on Pm, one offspring is randomly selected from the preliminary (first generation) offsprings for mutation. The selected offspring enters the VNS algorithm process. Here, after determining the number of ways of generating neighbourhoods and the highest number of repetitions for the VNS algorithm (which is shown as lmax), each offspring resulted from NSGA-II and selected for mutation are considered as preliminary outputs of the VNS algorithm and neighbourhood generation methods are applied to them in each repetition. In this paper 3 neighbourhoods structure that is used in the VNS procedure are k-exchange, swap, and move. Parameter values of hybrid algorithm are tuned after running different experiments.

Computational experiments and results .۴

Design of the test problems .۴.۱

In order to test the proposed model and evaluation its performance in problem solving, some test problems have been applied in various condition. The test problems have been obtained based on data in CSPLib considering different disturbance conditions. For this :purpose, two factors are treated that effect on the problem size. These factors are

;Number of car models that should be sequenced
.Total number of car that should be assembled

Based on combination of two mentioned factors, three categories problems are arranged as small, medium, and large-sized. The specifications of these problems are showed in .table 3

Table 3. Test problems

sizes	problem	Total number of car	Number of models
small	S-I	۱۰	۳
	S-II	۱۰	۴
	S-III	۱۰	۵
	S-IV	۱۵	۳
	S-V	۱۵	۴
	S-VI	۱۵	۵
medium	M-I	۲۵	۴
	M-II	۲۵	۵
	M-III	۲۵	۶
	M-IV	۴۰	۴
	M-V	۴۰	۵
	M-VI	۴۰	۶
large	L-I	۵۰	۵
	L-II	۵۰	۶
	L-III	۵۰	۷
	L-IV	۱۰۰	۵
	L-V	۱۰۰	۶
	L-VI	۱۰۰	۷

In addition to the problem scale, the main factors of supply disturbance are also considered. According to formerly researches, one important factor that should be considered in simulating the supply disturbance is blocking rate. Thus, three rates as: 0.05, 0.1 and 0.2.Is considered for this porous. Second item is related to resolving the supply disturbance. In this regard, we consider a real case in the instance automobile factory. According to this sample, two scenarios are considered to present required time for unblocking interval: 3-5 and 6-10. Third factor is related to policy of management for holding of WIP in PBS buffer. According to real case data, we consider two .scenarios 3 and 5 regarding to this item

Comparision of results .۴.۲

This section presents the results of solving test problems using mathematical model and proposed hybrid algorithm. The mathematical model was run in GAMS and the proposed algorithm was coded in MATLAB 7/10/0/499 (R2010a). The experiments are .executed on a Pc with a 2.0GHz Intel Core 2 Duo processor and 4GB of RAM memory

The test problems were categorized in three classes contain of small, medium, and large-sized problem. For the proposed algorithm, each problem has been run ten times and the best and or the average of results are evaluated. The performance of the proposed algorithm has been compared with a well-known multi-objective genetic .algorithm, NSGA-II

Detail characteristics of test problems and result analysis are description in the .following

Assess the effectiveness of proposed model totally .۴.۲.۱

In order to assure that the new proposed model has a good effect on objective functions in comparison of don’t resequencing, three test were done for three scale of test problems. Figure 8 shows the results of solving three sample problems using the proposed model for resequensing in comparison of do no resequensing. Figure 8-a shows this results for a small-sized problem. For this problem the result of mathematical model is also presented. As this figure show, the proposed model could improve solution for both two objective functions near the result of mathematical model. Figure 8-b, and 8-c show this comparison for a sample of medium and large-sized problem respectively. These results show successfully of the new proposed model in improving .objective functions in three levels of problems

Solutions without resequrncing ❉

Hybrid proposed solutions for resequencing □

Epsilon constraint solution for resequencing o

Figure 8-a. improving the objective function in small-sized problem

Solutions without resequrncing ❈
Hybrid proposed solutions for resequencing □
Figure 8-b. improving the objective function in medium-sized problem

Solutions without resequrncing ❈
Hybrid proposed solutions for resequencing □
Figure 8-c. improving the objective function in large-sized problem

Small-Sized Problems .۴.۲.۲

At the first, the proposed algorithm is applied to the small-sized problems and its performance is evaluated. In this evaluation the Pareto-optimal solutions is required that is obtained from the mathematical model. Many several of indexes can be used to compare the performance of different algorithms. Rahimi-Vahed et al., Fattahi et al. (2007) and Fattahi et al. use the number of Pareto solutions as a quantitative measure of [the performance of the studied algorithms. [24, 25

The number of Pareto-optimal solutions, Error Ratio (ER), and the generational distance (GD) are some example indicators that can be used as the performance measure indicators when the Pareto-optimal solutions are known [26]. These comparison . indicators that we implemented in this section, are explained as below

The Number of Pareto Solutions: This indicator shows the number of Pareto-optimal solutions that each algorithm has found. The number of Pareto optimal solutions corresponding to each algorithm is compared with the total Pareto-optimal solutions .found by mathematical model

Error Ratio (ER): At the end of solving process, the number of solutions on the final Pareto front (PFknown) is marked as |PF_known |and the number of solutions on the optimum Pareto-front (PFtrue) is marked as |PF_true |. The Error Ratio (ER) indicates the number of solutions on the final Pareto-front that are not members of the optimum .(Pareto-front. This indicator is calculated as (18

$$ER = \frac{\sum_{i=1}^{|PF_{known}|} e_i}{|PF_{known}|} \quad (18)$$

Where e_i is one if the i^{th} vector of PFknown is not an element of PFtrue, otherwise e_i will be zero. When ER=1, this shows that none of the points in PFknown are in PFtrue, it means that none solutions obtained from the proposed algorithm is positioned on the optimum Pareto-front. The optimum Pareto-front (PFtrue) for the small problems .has been determined from the proposed mathematical model

Generational distance (GD) :The Generational Distance (GD) reports how far, on average, PF_knownis from PF_true. This indicator is mathematically defined as .(equation (19

$$GD = \frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{|PF_{known}|} \quad (19)$$

The small-sized problems are presented as table 4, and 5. These problems were solved by mathematical model and also two proposed algorithms ten times. The average values of the number of Pareto solutions indicator according the average solutions of ten runs are presented in tables 4. This table shows that the NSGA-II algorithm has determined about 54% of the pareto solutions, where the hybrid proposed algorithm has presented .more than 81% of the pareto solutions

Table 4. Comparison in finding pareto-optimal solutions

Problem	Number of pareto solutions	Algorithm NSGA-II	NSGA-II+VNS
S-I	۸	۳.۲	۶.۸
S-II	۱۰	۶.۲	۸.۲
S-III	۴	۱.۶	۳.۱
S-IV	۷	۴.۱	۵.۲
S-V	۶	۳.۲	۵
S-VI	۷	۴.۴	۵.۸
Average	۷	۳.۸	۵.۷

Also, the Error Ratio (ER) and the Generational Distance (GD) index of the best solution of ten runs are presented in tables 5. It is found from this table that the proposed algorithm has also a well performance based on both of two indicator Error .Ratio (ER) and Generational Distance (GD) indexes

(Table 5. Comparison of the Error Ratio (ER) and Generational Distance (GD

Problem	ER		GD	
	NSGA-II	NSGA-II+VNS	NSGA-II	NSGA-II+VNS
S-I	۰	۰	۰	۰
S-II	۰	۰	۰	۰
S-III	۰	۰	۰	۰
S-IV	۰	۰	۰	۰
S-V	۰.۷۵	۰	۰.۴	۰
S-VI	۰.۶	۰	۰.۳	۰

Medium and Large-Sized problems .۴.۲.۲

Due to time complexity of medium and large-sized problems using mathematical model, the comparison indicators which are used in these problems must be restricted to indicators that don’t need to Pareto-optimal solutions. Therefore, in this section three indicators Overall Non-dominated Vector Generation (ONVG), Spacing (S), and

Diversification (D) are used to evaluate performance of the proposed algorithm in solving these problems.

Overall Non-Dominated Vector Generation (ONVG): The Overall Non-dominated Vector Generation (ONVG) determines the total number of nondominated vectors found during algorithm execution. This indicator is calculated as equation (20).

(۲۰) $$ONVG=|PF_{known}|$$

Spacing (S):The spacing (S) indicator shows the spread of the vectors in PF_{known} numerically. This indicator measures the distance variance of neighbouring vectors in PF_{known} as equation (21).

(۲۱) $$S=\sqrt{\frac{1}{|PF_{known}|-1}\times\sum_{i=1}^{|PF_{known}|}(d_i-\bar{d})^2}$$

In equation (21), d_i is equal to distances between the i^{th} solutions from the nearest solution to it.

Diversification indicator: Generally, multiobjective optimization problems differ based on their fitness assignment procedure, and elitism or diversification approaches. The diversification mechanism in the algorithm is based on niching that results in a wide spread of solutions in the parametric space. It is defined as (22).

(۲۲) $$D=\sqrt{\sum_{i=1}^{n}\max(\|X_i-X_i\|)}$$

Where $n=|PF_{known}|$ and $\|X_i-X_j\|$ is the Euclidean distance between the two non-dominated solutions.

Tables 6 shows the values of the Overall Non-Dominated Vector Generation (ONVG) indicator that two algorithms have found during ten times running of algorithms. It is clear from this table that proposed hybrid NSGA-II+VNS algorithm has a better performance from NSGA-II in all sized problems.

Also, table 7 represents the best values of two indicators S and D during ten times running of algorithms. These tables show better performance of the proposed hybrid NSGA-II+VNS algorithm in comparison of the NSGA-II in all size of problems.

Table 6. Comparisons of the number of Non-dominated solutions that algorithms found

Problem Algorithm

	NSGA-II	NSGA-II+VNS
M-I	۶	۶
M-II	۵	۵
M-III	۹	۱۳
M-IV	۷	۱۰
M-V	۶	۶
M-VI	۴	۷
L-I	۹	۱۰
L-II	۸	۸
L-III	۷	۹
L-IV	۸	۱۲
L-V	۱۰	۱۱
L-VI	۱۲	۱۴

Table 7. Comparison between algorithms with regard to Spacing and Diversity

Problem	Spacing		Diversity	
	NSGA-II	NSGA-II+VNS	NSGA-II	NSGA-II+VNS
M-I	۱.۶	۱.۲	۴.۶	۵
M-II	۱.۳	۱.۳	۳.۲	۵.۱
M-III	۲.۴	۱.۸	۴.۶	۸.۷
M-IV	۱.۵۴	۱.۴	۶.۱	۹.۱
M-V	۱.۲	۱.۲	۵.۵	۶.۱
M-VI	۱۲.۷	۱۱.۳	۶.۱	۱۱.۳
L-I	۱.۹۸	۱	۶.۷	۸.۳
L-II	۱.۲	۰.۴	۴.۱	۴.۷
L-III	۱۳.۴	۱۲.۷	۵.۹	۱۰.۲
L-IV	۱۷.۷	۱۱.۷	۱۲.۹	۱۷.۵
L-V	۳۸.۲۶	۲۱.۴	۱۵	۲۷.۶
L-VI	۳۵.۵	۲۲.۳	۲۲.۲	۲۹.۱

Table 8 presents a comparison the performance of two algorithms based on three indicators ONVG, S, and D in solving a moderate test problem, and under different conditions of disturbances factors. Blocking rate is changed in three levels, and two parameters Unblocking interval and Policy of holding WIP in PBS buffer are changed .in two levels. These results represents preference the hybrid proposed algorithm again

Table 8. performance of two algorithms under different conditions of disturbances factors

Policy of holding WIP in PBS buffer Unblocking interval Blocking rate
NSGAII+VNS NSGAII
Spacing ONVG Diversity Spacing ONVG
Diversity

۱.۹	۰.۳	۳	۲.۵	۰.۸	۳	۳	۵–۳	۰.۰۵
۲.۵	۰.۲	۴	۲.۹	۰.۳	۴	۵		
۲.۹	۰.۴	۴	۴.۴	۱.۱	۴	۳	۱۰–۶	
۷.۵	۱.۷	۷.۸	۷.۴	۱.۸	۷.۶	۵		
۸.۲	۱.۹	۸	۸.۱	۲.۵	۸	۳	۵–۳	۰.۱
۸.۲	۱.۳	۶	۷	۲.۶	۶	۵		
۴.۲	۰.۹	۴	۲.۷	۱	۴	۳	۱۰–۶	
۵.۳	۱	۶	۴.۶	۱.۲	۵	۵		
۶.۴	۲.۳	۶	۷.۳	۳.۹	۶	۳	۵–۳	۰.۲
۸.۱	۳.۶	۹	۱۱.۶	۴.۳	۹	۵		
۴.۱	۱.۵	۵	۴.۷	۲.۱	۶	۳	۱۰–۶	
۶.۲	۳.۷	۸	۹.۸	۳.۵	۷	۵		

To complete evaluation performance of the proposed algorithm, The Relative Deviation Index (RDI) is also used for statistical comparison. This indicator calculate deviation of the proposed algorithm from the best solutions, through relation (23).

RDI=|the proposed algorithm solution-the best solution|/((maximum solution-minimum solution)) (۲۳)

Obviously, the closer the limits obtained for an algorithm are to zero and the less its range is overlapping with that of other algorithms, the better the solutions obtained from that algorithm are deemed to be. For the statistical analysis of the results, a 95 % confidence interval was set for the Tukey tests. It should be noted that overlapping of the intervals of the algorithms is indicative of lack of any statistically significant difference between their performances (with regard to the metric under investigation).

This index was evaluated and is presented in figure (9), (10), and (11) for values of Diversity, ONVG, and Spacing respectively. These results show that the hybrid NSGA-II+ VNS algorithm is superior to all of three metrics.

Figure 9. Interval plot of distances for RDI values for Diversity

Figure 10. Interval plot of distances for RDI values for ONVG

Figure 11. Interval plot of distances for RDI values for Spacing

Conclusion .۵

In this paper the car resequencing problem considering unexpected supply disturbances was studied. In this regard,in addition to the classic objective function of car sequencing problem, another new objective function was added to this problem as minimizing work in process. By this new objective function, that remains in intermediate painted body storage (PBS) was treated. Therefore, a mathematical model based on integer linear programming was developed. Due to time consuming of exact solution methods for real case problems. A hybrid metaheuristic based on VNS and NSGAII algorithms were also proposed. For evaluating the proposed algorithm, sample problems in CSPLib were used. According to multi objective evaluation indicators, proposed hybrid NSGAII+VNS outperforms alternating NSGAII method in all categories small, medium and large-sized problem. To continue future work, we recommend investigating this problem with considering the internal structure of painted body storage. Also, to improve the performance of solution method other metaheuristics such as Particle Swarm Optimization (PSO), Imperialist Competitive Algorithm (ICA) algorithms are .recommended

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