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Car Resequencing Problem Optimization Under Unexpected Supply Disturbance Condition Considering Remaining in Painted Body Storage as a New Objective

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Abstract *– One of the most critical problems in managing the car manufacturing factories' final assembly line is Car Sequencing Problem (CSP). The optimal permutation of car models is determined in a mixed model assembly line by solving this problem. In real-world cases, the unforeseen occurrence of disturbances like shortage or delay in feeding required parts to the assembly line cause to stir up an initially planned sequence. In this situation, the car resequencing problem is another challenge that should be solved. This study treats the car resequencing problem with an intermediate buffer before the final assembly line to rearrange the given initial sequence. Two objective functions are considered: (1) minimizing the ratio constraint violations (definitive objective of the car sequencing problem), and (2) minimizing work in process that remained in painted body storage (PBS) buffer. For this problem, a mathematical model as MIP is developed. Since this problem is discussed as intensely NP-hard, a new hybrid algorithm is proposed based on NSGAII and VNS to solve the medium and large scales. The numerical experiments are used according to sample problems in CSP Lib. to run the mathematical model and evaluate the developed approach's performance. The computational results show that the proposed method 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.*

I. INTRODUCTION

Nowadays, because of increasing global competition in the automobile, gaining market share has become challenging for car manufacturing factories. They should try to introduce new products with competitive specifications to the market and, on the other hand, they should optimize their production processes to reduce the operation costs. The structure of production lines has a primary affecting on the efficiency of the production process. Traditionally, car assembly lines are based on single-model production with high volume products (Rahimi-Vahed, 2007). Obtaining customer satisfaction by producing products with the desired customer feature and the lowest investment costs are

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essential factors that force car manufacturing companies to use mixed-model assembly lines (MMAL). There is high-level flexibility in such lines in which a variety of similar car models in construction and configuration are made simultaneously. These assembly lines are also efficient to tackle demands diversification with a minimum possible cost and thus have received increasing attention in the car manufacturing industries (Drexl and Kimms, 2001 and Reis, 2007, José de Oliveira, 2007).

Car sequencing problem (CSP) is one of the most exciting issues in mixed-model assembly line optimization. At first, Parello et al. (1986) introduced this problem during an experimental study in 1986. The problem behind the idea is to create a daily production plan in which a set of different car models enter a final assembly line. Besides, various options such as air-conditioning, sun-roof, airbag, anti-lock braking system can be installed on the cars without over-burdening the predefined restrictions of different work stations throughout the assembly line. These restrictions are modeled by defining a ratio constraint for each option cp as N_{cp}/Q_{cp}means that for any production sequencing section of length $Q_{cp}$of the cars (i.e., window) assembled in the line, at most N_{cp} cars can encompass the respective option cp. It is clear that the smaller the ratio will make the constraint easier (Chutima and Olarnviwatchai, 2016).

Kis (2004) studied the car sequencing problem in detail and provided several reasons that indicate the problem's complexity. Gagne et al. (2006) investigated the scheduling problem in the paint shop and assembly stage of an automotive factory. Due to the problem's complexity, They used ant colony optimization to schedule different car models for the paint and assembly shops in the single-objective and multi-objective formulation. Riberio et al. (2008a, 2008b) continued studying this problem in bi-objective conditions. They investigated the problem considering the number of violations of operational constraints and the number of paint color changes to be minimized simultaneously as two new objective functions. After proposing the problem's mathematical model, they proposed several heuristic methods to solve the problem on a real-sized scale. Solnon (2008) conducted the car sequencing problem and used the ant colony optimization (ACO) algorithm to tackle this problem's complexity in large-sized instances. Joly and Frein (2008) also studied the problem in which both assembly and paint shop preferences are considered to be provided. They proposed some approximation methods for solving this problem in a real-world case. The authors used computation time and some other metrics to compare these methods' performance in some industrial cases. Due to the importance and numerous applications of the car sequencing problem in manufacturing industries, many researchers have focused on this problem during recent years that we can refer to Gavranovic (2008), Fliedner and Boysen (2008), Cordeau et al. (2008), Estellon, et al. (2008), Zhang, et al. (2018), Jahren, et al. (2018), and Thiruvady, et al. (2019) for instances.

Like any other planning, production sequences that have been prepared by solving the car sequencing problem may be encountered by unforeseen perturbations such as material shortages or material defects (supply disturbances). According to the study of Gunay et al. (2016), only 11-30% of vehicles leaving the paint department at their correct positions. In such cases, in a reactive approach, some orders should be taken out of the primary production sequence and re-located in the secondary production sequence. Boysen et al. (2012) denoted the replacement of orders into new positions in a sequence because of disruptions as a resequencing procedure. Some strategy approaches with several policies and methods have been proposed for the car sequencing problem by some researchers by Vieira et al. (2003). Boysen et al. (2011) and Boysen et al. (2013) investigated some final assembly lines by considering the car-sequencing approach and several different kinds of a buffer. Alszer and Krystek (2017) studied the car sequencing problem considering various types of buffer warehouses in a paint shop. Chutima and Kirdphoksap (2019) considered this problem with six objectives to be optimized simultaneously.

Gujjula and Günther (2009a, 2009b) proposed some approaches for the resequencing the orders in a mixed-model sequencing before the final assembly line as a sustainable sequence to minimize utility workers. Franza et al. (2014a, 2014b) investigated the resequencing problem of MMAL to minimize the number of deployments of utility workers in two static and dynamic versions and proposed some solution methods for these problems.

A central challenge in a car making manufacture is to optimum responding to requests for increasing buffer capacity. Requests for increasing buffer capacity are usually made to increase production flexibility and better answer to

Table I.Characteristics of the reviewed studies on car sequencing

Author and year	***Disturbance***	***Buffer type***	***Objective***								***Solution***
			Level scheduling	***Color changeover minimization***	***Minimization of assembly constraint violation***	***Minimization of line stoppage***	***Buffer size***	***Minimization of the number of utility workers***	***Stability***	***Remaining cars in a buffer***	
Inman and Schmeling (2003)	*	Virt	*	*	*						Simulation
Inman (2003)		AS/RS, Virt					*		*		Exact
Spieckermann et al. (2004)		MIX		*							Branch & bound
Moon et al. (2005)		MIX		*							Simulation
Fournier and Agard (2007)	*	Virt,MIX				*	*				Simulation
Gujjula and Günther (2009)	*	Pull				*		*			Local search
Lim and Xu (2009)		Pull		*							Local beam search, Iterative search
Boysen et al. (2011)		Pull			*						Linear programming, Graph search, Beam search
Boysen and Zenker (2013)		MIX			*						Graph search, Beam search, Ant colony
Franz et al. (2014)	*	AS/RS						*			Variable tabu search
Franz et al. (2015)	*	AS/RS						*			Variable search algorithm, Variable tabu search, Simulated annealing
Sun et al. (2015)		MIX		*							Branch & bound, Graph search
Zhipeng et al. (2015)		MIX	*					*			Small-World Optimization Algorithm
Lutfe Elahi et al. (2015)		MIX		*							Simulation
Chutima (2016)		AS/RS		*	*			*			Extended coincident algorithm, NSGA- II
Gunay and Kula (2016)	*	AS/RS							*		Stochastic programming
This study	*	MIX			*					*	$\epsilon -$ constraint, NSGA- II

supply disturbances. According to this matter (supply disturbances) in most real-life industries, a new approach is proposed in this study to help decision maker managers make a better decision in the trade-off between minimizing the remaining cars in the buffer and minimizing the assembly constraint violation. So three main contributions of this paper are below:

- Studying supply disturbances in-car sequencing problems that cause changes in initial sequencing. The car sequencing problem in original form is a reduced manner of the real situation in car plants. However, in reality, most plans are not executable, and one of the most important reasons for this deviation is supply disturbance.

- Considering a buffer between paint shop and assembly shop to close this problem to real-life industries. In the classical form of the car sequencing problem, it is assumed that just a simple situation occurs in the assembly shop. In this paper, we consider the intermediate production phase between the paint shop and assembly shop. The investigated situation in this study is a real problem that is more applicable in car manufacturing plants.
- Proposing a new model to solve the car resequencing problem in bi-objective conditions by considering minimizing remaining cars in a buffer as a new objective.

The most important previous studies regarding related factors are classified in Table I to structure a relevant literature review of the considered problem and show this paper's main contributions.

Remain sections of this work are organized as follows: Problem description and the mathematical model with parameters and decision variables are presented in section 2. The solution approach is described in section 3. Analyzing the results and performance evaluation is provided in section 4. Finally, a summary of the study with the main findings and some future research recommendations are presented in section 5.

II. PROBLEM DEFINITION

The car manufacturing factory's necessary process includes three successive stages: First, the body shop that robots and operators weld the metal panels to form the car body structure. Second, paint shop in which robots guns paint the car body with spray. Finally, in the assembly shop, various processes take place, and power train, interior and option parts are added to the painted body. Typically, buffer systems denoted as PBS (painted body storage) are usually installed after the paint shop and before the assembly stage to allow specified resequencing of jobs. Figure 1 represents a schematic view of a car manufacturing plant's standard process considering the primary phases.

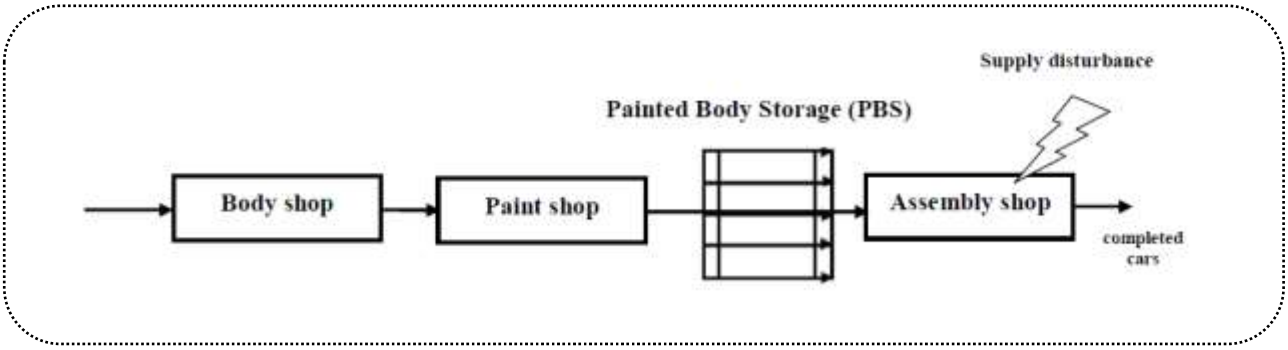


Fig. 1. Display of the considered problem

This paper considers a car resequencing problem with some unexpected supply disturbances in the assembly shop to sequence the assembly shop's painted bodies. To better understanding, suppose that the daily production plan is determined just a few days before starting production, and then in the next step, the orders are sequenced daily. According to unexpected supply disturbances, we have to resequence the cars to minimize the buffer in painted body storage (PBS), considering the constraint violations as the classic car sequencing problem's classic objective.

We will achieve ideal goals in the assembly shop if all processes work perfectly without any disruptions. However, it is generally inevitable changes occur during the initial plan. There are usually problems at the beginning of production that cause delays in the completion time of jobs, and so, suppliers would not be able to deliver the required parts in time. When a critical part of an important set is missed in order, the related order will be blocked and finally deferred from the initial sequencing. After arriving at the missing parts and sets, the related order will be unblocked to complete the assembly stages. However, we should consider the unblocked orders into a new position and repair the initial sequence. Reactive approaches for sequencing and scheduling are usually used to reduce the initial plan changes. Techniques used in reactive approaches for creating a new sequence to meet objectives are well known as resequencing used in this study.

When an order is unblocked, it should be resequenced and be placed into a new position within the initial sequence. Figure 2 represents an instance of resequencing three unblocked orders. This change is occurred before sending order number 42 to the assembly shop. The possible interval is before order 52 is denoted by a vertical line.

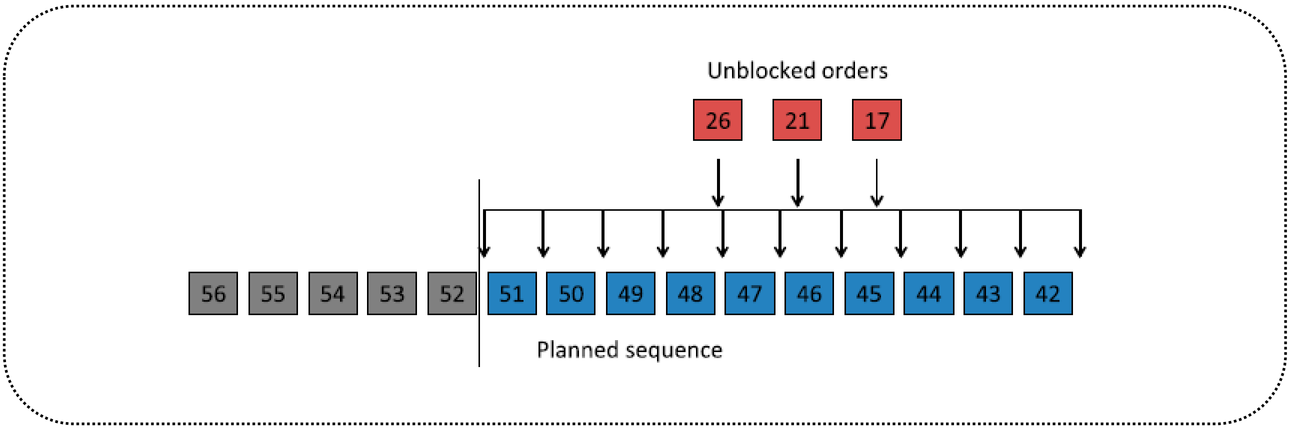


Fig. 2. Example of the problem

In order to control the new additional decisions and final delivery times, the resequencing procedure is usually limited to a specific fraction of cycle time (Franz et al., 2014)

This study aims to treat the 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 minimize work in process buffered in painted body storage (PBS).

The main assumptions of this study are as below:

1) Only supply disturbances that occur unexpectedly in the final assembly shop are treated. Due to such disturbances, producing of the disturbed car will be stopped.
2) After any supply disturbance for any model, that model will be blocked and cannot be sent to the final assembly shop.
3) After resolving the block, blocked cars will be unblocked and sent to the final assembly shop. Therefore, these unblocked cars should be resequenced.

Notation and parameter definition of the problem has been presented as bellow:

N: Total number of cars that their sequence should be determined.
i: Position index of cars in the sequence ($i = 1, \dots, I_{max}$).
j: Cars index ($j = 1, \dots, N$).
cp: Parts index ($cp = 1, \dots, NCp$).
I_{max}: Maximum time that latest car can be remained in PBS buffer according to stock policy.
a_j: Lower limit for availability of car j.
b_j: Upper limit for availability of car j.
$NConf$: Number of cars configuration.

N_{cp}/Q_{cp}: Ratio constraint for part cp. Based on a given ratio constraint N_{cp}/Q_{cp}, there should not exist more than N_{cp} cars affected by a specific part cp in each consecutive sequence of Q_{cp} cars.

δ_k : demand for car configuration k.
$AP_{cp,i}$: A binary matrix that determines whether car configuration i requires part cp or not.
$EP_{cp,m}$: A binary matrix that determines whether m^{th} car from previous planning period has part cp or not.
d_{cp}: Number of times that part cp is required.
$X_{j,i}$: 0-1 decision variable that indicates that whether car j assigned to position i or not.
Y_j: Position assigned to j^{th} car.
$r_{cp,i}$: 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.

In this section, the mathematical model of the considered problem is introduced based on its classic format presented by Prandtstetter et al. (2008). This model that has been adopted due to the new factors and decision variables is presented as follows:

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

$$Minimize\ (Z2) = \sum_{j=1}^{N} PBS_j \tag{2}$$

Subject to:

$$\sum_{i=1}^{Imax} x_{j,i} = 1 \qquad j = 1, \dots, N \tag{3}$$

$$\sum_{j=1}^{N} x_{j,i} \leq 1 \qquad i = 1, \dots, I_{max} \tag{4}$$

$$\sum_{i=1}^{Imax} \sum_{j=1}^{N} AP_{cp,j} \times x_{j,i} = d_{cp} \qquad cp = 1, \dots, NCp \tag{5}$$

$$r_{cp,i \geq 0} \qquad cp = 1, \dots, NCp \ \ , \ \ i = 1, \dots, I_{max} \tag{6}$$

$$r_{cp,1} = \sum_{j=1}^{N} AP_{cp,j} \, . \, x_{j,1} \qquad cp = 1, \dots, NCp \tag{7}$$

$$r_{cp,i} = r_{cp,i-1} + \sum_{j=1}^{N} AP_{cp,j} \, . \, x_{j,i} \qquad cp = 1, \dots, NCp \ \ , \ \ i = 2, \dots, I_{max} \tag{8}$$

$$g_{cp,i} \geq 0 \qquad cp = 1, \dots, NCp \ \ , \ \ i = 1, \dots, I_{max} \tag{9}$$

$$g_{cp,i} \geq r_{cp,i} + \sum_{m=1}^{Q_{cp}-1} EP_{cp,m} - N_{cp} \qquad cp = 1, \dots, NCp \ , \ i = 1, \dots, Q_{cp}\text{-}1 \tag{10}$$

$$g_{cp,i} \geq r_{cp,i} - r_{cp,(i-Q_{cp})} - N_{cp} \qquad cp = 1, \dots, NCp \ , \ i = Q_{cp}, \dots, I_{max} \tag{11}$$

$$a_j \leq \sum_{i=1}^{Imax} x_{j,i} \,.\, i \leq b_j \qquad j = 1, \dots, N \tag{12}$$

$$\sum_{i=1}^{Imax} x_{j,i} \,.\, i + 1 \leq \sum_{i=1}^{Imax} x_{j+1,i} \,.\, i \qquad j \in fixed\ cars \tag{13}$$

$$Y_j = \sum_{i=1}^{Imax} x_{j,i} \,.\, i \qquad j = 1, \dots, N \tag{14}$$

$$PBS_j = Max(Y_j - j\,, 0) \qquad j = 1, \dots, N \tag{15}$$

$$x_{ij} \in (0\,, 1) \qquad \forall\, i\,, j \tag{16}$$

The objective function (1) corresponds to minimize the ratio constraint violations (definitive objective of car sequencing problem). The 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) indicates that in total d_{cp} cars requiring component *cp* are produced. To count the number of occurring constraint violations, the 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. Constraints (9), (10), and (11) control the number of constraint violations occurring. Inequalities (12) ensures that assigned position to j^{th} the car should be between upper and lower limit. Due to the constraint (13), the order of fixed cars in the primary sequence should be unchanged in the second sequence after resequencing according to guarantee stability. Constraint (14) determines the position assigned to j^{th} car. Constraint (15) calculates the remaining time of car j in PBS buffer. Constraint (16) specifies the domain of decision variables x_{ij}.

III. THE PROPOSED SOLVING APPROACH

As mentioned before, car sequencing is an NP-hard problem in the classic format, so it is clear that this problem adding a new objective function is NP-hard. Therefore, due to the complexity of this study's problem, the exact method can be used just for small-sized instances, and so, we need to apply approximation methods to solve the problem with medium- and large-sized scales in a reasonable time. Therefore, a hybrid metaheuristic algorithm named NSGAII+VNS is introduced to solve the considered problem in medium and large-sized scales. These two powerful algorithms are widely used to conduct optimization problems in a multi-objective environment.

Multi-objective optimization in which more than one objective function should be optimized simultaneously has many applications in industries and has received very attention, especially in recent years. In such these problems, we should provide several preferences for different managers and stakeholders. This study investigates a bi-objective optimization to provide various alternatives for decision-makers to make trade-offs between these two considered conflict objective functions. Therefore, after solving the problem, there exists a possibly infinite number of solutions, so-called as Pareto-front (Asefi et al. 2014). The first two multi-objective optimization algorithms, Non-dominated Sorting Genetic Algorithm (NSGA) and Variable Neighbourhood Search (VNS), are introduced. A new hybrid approach based on the Non-dominated Sorting Genetic Algorithm revision II (NSGAII) and VNS is developed and used to solve the problem with different dimensions in a reasonable time.

A. Non-dominated Sorting Genetic Algorithm (NSGA)

The non-dominated sorting approach's basic idea is to select better points according to ranking the points based on the amount of domination. Since this method is based on the non-domination concept and applies the genetic algorithm procedure, so it is called the Non-dominated Sorting Genetic Algorithm (NSGA). Because of some weakness in the first version of NSGA, such as complexity of calculations, the new version, the so-called NSGA-II, was developed by Deb et al. (2002). This algorithm has high efficiency in solving multi-objective optimization problems based on the non-domination concept. Like other population-based meta-heuristic algorithms, the NSGA-II begins by generating some preliminary solutions as the first populations. This algorithm sorts each individual by considering the non-domination level. Similar to the classic GA, the evolutionary operations include crossover and mutation are applied to create new offspring. After that, the parents and offspring are combined, and new partitioning is done for 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.

To evaluate the solutions and calculate each solution's fitness, another metric called "crowding distance" is used. This index shows how far a Pareto-front solution is from the other members in its neighborhood. The more considerable amount of this factor for each point distance indicates more diversity of it. Figure 3 shows a flow diagram of the work procedure in NSGA-II.

In figure 3, the parents' population has been denoted by P_t and Q_t is the offspring at generation t. Moreover, F_1 indicates the first rank of Non-dominated solutions, F_2 shows the second rank and so on.

B. Variable Neighbourhood Search (VNS)

Variable neighborhood search (VNS) is another metaheuristic local search that works based on systematic changes of neighborhoods both in the descent phase to find a local minimum and in the perturbation, phase to emerge from the corresponding valley. This algorithm is also straightforward to use in solving combinatorial optimization problems. Hansen and Mladenovic (1997) introduced the VNS algorithm with the necessary procedure as bellow:

- ***Initialization***

✓ Select several neighborhood structures (N_k $k = 1, 2, \dots, k_{max}$) for searching the solution space.
✓ Create a solution x as an initial solution.
✓ Choose a stopping criterion.
✓ Consider $k = 1$

- ***Repeat the following steps until $\boldsymbol{k = k_{max}}$***

✓ Generate a point x' from k^{th} neighborhood of x $\left(x' \in N_k(x)\right)$.
✓ Apply some local search methods with x' as the initial solution; denote by x'' the obtained local optimum.
✓ If this local optimum x'' is better than the incumbent, consider $x = x''$ and continue search with N_k , otherwise set: $k = k + 1$.

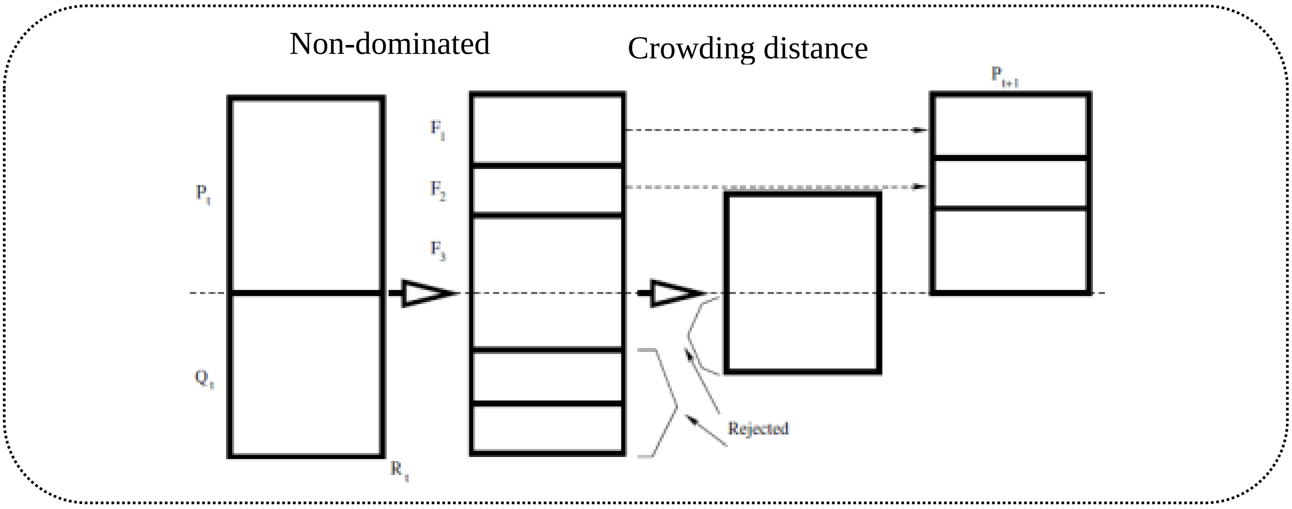


Fig. 3. A schematic view of the NSGA-II algorithm

Based on this procedure, the VNS algorithm first selects the proper neighborhood structure and then create an initial feasible solution $x \in S$ (S denotes the whole set of solution space). This algorithm manipulates the initial solution through a two-nested loop that the core one alters and explores via two main functions: 'shake' and 'local search'. The local search technique explores the solution space near the current solution to improve the current solution via replacement by a local neighborhood with a better fitness value. Since neighborhood functions' complementariness is the critical principle in VNS, the neighborhood search (NS) procedure should be chosen very intelligently to provide 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.

C. Hybrid NSGAII+VNS algorithm

Hybridization of metaheuristics has increasing experienced in optimization problems to use their robust features together. The hybridization of metaheuristic algorithms such as evolutionary algorithms with other ones, especially VNS has many multi-optimization sectors.

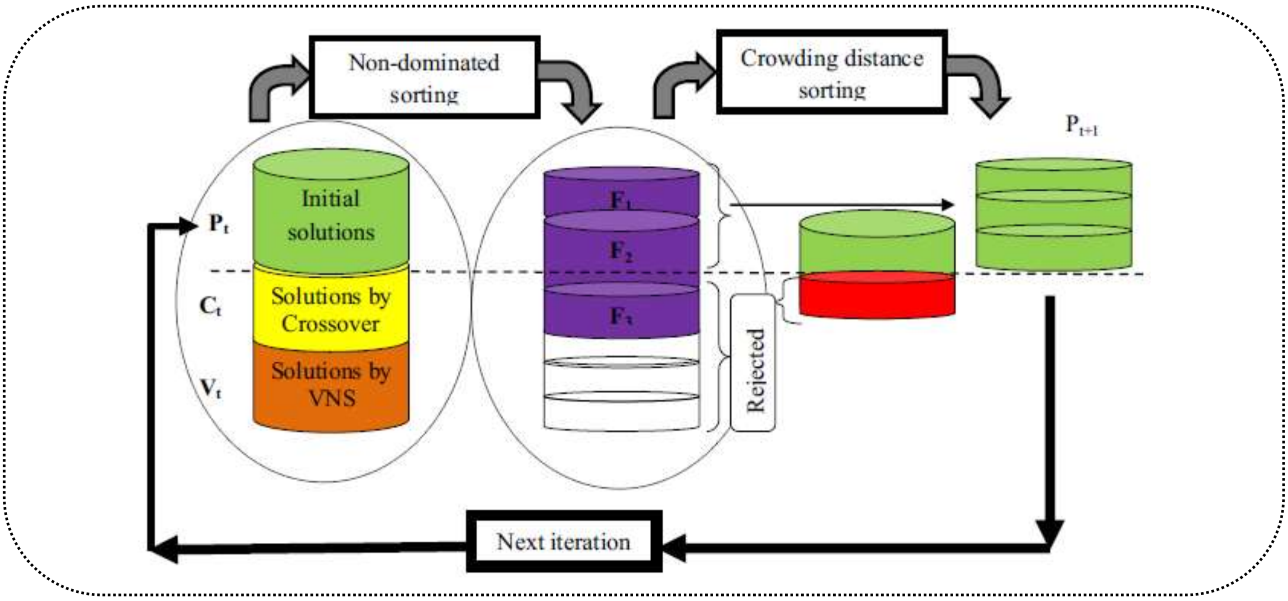


Fig. 4. Hybrid NSGAII+VNS procedure.

According to the Characteristics of the considered problem and various reviews that have been done in metaheuristics, a hybrid algorithm based on combination NSGA-II and VNS has been introduced by Asefi et al. (2014). Their hybrid algorithm was proposed to solve the classic car sequencing problem shown in figure 4. We adopt and use this algorithm considering new parameters and new conditions in this study.

```
Input: N, P_c, P_m, 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 [(P_c*N)/2];
        Select two individuals: (X_1 ,X_2);
        Apply Single Point Crossover and repairing procedure also delete of duplicate individuals;
    End for
    For j=1 to round [(P_m * N)/2]
        Select an individual X;
        Consider X as a first solution of VNS;
        Time =0;
    While time<= t_max
        While   k <= k_max
            Select the point x' from the k^th points in the neighborhood of x randomly;
            Apply one or more local search methods using x' as the initial solution;
            Consider the best-obtained solution by local search (local optimum) as x'';
            If this local optimum is better than the incumbent; then x = x'';
                Continue the search with N_l
                  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 the possibility of production in the available range;
End for
Output: Extract the best Pareto-front;
End
```

Fig. 5. The general structure proposed NSGA-II+VNS [23]

In this hybrid algorithm, first, the input parameters of the algorithm, including population size (N), probability of crossover (P_c), probability of mutation (P_m), and the maximum iteration ($Max-Gen$) is determined. Then the initial population (P_0) is generated randomly, and the fitness value of each solution is calculated based on the objective functions. The pseudo-code of the proposed hybrid algorithm is as figure 5. Also, the main steps of the proposed algorithm have been shown in figure 6.

The best value of the parameters for the hybrid proposed algorithm is obtained using Taguchi settings considering the plan of L_{27} in three levels. Three levels of each parameter were examined to recognize these parameters' best values shown in Table II.

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

Parameter	*Number of levels*	*Test values*
Max_Gen	3	25 , 30 , 35
N	3	45 , 50 , 55
P_c	3	0.6 , 0.7 , 0.8
P_m	3	0.2 , 0.3 , 0.4
t_{max}	3	1E-08 , 1E-07 , 1E-06

D. Solution representation

Solution representation in a meta-heuristic is one of the most important decisions with a high impact on the final solution's quality. Representation structure should be legal, feasible, and easy to decode and cause a reduction in the algorithm's run time. Solution representation for this problem has been represented in figure 7. In this scheme, any remained configuration is assigned to one existing position.

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

$$MID = \frac{\sum_{i=1}^{n} c_i}{n} \tag{17}$$

When $c_i = \sqrt{f_{i1}^2 + f_{i2}^2}$ $\qquad \forall i = 1.2.\dots.n$

This index is calculated for each set of Pareto solutions. So, for every 27 cases of the Taguchi plan, a number will be obtained. Based on this number, a comparison of the Relative Percentage Deviation (*RPD*) will be possible. Taguchi's result about the main effect of *RPD* values has been shown in figure 8. Moreover, figure 9 represents the average Signal/Noise (*S/N*) ratio, and the variance analysis has been shown in table III.

Table III. ANOVA table for S/N ratio

Source	*DF*	*Seq ss*	*Adj SS*	*Adj MS*	*F*	*P-Value*
Max_Gen	2	215.4	217.6	108.8	6.9	0.008
N	2	26.4	24.6	12,3	0.7	0.476
Pc	2	45.1	38.9	19.4	1.2	0.320
Pm	2	131.9	133.1	66.5	4.2	0.037

Continue Table III. ANOVA table for S/N ratio

Source	*DF*	*Seq ss*	*Adj SS*	*Adj MS*	*F*	*P-Value*
Tmax	2	18.4	18.4	9.2	0.5	0.570
Error	14	220.4	22.4	15.7		
Total	24	657.8				

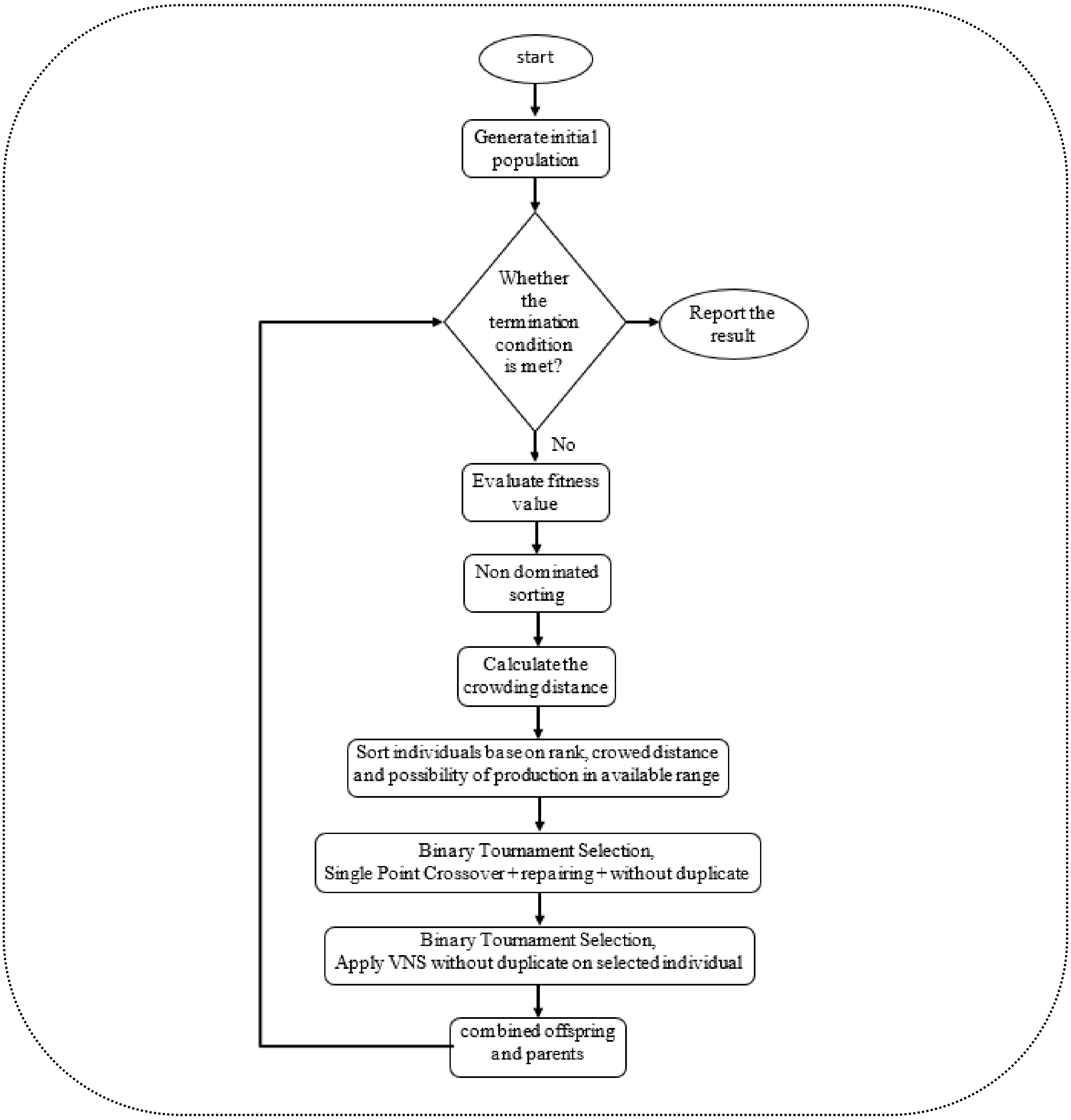


Fig. 6. NSGA II +VNS flowchart

Position	١	٢	....	n-1	n
Configuration	K_1	K_2	....	K_{n-1}	k_n

Fig. 7. Solution representation

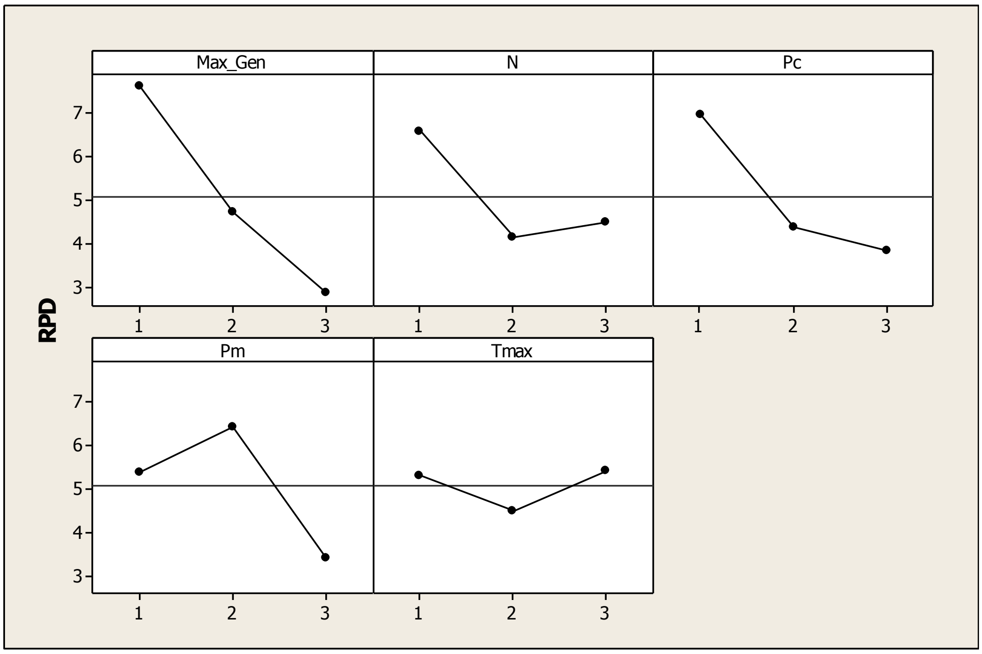


Fig. 8. The main effect of RPD

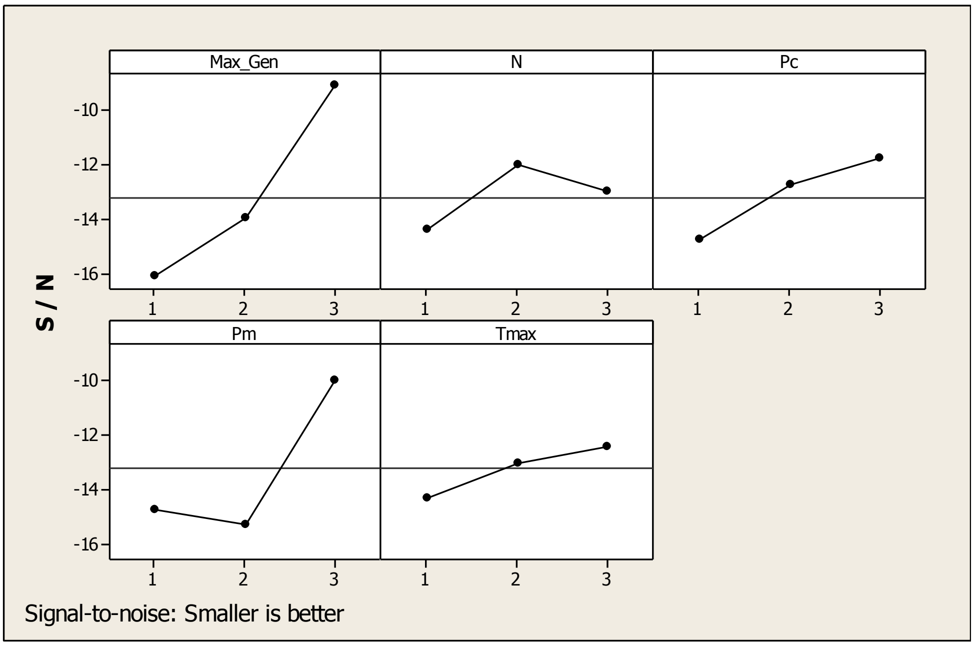


Fig. 9. The average of S/N ratio

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

P_c: *0.8*

P_m: *0.4*

Tmax: 1E-07

Besides, these experiments were done for the algorithm NSGA II, and the need parameters were determined as below:

I: 20

N: 40

P_c: *0.95*

P_m: *0.3*

Also, the single point crossover was used as the crossover operator to reproduce offspring. After that, one of the new chromosomes is randomly selected by considering P_m for mutation. Then, the VNS procedure starts by receiving the selected offspring for mutation. Here, after determining the number of ways of generating neighborhoods 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 neighborhood generation methods are applied to them in each repetition. In this paper, three neighborhood structures used in the VNS procedure are k-exchange, swap, and move. Parameter values of the hybrid algorithm are tuned after running different experiments.

IV.COMPUTATIONAL EXPERIMENTS AND RESULTS

A.Design of the test problems

Some test problems have been applied in various conditions to evaluate the proposed model and evaluate its problem-solving performance. The test problems have been obtained based on data in CSP Lib. considering different disturbance conditions. For this purpose, two factors have been treated that affect on the problem size. These factors are:

- Number of car models that should be sequenced;
- The total number of the car that should be assembled.

Based on the combination of the two mentioned factors, three categories of problems are arranged as a small, medium, and large-sized. The specifications of these problems are shown in Table IV.

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

Table IV.Test problem specifications

Problem size	*Problem name*	*Number of cars*	*Number of car models*
Small	S-I	10	3
	S-II	10	4
	S-III	10	5
	S-IV	15	3
	S-V	15	4
	S-VI	15	5
Medium	M-I	25	4
	M-II	25	5
	M-III	25	6
	M-IV	40	4
	M-V	40	5
	M-VI	40	6
Large	L-I	50	5
	L-II	50	6
	L-III	50	7
	L-IV	100	5
	L-V	100	6
	L-VI	100	7

B.Comparision of results

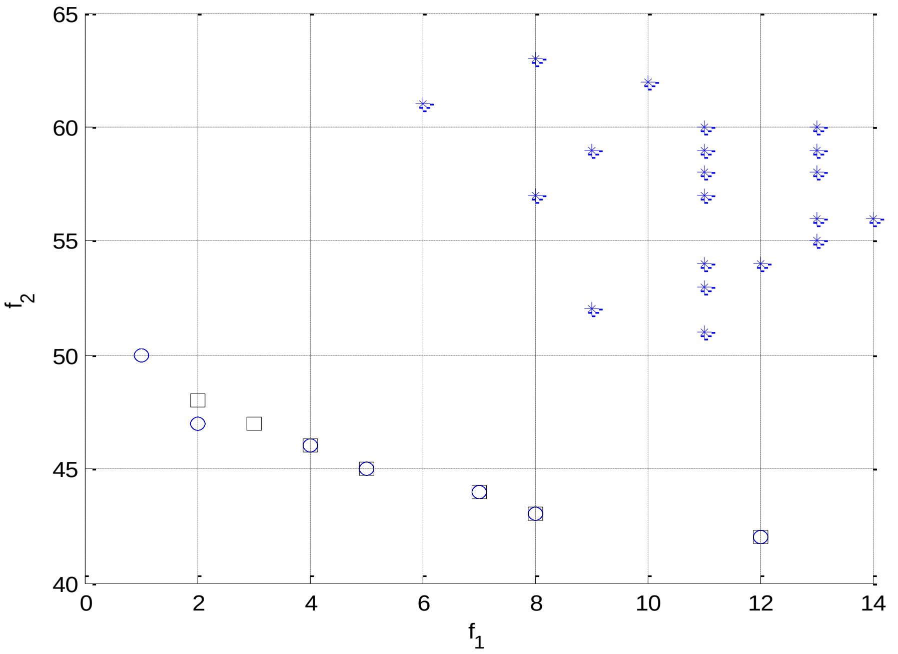
This section presents the results of solving test problems using a mathematical model and proposed hybrid algorithm. The mathematical model was run in GAMS, and the proposed algorithm was coded in MATLAB 7/10/0/499 (R2010a). The experiments are executed on a Pc with a 2.0GHz Intel Core 2 Duo processor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

The test problems were categorized into three classes contain small, medium, and large-sized problems. In 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.

The detailed characteristics of test problems and result analysis are described in the following.

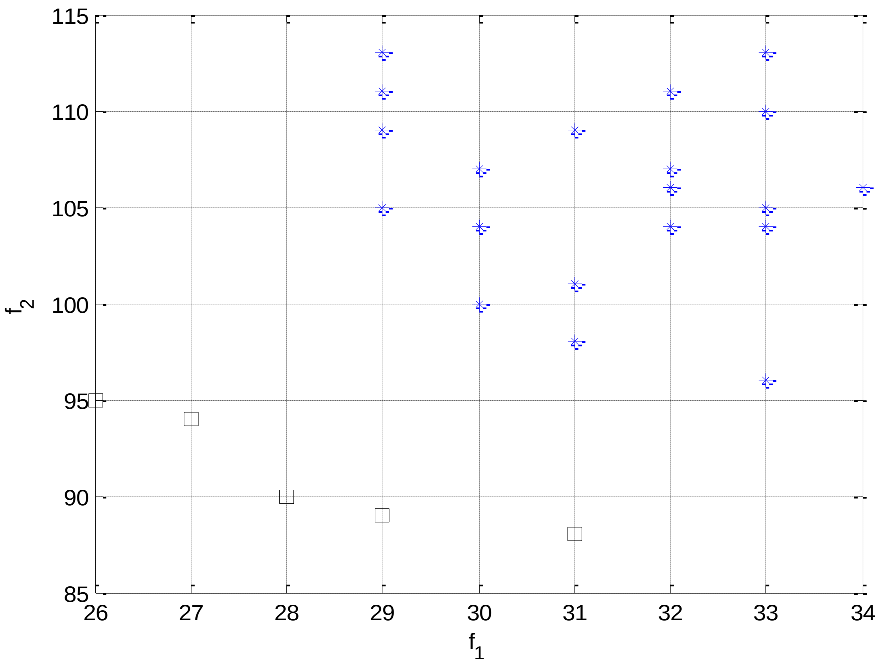
C. Assess the effectiveness of the proposed model totally

Three tests were done for three scales of test problems to assure that the new proposed model has a good effect on objective functions than do not resequence. Figure 10 shows the results of solving three sample problems using the proposed model for resequencing compared to do no resequencing. Figure (10-a) shows these results for a small-sized problem. For this problem, the result of the mathematical model is also presented. As this figure shows, the proposed model could improve the solution for both objective functions near the mathematical model. Figures (10-b) and (10-c) show this comparison for a sample of medium and large-sized problems, respectively. These results successfully show the new proposed model in improving objective functions in three levels of problems.



* Solutions without resequencing
□ Hybrid proposed solutions for resequencing
o Epsilon constraint solution for resequencing

Fig. 10-a. improving the objective function in small-sized problem



* Solutions without resequencing
□ Hybrid proposed solutions for resequencing

Fig. 10-b. improving the objective function in medium-sized problem

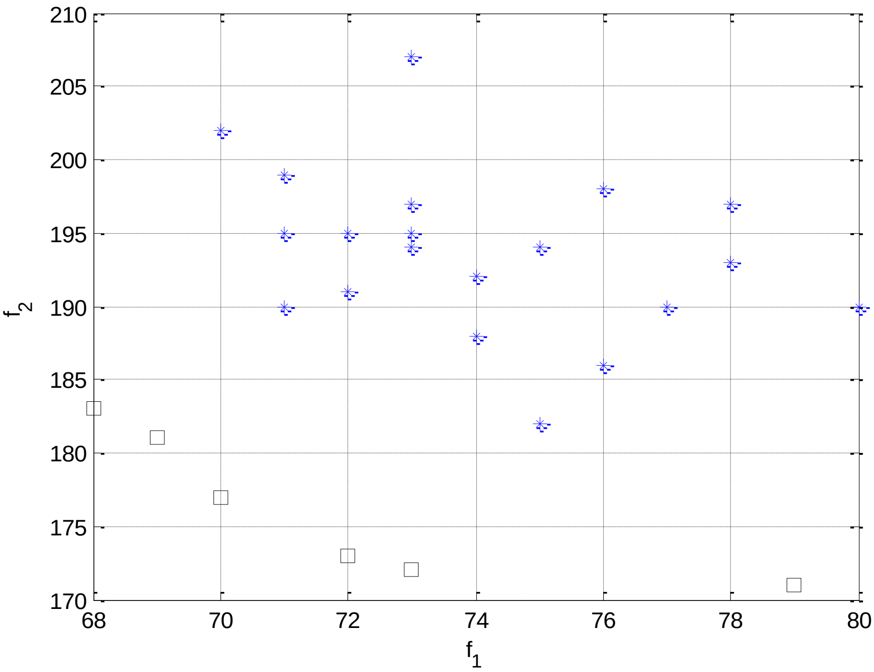


Fig. 10-c. improving the objective function in large-sized problem

D. Small-Sized Problems

We first carried out the problem in small-sized scales using both the mathematical and proposed solutions. Therefore, the Pareto-optimal solutions were provided using the MIP model, and then, the efficiency of the proposed method was evaluated using the optimality indices. Many several indices such as Pareto-optimal solutions, Error Ratio (*ER*), and the generational distance (*GD*) can be used as the performance measure indicators when the Pareto-optimal solutions are known (Coello et al. 2007; Fattahi et al., 2014). These comparison indicators that we implemented in this section are explained below.

E. The Number of Pareto Solutions

This indicator demonstrates the number of Pareto-optimal vectors found by the algorithms. The amount of this metric is usually compared with the total Pareto-optimal vectors provided by a mathematical model.

F. Error Ratio (ER)

At the end of solving process, the number of solutions on the final Pareto-front (PF_{known}) is marked as $|\boldsymbol{PF_{known}}|$and the number of solutions on the optimum Pareto-front (PFtrue) is marked as $|\boldsymbol{PF_{true}}|$. The Error Ratio (*ER*) indicates the number of solutions on the final Pareto-front that are not optimum Pareto-front members. This indicator is calculated as (18).

$$\boldsymbol{ER} = \frac{\sum_{i=1}^{|PF_{known}|} \boldsymbol{e_i}}{|\boldsymbol{PF_{known}}|} \tag{18}$$

Where $\boldsymbol{e_i}$ is one if the $\boldsymbol{i^{th}}$ vector of PFknown is not an element of PF_{true}, otherwise $\boldsymbol{e_i}$ will be zero. When ER=1, this shows that none of the points in PF_{known} are in PF_{true}, which means that no solutions obtained from the proposed algorithm are positioned on the optimum Pareto-front. The optimum Pareto-front (PF_{true}) for the small problems has been determined from the proposed mathematical model.

G. Generational distance (GD)

The Generational Distance (*GD*) reports how far, on average, $\boldsymbol{PF_{known}}$ is from $\boldsymbol{PF_{true}}$. This indicator is mathematically defined as equation (19).

$$\boldsymbol{GD = \frac{\sqrt{\sum_{i=1}^{n} d_i^2}}{|PF_{known}|}} \tag{19}$$

Where d_i^2 is the Euclidean distance between the ith member on the Pareto-front obtained by an approximate algorithm and its nearest member on the true Pareto-front.

The result of solving the small-sized problems have been presented in Tables V and VI. These problems were solved by mathematical models and also two proposed algorithms ten times. The average values of the number of Pareto solutions indicators have been shown in tables (5) based on average solutions of ten runs. 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. This result shows that the hybrid NSGA-II+VNS algorithm has more exploration power than NSGA-II and so could present more solution points on the Pareto-front.

Table V. Comparison in finding Pareto-optimal solutions

Problem	*Number of Pareto solutions*	*Algorithm*	
		NSGA-II	*NSGA-II+VNS*
S-I	8	3.2	6.8
S-II	10	6.2	8.2
S-III	4	1.6	3.1
S-IV	7	4.1	5.2
S-V	6	3.2	5
S-VI	7	4.4	5.8
Average	7	3.8	5.7

Table VI. Comparison result based on two indices *ER* and *GD*

Problem	*ER*		*GD*	
	NSGA-II	*NSGA-II+VNS*	*NSGA-II*	*NSGA-II+VNS*
S-I	0	0	0	0
S-II	0	0	0	0
S-III	0	0	0	0
S-IV	0	0	0	0
S-V	0.75	0	0.4	0
S-VI	0.6	0	0.3	0

Furthermore, two metrics *ER* and *GD* of the best solution of ten-time runs, are presented in tables (6). It is found from the table that the proposed algorithm also has a good performance based on these two indices. Although both of two proposed model are successful based on these indices, it emphasizes the superiority of the hybrid NSGA again.

H. Medium and Large-Sized problems

Due to the time complexity of medium and large-sized problems using mathematical models, the comparison indicators used in these problems must be restricted to indicators that do not need Pareto-optimal solutions. Therefore, in this section, three indicators, Overall Non-dominated Vector Generation (*ONVG*), Spacing (*S*), and Diversification (*D*), are used to evaluate the performance of the proposed algorithm in solving these problems.

I. Overall Non-Dominated Vector Generation (ONVG)

The total number of non-dominated solutions found on the final Pareto-front is denoted as *ONVG*. This indicator is calculated as equation (20).

$$\mathrm{ONVG} = |\mathrm{PF}_{known}| \tag{20}$$

J. Spacing (S)

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

$$S = \sqrt{\frac{1}{|\mathrm{PF}_{known}| - 1} \times \sum_{i=1}^{|\mathrm{PF}_{known}|} (d_i - \bar{d})^2} \tag{21}$$

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

K. Diversification indicator

Generally, multi-objective optimization problems differ based on their fitness assignment procedure and elitism or diversification approaches. The algorithm's diversification mechanism is based on niching that results in widespread solutions in the parametric space. It is defined as (22).

$$D = \sqrt{\sum_{i=1}^{n} \max(\parallel X_i - X_i \parallel)} \tag{22}$$

Where $n = |\mathrm{PF}_{known}|$ and $\parallel X_i - X_j \parallel$ calculates the distance between the two non-dominated solutions.

Table VII 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 the proposed hybrid NSGA-II+VNS algorithm has better performance than NSGA-II in all sized problems.

Table (8) also represents the best values of two indicators *S* and *D*, during ten algorithms' running. These tables show better performance of the proposed hybrid NSGA-II+VNS algorithm than the NSGA-II in all sizes of problems.

Table VII. Comparison result based on *ONVG*

Problem	*Algorithm*	
	NSGA-II	*NSGA-II+VNS*
M-I	6	6
M-II	5	5
M-III	9	13
M-IV	7	10
M-V	6	6
M-VI	4	7
L-I	9	10
L-II	8	8
L-III	7	9
L-IV	8	12
L-V	10	11
L-VI	12	14

Table VIII. Comparison between algorithms concerning Spacing and Diversity

Problem	*Spacing*		*Diversity*	
	NSGA-II	*NSGA-II+VNS*	*NSGA-II*	*NSGA-II+VNS*
M-I	1.6	1.2	4.6	5
M-II	1.3	1.3	3.2	5.1
M-III	2.4	1.8	4.6	8.7
M-IV	1.54	1.4	6.1	9.1
M-V	1.2	1.2	5.5	6.1
M-VI	12.7	11.3	6.1	11.3
L-I	1.98	1	6.7	8.3
L-II	1.2	0.4	4.1	4.7
L-III	13.4	12.7	5.9	10.2
L-IV	17.7	11.7	12.9	17.5
L-V	38.26	21.4	15	27.6
L-VI	35.5	22.3	22.2	29.1

Table IX presents a comparison between 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. The 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 represent a preference for the hybrid proposed algorithm again.

Table IX. The performance of two algorithms under different conditions of disturbances factors

Blocking rate	*Unblocking interval*	*The policy of holding WIP in PBS buffer*	*NSGAII*			*NSGAII+VNS*		
			ONVG	*Spacing*	*Diversity*	*ONVG*	*Spacing*	*Diversity*
0.05	3-5	3	3	0.8	2.5	3	0.3	1.9
		5	4	0.3	2.9	4	0.2	2.5
	6-10	3	4	1.1	4.4	4	0.4	2.9
		5	7.6	1.8	7.4	7.8	1.7	7.5
0.1	3-5	3	8	2.5	8.1	8	1.9	8.2
		5	6	2.6	7	6	1.3	8.2
	6-10	3	4	1	2.7	4	0.9	4.2
		5	5	1.2	4.6	6	1	5.3
0.2	3-5	3	6	3.9	7.3	6	2.3	6.4
		5	9	4.3	11.6	9	3.6	8.1
	6-10	3	6	2.1	4.7	5	1.5	4.1
		5	7	3.5	9.8	8	3.7	6.2

The Relative Deviation Index (*RDI*) is also used for statistical comparison to complete the proposed algorithm's performance evaluation. This indicator calculates the deviation of the proposed algorithm's solution from the best solution through relation (23).

$$RDI = \frac{|the\ proposed\ algorithm\ solution - the\ best\ solution|}{(maximum\ solution - minimum\ solution)} \tag{23}$$

This index was evaluated and is presented in figure (11), (12), and (13) for values of *Diversity*, *ONVG*, and *Spacing*, respectively. These results show the superiority of the hybrid proposed algorithm based on all three metrics.

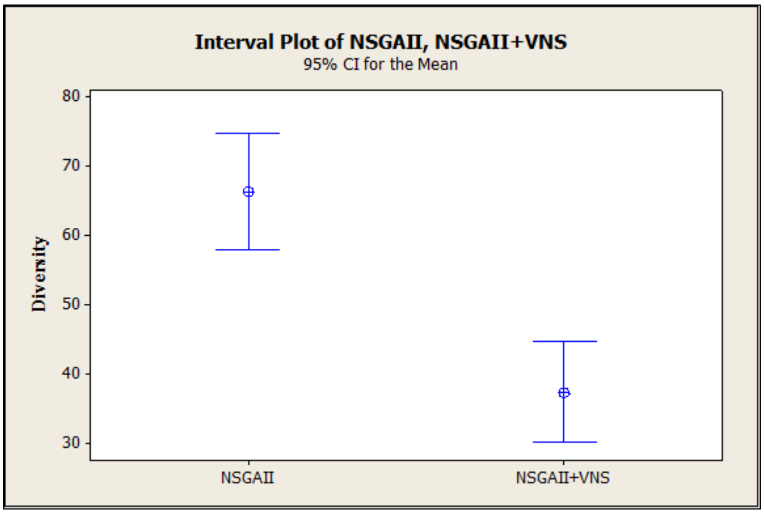


Fig. 11. The interval plot of distances for RDI values for diversity.

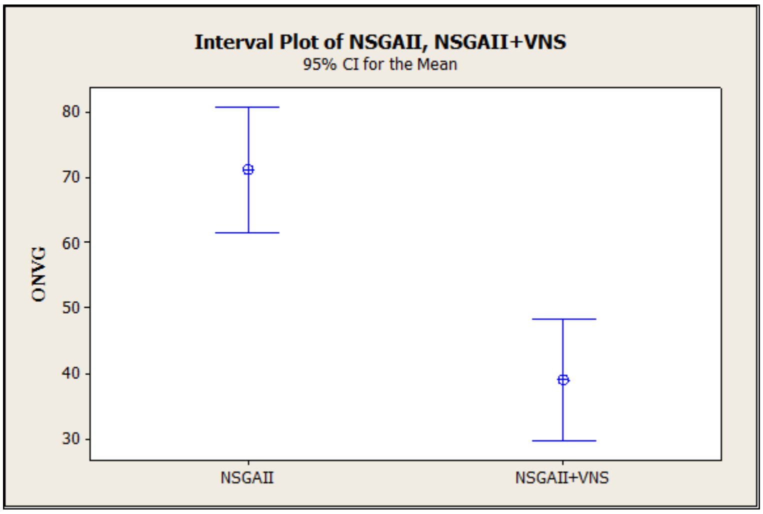


Fig. 12. Interval plot of distances for RDI values for ONVG

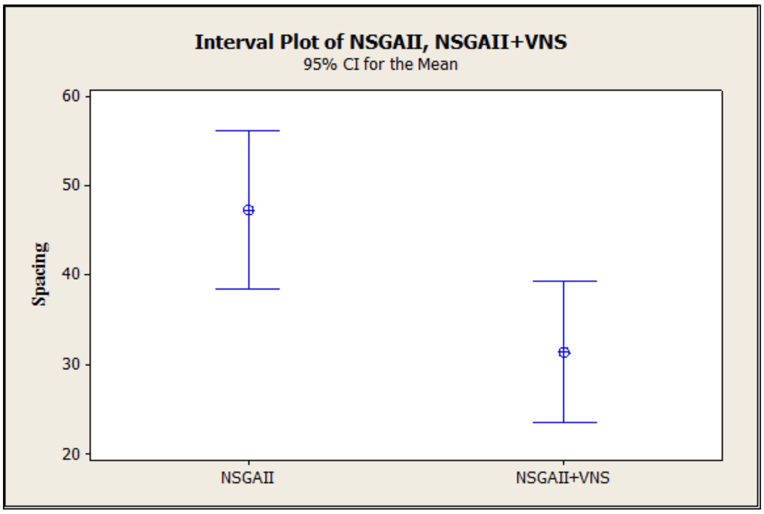


Fig. 13. Interval plot of distances for RDI values for Spacing

V. CONCLUSION

In this paper, the car resequencing problem considering unexpected supply disturbances was studied. For the considered problem, in addition to the classic objective function of the car sequencing problem, another new objective function was considered for this problem as minimizing work in process (cars that remain in intermediate painted body storage (PBS)). Therefore, the notation and mathematical model for the problem was introduced by defining problem parameters and decision variables. Due to the time-consuming of exact solution methods in solving real case instances, a hybrid metaheuristic based on VNS and NSGAII algorithms was also proposed. For evaluating the proposed algorithm, data of the sample problems in CSP Lib. were used. Result analysis was done in three sizes of the problem. These results indicated the superiority of the hybrid proposed algorithm in all three types of the problem via multi-objective evaluation indicators. In small-size problems that the Pareto-optimal is known from the exact solution via running a mathematical model in GAMS software, the proposed hybrid algorithm could find more than 81% of Pareto-optimal solutions NSGAII algorithm present only 54% of them. Two other optimal indicators consist of error ratio (*ER*), and generational distance (*GD*) show the proposed algorithm's superiority again. These two factors were zero for solutions presented by the hybrid NSGAII+VNS algorithm in all small size problems. These factors' value was more than zero for solution two of six test problems obtained by NSGAII. Three other indicators did the evaluation of the performance of the new proposed algorithm in solving medium and large size problems that there was no Pareto-optimal solutions consist of Overall Non-Dominated Vector Generation (*ONVG*), Spacing (*S*), and Diversity (*D*). These factors also validate the superiority of the proposed algorithm in solving all medium and large size problems. This study results can be useful for managers and experts of production planning departments in car manufacturing companies. Car Sequencing Problem (CSP) is one of the most critical phases in decision-making for each car manufacturing factories' final assembly line. The optimal permutation of car models launched down in a mixed-model assembly line is determined by solving this problem. When we face disturbances like shortage or delay in feeding vital parts to the assembly line, we have to stir up an initially planned sequence. The new proposed model in this study can be applied to do car resequencing to reduce car remaining in painted body storage (PBS). The new hybrid proposed model presents the Pareto solution with different values of two important objectives: the ratio constraint violations and car remaining in PBS, and so related managers can choose their right solution based on different conditions. To continue this issue as future works, we recommend investigating this problem considering the internal structure of painted body storage. Also, investigating the car sequencing and maintenance operation as an integrated problem may be another interesting subject to study.

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