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An Efficient Approach for Bottleneck Resource(s) Detection Problem in the Multi-objective Dynamic Job Shop Environments

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ABSTRACT

Nowadays energy saving is one of the crucial aspects in decisions. One of the approaches in this case is efficient use of resources in the industrial systems. Studies in real manufacturing systems indicating that one or more machines may also act as the Bottleneck Resource/ Resources (BR). On the other hand, according to the Theory of Constraints (TOC), the efficient use of resources in manufacturing systems is limited by the capacity of the BR(s). Hence, in order to improve the performance of such systems, the BR(s) should be identified and assessed and improved using capacity of such resources to the greatest extent possible. Studies indicating that Bottleneck Resource Detection (BRD) problem in the "Multi-Objective and the Dynamic conditions" of job-shop is an important issue which has not been studied so far due to its computational complexity. Hence, the development of an efficient approach to identify and assess BRs in Multi-objective Dynamic Job Shop (MODJS) has been considered as the subject of this paper. In this article, a BRD method based on the Taguchi method for MODJS (TM-MODJS) has been developed. This method takes the objectives of the MODJS as estimated indices and carries out typical and finite number of experiments by combining different suitable dispatching rules to detect BR(s) which have the greatest effect on the estimated index. Comparing the results indicates effectiveness of the developed method especially in scheduling which results in a reasonable time.

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NOMENCLATURE

Index		O_i	Operation, $i = \{1, 2, \dots, m\}$
		r_i	Each job (e.g. the job i) enters the shop for process a nonzero r_i time.
i	Job	y_{ipk}	If the job i is performed on the machine k prior to the job p, $y_{ipk} = 1$; otherwise, = 0.
j	Operation		
k	machine	**Variables**	
Parameters		x_{ik}	the job's completion time i on the machine k
h	great and positive number	t_{ijk}	the operation process time j from the job i is on the machine k
n	Number of jobs, $J = \{1, 2, \dots, n\}$	s_k	the scheduling scheme for machine k
m	Number of machines, $M = \{1, 2, \dots, m\}$	f_k	objective value

1. INTRODUCTION

Real manufacturing systems generally have Bottleneck Resource (BR) [1]. According to concepts of TOC, the throughput of the manufacturing systems is limited by the capacity of the BR(s) [2]. In a Multi-Objective Dynamic Job Shop (MODJS) environment ($J_m|r_i|\sum(W_1 \times C_{max} + W_2 \times \bar{F} + W_3 \times \bar{T})$), one or a combination of machines may act as the BR(s). Bottleneck Resources Detection (BRD) problem in the "Multi-Objective and the Dynamic" conditions of job shop (JS) is an important issue in real manufacturing systems. In the following, after definition and classification of BR(s), literature related to BRD methods in JS is reviewed.

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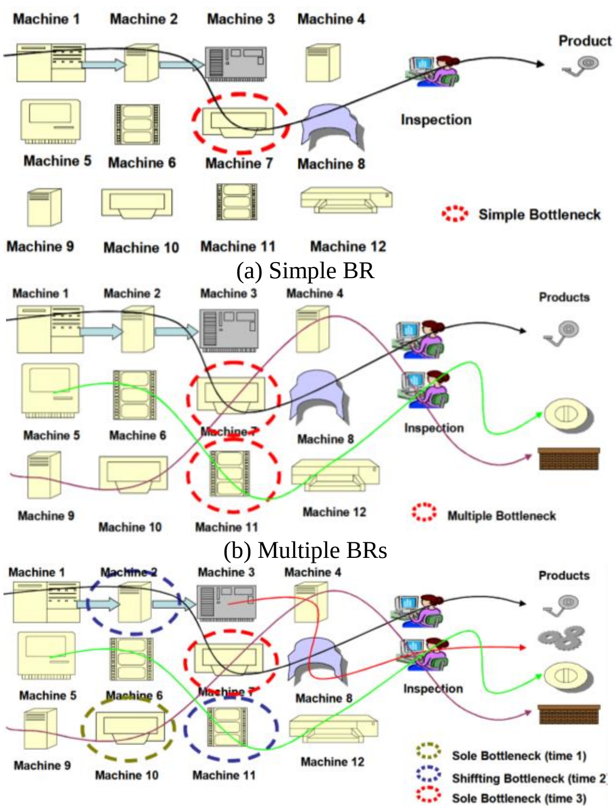
2. LITERATURE REVIEW

2. 1. Definition and Types of BR(S) BR(s) is machine(s) which prevent better function of the system. In a classification by Hinckeldeyn et al. [3], different types of BR(s) are: capacity, parts, flexibility, layout, budget, information, and know-how. On the other view, BR(s) is classified in three categories (Figure 1). In **Simple BR** only one of the machines acts as a bottleneck. In **Multiple BRs**, more than one machine acts as a bottleneck. But these bottlenecks are fixed throughout the considered period of time. In the **Shifting BR**, there is not just one bottleneck for the entire period, but during the period the bottleneck shifts from one machine to another [4].

2. 2. Literature Review BRD Methods Roser et al. [5] have identified and classified all the BRD methods up to 2002, in the following methods:

- UF (Utilization Factor),
- QSFM (Queue Size in Front of Machine),
- WTFM (Waiting Time in Front of Machine) and
- AP (Active Period).

In another research, Roser et al. [5] have detected BR by calculating active periods of machines and called it Shifting Bottleneck Detection (SBD).



(a) Simple BR
(b) Multiple BRs
(c) Shifting BRs

Figure 1. Simple, Multiple and Shifting BRs [4]

Yet, in another research, Roser et al. [6] have categorized BR in two types of "shifting BR" and "sole BR" and introduced the machine with the largest percentage of shifting and sole BR as the original BR of the system. Wang et al. [7] used disjunctive graphs to detect the BR in the SBD procedure for Classic Job Shop (CJS). Yan et al. [8] after developing a new definition of BR, proposed a BR-oriented heuristic algorithm for a large scale CJS. Tay and Ho [9] developed a method based on combining dispatching rules and genetic programming for solving Flexible Job Shop (FJS). Sengupta et al. [10] proposed a new methodology for BRD. Lima et al. [4] proposed a simulation-based method for BRD and successfully used it in the real manufacturing system. Zhang and Wu [11] studied BRD approaches for CJS using Genetic Algorithm (GA). Lin et al. [12] studied data-based detection process of BR(s) for serial manufacturing systems. Kasemset and Kachitvichyanukul [13] studied the decisions made in implementing TOC in a CJS by using a two level multi-objective mathematical model. Zhai et al. [14] proposed a new heuristic algorithm for large scale CJS. BR(s) in this algorithm are detected using orthogonal method. In order to reduce its complexity, based on the operations which must be processed on BR, large scale CJS is divided into three sub-problems: BN-OS, PBN-OS and FBN-OS. Zahi et al. [7, 15] proposed a prior-to-run method for BRD based on orthogonal experiences (BD-OE) in static JS. The above-mentioned method is developed based on a new definition of BR which is according to a principle in TOC stating "manufacturing systems function is determined by BR". This method take scheduling objectives as estimated index and constructs orthogonal trials by orthogonal arrays and dispatching rules to detect the BR which have the greatest effect on the estimated index. Abbasian and Nahavandi [16, 17] considered operation flexibility and parallel machines flexibility in FJS. They used these abilities to take an effective method against BR(s) problem. Zhang and Wu [1] developed a BRD method based on transferring the constraints by using GA for CJS. Zhenqiang et al. [16] studied manufacturing's BR based on a multi-factor study. Scholz-Reiter et al. [18] claimed that SBD method was a very efficient approach for BRD problems, especially for DJS in small and rather medium scales. The weaknesses of this method are time-consuming and reduction in its efficiency by increasing the scale of problem, especially in real industrial environments. Therefore, by combining SBD method and VNS algorithm, they proposed a new approach for DJS. They compared the results with SBD method proposed by Pinedo and Singer [19] for static JS and then showed the efficient of their proposed method, especially considering run times. Georgiadis and Politou [20] studied dynamic Drum-Buffer-Rope (DBR) approach for scheduling and production control in flow shop manufacturing systems which have capacity. Their dynamic conception includes demand changes and estimated production times. Glock and Jaber [21] studied the effects of learning and forgetting graphs parameters in a two-level serial manufacturing systems. They also investigated the phenomenon of shifting BR(s). They showed taking advantage of learning may lead to BR(s). By predicting the position of system's potential BR, this enables the system to take flexible reaction in shifting BR(s).

Hinckeldeyn et al. [3] strived to develop BR management from manufacturing discussions to engineering process and product design discussions by presenting a new conception of BR management. They presented this new conception using system theory simulation approach. Abbasian et al. [22] investigated FJS considering resource availability constraints. They presented an intelligent GA to solve it. In order to limit BR(s), they used parallel machine implementation approach, but they did not propose a method for BRD problem and postponed it to their future studies. Literature review indicates that BRD problem even in CJS is still in the center of attention for researchers as one of the recurrent research areas [3, 11]. Also, the BRD problem in the "Multi-Objective and the Dynamic" conditions of job-shop is an important issue which has not been studied in the previous literature due to its computational complexity.

2. 3. BRD Methods Classifications In order to rigorous comparisons among the different approaches reported in the literature, typical BRD methods available in the literature for CJS problem are classified and analyzed in Table 1. In general, regarding Table 1, it can be deduced that there are three common approaches for BRD in CJS, as follows:

- First group of BRD approaches (like MWL and UF) detect BR by measuring efficiency or workload. A machine with the greatest efficiency or workload is introduced as the BR. These approaches are very simple and easily implemented. However, they cannot detect the BR with confidence if more than one machine has the same workload.

TABLE 1. Comparison of typical BRD approaches available in the CJS' problem literature

R	Approach	Features	Criteria	Deficiencies
1	Maximum Workload (MWL)	The amount of time needed for process of jobs in production station is measured and the machine with the maximum workload is considered BR.	Time	• More than one resource may have MWL. • Considering only system resources and neglecting the role of systems' objective functions.
2	Utilization Factor (UF)	The time percentage of production station running over the whole system time is measured and the machine with maximum run time is considered BR.	Percentage	• More than one resource may have maximum UF. • Considering only system resources and neglecting the role of systems' objective functions.
3	Queue Size in Front of Machine Detection (QSFM)	The numbers of half manufactured products existing in waiting queue before machine (waiting for process) are counted. The machine with the longest queue is considered BR.	Amount of Product	• Queue size may be larger than the size of resource buffer. • Considering only system resources and neglecting the role of systems' objective functions.
4	Waiting Time in Front of Machine (WTFM)	This method is the same as QSFM. The only difference is that in this method the waiting time of product in queue for processing is taken into accounts.	Time	• Queue size may be larger than the size of resource buffer. • Considering only system resources and neglecting the role of systems' objective functions.
5	Active Period (AP)	For all types of machinery, two states of active and non-active is considered. The sum of entire periods in which the machine is active is measured. The machine with the greatest active period is considered BR.	Time Unit or Time Percentage	• Considering only system resources and neglecting the role of systems' objective functions.
6	Shifting Bottleneck Detection (SBD)	This method is among the group of backtracking methods in which periods or percentages of an active non-stop production station is calculated. The periods in which production station is a sole bottleneck along with the periods in which production station is shifting bottleneck are computed and summed up to gain total time. Since some machines can be bottleneck in each time, the machine with maximum time is considered the original BR.	Time Unit or Time Percentage	• Considering only system resources and neglecting the role of systems' objective functions. • Required long computational time. • Low efficiency in large scale of problems especially in BRD in real industrial environment.
7	Orthogonality Experiments (BD-OE)	Using experiment design method, in addition to considering the role of processor machines, the role of problems objective function is also considered in BRD.	Maximum Variance	• Lack of an appropriate approach for considering the rule of system's objective functions.

- Second group of BRD approaches (like QSFM and WTFM) detect BR by measuring queue length or waiting time for non-processed jobs in front of each machine. In such approaches, the machine with the greatest waiting time or queue length is detected as the JS's BR. However, this approach validation is in doubt if the number of non-processed jobs be greater than maximum size of machines' buffer.
- Common deficiency of both mentioned categories is the fact that these approaches only consider processor machines' role in solving BRD problem and neglect the rule of system's objective(s) as the most important criteria which decision makers attempts to improve it, and perhaps in some cases of BRD, this causes these approaches not to lead to the same results. Although the third group of BRD approaches attempted to omit this deficiency, but they could not create a suitable method for this reason. Accordingly, Zhang and Wu [1] reported in their researches that BR(s) change if scheduling objective(s) change.

From another point of view, BRD approaches divide into two general categories considering run times, as follows:

- **Prior-to-run BRD approaches:** these approaches are able to detect BR(s) before manufacturing system's run and then guide the production process to improve manufacturing system's function. These approaches, generally, perform BRD using data acquisition technique, simulation, and analysis after a long term period of production system run.
- **Posterior-to-run BRD approaches:** In these approaches BR(s) are detected after manufacturing system run.

Obviously, if we can detect BR(s) before setting up the system, it will be more valuable because detected BR(s) can, as an advantage, guide the management of operation and resources [7, 15].

3. PROBLEM MATHEMATIC MODEL

3. 1. Research Problem Definition BR(s) is a machine(s) which prevents better effective of the system. Immediate and exact detection of the location(s) of BR(s) can lead to important in operation management. In a MODJS manufacturing systems $(J_m|r_i|\sum(W_1 \times C_{max} + W_2 \times \bar{F} + W_3 \times \bar{T}))$, one (or more) machine may act as the BR(s). BRD problem in a MODJS is an important issue which is not investigated in the literature due to computational complexities. The MODJS is defined as follows:

There are n jobs, $J = \{1, 2, \dots, n\}$, and m machines, $M = \{1, 2, \dots, m\}$. Each job (e.g. the job i) enters the shop for process in a nonzero r_i time. The J_i includes a chain of operations $O = \{o_{j1}, o_{j2}, \dots, o_{jm}\}$.

3. 2. Bottleneck Definition In a MODJS, scheduling scheme is one of the most crucial factors which affect the performance of the system. From the perspective of the manufacturing system's objectives, different scheduling scheme for one machine may give rise to different objective value. According to TOC, BR(s) constraints the throughput of the manufacturing systems, so the alteration of scheduling schemes on the BR(s) will bring about the maximum change of the system's objective value [7].

Definition 1: Let m be the number of the machines and k be the index of the machine. Let s_k $(k = 1,2, \dots, m)$, denote the scheduling scheme for machine k, and f_k $(k = 1,2, \dots, m)$, denote the objective value. Then the sensitivity of the objective value to the scheduling scheme alteration of machine k is "alternations of the objective value" over "alternations of scheduling scheme" for the machine k, that is [7]:

$$e_k = \frac{\Delta f_k}{\Delta s_k}, \ k = 1, 2, \dots, m \tag{1}$$

Definition 2: The machine with the largest e_k is the corresponding BR(s). Namely,

$$BR(s) = \arg(\max_{k=1,2,\dots,m} e_k) \tag{2}$$

Therefore "The BR is a machine whose scheduling variation has the greatest effect (or variations) on the manufacturing system's objectives." [7].

3. 3. Definition of Decision's Parameters and Variable The MODJS problem can be formulated as a zero-one integer programming [16, 17]. In this model, each operation is shown with three indexes (i, j, k) which indicate operation j from job i be processed on machine k.

3. 4. The Problem's Mathematical Model Now supposing that k_i represent the machine by which the last operation of job i is processed, the MODJS problem is formulate as follows [16, 17]:

$$\text{Min } F = \propto_1 F_1 + \propto_2 F_2 + \propto_3 F_3 \tag{3}$$

$$F_1 = C_{max} = \text{Max}\{x_{ik_i} | i = 1, \dots, n\} \tag{4}$$

$$F_2 = \bar{F} = \frac{1}{n}\sum_{i=1}^{n}(x_{ik_i} - r_i) \tag{5}$$

$$F_3 = \bar{T} = \frac{1}{n}\sum_{i=1}^{n}\{\beta_i(x_{ik_i} - d_i), 0\} \tag{6}$$

$$x_{ik} - t_{ijk} \geq x_{ih} \quad 1 \leq i \leq n,\ 1 \leq j,k,h \leq m,\ (i, j-1, h) \ll (i, j-1, h), \tag{7}$$

$$x_{pk} - x_{ik} + H(1 - y_{ipk}) \geq t_{pqk} \quad 1 \leq i,p \leq n,\ 1 \leq k,q \leq m, \tag{8}$$

$$x_{ik} - x_{pk} + Hy_{ipk} \geq t_{ijk} \quad 1 \leq i,p \leq n,\ 1 \leq k,q \leq m, \tag{9}$$

$$x_{ik} \geq t_{i1k} + r_i \qquad 1 \leq i \leq n, \quad 1 \leq k \leq m, \tag{10}$$

$$r_i = U[0,20] \quad n < 30, \quad r_i = U[0,40] \quad n \geq 30 \tag{11}$$

$$x_{ik} \geq 0, \qquad y_{ipk} \in \{0,1\} \tag{12}$$

The three objectives in the definition are the typical objectives in production scheduling that frequently trade-off against each other [12]. In this study, all the objectives have the same priority ($\propto_1$,$\propto_2$ and $\propto_3$=$\frac{1}{3}$). Equations (3, 4, 5, and 6) represent these relations. Also, the penalty of tardiness is one ($\beta_i = 1$). The inequality (7) represents priority constraints between different operations of one job on the machines. The inequalities (8) and (9) represent the constraint of performing different jobs operations on one machine at unequal times. The inequality (10) is mentioned so that the completion time of the first jobs operations be equal or greater than the process time of that operation, in addition to the waiting time of the mentioned job in the shop. The job's entrance times to the shop adapted with sizes of test-problems and depend on the number of jobs at shop in a way that for the jobs less than 30, the $U[0,20]$ uniform distribution are used and for the jobs equal or greater than 30, the $U[0,40]$ uniform distribution are used [9].

Baker (1984) proposed a formula to estimate the due date of a job using the TWK-method [9]:

$$d_i = r_i + c \times \sum p_{ij} \quad , \qquad j = 1, \dots, n_i \tag{13}$$

where c denotes the tightness factor of the due date. In this paper, value of c is 1.6 which is mean tight, moderate, or loose due date tightness factor corresponding to values of c = 1.2, 1.5, and 2.

In the following, the proposed solution to the problems of BRD problem for MODJS will be presented. This solution is the developed case of Zhai et al. [7] method was proposed for BRD problem for static JS.

4. HURESTIC SOLUTION METHOD FOR BRD SUBPROBLEM IN MODJS (TA-MODJS)

4. 1. TA-MODJS Principles The orthogonal experiments (OE) are an effective method for multi-level factorial experimental design. This method covers infinite experiments by selecting a finite number of typical trials. Moreover, this method offers excellent factorial-fractional design and suitable experiments for investigating the effects of each factor on the estimated index. Literature review indicates that Taguchi Method and Orthogonal Arrays (OA) have been widely used in the Design of Experiments (DOE) [23].

In order to use the definitions (1) and (2) in BRD (section 3. 2), we need schedules at first. These schedules are determined by using suitable dispatching rules. Therefore, if the number of suitable dispatching rules is r, then the number of the combinations of suitable dispatching rules is r^m (m is the number of the machines). If the number of suitable dispatching rules increases, the computational times required for gaining schedules derived from them will greatly increase.

Also, in order to use these definitions, we need to calculate s_k variations in denominator. But s_k is not a quantitative parameter. So, we cannot directly use the relation in definitions (1) and (2) for BRD.

For this reason, in this paper, an indirect method for BRD problem using orthogonally and based on Taguchi Method for multi-criteria environment such as MODJS, (TA-MODJS) has been developed. In this method, there is no need to calculate Δf_k and Δs_k. It treats e_k as a whole, and can obtain e_k of each machine by using OE.

The essentials of Taguchi method based on OE are factors, levels, estimated index, and key factor. The factors are the elements or cause which affect the estimated index; the states that the factors being at are the levels. Because the change of the level of each factor can bring about the change of the estimated index value, the key factor is the factor where level change has the greatest effect on the estimated index. According to Definition (2), BR(s) is the machine(s) whose schedule alteration has the greatest effect on the objectives of the manufacturing system. So, if the objective of the manufacturing system corresponds to the estimated index of an OE, then the BR just corresponds to the key factor of the OE. Accordingly, the machines of the manufacturing system correspond to the factors of the OE, and the suitable dispatching rules for each machine correspond to Taguchi method based on OE. The corresponding relations between the elements of Taguchi method based on OE (TA-MODJS) and the element of BRD in a MODJS environment are shown in Table 2. Therefore, where factors (machines) considered equal to factors affecting estimated indexes (objectives), the states of factors determine levels (suitable dispatching rules).

Variation in each level (suitable dispatching rules) of each factor (machine) can lead to variation in estimated indexes (objectives).

TABLE 2. Corresponding relations TA-MODJS and BRD

Elements of TA-MODJS	Elements of BRD
Factors	Machines of the manufacturing system
Levels	Suitable Dispatching rules for machines
Estimated index	Objective of the manufacturing system
Key factor	BR(s)

As a result, the key factor (MODJS's BR) is a factor (machine) which has the greatest effect on the estimated index (MODJS's objectives).

In general, OEs are designed based on OAs. The form of an OA is $l_{t^u}(t^q)$, that [23]:

- l: the signal of orthogonal design,
- t: the number of levels in the OE,
- u: the integer series $u = 2, 3, \ldots$,
- q: the number of the factors in the OE or the number of column in the OA and:

$$q = (t^u + 1)/(t + 1), \qquad u = 2, 3, \ldots \tag{14}$$

- t^u: the number of orthogonal trials in the OE or the number of rows in the OA.

For example, $L_9(3^4)$, is shown in the Table 3.

According to the OE principles, the variance of each factor (R_k) is computed by:

$$I_{kj} = \sum y_{kj} \quad , \quad j = 1, \ldots, r \tag{15}$$

$$R_k = \frac{\max(I_{kj}) - \min(I_{kj})}{n/r} \quad , \quad k = 1, \ldots, m \tag{16}$$

R_k reflects the effects of different levels of factor k on the estimated index. Also R_k equals e_k in Definition (1). The factor with $\max(e_k)$ is the key factor whose level change has the greatest effect on the estimated index in OE. This phenomenon exactly corresponds to BR whose schedule alteration has the greatest effect on the objectives of the problem. Hence, $\arg(\max(R_k))$ corresponds BR(s) in Definition (2). This method is an extended case of the proposed method (Zhai et al. [14]) which is extended for the studied problem in a dynamic and multi-objectives environment and the results are brought in the following sections.

TABLE 3. The OA of $L_9(3^4)$

Trials	Factors			
	Factor 1	Factor 2	Factor 3	Factor 4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

4. 2. The Procedure of TA-MODJS

4. 2. 1. Selecting Factors, Levels, and Appropriate Oa

We adapted 13 selected suitable dispatching rules (Haupt et al. [24]) which are displayed in Table 4 as the levels for each factor.

The OA can be selected or constructed according to the number of machines and suitable dispatching rules in the specific detection problem.

4. 2. 2. Constructing the Orthogonal Trials in The OA of TA-MODJS

By transforming the digits of the OA into the dispatching rules, the corresponding orthogonal trials can be acquired. For example, a BRD problem with three machines and three dispatching rules corresponds to an OE including three factors and three levels, and the $L_9(3^4)$ OA should be selected. The parameters and the orthogonal trials are shown in Tables 5 and 6.

4. 2. 3. Carrying Out Trials in TA-MODJS

The work of this step is to obtain the estimated index value of each orthogonal trial.

The estimated index value is the scheduling objective value which can be obtained by decoding the combination of dispatching rules. In order to gain the objective value, the suitable dispatching rules of each experiment was decoded to scheduling design. The decoding algorithm is as follows:

Suppose $(r_1, \ldots, r_m)$ represent an orthogonal trial in the OE of TA-MODJS. $r_k (k = 1, \ldots, m)$ is dispatching rule for machine k. Let PS denote set of the operations which are scheduled, and S denote the set of operations to be scheduled currently.

TABLE 4. Selected Suitable Dispatching rule for TA-MODJS

No	Rule	Description Jobs selected which has ...
1	FCFS	Arrived at queue first; (''first come, first serve'')
2	LPT	The longest processing-time
3	LOR	The fewest number of operations remaining
4	MWR	The most work remaining
5	SPT	The shortest processing-time
6	LWR	The least work remaining
7	MOR	The greatest number of operations remaining
8	WINQ	The least total work in the queue of its next operation
9	NINQ	The least number of jobs in queue of its next operation
10	EDD	The earliest due date
11	ODD	The earliest operation due date
12	SL	The smallest slack time
13	OSL	The smallest operation slack time

TABLE 5. The parameters of the TA-MODJS

Levels \ Factors	Machine 1	Machine 2	Machine 3
1	FCFS	FCFS	FCFS
2	LPT	LPT	LPT
3	LOR	LOR	LOR

TABLE 6. The orthogonal trials in the TA-MODJS

Factors / Trials	Machine 1	Machine 2	Machine 3	Index value y_i
1	1(FCFS)	1(FCFS)	1(FCFS)	y1
2	1(FCFS)	2(LPT)	2(LPT)	y2
3	1(FCFS)	3(LOR)	3(LOR)	y3
4	2(LPT)	1(FCFS)	2(LPT)	y4
5	2(LPT)	2(LPT)	3(LOR)	y5
6	2(LPT)	3(LOR)	1(FCFS)	y6
7	3(LOR)	1(FCFS)	3(LOR)	y7
8	3(LOR)	2(LPT)	1(FCFS)	y8
9	3(LOR)	3(LOR)	2(LPT)	y9
I_{k1}	I_{11}	I_{21}	I_{31}	--
I_{k2}	I_{12}	I_{22}	I_{32}	--
I_{k3}	I_{12}	I_{23}	I_{33}	--
R	R_1	R_2	R_3	--

The earliest start time and earliest predicted completion time for operation i in S is σ_i and ϕ_i, respectively. C denotes the set of conflicting operations which satisfy the schedule condition.

- **Step 1:** Let $PS \leftarrow \emptyset$
- **Step 2:** Get $\phi^* = \min_{i \in SI}\{\phi_i\}$, and the corresponding machine m^*. If there is more than one machine, choose one machine randomly.
- **Step 3:** Establish C by the operations which are processed on m^* and satisfy the condition of $\sigma_i < \phi^*(i \in SI)$.
- **Step 4:** Select one operation s from C according to r_m (the dispatching rule form m^*).

If there is more than one operation, choose one operation randomly.

- **Step 5:** $PS \leftarrow PS \cup s$. Update PS.
- **Step 6:** If $SI = \emptyset$, then the algorithm stops and gives the scheduling value. Otherwise go to step 2.

4. 2. 4. Analyzing the Results of The Orthogonal Trials to Detect BR(S) After the estimated index value of each orthogonal trials is obtained, the effect of each machine's schedule alterations on the manufacturing system's objectives can be got by calculating the variance of each factor according to Equation (16).

4. 3. A Complete Analysis of Selection Method of Sample Problems In order to analyze the performance of TA-MODJS and the influence of the objective variation on the bottleneck shifting, we adopt the JS scheduling benchmark instances for simulation, including different scales of operations. The simulation details of each instance are placed in the route[2].

For performance analysis of BRD methods, the SBD method has more reliability than the other the common methods of BRD [4]. Apart from that, this method can present excellence for DJS [16]. Therefore, in this study, we compare the performance of the proposed TA-MODJS method with the performance of MWL, BDOE, and SBD methods in the BRD.

5. DESIGNING AND CARRYING OUT NUMERICAL EXPERIMENTS

5. 1. The TA-MODJS Results In this section, the results from simulation are presented. For this reason, TA-MODJS performance is compared to a prior-to-run BRD (BD-OE) and a posterior-to-run BRD (SBD). The results are shown in Tables 7-9 and Figures 2-5.

TABLE 7. BRD results of Dynamic TA-MODJS, Static TA-MODJS, BD–OE, SBD and MWL for Small scale problems

	Number of Machine	5							
	Number of Jobs	10				15			
	Problem's Number	LA 01	LA 02*	LA 03	LA 04*	LA 06	LA 07	LA 08*	LA 09
BR(s)	Dynamic TA-MODJS for MODJS	5	4	3	5	2	2	1	4
	Dynamic TA-MODJS with $MinC_{max}$	5	5	1	1	1	1	3	2
	Static TA-MODJS with $MinC_{max}$	5	1	2	5	1	1	4	2
	BD-OE	5	1	2	1,3,5	1	1	3	2
	SBD	5	4	2	1,3	1	1	5	2
	MWL	5	4	2	5	1	1	5	2
Computational Time (second)	Dynamic TA-MODJS with $MinC_{max}$	0.3	0.3	0.31	0.3	0.55	0.55	0.55	0.54
	Static TA-MODJS with $MinC_{max}$	1.35	1.37	1.33	1.3	2.42	2.4	2.35	2.38
	SBD	7.5	43.7	47.9	46.6	56.2	55.6	65.3	47.4

Instances with * express that the bottlenecks detected by the three methods are different.

[2] http:// people.brunel.ac.uk/~mastjjb/jeb/orlib/files/jobshop1.txt

TABLE 8. BRD results of Dynamic TA-MODJS, Static TA-MODJS, BD–OE, SBD and MWL for Median scale problems

	Number of Machine	**10**							
	Number of Jobs	**10**				**15**			
	Problem's Number	**LA 16***	**LA 17**	**LA 18**	**LA 19***	**LA 21**	**LA 22**	**LA 23**	**LA 24***
BR(s)	**Dynamic TA-MODJS for MODJS**	8	5	1	2	4	10	8	6
	Dynamic TA-MODJS with MinC$_{max}$	3	4	2	3	10	5	7	10
	Static TA-MODJS with MinC$_{max}$	3	4	1	10	10	5	7	2
	BD-OE	1,3	4	1	2	10	5	7	10
	SBD	1,3	4	1	7	10	5	7	10
	MWL	1	4	1	7	1	8	7	10
Computational Time (second)	**Dynamic TA-MODJS with MinC$_{max}$**	5.62	5.54	5.55	10.14	9.81	9.85	9.86	5.62
	Static TA-MODJS with MinC$_{max}$	2.46	2.45	2.43	2.41	4.38	4.46	4.32	4.31
	SBD	112.6	134.9	171.5	263.6	240.6	208.1	251.6	112.6

Instances with * express that the bottlenecks detected by the three methods are different.

TABLE 9. BRD results of Dynamic TA-MODJS, Static TA-MODJS, BD–OE, SBD and MWL for Large scale problems

	Number of Machine	**10**							
	Number of Jobs	**20**				**30**			
	Problem's Number	**LA 26***	**LA 27**	**LA 28**	**LA 29**	**LA 31**	**LA 32***	**LA 33**	**LA 34***
BR(s)	**Dynamic TA-MODJS for MODJS**	6	6	3	1	6	10	10	10
	Dynamic TA-MODJS with MinC$_{max}$	2	4	2	4	1	9	4	2
	Static TA-MODJS with MinC$_{max}$	2	4	2	4	1	2	4	2
	BD-OE	5	4	2	4	1	9	4	7
	SBD	5	4	2	4	1	7	4	7
	MWL	1	7	2	4	1	7	4	7
Computational Time (second)	**Dynamic TA-MODJS with MinC$_{max}$**	15.49	15.19	15.4	15.37	29.38	29.49	29.87	29.86
	Static TA-MODJS with MinC$_{max}$	7.06	6.92	6.64	6.63	13.32	13.29	12.93	12.6
	SBD	380.3	376.8	356.4	340.8	623.4	585.5	632.2	633.2

Instances with * express that the bottlenecks detected by the three methods are different.

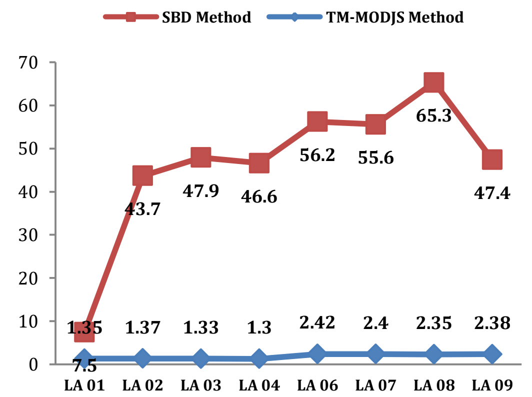


Figure 2. Comparing computational time for three methods in Small scale problems

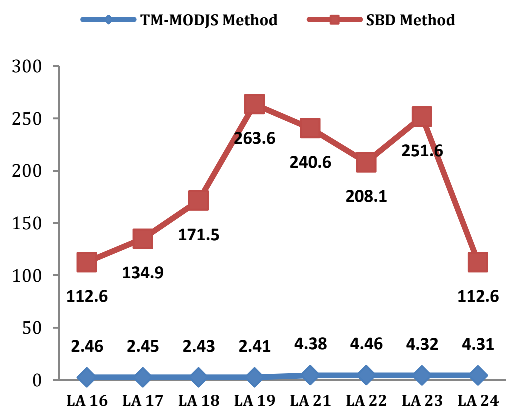


Figure 3. Comparing computational time for three methods in Medium scale problems

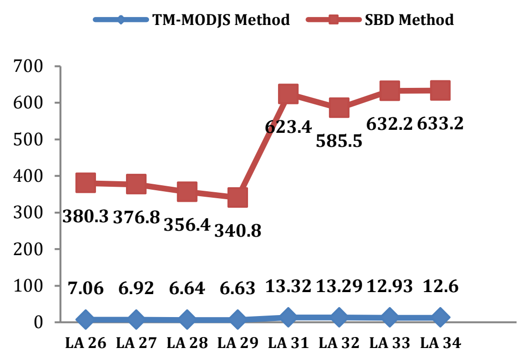


Figure 4. Comparing computational time for three methods in Large scale problems

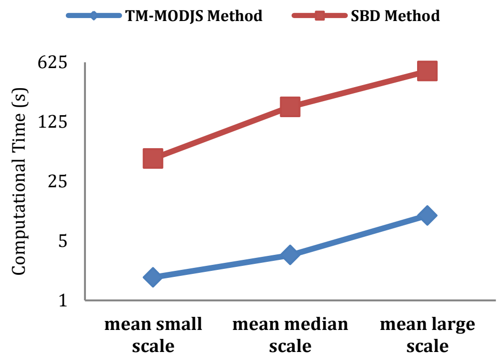


Figure 5. Comparing computational time for three scale

According to Hinckeldeyn et al. [3], there are various BR countermeasures such as scheduling solution, targeted source increase, increase of resource flexibility, process important, reduce workload of BR, and BR oriented counter-pricing. Among these, 75% of the investigated researches by Hinckeldeyn et al. [3] are carried counter out using scheduling solution approach as the BR countermeasures are. Accordingly, in this study, in order to analyze the results of differences for the three mentioned methods, the MODJS with the objective of maximum weighted sum (F) and based on the detected BR, has been solved and the results are presented in Tables 10 and 11 and Figures 6-9.

TABLE 10. The scheduling results using the bottlenecks detected by the three methods

Problem's Number		LA 02	LA 04	LA 08	LA 16	LA 19*	LA 24	LA 26	LA 32
BR(s)	Static TA-MODJS	1	5	4	3	10	2	2	2
	BD-OE	1	5	3	1	2	10	5	9
	SBD	4	3	5	3	7	10	5	7
Scheduling based on Bottleneck	Clasic GA	779	696	928	981	1010	1202	1467	2064
	Static TA-MODJS	717	633	875	924	931	1081	1393	1988
	BD-OE	717	633	878	927	943	1098	1398	1988
	SBD	722	633	878	927	931	1098	1398	1979
Improvment	Static TA-MODJS	7.96%	9.05%	5.71%	5.81%	7.82%	10.07%	5.04%	3.68%
	BD-OE	0.00%	0.00%	0.34%	0.32%	1.27%	1.55%	0.36%	0.00%
	SBD	0.69%	0.00%	0.34%	0.32%	0.00%	1.55%	0.36%	-0.45%

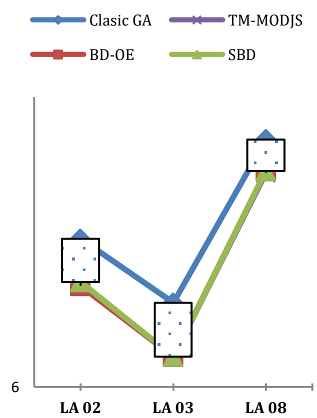


Figure 6. The scheduling results using the BRD by the three methods in a Small scale

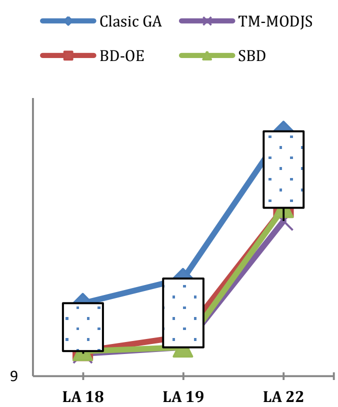


Figure 7. The scheduling results using the BRD by the three methods in a Medium scale

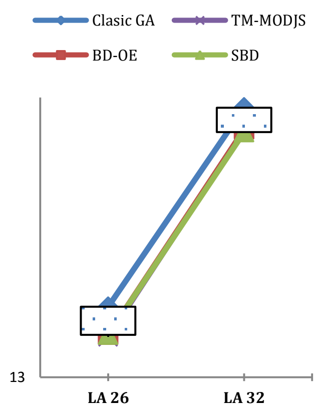


Figure 8. The scheduling results using the BRD by the three methods in a Large scale

TABLE 11. Mean improvement in the scheduling results using the BRD by the three methods

	mean small scale	mean median scale	mean large scale
Classic GA	801.1	1064.3	1765.5
TM-MODJS	741.7	978.7	1690.5
BD-OE	742.7	989.3	1693.0
SBD	744.3	985.3	1688.5

5. 2. Analyzing the Performance of TA-MODJS

According to the results reported in Tables 7 through 11 and also Figures 2 through 9, we can observe that:

- The BR's conforming rate for C_{max} in the two methods of BD-OE and SBD for small, medium, and large scales problems of DJS is up to 75% (6 out of 8 conforming samples), 88% (7 out of 8 conforming samples), and 88% (7 out of 8 conforming samples) respectively. Also, the BR's conforming rate for C_{max} in the two methods of BD-OE and SBD for problems to different scales of DJS is generally up to 83% (20 out of 24 conforming samples).
- The BR's conforming rate for C_{max} in the two methods of BD-OE and MWL for small, medium, and large scales of DJS is up to 75% (6 out of 8 conforming samples), 63% (5 out of 8 conforming samples), and 63% (5 out of 8 conforming samples) respectively. Also, the BR's conforming rate for C_{max} in the two methods of BD-OE and MWL for problems to different scales of DJS is generally up to 67% (16 out of 24 conforming samples).
- The BR's conforming rate for C_{max} in the two methods of SBD and MWL for small, medium, and large scales problems of DJS is up to 88% (7 out of 8 conforming samples), 75% (6 out of 8 conforming samples), and 75% (6 out of 8 conforming samples), respectively. Also, the bottleneck's conforming rate for C_{max} in the two methods of SBD and MWL for problems to different scales of DJS is generally up to 79% (19 out of 24 conforming samples).
- The BR's conforming rate for C_{max} in the two methods of TA-MODJS and BD-OE for small, medium, and large scales problems of DJS is up to 88% (7 out of 8 conforming samples), 75% (6 out of 8 conforming samples), and 63% (5 out of 8 conforming samples), respectively. Also, the bottleneck's conforming rate for C_{max} in the two methods of TA-MODJS and BD-OE for problems to different scales of DJS is generally up to 75% (18 out of 24 conforming samples).
- The BR's conforming rate for C_{max} in the two methods of TA-MODJS and SBD for different scales of DJS is up to 67% (16 out of 24 conforming samples).

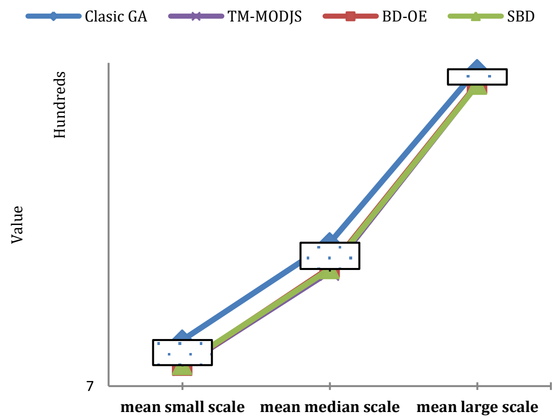


Figure 9. The scheduling results using the BRD by the three methods in a three scales

- The results from solving scheduling problem based on the detected BR for variations indicate improvment in 88% of problems (7 out of 8 better samples).
- The BR's conforming rate in the static and dynamic JS problems is up to 50% (4 out of 8 conforming samples), 63% (5 out of 8 conforming samples), and 88% (7 out of 8 conforming samples) respectively. Also the BR's conforming rate for the problems of static and dynamic with different scales is up to 67% (16 out of 24 conforming samples).
- Another advantage of TA-MODJS over other methods, especially over SBD method, is its reduction in each sample's run time to 5 seconds. Since the SBD method requires improved scheduling for calculating each machine's active period to detect the BR, run time depends on the function of the improved algorithm and the corresponding parameters.

The above-mentioned results indicate that the proposed TA-MODJS method is an efficient method for the BRD problem in the static and dynamic MODJS problems. In other words, it can be stated that the TA-MODJS method (considering run time, complexity, and scheduling results) functions better than any of the existing three methods (BD-OE, SBD, and MWL) in the BRD problems literature.

5. 3. Analyzing the Performance of Ta-Modjs

According to concepts of the TOC, the throughput of all manufacturing systems is limited by the capacity of the BR(s) [2]. Hence, in order to improve system performance in flexibility DJS environments we applied TA-MODJS. The results based on Kacem, Brandimarte and Dauzere-peres instances [25] are indicated in Tables 12 through 14.

TABLE 12. BD results for the Kacem instances

problem	n×m	static scheduling		dynamic scheduling	
		bottleneck resource	computational time(s)	bottleneck resource	computational time(s)
01	8×8	7	2.13	4	2.00
02	10×10	8	2.29	2	2.29
03	15×10	4	4.98	10	5.05

TABLE 13. BD results for the Brandimarte instances

problem	n×m	static scheduling		dynamic scheduling	
		bottleneck resource	computational time(s)	bottleneck resource	computational time(s)
MK 01	10×6	2	2.29	2	4.29
MK 02	10×6	2	4.70	2	4.42
MK 03	15×8	1	13.80	1	13.79
MK 04	15×8	1	8.70	1	8.83
MK 05	15×4	4	10.68	3	10.75
MK 06	10×15	7	11.69	7	11.69
MK 07	20×5	4	12.14	4	11.79
MK 08	20×10	10	25.39	10	24.82
MK 09	20×10	8	25.59	8	25.51
MK 10	20×15	5	25.82	2	26.47

TABLE 14. BD results for the Dauzere-peres instances

Problem	n×m	Static Scheduling		Dynamic Scheduling	
		Bottleneck Resource	Computational Time(s)	Bottleneck Resource	Computational Time(s)
01a	10×5	2	14.70	2	14.91
02a	10×5	4	16.08	4	14.91
03a	10×5	4	14.66	4	14.96
04a	10×5	2	14.91	2	14.71
05a	10×5	4	17.44	3	15.13
06a	10×5	3	15.04	2	14.60
07a	15×8	6	26.83	6	25.95
08a	15×8	7	25.95	2	25.72
09a	15×8	3	26.07	3	25.76
10a	15×8	6	26.66	6	26.46
11a	15×8	2	29.16	3	27.95
12a	15×8	1	27.74	1	26.75
13a	20×10	6	40.89	6	40.95
14a	20×10	2	41.51	10	40.92
15a	20×10	6	41.33	10	41.19
16a	20×10	6	41.36	6	41.12
17a	20×10	7	41.37	2	41.66
18a	20×10	9	42.18	10	41.30

6. CONCLUSIONS

Inefficient use or idling resource(s) in manufacturing systems is instance of energy wastage. Since nowadays energy saving is one of the crucial decisions, one of the ways in this case is efficient use of resources in industrials systems. Most manufacturing systems have BR(s). The BR is a machine or a number of machines which prevent better performance of the systems. The existence of BR in a manufacturing causes considerable reduction in efficiency. Quick and appropriate detection of BR(s) place(s) can lead to improvement in operation management of production resources, increase in system's throughput, and also reduction of total energy consumption costs. In MODJS systems, one or more machines may also act as a BR(s). Literature review indicates that BRD problem in JS problems, by using different suitable dispatching rules on each machine is NP-Hard. In spite of the mentioned fact, in such problems, the way a BR is defined and an easily implemented method is designed for BRD is still challenging and interesting area for the researchers of this issue. Being dynamic and multi-objective for these environments adds to their computational complexities. Literature review indicates that Bottleneck Resources Detection (BRD) problem in the "Multi-Objective and the Dynamic conditions of job-shop" is an important issue which has not been studied before, due to its computational complexity. In this paper, by using Taguchi method, a prior-to-run BRD method namely, TA-MODJS has been developed. Simulation results of the TA-MODJS in a static and single-objective case of this type of problems, and the existing three methods in BRD literature (MWL, SBD, and BD-OE methods) for different size samples of problem indicate that the four mentioned methods have the same results most of the times; however, the efficiency of TA-MODJS method, in contrast to the three existing methods in BRD literature (MWL, SBD, and BD-OE methods), especially in scheduling results is greater. Moreover, the TA-MODJS method can detect BR(s) before setting up a MODJS system. Planning the material flow and combining it with scheduling in MODJS is among the issues for further research.

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An Efficient Approach for Bottleneck Resource(s) Detection Problem in the Multi-objective Dynamic Job Shop Environments

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چکیده

امروزه صرفه‌جویی در انرژی یکی از وجوه اساسی در تصمیم‌گیری‌ها محسوب می‌شود. یکی از راه‌کارهای مهم در این زمینه، بهره‌برداری کارآ از منابع تولیدی در محیط‌های صنعتی است. مطالعات انجام‌گرفته در سیستم‌های ساخت و تولید واقعی حاکی از این است که در این محیط‌ها و در اغلب مواقع، یک یا مجموعه‌ای از ماشین‌ها به عنوان گلوگاه (BR) عمل می‌نمایند. از سویی دیگر، بر اساس تئوری محدودیت‌ها (TOC) بهره‌گیری کارآمد از منابع تولیدی در سیستم‌های تولیدی بر اساس ظرفیت منبع/ منابع گلوگاهی محدود می‌شود. از این رو به منظور بهبود عملکرد چنین سیستم‌هایی، بایستی اقدام به شناسایی، ارزیابی و بهبود عملکرد (تا حد ممکن) چنین منابع ارزشمندی نمود. مطالعات حاکی از این است که مسئله شناسایی منابع گلوگاهی در محیط‌های کارکارگاهی پویای چندهدفی، از جمله مسائلی است که به دلیل پیچیدگی محاسباتی کمتر در ادبیات مورد بررسی قرار گرفته‌اند. از این رو توسعهٔ رویکردی کارآمد به منظور شناسایی گلوگاه(ها) در محیط‌های کارکارگاهی پویای چندهدفی، هدف این تحقیق علمی می‌باشد. در این مقاله، یک روش شناسایی منابع گلوگاهی مبتنی بر روش تاگوچی برای محیط‌های کارکارگاهی پویای چندهدفی (تحت عنوان TM-MODJS) توسعه داده شده است. روش مذکور اهداف مسئله را به عنوان شاخص برآوردی درنظر گرفته و آزمایشات محدود و نمونه‌ای را با ترکیب قواعد توزیعی مختلف برای حل مسئله شناسایی منابع گلوگاهی در محیط‌های کارکارگاهی پویای چندهدفی، ارائه می‌دهد. مقایسهٔ نتایج روش پیشنهادی حاکی از کارآمدی بالای آن از بُعد معیارهایی نظیر نرخ بهبود در نتایج زمان‌بندی در یک زمان معقول است

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