Journal of Quality Engineering and Production Optimization

Vol. 4, No. 2, Summer & Autumn 2019

http://jqepo.shahed.ac.ir

DOI: 10.22070/JQEPO.2020.4986.1120

An Integrated Model for Storage Location Assignment and Storage/Retrieval Scheduling in AS/RS system

Hananeh Habibi Tostani [1] **, Hassan Haleh** [2*] **, Seyyed Mohammad Hadji Molana** [1] **, Farzad Movahedi Sobhani** [1]

[1] *Department of Industrial Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran*

[2] *Department of Industrial Engineering, Golpayegan University of Technology, Golpayegan, Iran*

****Corresponding author:*** *H. Haleh (Email: hhaleh@gut.ac.ir)*

Abstract *– An integrated optimization framework, including location assignment under grouping class-based storage policy and schedule of dual shuttle cranes, is offered by presenting a new optimization programming model. The objective functions, which are considered at this level, are the minimization of total costs and energy consumption. Scheduling of dual shuttle cranes among specified locations, which were determined in the upper-level, is conducted in the lower-level by considering time windows and balance constraints under multi-period planning conditions. A modified nested differential evolution-based algorithm is introduced to solve the proposed model because it is an Np-hard bi-level bi-objective optimization model. Eventually, with the intention of illustrating the validation of the presented optimization model and solution methodology, various numerical experiments are tailored, and different comparative numerical examples are provided based on two current algorithms in the literature. Sensitivity analyses illustrate that grouping class-based storage policy could be rendered superior planning of operations in both levels of the investigated problem.*

Keywords *– Dual Shuttle; grouping constraint; class-based storage; scheduling*

I. INTRODUCTION

One of the efficient automatic systems that have been employing in a broad range of fields such as distribution centers, warehouses and cross-docking with the intention of offering better projecting of tasks is Automated Storage and Retrieval Systems (AS/RS), which were introduced in the 1950s (Nia, 2017a,b). Improvement of inventory control, proper utilization of space, economical labor costs and seasonable storage and retrieval procedures are some of the main advantages of this system, which lead to expanding application and attention of these systems over traditional ones (Boysen and Stephan, 2016; Tappia et al., 2019).

Unquestionably, there are a limited number of cranes to handle requests for aisles, so offering rewarding planning in terms of scheduling and sequencing of these cranes is a crucial challenge. Also, another challenge of these cranes is concerning the unit-load capacity of them, which leads to emerging multi-shuttle cranes and its concerns. Indeed, if these cranes can transmit two requests, it is a dual shuttle cranes system. Although the implementation of this system can provide some possible advantages to a single shuttle crane, the complexity of their planning leads to diminishing academic attention (Roodbergen and Vis, 2009; Wauters et al., 2016). Sketching out an AS/RS involves two vital phases, including strategic and control (Wauters et al., 2016; Roodbergen & Vis, 2009), and each phase is included a

Manuscript Received: 2-July-2019 & Revised: 24-Aug-2019 & Accepted: 21-Dec-2019
ISSN: 2423-3781

broad range of decisions. So that strategic phase is typically encompassed layout specification, the locations of requests, namely storing and retrieving, and prerequisite equipment (Azzi et al., 2011; Ma & Wang, 2019). Unavoidably, the quality of these decisions could be affected the decisions of the control phase, this becomes even more important when the strategic decisions cannot alter in the course of limited time, so it is crucial to determine correctly. By the way, different performance indicators such as cost and time of order picking and delivery and energy consumption of cranes closely depend on the location assignment of products (Yang et al., 2019).

There are three main significant storage policies, which are included class-based storage, dedicated storage, and random storage to achieve a suitable arrangement of warehouse products. Among them, the implementation of the class-based storage policy can specify the number of classes, the locations of each class, including storage and retrieval and the allocation of products to locations and, according to that the classes, which can lead to obtaining rewarding planning of operations. Moreover, in some cases, each product might have a limited number of items, so each location can employ to store or retrieve one item rather than one product, and it is practical to assign each item as an inseparable storing unit. Therefore, considering this situation can provide a real perspective of the problem.

Another concern of the control phase of planning an AS/RS is typically the energy consumption, which is expended by shuttle cranes concerning storage and retrieval requests. Since energy consumption has emerged as a crucial challenge in the course of time, the management of this consumption is typically important for the managers. In this regard, it depends on locating the items in AS/RS. The other aspect of control phase that should be considered to manage the operations of shuttle cranes is related to determine sequence and schedule of them with the intention of minimizing total costs or makespan. It should be noted that this planning will be conducted for storage and retrieval requests simultaneously. Moreover, providing a proper workload balance between cranes could enhance the performance of an AS/RS in the course of time (Roodbergen & Vis, 2009). Hence, an integrated optimization framework, including location assignment under grouping class-based storage policy and schedule of dual shuttle cranes, is offered by presenting a new bi-level multi-objective programming model.

With regard to the solution approach to overcome solving bi-level model, not only do the mainstream of these approaches accent linear bi-level models, which the majority of the lower-level model can be solved in an appropriate amount of time, but also they typically emphasize bi-level models in which each of levels has one objective. Hence, a modified version of the nested differential evolution-based algorithm is offered with the intention of overcoming the above-mentioned barriers of the existed solution method. For this purpose, a self-adaptive mechanism for crossover and mutation probability is utilized to improve the performance of this algorithm.

The remnant of this paper is structured as follows: Section II investigates the literature in the related research area. A framework of the proposed model is provided in Section III. The upper and lower-levels optimization models are formulated in Sections IV and V, respectively. The proposed solution methodology is explained in Section VI. The numerical results and conclusions are described in Sections VII and VIII, respectively.

II. LITERATURE REVIEW

A location assignment problem by considering class-based storage policy was proposed by Muppani and Adil (2008) under multi-period condition. For this problem, they offered an optimization model in which total costs were minimized as the objective function. To solve the offered model, a branch & bound algorithm was also presented, although inventory level of products, grouping constraint and request of retrieval were not investigated. A location assignment location problem in AS/RS by working out storage and retrieval requests and bearing corrosion was proposed by Liu et al. (2013). For this problem, they offered an optimization model in which total energy consumption was minimized as the objective function. With the intention of solving the proposed model, a genetic algorithm was also presented, although inventory level of products, class-based storage policy, grouping constraint and multi-period condition were not investigated.

Another research in this field, which was investigated class-based storage policy and life cycle picking patterns under a multi-period condition was proposed by Manzini et al. (2015). In this regard, they proposed an optimization model by working out the possibility of product displacement among various classes in consecutive periods, although grouping constraint and request of retrieval were not investigated. A grouping location assignment model was proposed by Xie et al. (2016) in which the entire items of the same group have to be allocated in neighbor locations. For this problem, they offered a bi-level optimization model, and so as to solve the offered model, a specific heuristic algorithm was also presented, although inventory level of products, retrieval request, and multi-period condition were not investigated.

Synchronization of assignment and order batching problem was investigated by Xiang et al. (2018) in a Kiva mobile system. In this regard, they proposed a mathematical model in which the similarity of products in all pods was minimized. With the intention of solving the proposed model, a variable neighborhood search heuristic algorithm was also sketched out, although the considerations of retrieval request, inventory level of products, grouping constraint, class-based storage policy and multi-period condition were not investigated. A unit-Load AS/RS was investigated by Cunkas and Ozer (2019) in which there was a dual shuttle crane. In order to solve this problem in the location assignment phase, a particle swarm optimization algorithm was also designed, although they did not provide any mathematical model for this problem, even the considerations of retrieval request, inventory level of products, grouping class-based storage policy and multi-period condition were not analyzed.

A multi-shuttle scheduling problem in AS/RS was investigated by Jiang and Yang (2017). For this problem, they offered an optimization model in which the total travel time of shuttle cranes was minimized as the objective function. The main focus of this optimization model was related to scheduling of retrieval requests, although it could convert to a storage/retrieval scheduling problem by working out necessities definitions. With the intention of solving the proposed model, an efficient heuristic algorithm based on the nearest neighbor approach was also proposed, although workload balance between shuttle cranes, time windows constraints and multi-period condition were not investigated. It should be noted that this model only offered a sequence of the requests and did not present a schedule of shuttle cranes.

A multi-shuttle scheduling problem under uncertain environment was investigated by Mostofi and Erfanian (2018) under a shared storage framework. They presented a mathematical model in which the total travel time of shuttle cranes was minimized as the objective function, and so as to solve this model a genetic algorithm was also presented; also, the barriers of this study were similar to the previous research. A novel version of shuttle-based storage and retrieval system under time windows constraints, which was called part-to-picker system, was introduced by Zhao et al. (2019) in which there were two subsystems, including lift and shuttle, so this system could be responsible for dissimilar movements, including vertical and horizontal. An optimization model was also proposed for this problem in which the total completion of the operations was minimized as the objective function. With the intention of solving the proposed model, a Gurobi linear programming solver was utilized.

A combination of dynamic programming and optimization model for the aforementioned integrated problem in AS/RS was investigated by Yang et al. (2015a) in which in the phase of scheduling a multi shuttle cranes problem was considered. Throughout the implementation of dynamic phase, each step of which relays to an operation cycle, with the intention of optimizing the decision of location assignment underneath a dynamic environment for progressive operation cycles. Also, the proposed optimization model must be solved for each step of this procedure, so as to obtain an optimal location for a single operation cycle and schedule the shuttle crane. With the intention of solving the proposed model, a heuristic algorithm was also proposed. In an AS/RS environment, an integrated shared storage location assignment and multi-shuttle crane scheduling problem was offered by Yang et al. (2015b) in which the total travel time of shuttle cranes was minimized as the objective function. With the intention of solving the proposed model, a variable neighborhood search heuristic was also proposed.

A bi-level framework for integrated location assignment and dual shuttle cranes scheduling problem in AS/RS was offered by Wauters et al. (2016) proposed. Two different methods were employed for the upper-level: 1) location assignment sequentially, 2) location assignment simultaneously. In fact, the first one is a heuristic approach, and classical assignment model, which was proposed by Munkres (1957), was the second one. For the scheduling phase, a mathematical model was proposed in which the total weighted remain time of requests was minimized as the objective function. With the intention of solving the proposed model, a heuristic algorithm was also presented.

III. A FRAMEWORK OF THE PROPOSED MODEL

A. The bi-level multi-objective optimization

Each bi-level optimization model has two levels, which are called upper and lower levels. Actually, this problem is an expanded version of the classical version of the optimization model, which has a single-level model. There are distinctive objective functions, parameters, variables, and constraints for each level. In order to specify characteristics of these levels, the subscripts u and l will be henceforth employed for the upper and lower levels, respectively. The essential linkage between these levels is that forgiven X_u, which is the upper-level solution, the appraisal of its function is creditable only if the X_l for the equivalent lower-level problem (with X_u fixed) is the optimum of the lower-level problem. Regularly, a general bi-level optimization model is represented as follows:

$$\min_{X_u} F_1(X_u, X_l), F_2(X_u, X_l), \dots, F_{M_u}(X_u, X_l),$$

$$S.t.:\ G_k(X_u, X_l) \leq 0, \qquad k = 1, \dots, q_u,$$

$$H_k(X_u, X_l) = 0, \qquad k = 1, \dots, r_u,$$

$$\min_{X_l} f_1(X_u, X_l), f_2(X_u, X_l), \dots, f_{M_l}(X_u, X_l),$$

$$S.t.:\ g_k(X_u, X_l) \leq 0, \qquad k = 1, \dots, q_l,$$

$$h_k(X_u, X_l) = 0, \qquad k = 1, \dots, r_l,$$

$$\text{where } X_u \in \mathbb{X}_u, X_l \in \mathbb{X}_l,$$

In this formation, $F_i(X_u, X_l), i = 1,2, \dots, M_u$ and $f_i(X_u, X_l), i = 1,2, \dots, M_l$ are upper and lower objective functions, respectively. X_u and X_l are the vectors of the n_u and n_l upper and lower variables in the domains $\mathbb{X}_u$ and $\mathbb{X}_l$. Similarly, G and g demonstrate the sets of q_u and q_l inequality constraints, and H and h demonstrate the sets of r_u and r_l equality constraints for the upper and lower levels, respectively. It should be noted that the objective function of the upper-level is optimized concerning X_u, where X_l operates as a fixed parameter. Also, this process is employed for the lower-level concerning X_l, and working out X_u as a fixed parameter. In this paper, the upper-level is bi-objective and the lower-level is single objective, i.e., $M_u = 2, M_l = 1$.

B. Outline of the presented bi-level optimization model

Responding to two main sequential questions, including where and when each request should be stored, is essential precedence to obtain a proper schedule of requests in AS/RS. Actually, in this paper, the proposed integrated problem involves two main sub-problems, in which the grouping class-based storage location assignment problem with two objective functions is considered as upper-level, and the problem of scheduling of dual shuttle cranes with the single objective by working out workload balance and time windows is considered as lower-level. The main outcome of the upper-level model is the best locations of storage and retrieval requests, and for the second one is the best sequence and schedule of shuttle cranes.

In the upper-level, all items of products must be allocated to locations of classes, for this purpose a special storing index, namely cube-per-order index (COI), which was introduced (Heskett, 1963) is employed. In fact, this index is utilized to implement the class-based storage policy because this index can work out product popularity and storage space requirements. This index is described as the ratio of the product' cube to the number of requests (storage or retrieval). With the intention of implementing this approach, Goetschalckx and Ratliff (1990) considered n-class assignment pattern in which the items of products based on lowest COI are stored in the most suitable locations. The optimality of this pattern in terms of allocation products from the viewpoint of time of order packing was proved by them. Also, each location in each class is utilized to respond to the request of storage or retrieval, homogeneously, so a uniform distribution of allocation of products would be obtained. It is worth noting that there is no permission for the relocation of products, and the congestion between cranes is ignored.

Moreover, in some cases, each product might have a limited number of items, so each location can employ to store or retrieve one item rather than one product, and it is practical to assign each item as an inseparable storing unit. Therefore, considering this situation can provide a real perspective of the problem. Consequently, the correlations among items of the identical product need to be working out. Needless to say, when the items of the same products are scattered, the costs of the operating system tremendously increase, so the grouping constraint is considered for this situation. Underneath this constraint, inevitably, each product cannot be divided into more than two groups of items, and the whole items of the identical group must be placed in adjacent locations. By implementing this pattern, total cost and energy consumption, which is related to store or retrieve requests, could be minimized because it can assist in exploiting the preserving in requisite storage space. It should be noted that in the lower-level, there is not possibility of storage or retrieval a request at the same position and time.

IV. THE UPPER-LEVEL MODEL

A. Set and indices

P: Set of products $(p, p' = 1,2, \dots, \mathbb{p})$

I_p: Set of all items in the product set $(i, i' = 1,2, \dots, \mathbb{IP})$, where p^i indicates product encompassing item i

T: Set of periods $(t = 1,2, \dots, \mathbb{T})$

H: Set of shelves $(h = 1,2, \dots, \mathbb{H})$

B: Set of bins on each shelf $(b = 1,2, \dots, \mathbb{B})$

L: Set of storage locations which is included the $b-$th bin on $h-$th shelf $(l, l', = 1, \dots, \mathbb{HB})$

N: Set of storage classes $(j, j' = 1,2, \dots, \mathbb{N})$, where j^l specifies class encompassing location l

B. Parameters

f_l: Footprint area of location l

f'_{p^i}: Footprint area necessitated to store item i of product p

SC: Space cost per unit square foot

CAP_j: Capacity of class j

AST_j : Average store cost of all locations in class j per unit of distance and per unit of product

ARC_j : Average retrieve cost of all locations in class j per unit of distance and per unit of product

COI_i: Cube-per-order index for item i

$m_{p^i}^t$: Number of product p encompassing item i arriving at the start of period t

$n_{p^i}^t$: Number of product p encompassing item i that are ordered in period t

ES_p: Energy consumption is necessitated to store one of product p

ER_p: Energy consumption is necessitated to retrieve one of product p

M: An enough big number

C. Decision Variables

$X_{ij^l}^t$: 1 if item i is allocated to location l of class j in period t; 0 otherwise

Y_{lj}^t: 1 if location l is allocated to class j in period t; 0 otherwise

$U_{pj^l}^t$: 1 if location l in class j is a starting point of product p in period t; 0 otherwise

V_{pj}^t: Number of arriving product p that are allocated to class j in period t

W_{pj}^t: Number of product p that are retrieved from class j in period t

D. Mathematical model:

$$\min \mathbb{Z}_1 = SC \sum_{j\in N}\sum_{l\in L}\sum_{t\in T} f_l Y_{lj}^t + \sum_{j\in N}\sum_{p\in P}\sum_{t\in T}\sum_{l\in L}\left(AST_j V_{pj}^t + ARC_j W_{pj}^t\right) \tag{1}$$

$$\min \mathbb{Z}_2 = \sum_{j\in N}\sum_{p\in P}\sum_{t\in T}\left(ES_p V_{pj}^t + ER_p W_{pj}^t\right) \tag{2}$$

$S.t.$:

$$\sum_{l\in L} X_{ij^l}^t = 1 \quad \forall i \in I_p, \forall t \in T, j \in N \tag{3}$$

$$\sum_{i\in I_p} X_{ij^l}^t = 1 \quad \forall l \in L, \forall t \in T, j \in N \tag{4}$$

$$\sum_{j \in N} Y_{lj}^{t} \leq 1 \quad \forall l \in L, \forall t \in T \tag{5}$$

$$2 \cdot U_{p^i j^l}^{t} \leq X_{ij^l}^{t} + Y_{lj}^{t} \quad \forall i \in I_p, \forall p \in P, \forall t \in T, \forall j \in N, \forall l \in L \tag{6}$$

$$\sum_{l \in L} \sum_{j \in N} \sum_{i \in I_p} V_{pj}^{t} \cdot X_{ij^l}^{t} = \sum_{i \in I_p} m_{p^i}^{t} \quad \forall p \in P, \forall t \in T \tag{7}$$

$$\sum_{l \in L} \sum_{j \in N} \sum_{i \in I_p} W_{pj}^{t} \cdot X_{ij^l}^{t} = \sum_{i \in I_p} n_{p^i}^{t} \quad \forall p \in P, \forall t \in T \tag{8}$$

$$V_{pj}^{t} \leq M \cdot X_{ij^l}^{t} \quad \forall i \in I_p, \forall p \in P, \forall t \in T, \forall j \in N, \forall l \in L \tag{9}$$

$$W_{pj}^{t} \leq M \cdot X_{ij^l}^{t} \quad \forall i \in I_p, \forall p \in P, \forall t \in T, \forall j \in N, \forall l \in L \tag{10}$$

$$\sum_{l \in L} U_{pj^l}^{t} \leq 2 \quad \forall p \in P, \forall t \in T, \forall j \in N \tag{11}$$

$$X_{ij(h,b)}^{t} \leq U_{p^i j(h,b)}^{t} + \sum_{i' \in p^i, i \neq i'} X_{i' j(h,b-1)}^{t} \quad \forall i \in I_p, (h.b) \in L, \forall j \in N, \forall t \in T \tag{12}$$

$$U_{pj^l}^{t} \leq \sum_{i \in I_p} X_{ij^l}^{t} \quad \forall p \in P, \forall t \in T, \forall j \in N, \forall l \in L \tag{13}$$

$$\sum_{i \in I_p} \sum_{l \in L} \sum_{p \in P} m_{p^i}^{t} f'_{p^i} X_{ij^l}^{t} \leq \sum_{l \in L} f_l Y_{lj}^{t} \quad \forall j \in N, \forall t \in T \tag{14}$$

$$COI_i X_{ij^l}^{t} \leq COI_{i'} X_{i'_{j'} l'}^{t} \quad \forall i \neq i', \ \forall j < j', \forall l \neq l', \forall t \in T \tag{15}$$

$$l \cdot Y_{lj}^{t} \leq l' \cdot Y_{l' j'}^{t} \quad \forall l \neq l', \ \forall j < j', \forall t \in T \tag{16}$$

$$Z_{pj}^{t+1} = Z_{pj}^{t} + V_{pj}^{t} - W_{pj}^{t} \quad \forall p \in P, \forall t \in T, \forall j \in N \tag{17}$$

$$\sum_{t \in T} \sum_{i \in I_p} n_{p^i}^{t} \leq \sum_{j \in N} Z_{pj}^{1} + \sum_{t \in T} \sum_{i \in I_p} m_{p^i}^{t} \quad \forall p \in P, \forall t \in T \tag{18}$$

$$\sum_{p \in P} \left(Z_{pj}^{t} + V_{pj}^{t} \right) \leq CAP_j \quad \forall j \in N, \forall t \in T \tag{19}$$

$$X^t_{ij^l}, Y^t_{lj}, U^t_{pj^l} \in \{0,1\} \tag{20}$$

$$V^t_{pj}, W^t_{pj}, Z^t_{pj} \geq 0 \tag{21}$$

The first objective function computes storage space costs and travel costs of storing and retrieving products, and the second one (2) calculates the consumption of energy in the process of storing and retrieving products. Constraint (3) ensures that in each period of planning, each item of the product can be assigned to one location of each class. Constraint (3) ensures that in each period of planning, each location of each class can be assigned to one item of product. Constraint (5) ensures that in each period of planning, each location can be assigned maximum to one class. Constraint (6) guarantees that when the location of a class can be a starting point of the product that the items of the product have been allocated to the location, also the location has been allocated to the class. Constraint (7) ensures that all received items of each product must be assigned to that class which item was assigned to it in each period. Constraint (8) ensures that all wanted items of the product must be retrieved from that class which item was assigned to it in each period. Constraints (9) and (10) are dialectic constraints. Constraint (11) restricts the maximum number of starting locations that one product can have. Constraint (12) ensures that one location of each class is either an initial point for a product or proceeded by an item of the identical product in each period. Constraint (13) ensures that an initial point of the product should be allocated with an item of the product. Constraint (14) demonstrates the storage space capacity of each class in each period. Constraints (15) and (16) ensure that if an item with smaller COI is assigned to class j and items that have bigger COI assigned to the class j' subsequently, j is located nearer to the I/O point than the j'. Constraint (17) demonstrates the inventory of the product at the beginning of period $t+1$ in each class. Constraint (18) ensures that a feasible solution could be obtained for the problem. Constraint (19) demonstrates the capacity of each class in each period. Constraints (20) and (21) determine the types of decision variables.

V. THE LOWER-LEVEL MODEL

In the lower-level model, since there may be one storage request and one retrieval request in each of the$\mathbb{HB}$ locations, there are $2\mathbb{HB}$ handling requests to be handled by the two shuttle cranes. The $2\mathbb{HB}$ requests are indexed such that requests of locations $2l-1$ and $2l$ $(l = 1,2,\dots,\mathbb{HB})$ signify the retrieval and storage requests of location l, respectively. Henceforth, request r $(r = 1,2,\dots,2\mathbb{HB})$ of location l is one of the two handling requests in location $\lceil r/2\rceil$. A dummy storage (retrieval) request of zero handling time is surcharged to locations with a retrieval (storage) request only.

A. Sets and indices

$\boldsymbol{S}$: Set of shuttle cranes $\{\boldsymbol{s = 1, 2}\}$

$\boldsymbol{R}$: Set of requests $(\boldsymbol{r, r' = 1, 2, \dots, 2}\mathbb{HB})$

$\boldsymbol{q(l)}$: Set of locations in which it could be located in period $\boldsymbol{t-1}$, and for a shuttle crane in location $\boldsymbol{l}$ $(\boldsymbol{l = 1}, \dots, \mathbb{HB})$ at period $\boldsymbol{t}$ $(\boldsymbol{t = 0, 1, 2}, \dots, \mathbb{T} - \boldsymbol{1})$

$\boldsymbol{k(l)}$: Set of locations in which it could be located at period $\boldsymbol{t+1}$

$\boldsymbol{TW_s}$: Set of time windows for shuttle crane $\boldsymbol{s}$ $(\boldsymbol{e = 1, 2}, \dots, \mathbb{TW})$

B. Parameters

p_r: Required time for shuttle crane to handle request r

$\mathbb{G}$: Maximum unbalance level of workload allocation where $\mathbf{0} < \mathbb{G} < \mathbf{1}$.

C. Decision variables

$Q_{rr'}^{se}$: 1 if shuttle crane s handles request r before request r'in in time window e; 0 otherwise

O_{sl}^{te}: 1 if shuttle crane s is in location l at period t in time window e; 0 otherwise

D_{rs}^{te}: 1 if shuttle crane s completes handling of request r at period t in time window e; 0 otherwise

D. Mathematical model:

$$\min \mathbb{Z}_3 \tag{22}$$

S.t.:

$$\mathbb{Z}_3 \geq \sum_{e \in \boldsymbol{TW_s}} \sum_{t \in T} t\, D_{rs}^{te} \qquad \forall r \in R, \forall s \in S \tag{23}$$

$$\sum_{s \in S} \sum_{t \in T} \sum_{e \in \boldsymbol{TW_s}} t\, D_{rs}^{te} \geq p_r \quad \forall r \in R \tag{24}$$

$$\sum_{s \in S} \sum_{t \in T} \sum_{e \in \boldsymbol{TW_s}} D_{rs}^{te} = 1 \quad \forall r \in R \tag{25}$$

$$\sum\nolimits_{r'=0}^{p_r} \sum_{e \in \boldsymbol{TW_s}} O_{s,\lceil r/2 \rceil}^{t-r',e} - p_r - 1 \geq M \left(\sum_{e \in \boldsymbol{TW_s}} D_{rs}^{te} - 1 \right) \quad \forall s \in S, \forall r \in R, \forall t = p_r, p_r + 1, \dots, \mathbb{T} \tag{26}$$

$$\sum_{e \in \boldsymbol{TW_s}} O_{sl}^{te} \leq \sum_{e \in \boldsymbol{TW_s}} \sum_{r' \in q(l)} O_{sl}^{t-1,e} \qquad \forall s \in S, \forall \boldsymbol{l} = \mathbf{1}, \dots, \mathbb{HB}, \forall t = 1,2, \dots, \mathbb{T} \tag{27}$$

$$\sum_{e \in \boldsymbol{TW_s}} O_{sl}^{te} \leq \sum_{e \in \boldsymbol{TW_s}} \sum_{r' \in k(l)} O_{sl}^{t+1,e} \qquad \forall s \in S, \forall \boldsymbol{l} = \mathbf{1}, \dots, \mathbb{HB}, \forall t = 0,1,2, \dots, \mathbb{T} - 1 \tag{28}$$

$$\sum_{r' \in R} \sum_{e \in \boldsymbol{TW_s}} O_{s-1,l}^{te} \leq M \left(1 - \sum_{e \in \boldsymbol{TW_s}} O_{sl}^{te} \right) \quad \forall s = 2, \forall \boldsymbol{l} = \mathbf{1}, \dots, \mathbb{HB}, \forall t \in T \tag{29}$$

$$\sum_{l=1}^{\mathbb{HB}} \sum_{e\in \boldsymbol{TW_s}} O_{sl}^{te} = 1 \quad \forall s \in S, \forall t \in T \tag{30}$$

$$\sum_{t\in T} t \sum_{e\in \boldsymbol{TW_s}} \left(D_{r's}^{te} - D_{rs}^{te}\right) \geq p_r - M\left(1 - \sum_{e\in \boldsymbol{TW_s}} Q_{rr'}^{se}\right) \quad \forall r, r' \in R, r \neq r', \forall s \in S \tag{31}$$

$$\sum_{t\in T} \sum_{e\in \boldsymbol{TW_s}} \left(D_{r's}^{te} + D_{rs}^{te}\right) - 1 \leq Q_{rr'}^{se} + Q_{r'r}^{se} \quad \forall r, r' = 1,2, \ldots, \mathbb{HB}, r \neq r', \forall s \in S \tag{32}$$

$$\sum_{r\in R} \sum_{r'\in R\backslash r} \sum_{e\in \boldsymbol{TW_s}} Q_{rr'}^{se} \leq (1 + \mathbb{G}) \frac{2\mathbb{HB}}{2} \quad \forall s \in S \tag{33}$$

$$\sum_{r\in R} \sum_{r'\in R\backslash r} \sum_{e\in \boldsymbol{TW_s}} Q_{rr'}^{se} \geq (1 - \mathbb{G}) \frac{2\mathbb{HB}}{2} \quad \forall s \in S \tag{34}$$

$$Q_{rr'}^{se}, O_{sl}^{te}, D_{rs}^{te} \in \{0,1\} \tag{35}$$

The makespan of shuttle cranes is minimized as the objective function (22) which is computed by constraint (23). The connection between handling time of requests and completion time is provided by constraint (24). Constraint (25) guarantees that each request has only one non-zero completion time. Constraint (26) guarantees that the shuttle crane remains at the location of request during the related operation. The connection between shuttle cranes and visited locations in consecutive periods are stated by constraints (27) and (28). No interference between shuttle cranes is ensured by constraint (29). Constraint (30) guarantees that each shuttle crane could only be in a location in each period. The connection between request completion time and those of its successors is stated by constraint (31). Constraint (32) is a dialectic constraint for requests conducted by the identical shuttle crane. The workload balances between shuttle cranes are stated by constraints (33) and (34). Constraint (35) determines the types of decision variables.

VI. SOLUTION METHODOLOGY

Islam et al. (2016) proposed an evolutionary algorithm to overcome solving bi-level multi-objective model, which was called a nested differential evolution based algorithm. In this research, a modified version of it is offered, which is referred to here MDBMA. In synopsis, the procedure of this algorithm is as follows. For the upper-level model, a random population with a size of N_u is generated. For each individual in upper-level (X_u), by employing a differential evolution algorithm, which is described as below, the lower-level model with population N_l is optimized. By conducting this process, an optimal solution for the given (X_u) can be obtained. Afterwards, an evaluation process is conducted for the upper-level objective functions with respect to the optimal lower-level solution. Then, DE operators, including crossover and mutation, are employed with the intention of generating new solutions, and they are appraised in the same manner. The entire of solutions are gathered at the upper-level and then sorted, after that for the next generation, the top N_u solutions are selected at the upper-level. This procedure recurs until maximum iterations so as to give the final solutions. It should be noted that the non-dominated sorting and crowding distance measure, which were defined by (Deb et al., 2002), are employed at both levels to sort the solutions.

A. Upper-level operators

In the upper-level, two types of operators, namely Umut and UXover, which were offered by Deb and Goyal (1996);

Deb and Agrawal (1995), are employed. Umut is a mutation operator and surcharges a real value $r_{lmut} \in [-0.5,0.5]$ with a p_{lmut}probability to each part of the solution matrix. UXover is a crossover in which the elements for each parent are selected uniformly and be substituted in the offspring.

B. lower-level operators

In the lower-level, three types of operators namely RBX, SBX and Or-opt which were offered by Potvin and Bengio (1996); Or (1977), are employed. RBX is a crossover in which a parent provides a copy of sequence for offspring; afterwards the remnant of sequence is supplemented by the sequences of another parent noting that the encountered requests are also eliminated. SBX is also a crossover, in which a new sequence is generated, by working out the half of a sequence starting from the initial situation of shuttle crane in each of parents, preserving the order of each half, and complementing the offspring with the other sequences and removing encountered requests. Or-opt is a mutation, in which a number of requests from a sequence are taken, and it will be used in another.

C. A self-adaptive mechanism to adapt the crossover and mutation probabilities

A self-adaptive approach, which was proposed by Yong (2006), is utilized in this approach in order to adapt the probabilities of crossover and mutation. During the process of this approach, the best solution with the higher fitness is more likely to be maintained, and the solution, which has lower fitness, tends to be substituted by a new solution.

$$P_c = \begin{cases} P_{c2} - \frac{(P_{c2}-P_{c3})(F'-F_{avg})}{F_{max}-F_{avg}} & F' \geq F_{avg} \\ P_{c1} - \frac{(P_{c1}-P_{c2})(F'-F_{min})}{F_{avg}-F_{min}} & F' < F_{avg} \end{cases} \tag{44}$$

$$P_m = \begin{cases} P_{m2} - \frac{(P_{m2}-P_{m3})(F'-F_{avg})}{F_{max}-F_{avg}} & F' \geq F_{avg} \\ P_{m1} - \frac{(P_{m1}-P_{m2})(F'-F_{min})}{F_{avg}-F_{min}} & F' < F_{avg} \end{cases} \tag{45}$$

The higher fitness vale of two solutions is represented by F', $P_{c1} > P_{c2} > P_{c3}$, and $P_{m1} > P_{m2} > P_{m3}$.

D. Performance assessment

Legillon et al. (2012) investigated the structure of the bi-level multi-objective model and stated that the approaches, which are employed to assess the quality of the solutions of multi-objective model, cannot afford a suitable appraisal for the bi-level multi-objective model. Because the aim of it is to obtain solutions (X_u, X_l), which offer a suitable appraisal of upper-level objective functions, while being nearby to the optimal solution concerning lower-level objective function for a X_u fixed. Therefore, this matter could lead to obtaining some good quality solutions, which they do not belong to the Pareto frontier and the solutions that belong to the Pareto frontier not inexorably being good quality, so two specified performance metrics, namely direct rationality, and weighted rationality were proposed by Legillon et al., (2012) to handle this situation. In the direct rationality, the ability of improvability is assessed for a population, so an efficient lower-level procedure is utilized for a predefined number of times, and how many times, which examined algorithm really can enhance the solution, are counted. But, in the weighted rationality, the amount of solution enhancement is appraised.

VII. EXPERIMENTAL RESULTS

A. Numerical results

A broad range of numerical analysis in order to appraise the performance proposed model and solution approach with respect to the CoBRA and classical repairing algorithm is provided in this section. It should be noted that the first one is a new evolutionary algorithm, which was proposed by (Legillon et al., 2012), to solve the bi-level optimization model. In the second one, the optimal solution of the lower-level model is working out as a constraint, and looking for to find the best solution for the upper-level, so it does not have any archiving or coevolution operator in its process. The entire experimental analysis were implemented on a personal computer (Dual Core processor: 2.5GHz with 3GB of memory), and Matlab software. With the intention of investigating the performance of these algorithms, three metrics, including 1) the value of upper-level fitness, 2) direct rationality, 3) weighted rationality are considered based on 20 implementations for the 60 sketched problems. Among them, there are three different sizes of requests involve 15, 30 and 50 products with its items. Also, for each size of these problems, 20 instants are considered.

Table I. The sources of random generation of parameters

Model parameters	Values	Model parameters	Values	Metaheuristic parameters	Values
$\boldsymbol{f_l}$	48×60 square ft.	$\boldsymbol{m^t_{p^i}}$,$\boldsymbol{n^t_{p^i}}$	~uniform (1,4)	$\boldsymbol{N_u}$	200
$\boldsymbol{f'_{p^i}}$	1×1 square ft.	$\boldsymbol{ES_p}$,$\boldsymbol{ER_p}$	~uniform (15,30)	$\boldsymbol{N_l}$	200
$\boldsymbol{SC}$	1.5 per square ft.	$\boldsymbol{p_r}$	~uniform (5,7)	$\boldsymbol{Gen_{max_u}}$	50
$\boldsymbol{CAP_j}$	~uniform (10,20)	$\mathbb{G}$	~uniform (0,1)	$\boldsymbol{Gen_{max_l}}$	50
$\boldsymbol{AST_j}$	~uniform (5,7)				
$\boldsymbol{ARC_j}$	~uniform (3,5)				

Table II. Product classes formed

Class number	Product and related items Assigned	Locations Assigned
1	$P_3(i = 1,2,3), P_1(i = 1,2),$ $P_{10}(i = 1,2,3), P_5(i = 1,2), P_{11}(i = 1,2)$	$P_3(l_5, l_6, l_7)$,$P_1(l_8, l_9)$, $P_{10}(l_{10}, l_{20}, l_{30})$,$P_5(l_1, l_2)$, $P_{11}(l_3, l_4)$
2	$P_6(i = 1,2,3), P_8(i = 1,2,3),$ $P_2(i = 1,2,3), P_{14}(i = 1,2,3)$	$P_6(l_{17}, l_{18}, l_{19})$, $P_8(l_{21}, l_{22}, l_{23})$, $P_2(l_{11}, l_{12}, l_{13})$, $P_{14}(l_{14}, l_{15}, l_{16})$
3	$P_7(i = 1,2), P_9(i = 1,2), P_{12}(i = 1,2,3)$	$P_7(l_{28}, l_{29})$, $P_9(l_{24}, l_{25})$, $P_{12}(l_{31}, l_{32}, l_{33})$
4	$P_{15}(i = 1,2,3), P_4(i = 1,2,3,4),$ $P_{13}(i = 1,2)$	$P_{15}(l_{38}, l_{39}, l_{40})$, $P_4(l_{34}, l_{35}, l_{36}, l_{37})$ $P_{13}(l_{26}, l_{27})$

In the following, Table I provides the details values of input parameters, and Tables II-IV present the obtained solution from MDBMA for the first instant of experiment 1 in the first period of planning (15 products) with the intention of demonstrating the correctness of the proposed model and solution approach. The obtained solution for the upper-level model is provided in Table II, in which there are 15 product types including related items that are assigned to available locations within 4 classes, so that the first class, 5 product types, the second class, 4 types of products, the third class, 3 types of products and the fourth class, 3 types of products are allocated, so the number of allocated locations to these classes are 12, 12, 7 and 9, respectively. It is worth noting that the type of requests for the allocated allocations involves storage and retrieval that are specified in Table III. The obtained solution for the shuttle cranes scheduling is provided in Table IV, in which the sequence, completion times for each of shuttle cranes and makespan are represented. Afterward, the performance appraisals for the 60 sketched problems from the aforementioned algorithms are demonstrated in Tables V, IX and XIII. Moreover, so as to obtain better evaluation of performances of these algorithms, the ANOVA statistical analyses are performed, which their results are provided in Tables VI-VIII, X-XII, and XIV-XVI. As can be seen in these tables, the p-values are less than 0.05 for the whole of experiments, so there are significant differences between them.

Table III. First of the 20 instants of 15 products in which 40 requests need to be sequenced

Request	Location	Type of request	Request	Location	Type of request
1	2	Retrieval	21	18	Retrieval
2	28	Retrieval	22	36	Storage
3	14	Storage	23	22	Retrieval
4	5	Storage	24	9	Storage
5	34	Retrieval	25	39	Retrieval
6	17	Retrieval	26	32	Storage
7	31	Retrieval	27	13	Storage
8	1	Retrieval	28	30	Storage
9	21	Storage	29	7	Storage
10	40	Storage	30	11	Retrieval
11	10	Storage	31	16	Retrieval
12	23	Storage	32	35	Storage
13	4	Storage	33	8	Storage
14	33	Retrieval	34	24	Storage
15	38	Retrieval	35	37	Retrieval
16	12	Storage	36	27	Storage
17	3	Retrieval	37	15	Retrieval
18	25	Storage	38	29	Storage
19	6	Storage	39	19	Storage
20	20	Retrieval	40	26	Storage

Table IV. The best result from MDBMA

The sequence of shuttle crane 1	The sequence of shuttle crane 2	Makespan
25	3	514
40	2	
1	30	
26	7	
31	12	
10	13	
6	27	
36	9	
37	28	

Continue Table IV. The best result from MDBMA

The sequence of shuttle crane 1	The sequence of shuttle crane 2	Makespan
19	32	
4	23	
16	24	
11	34	
39	14	
20	18	
15	33	
29	5	
35	22	
17	38	
8	$\boldsymbol{FT^2}$	
21		
$\boldsymbol{FT^1}$		
514	484	

Table V. Results for each of the 20 instances of experiment 1 (15 products)

Inst.	Upper-level fitness			Lower-level fitness Direct rationality			Lower-level fitness Weighted rationality		
	Repair	CoBRA	MDBMA	Repair	CoBRA	MDBMA	Repair	CoBRA	MDBMA
1	**1042**	1475	1080	20.1	5.4	**0.5**	867.7	**290.7**	348.6
2	**1061**	1238	1137	31.5	4.9	**2.3**	162.8	377.2	**148.8**
3	1286	1085	**991**	47.0	**0.8**	5.3	547.4	285.1	**250.0**
4	1205	1260	**1192**	41.1	**2.3**	2.5	737.0	388.6	**252.5**
5	1173	1085	**1034**	13.8	5.2	**1.0**	1016.9	**80.7**	193.2
6	1132	1100	**1025**	36.2	5.4	**3.5**	797.5	**148.5**	251.8
7	1228	1227	**1153**	43.9	**3.5**	4.0	485.4	**70.4**	129.9
8	1248	**1154**	1206	43.1	**2.4**	3.6	641.6	156.8	**132.5**
9	1152	1133	**1105**	13.9	4.6	**4.5**	950.8	**112.0**	281.0
10	1106	**1090**	1237	9.6	5.4	**0.6**	777.3	282.0	**212.9**
11	1186	1074	**985**	30.0	**1.9**	5.4	598.6	134.3	**75.8**
12	1207	1072	**1002**	23.9	**3.2**	5.1	701.1	**77.0**	363.7
13	1192	**1184**	1241	23.3	5.4	**4.7**	504.5	**82.1**	205.3
14	1138	1173	**1043**	54.2	2.0	**0.5**	886.0	53.7	**47.4**
15	**1037**	1153	1121	27.8	3.4	**3.8**	646.6	279.7	**113.2**
16	1229	**1038**	1110	30.2	**1.4**	5.4	745.7	196.9	**53.6**
17	1147	1133	**1018**	8.8	5.3	**0.8**	165.4	**44.1**	46.0
18	1232	**1072**	1195	45.8	**2.8**	3.7	295.3	**39.2**	154.4
19	1087	1040	**966**	42.2	5.1	**4.5**	763.5	397.0	**267.6**
20	1304	1223	**1126**	54.0	4.6	**5.1**	238.8	155.5	**71.8**
Average	1169.6	1150.45	**1098.35**	32.02	3.75	**3.34**	626.49	182.57	**180**

Table VI. The ANOVA results of experiment 1 for upper-level fitness

Source	DF	SS	MS	F-value	P-value
Factor (Repair, CoBRA, MDBMA)	2	54385	27192	3.42	0.040
Error	57	453694	7960		
Total	59	508079			

Table VII. The ANOVA results of experiment 1 for lower-level fitness- direct rationality

Source	DF	SS	MS	F-value	P-value
Factor (Repair, CoBRA, MDBMA)	2	10812.7	5406.3	77.51	0.00
Error	57	3975.8	69.8		
Total	59	14788.5			

Table VIII. The ANOVA results of experiment 1 for lower-level fitness- weighted rationality

Source	DF	SS	MS	F-value	P-value
Factor (Repair, CoBRA, MDBMA)	2	2642863	1321431	44.93	0.00
Error	57	1676566	29413		
Total	59	4319429			

Table IX. Results for each of the 20 instances of experiment 2 (30 products)

Inst.	Upper-level fitness			Lower-level fitness Direct rationality			Lower-level fitness Weighted rationality		
	Repair	CoBRA	MDBMA	Repair	CoBRA	MDBMA	Repair	CoBRA	MDBMA
1	2623	**2318**	2347	46.4	1.7	**1.5**	1152.6	196.5	**177.6**
2	2659	2482	**2250**	38.5	4.2	**3.4**	1161.5	**77.2**	303.9
3	2374	**2162**	2503	55.9	6.7	**3.7**	1539.3	252.5	**127.6**
4	2231	2158	**2022**	32.6	6.8	**3.1**	1330.2	324.2	**273.2**
5	2286	2578	**2129**	41.9	**3.2**	3.5	667.8	**112.4**	170.7
6	**2158**	2216	2204	43.3	3.8	**2.3**	1746.9	245.1	**69.8**
7	2657	2579	**2069**	50.9	6.6	**3.1**	1202.2	**112.5**	182.4
8	2519	**2042**	2326	57.3	**2.0**	3.6	806.0	301.6	**234.6**
9	2412	2411	**2005**	49.2	5.1	**2.2**	1226.2	179.2	**144.7**
10	2773	2466	**2352**	21.9	5.5	**3.7**	500.8	**201.2**	224.5
11	2430	2418	**2023**	50.9	4.1	**2.6**	500.1	243.1	**143.2**
12	**2018**	2162	2344	32.6	6.7	**2.4**	797.3	274.3	**112.8**
13	2101	2645	**2082**	22.3	4.5	**2.9**	1382.2	108.1	**80.6**
14	2725	2668	**2257**	54.7	3.6	**2.1**	1157.5	257.4	**139.4**
15	**2244**	2364	2488	23.0	3.7	**2.2**	534.6	**167.4**	223.3
16	2749	2544	**2377**	24.7	**3.3**	3.9	814.2	**184.4**	272.7

Continue Table IX. Results for each of the 20 instances of experiment 2 (30 products)

Inst.	Upper-level fitness			Lower-level fitness Direct rationality			Lower-level fitness Weighted rationality		
	Repair	CoBRA	MDBMA	Repair	CoBRA	MDBMA	Repair	CoBRA	MDBMA
17	2253	**2128**	2220	51.0	4.6	**4.1**	1182.5	**98.8**	131.5
18	2594	2445	**2128**	49.8	5.6	**2.0**	1736.0	247.0	**79.7**
19	2327	2647	**2093**	20.0	**2.0**	2.4	773.5	**86.7**	146.1
20	**2154**	2617	2410	27.0	2.9	**2.1**	934.8	237.0	**173.5**
Average	2414.35	2402.5	**2231.45**	39.69	4.33	**2.84**	1057.31	195.33	**170.59**

Table X. The ANOVA results of experiment 2 for upper-level fitness

Source	DF	SS	MS	F-value	P-value
Factor (Repair, CoBRA, MDBMA)	2	419006	209503	5.26	0.008
Error	57	2271444	39850		
Total	59	2690451			

Table XI. The ANOVA results of experiment 2 for lower-level fitness- direct rationality

Source	DF	SS	MS	F-value	P-value
Factor (Repair, CoBRA, MDBMA)	2	17408	8704	151.89	0.00
Error	57	3266.3	57.3		
Total	59	20674.2			

Table XII. The ANOVA results of experiment 2 for lower-level fitness- weighted rationality

Source	DF	SS	MS	F-value	P-value
Factor (Repair, CoBRA, MDBMA)	2	10199293	5099646	97.97	0.00
Error	57	2967178	52056		
Total	59	13166471			

Table XIII. Results for each of the 20 instances of experiment 3 (50 products)

Inst.	Upper-level fitness			Lower-level fitness Direct rationality			Lower-level fitness Weighted rationality		
	Repair	CoBRA	MDBMA	Repair	CoBRA	MDBMA	Repair	CoBRA	MDBMA
1	6166	6323	**6078**	21.6	3.1	**3.0**	1217.0	202.8	**89.4**
2	6292	6237	**5718**	31.0	4.1	**2.0**	3727.8	560.6	**37.3**
3	6151	**6031**	6469	14.4	7.3	**3.3**	3335.8	333.0	**176.0**
4	6658	6452	**6316**	59.8	3.9	**1.4**	1964.2	344.3	**117.8**
5	6083	5943	**5907**	21.8	6.0	**2.5**	1499.4	**189.3**	220.3
6	**5908**	6272	6120	35.9	3.6	**2.7**	2043.4	838.2	**377.3**

Continue Table XIII. Results for each of the 20 instances of experiment 3 (50 products)

Inst.	Upper-level fitness			Lower-level fitness Direct rationality			Lower-level fitness Weighted rationality		
	Repair	CoBRA	MDBMA	Repair	CoBRA	MDBMA	Repair	CoBRA	MDBMA
7	**6121**	6260	6293	65.6	6.3	**3.6**	4337.8	**196.5**	220.4
8	6396	6560	**6210**	33.6	**4.0**	4.2	2960.5	841.0	**215.4**
9	6050	6302	**5685**	9.5	7.2	**2.6**	656.3	**133.7**	425.6
10	6487	**6010**	6275	48.9	5.5	**3.6**	3384.0	**161.9**	476.4
11	6172	**5909**	6060	23.2	3.8	**3.1**	2606.2	393.7	**46.9**
12	6212	6122	**5733**	55.7	**4.8**	5.2	4023.7	789.2	**390.8**
13	6809	6623	**6398**	18.3	7.1	**3.7**	3140.7	473.1	**167.9**
14	6642	6297	**5961**	61.6	**1.4**	2.3	4252.1	714.7	**59.8**
15	**6329**	6622	6401	50.0	3.4	**1.1**	3063.7	650.1	**269.7**
16	6312	6413	**5845**	44.3	4.5	**1.5**	910.3	**315.3**	468.5
17	6585	6273	**5956**	54.4	3.6	**2.2**	2803.7	823.2	**436.8**
18	6241	6677	**5735**	38.7	**2.6**	4.2	1418.9	221.0	**62.3**
19	6809	6715	**6334**	62.0	3.8	**2.8**	4052.7	729.3	**219.0**
20	**6036**	6536	6231	46.8	4.1	**1.6**	4489.5	303.2	**181.7**
Average	6322.95	6328.85	**6086.25**	39.85	4.50	**2.83**	2794.38	460.705	**232.96**

Table XIV. The ANOVA results of experiment 3 for upper-level fitness

Source	DF	SS	MS	F-value	P-value
Factor (Repair, CoBRA, MDBMA)	2	766110	383055	5.91	0.005
Error	57	3694169	64810		
Total	59	4460279			

Table XV. The ANOVA results of experiment 3 for lower-level fitness- direct rationality

Source	DF	SS	MS	F-value	P-value
Factor (Repair, CoBRA, MDBMA)	2	17489	8744	84.28	0.00
Error	57	5914	104		
Total	59	23403			

Table XVI. The ANOVA results of experiment 3 for lower-level fitness- weighted rationality

Source	DF	SS	MS	F-value	P-value
Factor (Repair, CoBRA, MDBMA)	2	80392002	40196001	78.08	0.00
Error	57	29344467	514815		
Total	59	109736469			

B. Sensitivity analysis

The influence of the upper-level decisions on the lower-level results is the main question when there is a bi-level optimization model. Hence, some sensitivity analyses by conducting numerical investigations are provided in order to respond suitable answer to this issue. For the first one, a comparative investigation for four situations of studied system, including with and without considering class-based storage assignment and grouping constraint are provided for each objective function of each level in Figs. 1-3. For this aim, 12 test problems from the aforementioned instants are selected. The obtained results reveal that these considerations have a significant rewarding influence on the entire objective functions, and the classification has a greater effect on decreasing objective function values to grouping products. The second aspect, which is investigated in this section, is related to the workload balance between shuttle cranes, so six test problems are considered that their outcomes are depicted in Fig. 4. The obtained results reveal that by considering these constraints, an equal and proper balance between shuttles cranes are appeared in terms of workload.

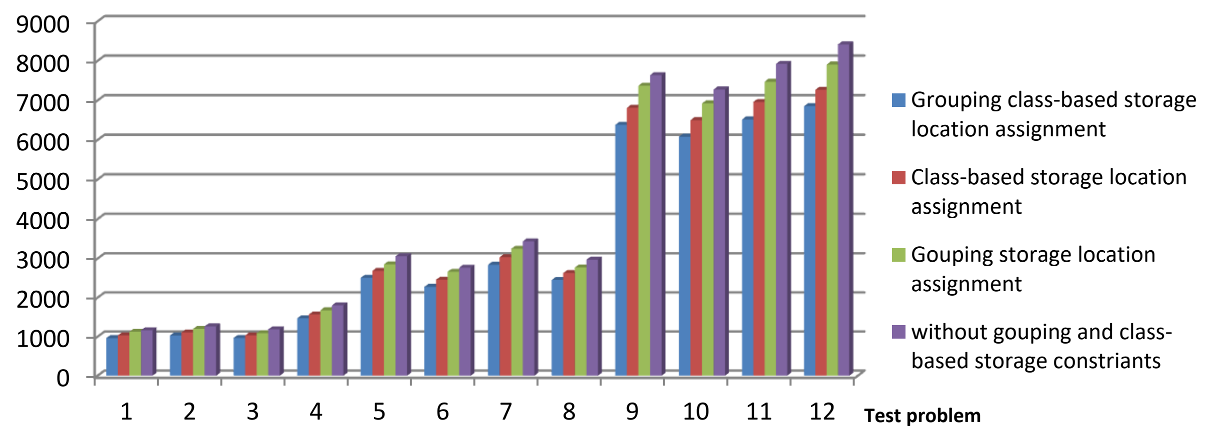

Fig. 1. Impact of class-based storage assignment and grouping considerations on total costs in upper-level

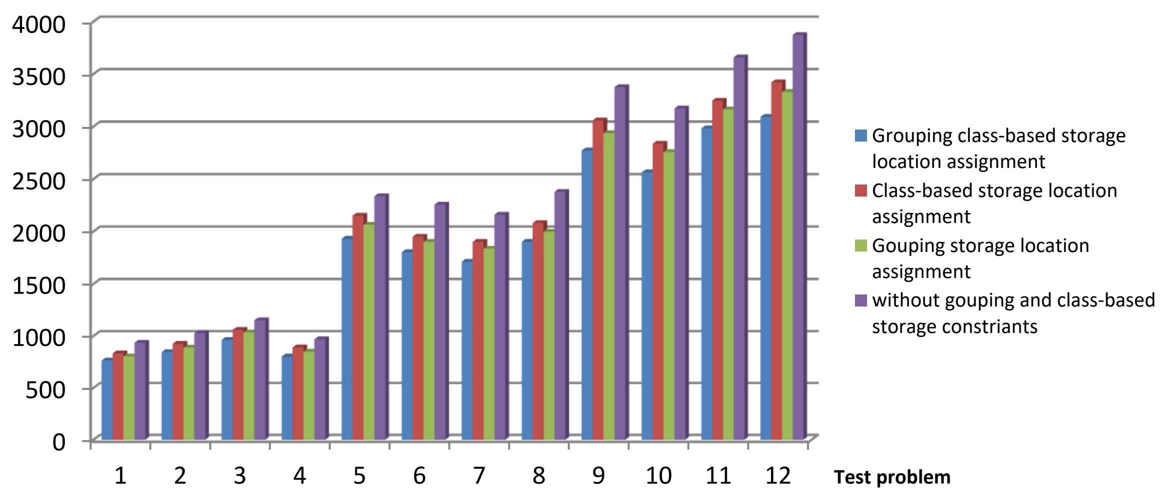

Fig. 2. Impact of class-based storage assignment and grouping considerations on energy consumptions in upper-level

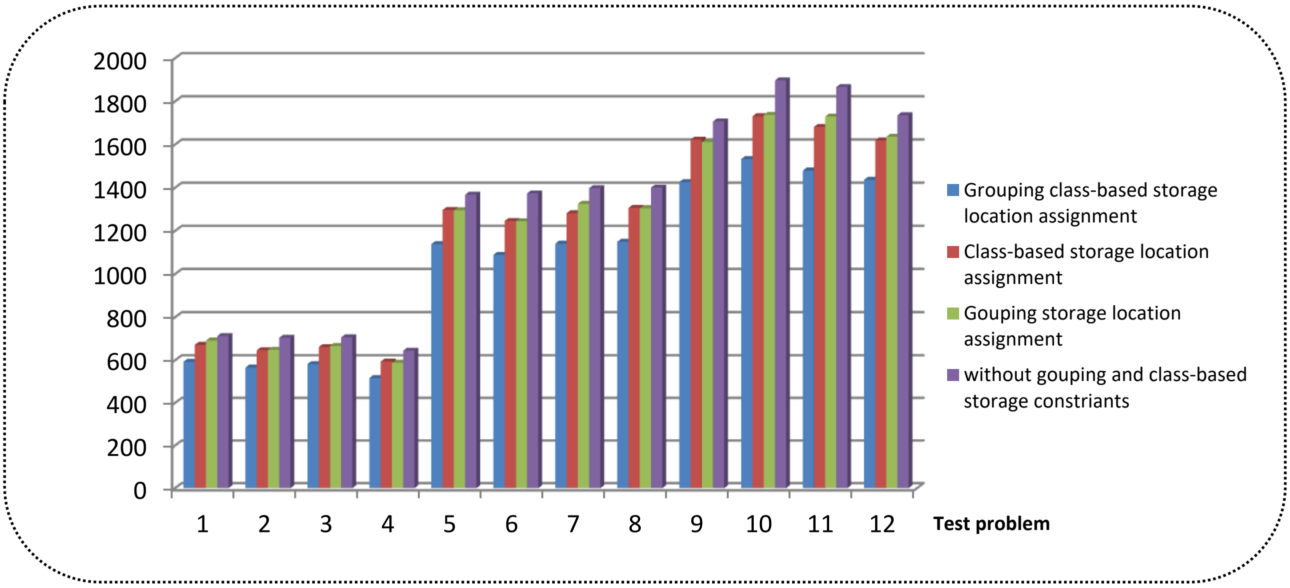

Fig. 3. Impact of class-based storage assignment and grouping considerations on makespan in lower-level

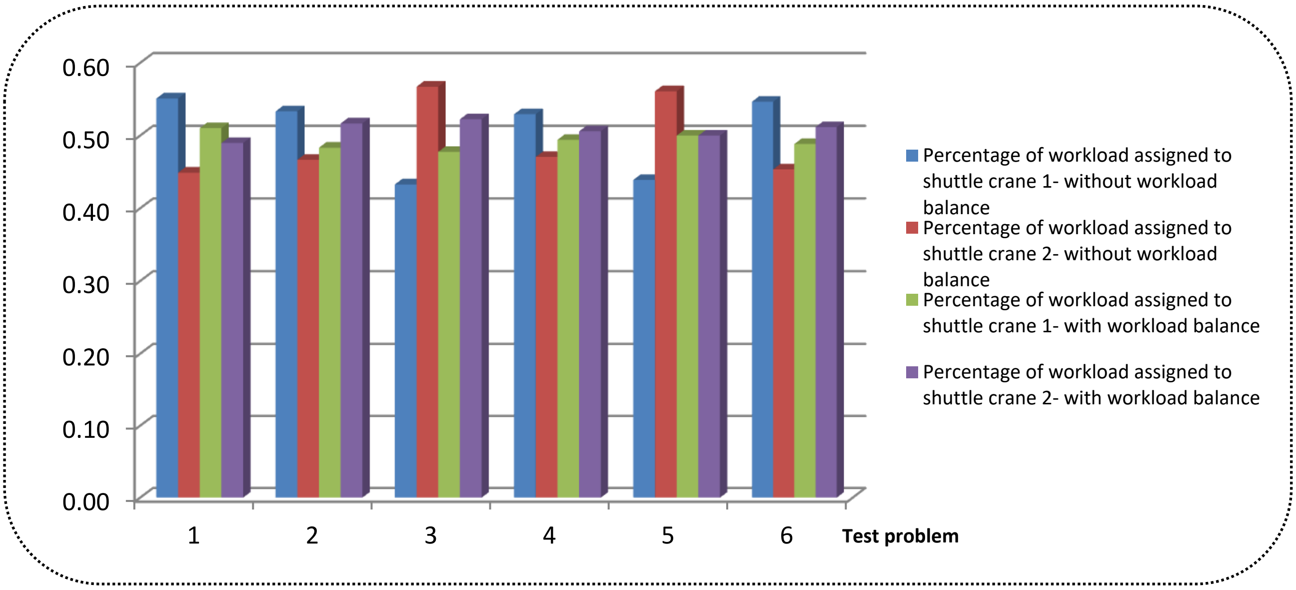

Fig. 4. Impact of work load balance constraints on the percentage of assigned requests to shuttle cranes

VIII. CONCLUSIONS AND FUTURE RESEARCH

In this paper, a bi-level optimization model has been presented to incorporate storage location assignment as the upper-level problem and scheduling of dual shuttle cranes as the lower-level problem in AS/RS. Different decisions in the upper-level by considering various considerations, which are included locations and classes of storing and retrieving items of products under grouping same product items, class-based storage policy, inventory, and multi-period planning, have been determined by a bi-objective optimization model, in which the objective functions minimized the total costs and energy consumption. Similarly, different decisions in the lower-level by working out various considerations, which are included time windows and balance constraints under multi-period planning, have been determined by an optimization model, in which the objective function minimized the makespan of dual shuttle cranes. Since the proposed model is an Np-hard bi-level bi-objective optimization model, a modified nested differential evolution-based algorithm has been introduced to solve the presented model. Then, so as to demonstrate the validation of the offered model and solution methodology, different numerical experiments have been tailored, and comparative instigations amongst presented method, classical repairing algorithm and CoBRA are conducted. The achieved results exposed that the offered solution method has a better accomplishment toward them. Moreover, the performed sensitivity analyses reveal that considered aforementioned constraints have a significant rewarding influence on the planning of system, and the classification has a greater effect than grouping products. Finally, working out the possibility of displacing products among different classes in consecutive periods and considering the investigated problem under uncertainty are a limited number of future directions.

REFERENCES

Azzi, A., Battini, D., Faccio, M., Persona, A., & Sgarbossa, F. (2011). Innovative travel time model for dual-shuttle automated storage/retrieval systems. *Computers & Industrial Engineering*, 61(3), 600–607.

Boysen, N. and Stephan, K., (2016). A survey on single crane scheduling in automated storage/retrieval systems. *European Journal of Operational Research*, 254(3), pp.691-704.

Colson, B., Marcotte, P. and Savard, G., 2007. An overview of bilevel optimization. *Annals of operations research*, 153(1), pp.235-256.

Cunkas, M. and Ozer, O., (2019). Optimization of Location Assignment for Unit-Load AS/RS with a Dual-Shuttle. *International Journal of Intelligent Systems and Applications in Engineering*, 7(2), pp.66-71.

Deb, K. and Goyal, M., (1996). A combined genetic adaptive search (GeneAS) for engineering design. *Computer Science and informatics*, 26, pp.30-45.

Deb, K. and Agrawal, R.B., (1995). Simulated binary crossover for continuous search space. *Complex systems*, 9(2), pp.115-148.

Deb, K., Pratap, A., Agarwal, S. and Meyarivan, T.A.M.T., (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation*, 6(2), pp.182-197.

Expósito-Izquierdo, C., de Armas, J., Lalla-Ruiz, E., Melián-Batista, B. and Moreno-Vega, J.M., (2018). Multi-stage approach for the transshipment of import containers at maritime container terminals. *IET Intelligent Transport Systems*, 13(4), pp.714-728.

Goetschalckx, M. and Ratliff, H.D., (1990). Shared storage policies based on the duration stay of unit loads. *Management Science*, 36(9), pp.1120-1132.

Han, M.H., McGinnis, L.F., Shieh, J.S. and White, J.A., (1987). On sequencing retrievals in an automated storage/retrieval system. *IIE transactions*, 19(1), pp.56-66.

Heskett, J.L., (1963). Cube-Per-Order Index – A key to warehouse stock location. *Transportation and Distribution Management 3*, 27–31.

Islam, M.M., Singh, H.K. and Ray, T., (2016), February. A Nested Differential Evolution Based Algorithm for Solving Multi-objective Bilevel Optimization Problems. *In Australasian Conference on Artificial Life and Computational Intelligence* (pp. 101-112). Springer, Cham.

Jiang, M. and Yang, P., (2017). Retrieval scheduling for end-of-aisle multi-shuttle automated storage and retrieval systems. *In 2017 4th International Conference on Industrial Engineering and Applications* (ICIEA) (pp. 300-304). IEEE.

Legillon, F., Liefooghe, A. and Talbi, E.G., (2012), June. Cobra: A cooperative coevolutionary algorithm for bi-level optimization. *In 2012 IEEE Congress on evolutionary computation* (pp. 1-8). IEEE.

Liu, S.A., Wang, Q. and Sun, J., (2013), May. Integrated optimization of storage allocations in automated storage and retrieval system of bearings. *In 2013 25th IEEE Chinese Control and Decision Conference* (CCDC) (pp. 4267-4271).

Ma, Y. and Wang, J., (2019), July. Travel time analysis for shuttle-based storage and retrieval system with middle input/output location. *In 2019 16th IEEE International Conference on Service Systems and Service Management* (ICSSSM) (pp. 1-6).

Manzini, R., Accorsi, R., Gamberi, M. and Penazzi, S., (2015). Modeling class-based storage assignment over life cycle picking patterns. *International Journal of Production Economics*, 170, pp.790-800.

Mostofi, A. and Erfanian, H., (2018). Multi-Shuttle Automated Storage and Retrieval System. *Review of Industrial Engineering Letters*, 4(1), pp.12-20.

Munkres, J., (1957). Algorithms for the assignment and transportation problems. *Journal of the society for industrial and applied mathematics*, 5(1), pp.32-38.

Muppani, V.R. and Adil, G.K., (2008). A branch and bound algorithm for class based storage location assignment. *European Journal of Operational Research*, 189(2), pp.492-507.

Nia, A.R., Haleh, H. and Saghaei, A., (2017a). Energy-conscious dynamic sequencing method for dual command cycle unit-load multiple-rack automated storage and retrieval systems. *Scientia Iranica. Transaction E, Industrial Engineering*, 24(6), pp.3371-3393.

Nia, A.R., Haleh, H. and Saghaei, A., (2017b). Dual command cycle dynamic sequencing method to consider GHG efficiency in unit-load multiple-rack automated storage and retrieval systems. *Computers & Industrial Engineering*, 111, pp.89-108.

Nguyen, P.H., Kling, W.L., Georgiadis, G., Papatriantafilou, M. and Bertling, L., (2010), October. Distributed routing algorithms to manage power flow in agent-based active distribution network. *In 2010 IEEE PES Innovative Smart Grid Technologies Conference Europe* (ISGT Europe) (pp. 1-7). IEEE.

Oduguwa, V. and Roy, R., (2002), September. Bi-level optimisation using genetic algorithm. *In Proceedings 2002 IEEE International Conference on Artificial Intelligence Systems* (ICAIS 2002) (pp. 322-327). IEEE.

Or, I., (1977). Traveling Salesman Type Combinatorial Problems And Their Relation To The Logistics Of Regional Blood Banking.

Potvin, J.Y. and Bengio, S., (1996). The vehicle routing problem with time windows part II: genetic search. *INFORMS journal on Computing*, 8(2), pp.165-172.

Roodbergen, K.J. and Vis, I.F., (2009). A survey of literature on automated storage and retrieval systems. *European journal of operational research*, 194(2), pp.343-362.

Reyes, J., Solano-Charris, E. and Montoya-Torres, J., (2019). The storage location assignment problem: A literature review. *International Journal of Industrial Engineering Computations*, 10(2), pp.199-224.

Takahama, T. and Sakai, S., (2006), July. Constrained optimization by the ε constrained differential evolution with gradient-based mutation and feasible elites. *In 2006 IEEE International Conference on Evolutionary Computation* (pp. 1-8).

Tappia, E., Roy, D., Melacini, M. and De Koster, R., (2019). Integrated storage-order picking systems: Technology, performance models, and design insights. *European Journal of Operational Research*, 274(3), pp.947-965.

Wang, G.M., Wan, Z. and Wang, X.J., (2007a). Bibliography on bilevel programming. *Advances in Mathematics*, 36(5), pp.513-529.

Wang, D.W., Wang, J.W., Wang, H., Zhang, R. and Guo, Z., (2007b). *Intelligent optimization methods*. China: Higher Education Press.

Wauters, T., Villa, F., Christiaens, J., Alvarez-Valdes, R. and Berghe, G.V., (2016). A decomposition approach to dual shuttle automated storage and retrieval systems. *Computers & Industrial Engineering*, 101, pp.325-337.

Vis, I.F. and Carlo, H.J., (2010). Sequencing two cooperating automated stacking cranes in a container terminal. *Transportation Science*, 44(2), pp.169-182.

Xiang, X., Liu, C. and Miao, L., (2018). Storage assignment and order batching problem in Kiva mobile fulfilment system. *Engineering Optimization*, 50(11), pp.1941-1962.

Xie, J., Mei, Y., Ernst, A.T., Li, X. and Song, A., (2016). A bi-level optimization model for grouping constrained storage location assignment problems. *IEEE transactions on cybernetics*, 48(1), pp.385-398.

Yang, P., Miao, L., Xue, Z. and Qin, L., (2015a). An integrated optimization of location assignment and storage/retrieval scheduling in multi-shuttle automated storage/retrieval systems. *Journal of Intelligent Manufacturing*, 26(6), pp.1145-1159.

Yong11, K.H.J.J.S., (2006). Improving crossover and mutation for adaptive genetic algorithm. *Computer Engineering and Applications*, 12, p.027.

Yang, P., Miao, L., Xue, Z. and Ye, B., (2015b). Variable neighborhood search heuristic for storage location assignment and storage/retrieval scheduling under shared storage in multi-shuttle automated storage/retrieval systems. *Transportation Research Part E: Logistics and Transportation Review*, 79, pp.164-177.

Yang, Y., Zhu, X. and Haghani, A., (2019). Multiple Equipment Integrated Scheduling and Storage Space Allocation in Rail–Water Intermodal Container Terminals Considering Energy Efficiency. *Transportation Research Record*, 2673(3), pp.199-209.

Zhao, X., Wang, Y., Wang, Y. and Huang, K., (2019). Integer Programming Scheduling Model for Tier-to-Tier Shuttle-Based Storage and Retrieval Systems. *Processes*, 7(4), p.223.