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

Hananeh Habibi Tostani¹, Hassan Haleh²*, Seyyed Mohammad Hadji Molana¹, Farzad Movahedi Sobhani¹

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
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:

$$\begin{align*}
\text{Min } & F_1(X_u, X_l), F_2(X_u, X_l), \ldots, F_{M_u}(X_u, X_l), \\
\text{S. t.: } & G_k(X_u, X_l) \leq 0, \quad k = 1, \ldots, q_u, \\
& H_k(X_u, X_l) = 0, \quad k = 1, \ldots, r_u, \\
\text{Min } & f_1(X_u, X_l), f_2(X_u, X_l), \ldots, f_{M_l}(X_u, X_l), \\
\text{S. t.: } & g_k(X_u, X_l) \leq 0, \quad k = 1, \ldots, q_l, \\
& h_k(X_u, X_l) = 0, \quad k = 1, \ldots, r_l,
\end{align*}$$

where $X_u \in X_u, X_l \in X_l$.

In this formation, $F_i(X_u, X_l), i = 1, 2, \ldots, M_u$ and $f_i(X_u, X_l), i = 1, 2, \ldots, M_l$ 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 $X_u$ and $X_l$. 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’s 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 \((p, p' = 1, 2, ..., p)\)

\( I_p \): Set of all items in the product set \((i, i' = 1, 2, ..., \Pi_p)\), where \(p'\) indicates product encompassing item \(i\)

\( T \): Set of periods \((t = 1, 2, ..., \Gamma)\)

\( H \): Set of shelves \((h = 1, 2, ..., \Xi)\)

\( B \): Set of bins on each shelf \((b = 1, 2, ..., \bar{B})\)

\( L \): Set of storage locations which is included the \(b \) th bin on \(h \) th shelf \((l, l' = 1, 2, ..., \bar{H})\)

\( N \): Set of storage classes \((j, j' = 1, 2, ..., \Pi)\), where \(j'\) specifies class encompassing location \(l\)

B. Parameters

\( f_l \): Footprint area of location \(l\)

\( f_{p_l}^{i} \): 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 \( i \)
\( m^t_p \): Number of product \( p \) encompassing item \( i \) arriving at the start of period \( t \)
\( n^t_p \): 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

\textbf{C. Decision Variables}

\( X^t_{ij} \): 1 if item \( i \) is allocated to location \( l \) of class \( j \) in period \( t \); 0 otherwise

\( Y^t_{ij} \): 1 if location \( l \) is allocated to class \( j \) in period \( t \); 0 otherwise

\( u^t_{pj} \): 1 if location \( l \) in class \( j \) is a starting point of product \( p \) in period \( t \); 0 otherwise

\( V^t_{pj} \): Number of arriving product \( p \) that are allocated to class \( j \) in period \( t \)

\( W^t_{pj} \): Number of product \( p \) that are retrieved from class \( j \) in period \( t \)

\textbf{D. Mathematical model:}

\[
\min \ z_1 = SC \sum_{j \in N} \sum_{t \in T} \sum_{i \in L} f_i Y^t_{ij} + \sum_{j \in N} \sum_{p \in P} \sum_{t \in T} \sum_{l \in L} (AST_j V^t_{pj} + ARC_j W^t_{pj})
\]

(1)

\[
\min \ z_2 = \sum_{j \in N} \sum_{p \in P} \sum_{t \in T} (ES_p V^t_{pj} + ER_p W^t_{pj})
\]

(2)

\[\text{s.t.:}\]

\[
\sum_{i \in L} X^t_{ij} = 1 \quad \forall i \in L_p, \forall t \in T, j \in N
\]

(3)

\[
\sum_{l \in L_j} X^t_{ij} = 1 \quad \forall l \in L, \forall t \in T, j \in N
\]

(4)
\[ \sum_{j \in N} Y_{ij}^t \leq 1 \quad \forall l \in L, \forall t \in T \]  

\[ 2 \cdot U_{pj}^t \leq \sum_{i \in l_p} \sum_{t \in T} X_{ij}^t \quad \forall i \in l_p, \forall p \in P, \forall t \in T, \forall j \in N, \forall l \in L \]  

\[ \sum_{i \in l_p} \sum_{j \in N} \sum_{t \in T} V_{pj}^t \cdot X_{ij}^t = \sum_{i \in l_p} m_{pj}^t \quad \forall p \in P, \forall t \in T \]  

\[ \sum_{i \in l_p} \sum_{j \in N} \sum_{t \in T} W_{pj}^t \cdot X_{ij}^t = \sum_{i \in l_p} n_{pj}^t \quad \forall p \in P, \forall t \in T \]  

\[ V_{pj}^t \leq M \cdot X_{ij}^t \quad \forall i \in l_p, \forall p \in P, \forall t \in T, \forall j \in N, \forall l \in L \]  

\[ W_{pj}^t \leq M \cdot X_{ij}^t \quad \forall i \in l_p, \forall p \in P, \forall t \in T, \forall j \in N, \forall l \in L \]  

\[ \sum_{i \in l_p} U_{pj}^t \leq 2 \quad \forall p \in P, \forall t \in T, \forall j \in N \]  

\[ X_{ij(h,b),t}^t \leq U_{pj(h,b),t}^t + \sum_{i' \in l_p, i \neq i'} X_{ij(h,b),t}^t \quad \forall i \in l_p, (h, b) \in L, \forall j \in N, \forall t \in T \]  

\[ U_{pj}^t \leq \sum_{i \in l_p} X_{ij}^t \quad \forall p \in P, \forall t \in T, \forall j \in N, \forall l \in L \]  

\[ \sum_{i \in l_p} \sum_{p \in P} \sum_{t \in T} m_{pj}^t f_{pj}^t \cdot X_{ij}^t \leq \sum_{i \in l_p} f_{pj}^t Y_{ij}^t \quad \forall j \in N, \forall t \in T \]  

\[ COI_i X_{ij}^t \leq COI_{i'} X_{ij}^{t'} \quad \forall i \neq i', \forall j < j', \forall l \neq l', \forall t \in T \]  

\[ l \cdot Y_{ij}^t \leq l' \cdot Y_{ij}^{t'} \quad \forall l \neq l', \forall j < j', \forall t \in T \]  

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

\[ \sum_{t \in T} \sum_{i \in l_p} n_{pj}^t \leq \sum_{j \in N} Z_{pj}^t + \sum_{t \in T} \sum_{i \in l_p} m_{pj}^t \quad \forall p \in P, \forall t \in T \]  

\[ \sum_{j \in N} (Z_{pj}^t + V_{pj}^t) \leq CAP_j \quad \forall j \in N, \forall t \in T \]
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 locations, there are $2 \times 2$ handling requests to be handled by the two shuttle cranes. The $2 \times 2$ requests are indexed such that requests of locations $2l - 1$ and $2l$ ($l = 1, 2, \ldots, 2 \times 2$) signify the retrieval and storage requests of location $l$, respectively. Henceforth, request $r$ ($r = 1, 2, \ldots, 2 \times 2$) of location $l$ is one of the two handling requests in location $[r/2]$. A dummy storage (retrieval) request of zero handling time is surcharged to locations with a retrieval (storage) request only.

A. Sets and indices

$S$: Set of shuttle cranes ($s = 1, 2$)

$R$: Set of requests ($r, r' = 1, 2, \ldots, 2 \times 2$)

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

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

$TW_s$: Set of time windows for shuttle crane $s$ ($e = 1, 2, \ldots, TW$)
**B. Parameters**

\( p_r \): Required time for shuttle crane to handle request \( r \)

\( \mathcal{G} \): Maximum unbalance level of workload allocation where \( 0 < \mathcal{G} < 1 \).

**C. Decision variables**

\( Q_{rs}^{te} \): 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:**

\[
\text{min } z_3
\]

s.t.:

\[
z_3 \geq \sum_{e \in \text{TW}_s} \sum_{t \in \mathcal{T}} t D_{rs}^{te} \quad \forall r \in R, \forall s \in S
\]  
(23)

\[
\sum_{s \in S} \sum_{t \in \mathcal{T}} \sum_{e \in \text{TW}_s} t D_{rs}^{te} \geq p_r \quad \forall r \in R
\]  
(24)

\[
\sum_{s \in S} \sum_{t \in \mathcal{T}} \sum_{e \in \text{TW}_s} D_{rs}^{te} = 1 \quad \forall r \in R
\]  
(25)

\[
\sum_{r' = 0}^{Pr} \sum_{e \in \text{TW}_s} O_{sl[r'/2]}^{t-r'Ve} - p_r - 1 \geq M \left( \sum_{e \in \text{TW}_s} D_{rs}^{te} - 1 \right) \quad \forall s \in S, \forall r \in R, \forall t = p_r, p_r + 1, \ldots, T
\]  
(26)

\[
\sum_{e \in \text{TW}_s} O_{sl}^{t-1,e} \leq \sum_{e \in \text{TW}_s} \sum_{r' \in \mathcal{E}(l)} O_{sl}^{t-1,e} \quad \forall s \in S, \forall l = 1, \ldots, \mathcal{H}, \forall t = 1, 2, \ldots, T
\]  
(27)

\[
\sum_{e \in \text{TW}_s} O_{sl}^{t-1,e} \leq \sum_{e \in \text{TW}_s} \sum_{r' \in \mathcal{E}(l)} O_{sl}^{t+1,e} \quad \forall s \in S, \forall l = 1, \ldots, \mathcal{H}, \forall t = 0, 1, 2, \ldots, T - 1
\]  
(28)

\[
\sum_{r' \in E} \sum_{e \in \text{TW}_s} O_{sl}^{t-1,e} \leq M \left( 1 - \sum_{e \in \text{TW}_s} O_{sl}^{t,e} \right) \quad \forall s = 2, \forall l = 1, \ldots, \mathcal{H}, \forall t \in T
\]  
(29)
∑_{i=1}^{N_B} \sum_{e \in TW_s} O_{st}^{le} = 1 \, \forall s \in S, \forall t \in T \tag{30}

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

\sum_{t \in T} \sum_{e \in TW_s} (D_{rs}^{te} + D_{rs}^{te}) - 1 \leq Q_{rr'}^{se} + Q_{rr'}^{se} \, \forall r, r' = 1, 2, ..., \#R, r \neq r', \forall s \in S \tag{32}

\sum_{r \in R} \sum_{r' \in R \setminus r} \sum_{e \in TW_s} Q_{rr'}^{se} \leq (1 + \varepsilon) \frac{2\#R}{2} \, \forall s \in S \tag{33}

\sum_{r \in R} \sum_{r' \in R \setminus r} \sum_{e \in TW_s} Q_{rr'}^{se} \geq (1 - \varepsilon) \frac{2\#R}{2} \, \forall s \in S \tag{34}

Q_{rr}, O_{st}^{le}, 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 \( r_{mut} \in [-0.5,0.5] \) with a \( p_{mut} \) 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.

\[
P_c = \begin{cases} 
  p_{c2} = \frac{(p_{c2}-p_{c3})(F' - F_{avg})}{F_{max} - F_{avg}} & F' \geq F_{avg} \\
  p_{c1} = \frac{(p_{c1}-p_{c2})(F' - F_{min})}{F_{avg} - F_{min}} & F' < F_{avg}
\end{cases}
\]

\[
P_m = \begin{cases} 
  p_{m2} = \frac{(p_{m2}-p_{m3})(F' - F_{avg})}{F_{max} - F_{avg}} & F' \geq F_{avg} \\
  p_{m1} = \frac{(p_{m1}-p_{m2})(F' - F_{min})}{F_{avg} - F_{min}} & F' < F_{avg}
\end{cases}
\]

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 \( (X_u,X_i) \), 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>
<thead>
<tr>
<th>Model parameters</th>
<th>Values</th>
<th>Model parameters</th>
<th>Values</th>
<th>Metaheuristic parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f_i )</td>
<td>48 \times 60 \text{ square ft.}</td>
<td>( m_p^i,n_p^i )</td>
<td>\sim \text{uniform (1,4)}</td>
<td>( N_u )</td>
<td>200</td>
</tr>
<tr>
<td>( f_p^i )</td>
<td>1 \times 1 \text{ square ft.}</td>
<td>( ES_p, ER_p )</td>
<td>\sim \text{uniform (15,30)}</td>
<td>( N_l )</td>
<td>200</td>
</tr>
<tr>
<td>( SC )</td>
<td>1.5 \text{ per square ft.}</td>
<td>( p_r )</td>
<td>\sim \text{uniform (5,7)}</td>
<td>( Gen_{max_u} )</td>
<td>50</td>
</tr>
<tr>
<td>( CAP_j )</td>
<td>\sim \text{uniform (10,20)}</td>
<td>( G )</td>
<td>\sim \text{uniform (0,1)}</td>
<td>( Gen_{max_l} )</td>
<td>50</td>
</tr>
<tr>
<td>( AST_j )</td>
<td>\sim \text{uniform (5,7)}</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( ARC_j )</td>
<td>\sim \text{uniform (3,5)}</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table II. Product classes formed

<table>
<thead>
<tr>
<th>Class number</th>
<th>Product and related items Assigned</th>
<th>Locations Assigned</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( P_5(i = 1,2,3), P_1(i = 1,2), )</td>
<td>( P_5(l_{15}, l_{16}, l_{17}), P_1(l_{15}, l_{16}), )</td>
</tr>
<tr>
<td></td>
<td>( P_{10}(i = 1,2,3), P_5(i = 1,2), P_{14}(i = 1,2), )</td>
<td>( P_{10}(l_{15}, l_{16}, l_{17}) , P_5(l_{15}, l_{16}), P_{14}(l_{15}, l_{16}) )</td>
</tr>
<tr>
<td>2</td>
<td>( P_6(i = 1,2,3), P_6(i = 1,2,3), )</td>
<td>( P_6(l_{15}, l_{16}, l_{17}) , P_6(l_{15}, l_{16}), P_6(l_{15}, l_{16}) )</td>
</tr>
<tr>
<td></td>
<td>( P_5(i = 1,2,3), P_{14}(i = 1,2,3), )</td>
<td>( P_5(l_{15}, l_{16}, l_{17}) , P_{14}(l_{15}, l_{16}) )</td>
</tr>
<tr>
<td>3</td>
<td>( P_7(i = 1,2), P_9(i = 1,2), P_{12}(i = 1,2,3), )</td>
<td>( P_7(l_{26}, l_{27}), P_9(l_{24}, l_{25}), P_{12}(l_{31}, l_{32}, l_{33}) )</td>
</tr>
<tr>
<td>4</td>
<td>( P_{15}(i = 1,2,3), P_4(i = 1,2,3,4), )</td>
<td>( P_{15}(l_{38}, l_{39}, l_{40}), P_4(l_{34}, l_{35}, l_{36}, l_{37}) )</td>
</tr>
<tr>
<td></td>
<td>( P_{13}(i = 1,2) )</td>
<td>( P_{13}(l_{26}, l_{27}) )</td>
</tr>
</tbody>
</table>

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

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

Table IV. The best result from MDBMA

<table>
<thead>
<tr>
<th>The sequence of shuttle crane 1</th>
<th>The sequence of shuttle crane 2</th>
<th>Makespan</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>3</td>
<td>514</td>
</tr>
<tr>
<td>40</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>26</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>31</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>27</td>
<td></td>
</tr>
<tr>
<td>36</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td>37</td>
<td>28</td>
<td></td>
</tr>
</tbody>
</table>
Continue Table IV. The best result from MDBMA

<table>
<thead>
<tr>
<th>The sequence of shuttle crane 1</th>
<th>The sequence of shuttle crane 2</th>
<th>Makespan</th>
</tr>
</thead>
<tbody>
<tr>
<td>19</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>23</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>24</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>34</td>
<td></td>
</tr>
<tr>
<td>39</td>
<td>14</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>33</td>
<td></td>
</tr>
<tr>
<td>29</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>35</td>
<td>22</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>38</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>$FT^2$</td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>$FT^1$</td>
<td></td>
</tr>
<tr>
<td>514</td>
<td>484</td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Inst.</th>
<th>Upper-level fitness</th>
<th>Lower-level fitness</th>
<th>Lower-level fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Repair</td>
<td>CoBRA</td>
<td>MDBMA</td>
</tr>
<tr>
<td>1</td>
<td>1042</td>
<td>1475</td>
<td>1080</td>
</tr>
<tr>
<td>2</td>
<td>1061</td>
<td>1238</td>
<td>1137</td>
</tr>
<tr>
<td>3</td>
<td>1286</td>
<td>1085</td>
<td>991</td>
</tr>
<tr>
<td>4</td>
<td>1205</td>
<td>1260</td>
<td>1192</td>
</tr>
<tr>
<td>5</td>
<td>1173</td>
<td>1085</td>
<td>1034</td>
</tr>
<tr>
<td>6</td>
<td>1132</td>
<td>1100</td>
<td>1025</td>
</tr>
<tr>
<td>7</td>
<td>1228</td>
<td>1227</td>
<td>1153</td>
</tr>
<tr>
<td>8</td>
<td>1248</td>
<td>1154</td>
<td>1206</td>
</tr>
<tr>
<td>9</td>
<td>1152</td>
<td>1133</td>
<td>1105</td>
</tr>
<tr>
<td>10</td>
<td>1106</td>
<td>1090</td>
<td>1237</td>
</tr>
<tr>
<td>11</td>
<td>1186</td>
<td>1074</td>
<td>985</td>
</tr>
<tr>
<td>12</td>
<td>1207</td>
<td>1072</td>
<td>1002</td>
</tr>
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<td>13</td>
<td>1192</td>
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<td>1241</td>
</tr>
<tr>
<td>14</td>
<td>1138</td>
<td>1173</td>
<td>1043</td>
</tr>
<tr>
<td>15</td>
<td>1037</td>
<td>1153</td>
<td>1121</td>
</tr>
<tr>
<td>16</td>
<td>1229</td>
<td>1038</td>
<td>1110</td>
</tr>
<tr>
<td>17</td>
<td>1147</td>
<td>1133</td>
<td>1018</td>
</tr>
<tr>
<td>18</td>
<td>1232</td>
<td>1072</td>
<td>1195</td>
</tr>
<tr>
<td>19</td>
<td>1087</td>
<td>1040</td>
<td>966</td>
</tr>
<tr>
<td>20</td>
<td>1304</td>
<td>1223</td>
<td>1126</td>
</tr>
<tr>
<td>Average</td>
<td>1169.6</td>
<td>1150.45</td>
<td>1098.35</td>
</tr>
</tbody>
</table>
Table VI. The ANOVA results of experiment 1 for upper-level fitness

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F-value</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor (Repair, CoBRA, MDBMA)</td>
<td>2</td>
<td>54385</td>
<td>27192</td>
<td>3.42</td>
<td>0.040</td>
</tr>
<tr>
<td>Error</td>
<td>57</td>
<td>453694</td>
<td>7960</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>59</td>
<td>508079</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F-value</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor (Repair, CoBRA, MDBMA)</td>
<td>2</td>
<td>10812.7</td>
<td>5406.3</td>
<td>77.51</td>
<td>0.00</td>
</tr>
<tr>
<td>Error</td>
<td>57</td>
<td>3975.8</td>
<td>69.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>59</td>
<td>14788.5</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F-value</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor (Repair, CoBRA, MDBMA)</td>
<td>2</td>
<td>264286</td>
<td>1321431</td>
<td>44.93</td>
<td>0.00</td>
</tr>
<tr>
<td>Error</td>
<td>57</td>
<td>167656</td>
<td>29413</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>59</td>
<td>4319429</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Inst.</th>
<th>Upper-level fitness</th>
<th>Lower-level fitness Direct rationality</th>
<th>Lower-level fitness Weighted rationality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Repair</td>
<td>CoBRA</td>
<td>MDBMA</td>
</tr>
<tr>
<td>1</td>
<td>2623</td>
<td>2318</td>
<td>2347</td>
</tr>
<tr>
<td>2</td>
<td>2659</td>
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Continue Table IX. Results for each of the 20 instances of experiment 2 (30 products)

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<th>Lower-level fitness</th>
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Table X. The ANOVA results of experiment 2 for upper-level fitness

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

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

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<th>P-value</th>
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Table XIII. Results for each of the 20 instances of experiment 3 (50 products)

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<th>Lower-level fitness</th>
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Continue Table XIII. Results for each of the 20 instances of experiment 3 (50 products)

<table>
<thead>
<tr>
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<th>Lower-level fitness</th>
<th>Lower-level fitness</th>
</tr>
</thead>
<tbody>
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<td></td>
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<td>Weighted rationality</td>
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Table XIV. The ANOVA results of experiment 3 for upper-level fitness

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

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

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<tbody>
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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
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

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


