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Storage assignment in the steel manufacturing industry: Mathematical modeling and a priority-based heuristic approach

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Abstract – This paper presents a multi-criteria storage assignment model for the manufacturing system of the steel industry. The manufacturing system involves several plants, dozen of the production line, and thousands of different products. The products have to be routed and stored in various stages till it is dispatched to the end customer. Due to the size and weight of produced items, material handling is a costly operation. The handling cost is related to the number of handling, product storage time, and meeting the due date. This paper presents several storage assignment algorithms to reduce material handling costs. We have tested our algorithms with the data provided by a large steel company in Europe. The results indicate that considering product features in the storage assignment offers better performance on handling, storage time, and meeting the due date.

Keywords*:* Storage assignment; multi-criteria decision-making; priority-based heuristic

1. Introduction

The steel industry has a large and complicated manufacturing process. The manufacturing site generally consists of dozens of production facilities disperse in a large area (Chen et al. 2012). In between, several warehouses are used as intermediate or final storage of produced goods. In this system handling large products is a time-consuming and costly task (Bartholdi III and Gue 2000). A typical steel product can weigh up to 33 tons. Each item has a specific handling requirement, which has to be done separately.

In existing literature, studies in storage assignment mostly focus on determining the optimal storage for small products (see, for example, Macro and Salmi (2002), Gagliardi et al (2007), Muppani and Adil (2008), and Chan and Chan (2011)) disregarding handling issues related to the large items. The storage assignment for steel products has three distinctive characteristics that differentiate it from traditional storage assignment problems. First, there should be a match between the assigned location and the product. Each location has specific storage conditions, and each product has some storage requirements. Second, it should consider the trade-off between the estimated storage time and remaining capacity. Third, relocating products to the loading bay is time-consuming, which delays the order fulfillment process.

To overcome the challenges mentioned above, we present a priority-based heuristic to tackle the storage assignment problem. Steel manufacturing companies produce a variety of steel products which complicate the assignment problem (Sethi et al. 2002). To simplify the problem, we apply the ABS inventory classification to reduce the number of products stored in the system. We then propose a class of priority-based heuristic assignment algorithms. We test our algorithm on the studied case provided by our industrial partner to show its performance. Finally, examine the system performance when disruption occurs in the production facilities of the steel manufacturer.

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The remainder of the paper is organized as follows. Section 2 presents the literature review, and Section 3 describes the problem. Section 4 discusses the mathematical formulation, after which the priority-based heuristic approach follows in Section 5. Section 6 shows the computational results of the studies, which is finally followed by a conclusion in Section 7.

2. Literature Review

In this section, we first review the existing literature considering the storage assignment problem. Here the main focus is on the assignment of products to a specific location. Here the main focus is on finding the proper place to store products that the material handling does not consider. This problem is mainly studied in cross-docking terminals. The related literature for material handling is reviewed in Section 2.2.

2.1. Storage Assignment

Storage assignment policies provide an efficient way of locating products in a warehouse to improve space utilization. According to Van Den Berg (1999) and Rouwenhorst et al. (2000), the efficiency of warehouse operations is highly dependent on the storage allocation. Important factors affecting the efficiency of storage assignment are the demand pattern of each item, the product characteristics, the size of the warehouse, and the material handling system (Petersen 1999, Chan and Chan 2011). In literature, the storage assignment is fairly limited to small products within a single warehouse. This is not the case for steel products, as they can be stored in multiple warehouses. In addition, double-handling for the large product is costly and time-consuming that has to be avoided.

In literature, there exist various storage allocation policies. Among them, we are interested in a random assignment, closest open location, and class-based storage. Interested readers are referred to (Ang et al 2012) for other types of assignments. In the random assignment, the products are assigned to the possible warehouses with equal probability (De Koster et al 2007). Ong and Joseph (2014) stated that random storage maximizes the utilization of storage space; although, it generates unnecessary travel distances (Pan et al 2012). Previous research focuses on the allocation within a single warehouse. The random allocation is not desirable as there exist several pickup and drop-off points. The network in this system will ensure the deterioration of this policy, and consequently, the inventory levels will be irrelevant high. Also, the research of Chan and Chan (2011) concludes that the performance of the random assignment is dependent on the system features. Two other policies are the closest open location from the origin (CO) or destination (CD). The closest open location policy assign products from the origin to the closest empty location. This policy results in full places around the depot and a gradually less dense area further away (De Kosteret al. 2007). The closest open location is, to a lower extent, analyzed in current literature. De Koster et al. (2007) argue that the random storage and closest open location storage have a similar performance. In our studied problem, the warehouses are scattered, and each product is assigned a specific inbound and outbound location, which are not dependent on the distances. As a result, the CO and CD policy cannot be adapted to the characteristics of the studied system. Furthermore, our interest is to reduce the double handling rather than the travel distance. Here, we should note that CD does deviate from the concept of this policy in literature. The first empty location is checked when products arrive from the supplier side instead of the demand side.

Another policy applied in previous research is the class-based storage (Petersen et al. 2004, Choy et al. 2013, Fontana and Nepomuceno 2017). Each class of SKU type is assigned to a dedicated location (De Koster et al. 2007). Research of Jaikumar and Solomon (1990) has shown that class-based policies result in better performance over random policies. In addition, according to the study by Mirabelli et al. (2015) that aims to reduce the handling costs, all class-based cases have a better performance than the current practice. Traditionally, a warehouse is divided into a couple of areas corresponding to the classes (Li et al. 2016), though here the areas are covered over multiple warehouses, which might result in a different performance of the class-based assignment in this system.

Even though the aforementioned storage assignment policies mostly have some pitfalls in this problem, it is still interesting to test the performance of this specific system when implementing these rules. This paper goes beyond the existing literature as it also develops product-oriented policies. The characteristics of the system and the various goods should be explicitly considered in the storage assignment in the steel industry.

2.2. Cross-Docking

Scheduling problems in cross-dock facilities aim to reduce the handling cost. In the cross-dock terminal, products are going from inbound to outbound doors with a possibility of temporary storage between (Maknoon et al. 2016). Two types of decisions are determined simultaneously: 1) the product assignments to the trucks and 2) the docking sequences of the inbound and outbound trucks. In most of the scheduling problems at the cross-dock facility, it is assumed that the content of arriving and departing trucks is known. The scheduling model then determines how to load and unload trucks to minimize the material handling cost. The handling cost is either expressed as minimizing the makespan, see for example Yu and Egbelu (2008), or minimizing the double-handling Maknoon et al. (2014), Maknoon et al. (2016), and Maknoon et al. (2017). Interested readers are referred to Van Belle et al. (2012) for an overview of the scheduling models. Similar to the studies in cross-dock scheduling, we are interested in minimizing the handling cost. In contrast, in cross-dock scheduling problems, most of the time, it is assumed that the terminal is incapacitated, and there is no restriction on storing products. This is not the case in our studied problem.

3. Problem Description

We consider a production-distribution system with m production facilities and n warehouses (see Figure 1). In this figure, there are 2 plants ($m = 2$) and 3 warehouses ($n = 3$). The inbound consists of the production. The outbound is formed by end warehouses. Each product i is dedicated to a specific outbound, which means that the good has to be loaded from this warehouse. At the outbound, it is already fixed where the various transportation modes will be loaded due to logistic requirements and load sizes (e.g., loading and unloading facilities, infrastructure). Every product starts at the inbound and ends at the dedicated outbound warehouse. Therefore, at production it is known where the product has to be loaded; there is no influence on scheduling at the outbound.

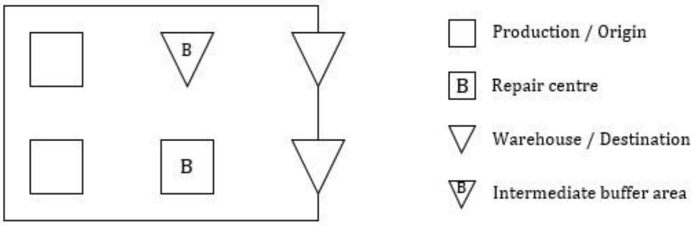

Figure 1. Schematic representation of the production-distribution system.

Between the inbound and outbound, there is a staging area. Furthermore, sometimes the goods need to be repaired after production, which occurs in k repair centers ($k = 1$ in Figure 1). When products need a service, it has a fixed route from the inbound to the repair center. If products do not need a service, it has an assignment decision: either directly to its respective outbound or to a staging area in any warehouse other than its corresponding outbound location. Hence, outbound warehouses can function as buffer areas for products dedicated to another outbound location. In case the product is assigned to a repair center or a staging area, it is later allocated to its outbound warehouse when there is a release by a demand request for this product.

Every plant can produce all the product types. The plants have their specific storage areas inside where the products are directly allocated to the manufacturing line. The production goods have a daily fixed interarrival time dependent on the total number of products produced each day. We assume that there is enough inventory to meet the demand and that inventories are not negative. The factories operate continuously which leads to high stock levels. Disruptions can occur where (part of) the production is temporary down.

We present each warehouse with $W = \{y, g, V, l\}$ where y and g denote the layout features of the warehouse that specify the storage conditions, i.e., what type of product can be stored in the corresponding storage location. Each warehouse has capacity limitations due to the high stock levels; the inventory often approaches or exceeds the capacity V. The set $l \in L$ denotes the location in the production-distribution network (inbound, outbound, or in-between). Some warehouses are far away from another facility, and some of the storage locations are close by. Each product movement requires (un)loading by a crane. If the warehouses are adjacent, the distances are rather short, and a forklift truck is used for the movement. However, the distances are larger if the facilities are further away, and in this case, train movements are required.

There are no pickup decisions in this problem. When there is a demand request, a product needs to be picked from one of the warehouses, which occurs in the same approach. An order list of warehouses is retrieved that is fixed per outbound location. Similarly, to the product's arrival, the demand has a daily fixed interarrival time dependent on the total number of demand requests per day. First, the outbound warehouse is checked, second the warehouse of the main inbound location, then the repair center, and afterward the other staging areas in consecutive order related to the outbound (based on capacity and distance). To formalize the product movements across these facilities with a unit, we define a unit of effort. This unit of effort incorporates the crane handling, the forklift truck, and the train with the following categories:

Two: one movement between two adjacent warehouses, i.e., directly to outbound. Products are transferred using the crane and forklift truck.

Four: one movement between two warehouses with larger distance, also directly to outbound. Products are handled using the crane and moved by train.

Six: two movements, i.e., the product is first assigned to a staging warehouse before heading to the outbound location. One movement is between two adjacent warehouses by a forklift truck, and the other has higher distances that need a train to carry out the transfer.

Eight: two movements, through a staging location to outbound. Both displacements are between facilities located further away; hence, trains are necessary.

Ten: three movements, through a staging location and repair center to outbound. Two movements are between facilities located further away; hence, trains are necessary, and the third displacement is with an adjacent facility.

We present each product with $I = \{o, d, s, y, g, a, e, c\}$. Every product is assigned an inbound $o \in O$, an outbound $d \in D$, and if it needs a service $s \in S$. The storage conditions, y and g determine which warehouses can store this particular good. To distinguish the enormous amount of different goods produced in this manufacturing environment, two characteristics are relevant. First of all, each product is categorized into a Stock Keeping Unit (SKU) type based on a combination of the ABC inventory classes $a \in A$ and the annual demand pattern $e \in E$. Secondly, every product has a color $c \in C$ where the color category denotes the due date. The due date represents the latest departure time of the product through a demand request. Each demand request matches the product on the outbound and SKU types (Q^{aed}).

Applying the ABC classification is that the range of different SKUs is too large to implement specific inventory control methods for each SKU. Hence, the reduction in the number of SKU types will make the inventory more controllable. The traditional ABC method is performed on the storage assignment decisions with three classes based on the annual consumption. After forming the classes, the service level per class needs to be decided on. This paper aims for a higher service level for class A than the other classes, which means that class A items should mostly be allocated to its outbound location. In contrast, class C will be allocated to staging areas.

The decision to be made is the storage allocation of products to the warehouses to prevent multiple re-assignments. This storage assignment model aims to minimize the unit of effort. It considers explicitly which product to send directly to its respective outbound or to a staging warehouse resulting in additional effort. There are two more objectives to measure the performance of the production-distribution system. The second performance indicator to be minimized is the storage time. The third measure is maximizing the immediate release. If there is a demand request, we have an immediate release where the product is often already at the outbound such that it can be directly loaded. On the contrary, a late release means that the product cannot be directly loaded, and it takes more time, which is regularly the case if the good is assigned to a staging warehouse. Note that the product is loaded from one of the warehouses according to the pickup retrieval list. There is a trade-off between these three measures.

A minimum unit of effort is not necessarily the same solution as the minimum late release. There may be another better solution; even though both are in the same direction, it is not necessarily optimal.

Example: To illustrate the production-distribution system, we consider a network with 2 plants ($m = 2$), 3 warehouses ($n = 3$), and no repair center ($k = 0$). The production facilities form the inbound, one warehouse is only a buffer area, and two warehouses are the outbound. Each movement between two facilities requires 4 unit of effort, except between O_1 and D_1 where the effort is only 2. Table 1 shows the example data. There are in total 6 items produced. As the table depicts, 4 goods are produced in O_1 out of which 3 are dedicated to D_1, and 1 product to D_2. The demand arrives at day 5 where both outbound locations request 3 products. Hence, the production is equal to the demand. The capacity V of the warehouses is low.

Table 1. Example data.

	O_1	O_2	D_1	D_2	B
Total	4	2	3	3	0
D_1	3	0	-	-	-
D_2	1	2	-	-	-
V	-	-	4	2	1

These products need to be moved to their corresponding outbound locations. Numerous possibilities exist to send these products. Table 2 merely present three solutions with the considered routes and the performance on the objectives. If we send the product for D_2 first to D_1 (solution 1), we have the lowest unit of effort compared to the other two solutions where the buffer warehouse is required. However, using another outbound as a staging area has a lower performance on the other two measures due to the sequence of the pickup list. Even though the outcome on immediate release is the same for solutions 2 and 3, solution 3 performs better on the storage days. Fewer routes are used, and as a consequence, it takes less time to collect the products. Note that the storage conditions, SKU type, and various due dates are not applied in this simple example, which would make the assignment more complicated.

Table 2. Possible solutions.

	Solution 1	**Solution 2**	**Solution 3**
Routes	$3\ O_1 \rightarrow D_1$ $1\ O_1 \rightarrow D_1 \rightarrow D_2$ $2\ O_2 \rightarrow D_2$	$3\ O_1 \rightarrow D_1$ $1\ O_1 \rightarrow D_2$ $1\ O_2 \rightarrow B \rightarrow D_2$ $1\ O_2 \rightarrow D_2$	$3\ O_1 \rightarrow D_1$ $1\ O_1 \rightarrow B \rightarrow D_2$ $2\ O_2 \rightarrow D_2$
KPI 1: unit of effort	20	22	22
KPI 2: avg storage days	6	5.5	5
KPI 3: immediate release	5/6	5.5/6	5.5/6

4. Mathematical Formulation

In this section, we propose a mathematical model of the storage assignment problem. The number of products generated between $t-1$ and t is denoted by P_t, in which the time slice is one day. Thus, we have enough flexibility to optimize the model per day. The number of arriving products follows a Poisson distribution with λ_t where the arrival rate can be different among time slices. Therefore, the interarrival time at a time step IAT_t is exponentially distributed with $IAT_t = \frac{1}{\lambda_t}$.

For each inbound $o \in O$ and outbound $d \in D$, all the possible routes are enumerated that is represented by R^{od}. If the product needs a service s, or the storage conditions y and g are incorporated, there are fewer possible routes. Binary variable $X_i^{aecR^{od}}$ denotes the assignment decision of product i dependent on its attributes. The pick-up or release of a product is shown with the binary variable Z_i^{aer}. The variable B^w denotes the inventory of each warehouse $w \in W$. To measure the KPI's, three parameters are defined: U^r the unit of effort of route r, ST_i the storage time of product i, and LR_i the late release of product i. The notations are summarised in Table 3. Based on this, the problem can be formulated as follows:

Table 3. Summary of notations.

Sets	
w	Set of warehouses $w \in W$
o	Set of inbound locations $o \in O$
d	Set of outbound locations $d \in D$
s	Set of service centers $s \in S$
l	Set of location in network $l \in L$
a	Set of ABC classes $a \in A$
e	Set of demand patterns $e \in E$
c	Set of colors $c \in C$
r	Enumeration of all possible routes $r \in R^{od}$ that starts from $o \in O$ and ends at $d \in D$
Indices	
i	Products
t	Time periods
Parameters	
P_t	Generated number of products between t and $t-1$
λ_t	Arrival rate of products
IAT_t	Interarrival time of products

y	If requirement of dry storage
g	If requirement of rest time
V^w	Capacity of warehouse $w \in W$
Q^{aed}	Demand requests for ABC class $a \in A$, demand pattern $e \in E$ and outbound location $d \in D$
U^r	Unit of effort of route r
ST_i	Storage time of product i
LR_i	Late release of product i
F_i	Spare time of delivery of product i
OL_{odaec}	Order list per combination of attribute values
Variables	
$X_i^{aecR^{od}}$	binary variable, 1 for assignment decision of product i dependent on its attributes, 0 otherwise
Z_i^{aer}	binary variable, 1 for pick-up of product i dependent on its attributes, 0 otherwise
B^w	Inventory of warehouse $w \in W$

$$min \sum_{i \in I} \sum_{t \in T} \left(\sum_{a \in A} \sum_{e \in E} \sum_{c \in C} \sum_{r \in R^{od}} \sum_{o \in O} \sum_{d \in D} U^r X_{it}^{aecR^{od}} + ST_{it} + LR_{it} \right) \quad (1)$$

s.t.

$$P_t = \lambda_t = \int_{t-1}^{t} I(t)\ dt \qquad t \in T \quad (2)$$

$$B_{t+1}^w = B_t^w + \sum_{i \in I} X_{it}^{aecR^{od}} - \sum_{i \in I} Z_{it}^{aer}, \qquad w \in W, t \in T, a \in A, e \in E, c \in C, r \in R^{od} \quad (3)$$

$$B_t^w \le V^w, \qquad w \in W, t \in T \quad (4)$$

$$\sum_{i \in I} X_{it}^{aecR^{od}} = P_t, \quad t \in T, a \in A, e \in E, c \in C, r \in R^{od} \quad (5)$$

$$\sum_{i \in I} Z_{it}^{aer} = Q_t^{aed}, \quad t \in T, a \in A, e \in E, r \in R^{od}, d \in D \quad (6)$$

$$Z_{it}^{aer} \le X_{it}^{aecR^{od}}, \quad i \in I, t \in T, a \in A, e \in E, c \in C, r \in R^{od} \quad (7)$$

$$tZ_{it}^{aer} - tX_{it}^{aecR^{od}} \le ST_{it}, \quad i \in I, t \in T, a \in A, e \in E, c \in C, r \in R^{od} \quad (8)$$

$$c_i - ST_{it} = \begin{cases} f_i, LR_{it} = 0, \\ -f_i, LR_{it} = 1, \end{cases} \quad i \in I, t \in T \quad (9)$$

$$X_{it}^{aecR^{od}} \in \{0,1\}, \quad i \in I, t \in T, a \in A, e \in E, c \in C, r \in R^{od} \quad (10)$$

$$Z_{it}^{aer} \in \{0,1\}, \quad i \in I, t \in T, a \in A, e \in E, r \in R^{od} \quad (11)$$

$$B_t^w \ge 0, \quad w \in W, t \in T \quad (12)$$

The objective function (1) minimizes the unit of effort, the storage time, and the number of late releases. Constraints (2) generate the number of products between two time periods. Constraints (3) track the inventory at the warehouses, and constraints (4) respect the capacity. Equality (5) ensures that the number of assignment decisions is equal to the generated number of items at that time, and equality (6) makes sure that the number of releases from the warehouses is equal to the demand. Constraints (7) ensure that a product can only be picked up if it is assigned to that location. Constraints (8) determine the storage time of a product. When the storage time is higher than the delivery time window, the product is released late, which is enforced by constraints (9). The bound and the type of variables are presented by constraints (10)-(12).

5. Priority-Based Heuristic Approach

The mathematical representation of the problem in Section 4 cannot be solved exactly. Therefore, we have many routes, and it is difficult to retrieve a solution by an optimization solver. Furthermore, to have a solution for practical-sized problems, we develop a priority-based heuristic approach.

The storage assignment model consists of three components: the arrival, assignment, and pickup (see Figure 2). The figure can also be presented in a conceptual algorithm, which describes the general steps every product follows in the model. This concept is presented in Algorithm 1. As the pickup is fixed within the problem, the only decision to be made is the storage assignment. Hence, the heuristic is developed to decide on the assignment warehouse or route R^{od} (Step 4 in Algorithm 1). The main idea of the heuristic is based on the following observations:

- The unit of effort U^r is specified per route R^{od}. Hence, it is known which path results in a better or worse performance. Though the routes can have the same unit of effort, we have seen that it is not wise to use paths including warehouses with very low and restricting capacities as staging area, since this will result in a lower performance for other goods. Therefore, the unit of effort of the routes and the warehouse characteristics are related.
- Many products have a rest time of 4 days, which means that these goods cannot be picked up before surpassing the rest time. If so, the variable Z_i^{aer} is bounded by the rest time: if $g = 1$, then $tZ_i^{aer} \geq 4$ and $ST_i \geq 4$. It influences the storage time leading to a lower objective value. Hence, there is less control on steering the performance on the storage time as the Z_i^{aer} occurs arbitrarily: any product matching the demand Q^{aed}can be released, e.g., a product stored for 5 days can be picked instead of a product stored within the same warehouse for 20 days.
- The performance on immediate release depends on the width of the delivery time window c_i. The lower the delivery time window, the more difficult for optimisation. Similar to the storage time, there is less control on optimising the immediate release since Z_i^{aer} does not release a product taken the delivery window into account, e.g., it might be that a product with a due delivery in 17 days is first released than a good with a due date in 6 days.

The main idea of the heuristic is to incorporate important attributes of each item in the assignment decision. According to the aforementioned observations, the item features have an impact on the performance measures. The algorithm is constructed by implementing an order list of warehouses per composition of the attributes. Hence, the routing decision for an item is taken by choosing a warehouse corresponding to its order list. This priority-based heuristic is constructed by implementing multi-criteria decision-making (MCDM) where relevant decision-makers select an alternative from a set of alternatives considering multiple criteria. Through MCDM, an order list of warehouses is constructed per combination of product features or attributes values.

A linear function f_w is computed to determine the order list of warehouses in decreasing value of f_w. The highest score results in the first warehouse to assign the product to, the second highest score the second option, etcetera. The priority is given to $\{o, d, a, e, c\}$, which are the production route (inbound and outbound, defining R^{od}), the SKU type, and the delivery time window (color). These product attributes influence the routing decision. This leads to the following linear function f_w:

$$f_w = \beta_{od} od_w + \beta_{ae} ae_w + \beta_c c_w \tag{13}$$

where f_w is the sum of the scores for warehouse $w \in W, od_w$ is the score on production route for warehouse $w \in W, ae_w$ is the score on SKU type for warehouse $w \in W$, and c_w is the score on color for warehouse $w \in W$. The betas $(\beta_{od}, \beta_c, \beta_{ae})$ are the respective weights of the attributes showing the importance.

Algorithm 2 presents the priority-based heuristic. For each combination of attribute values, a list is constructed. First, if a product needs a service it is assigned to the repair center. When this is not the case, the order list is retrieved. The product is assigned to a warehouse if there is space, and the corresponding warehouse satisfies the storage conditions of the item.

6. Computational Studies

The heuristic is coded in MATLAB 2018b and tested on a laptop PC with 4 GHz and 16 GB of RAM. In the following sections, we first discuss the experimental data. Then, we describe the event-based approach. Afterwards the computational results will follow, which consist of two parts: 1) value of the assignment policies, and 2) value of the disruption.

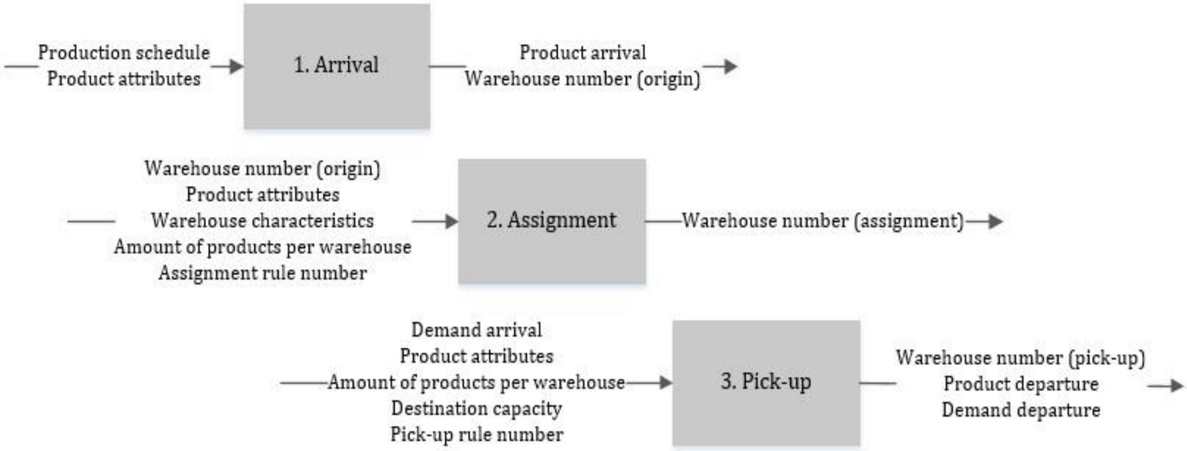

Figure 2. General framework of modelling approach.

Algorithm 1 Conceptual algorithm

for all products $\boldsymbol{i} \in \boldsymbol{I}$ **do**
  Assign attributes $\{o, d, s, y, g, a, e, c\}$ and time stamp of arrival
  Move to supplier warehouse $w \in W$
  Determine assignment warehouse $w \in W$
  Move to assignment warehouse $w \in W$
for all demand requests $q \in Q$ **do**
  Assign attributes $\{d, a, e\}$
  Determine pickup warehouse $w \in W$
  Retrieve product $i \in I$ from pickup warehouse $w \in W$
  Match with product $i \in I$ to leave the system
  Assign time stamp of departure and storage, and unit of effort to product $i \in I$

6.1. Experimental Data

The algorithm is tested using the data from a steel manufacturer. Figure 3 depicts the network representation of the case study. Table 4 describes the relevant characteristics of the warehouses, and Table 5 presents the product features. In the pattern of the demand, Runner is most frequently ordered and Stranger the least. Since three classes do not exist, there are six SKU types. The products and demand orders are specified per SKU type and outbound. The combination of six SKU types and five outbound locations leads to 30 combinations of SKU per type and outbound, with A-Runner to C-Stranger ($T_1 - T_6$) and D_1 to D_5. Black labelled products have the highest priority, and the blue products the lowest priority. The remaining product attributes are implemented using stochastic distributions from datasets of the steel manufacturer; though, these are fixed among the runs.

Algorithm2 Priority-based heuristic

Output: Assignment warehouse

for every pair of inbound $o \in O$, outbound $d \in D$, ABC class $a \in A$, demand pattern $e \in E$, and colour $c \in C$ **do**
$OL_{odaec} \leftarrow$ Compute function f_w and sort all warehouses $w \in W$ in decreasing order based on the value of function f_w
  for all products $i \in I$ **do**
    if $s \in S = 1$ **then**
      assign product $i \in I$ to s_1 warehouse $w \in W$
    else if $\boldsymbol{s} \in \boldsymbol{S} = \boldsymbol{2}$ **then**
      assign product $i \in I$ to $s_2$warehouse $w \in W$
    for all warehouses $w \in W$ in the order of list OL_{odaec} **do**
      if $B_t^w < V^w w \in W, t \in T \ \wedge$ satisfies storage conditions y and g **then**
        assign product $i \in I$ to warehouse $w \in W$

The heuristic is run with five input files representing the uncertainty in production and demand. The first two input files are deterministic, and the other three are constructed using the normal distribution with $\mu = 580$ and $\sigma = 37$ for the daily demand. In addition, a stochastic value is added for the type and the outbound with a uniform distribution. The intervals are different for each type and each outbound location dependent on the datasets. A feasible production pattern is manually constructed for every demand input because of the pull production system.

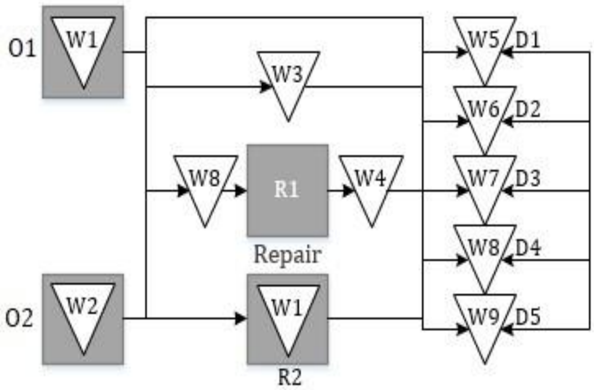

Figure 3. Case representation of the production-distribution system.

Table 4. Warehouse characteristics.

Warehouse	Location	Type product	Capacity
W_1	O_1 R_2	Hot, Dry	2000
W_2	O_2	Hot, Dry	None
W_3	Not dedicated	Hot, Wet	3750
W_4	Output R_1	Cold, Dry	1800
W_5	D_1	Cold, Dry	2400
W_6	D_2	Hot, Dry	1450
W_7	D_3	Hot, Dry	1150
W_8	D_4 Input R_1	Hot, Dry	2350
W_9	D_5	Hot, Wet	850

Table 5. Product characteristics.

SKU Type	Amount (#)	**Color**	Delivery time window (days)	In system (%)
A-Runner	153	Black	3	3
A-Repeater	1327	Red	6	46
A-Stranger	2400	Amber	10	26
B-Runner	0	Green	17	14
B-Repeater	74	Blue	31	1
B-Stranger	5747			
C-Runner	0			
C-Repeater	0			
C-Stranger	5793			

6.2. Event-Based Approach

In order to test the performance of the priority-based heuristic, we set up an event-based approach. In this model, the network and data of the case study are implemented. A dummy warehouse is included in case the warehouses reach their capacities. The products arrive to the system with a deterministic interarrival time dependent on the daily production, which is specified per SKU type and outbound. These products have an expected demand on certain days with also a daily fixed interarrival time. Then in the model, we apply the assignment rules.

The runtime of the model is 180 days. It is a non-terminating model with a warmup period of 10 days. The initial state of the system can influence the KPI's. During the initialization phase, production is generated while the demand will arrive after 10 days in order to partially fill the warehouses with goods. There are no replications considered as the attribute values should be fixed so that solely the effect of different assignment rules can be measured.

The current situation of the steel manufacturer is developed as the base case. The current state rules do not consider the SKU type or the due dates of the products. Neglecting these important attributes and the capacity limits of the warehouses result in an inefficient current assignment with much unit of effort. The unit of effort on the connection is 2 in case of movements between adjacent warehouses (W_1, W_4, W_8), and otherwise 4. The current assignment is partly random.

Some storage assignment policies from literature are also tested: (completely) random assignment, CO, and CD. The first empty available location will be used to store the product in CO or CD in which the closest location is derived from the Euclidean distance. Besides the policies in current research, numerous variants of the priority-based heuristic as in section 5 are implemented. The variants differ in the considered product attributes; each modification consists of a certain composition. The weights show the priority of the attributes and are derived from a survey within the company (see Table 6). Two variants of PRSTC (production route, SKU type and color) are taken into account to test the sensitivity of features with a high priority. It should be noted that the variants considering the SKU type are a derivation of the class-based policy as stated in previous literature.

Table 6. Weights.

	β_{od}	β_{ae}	β_c
PR	1	0	0
PRST	0.7	0.3	0
PRC	0.57	0	0.43
PRSTCa	0.52	0.06	0.42
PRSTCb	0.42	0.06	0.52

6.3. Value of The Assignment Policies

This section describes the results of the assignment policies on the three performance measures: unit of effort, average storage days, and percentage of immediate release. The aim is to achieve high performances on the overall value of the system as well as on relevant products. These crucial goods are the high priority products (black and red), and the combination of high priority and important SKU types (with A-Runner and A-Repeater). The delivery time windows of these products are very short, which increases the risk of lower performance. There is more room for improvement on these products, although it is more difficult to achieve. The results in this section are only presented for these categories. Furthermore, the runs that make excessive use of the dummy warehouse are excluded (CO 1-5 and CD2). Two results are shown: the bounds on the unit of effort, and the average-best cases on all KPI's.

Figure 4 shows the bounds on the unit of effort. As each model run has a different throughput of products, the absolute value is not a reliable measure for comparison. Hence, for each run the minimum, maximum, and extra possible effort is determined, which are dependent on the product attributes $\{o, d, s, g\}$. As expected, the random policy has the highest share of extra effort, and the current situation the second highest. The second input file has always the worst performance because of the high inventory levels.

Table 7 presents the results on all KPI's as average values (upper part) and best cases (lower part) over the five input files for every heuristic. Note that here KPI 1 is measured as the percentage of extra effort. The table depicts the relatively poor values of the random policy and the current state on all the KPI's. The CD has a high performance, although the second input file had to be excluded. The other policies do incorporate this file, which deteriorates the average value. PRC and PRSTC have the highest share of improvements. The performance is high on the overall value considering all products, and also on the high priorities. It should be pointed out that the differences in KPI 2 and KPI 3 are lower than the impact on KPI 1.

Table 7. Average-best results of heuristics.

		KPI's (Average values)							
		BC	**R**	**CD**	**PR**	**PRST**	**PRC**	**PRSTCa**	**PRSTCb**
All	1 [%]	30	52	14	16	15	17	16	16
	2 [d]	13.5	14.2	11.9	12.3	12.2	12.3	12.4	12.3
	3 [%]	66	63	74	73	72	71	72	72
Black	1 [%]	31	52	7	10	9	10	7	8
	2 [d]	12.9	14	11	11.1	10.9	11.1	11.2	11.2
	3 [%]	41	38	47	48	49	46	45	45
Red	1 [%]	35	48	15	19	18	12	13	10
	2 [d]	13.5	14	12	12.1	12.1	12.1	12.1	11.9
	3 [%]	53	52	64	63	62	61	62	62
Black & A-Run	1 [%]	29	50	6	9	9	10	7	7
	2 [d]	14.9	15.5	12.9	13.3	13	13	12.9	13.1
	3 [%]	33	31	33	35	37	33	33	33
Black & A-Rep	1 [%]	31	52	7	11	10	10	7	8
	2 [d]	12.4	12.9	9.9	10	9.5	9.8	10.1	10.1
	3 [%]	45	42	53	54	55	52	50	51
Red & A-Run	1 [%]	35	50	15	18	18	12	10	10
	2 [d]	15.4	15.8	14	13.9	13.8	13.7	13.8	13.6
	3 [%]	45	44	54	55	55	53	53	53
ed & A-Rep	1 [%]	35	51	15	19	18	15	10	10
	2 [d]	12.5	12.9	10.9	11	10.9	10.9	10.9	10.8
	3 [%]	57	56	68	67	67	66	66	66
		KPI's (Best values)							
		BC	**R**	**CD**	**PR**	**PRST**	**PRC**	**PRSTCa**	**PRSTCb**
All	1 [%]	29	47	12	10	10	8	9	9
	2 [d]	12.9	13.1	11.3	11.7	11	11	10.9	11.1
	3 [%]	68	66	75	74	75	77	76	74
Black	1 [%]	30	47	5	4	4	1	1	1
	2 [d]	12.1	13.4	10	10.8	10.3	10.6	9.9	10.8
	3 [%]	55	44	52	56	59	51	58	53
Red	1 [%]	34	35	14	13	14	2	6	3
	2 [d]	12.7	12.8	11.3	11.4	10.9	11	10.9	11.2
	3 [%]	57	56	67	65	65	68	66	65
Black & A-Run	1 [%]	27	44	4	3	3	0	0	1
	2 [d]	11.9	13.5	10.7	10.7	10.1	10.8	10.6	11.2
	3 [%]	58	50	57	51	56	47	47	47
Black & A-Rep	1 [%]	30	48	6	5	5	1	1	1
	2 [d]	11.9	12.5	9.2	9.6	9.1	8.8	8.6	9.4
	3 [%]	56	49	54	63	68	59	65	60
Red & A-Run	1 [%]	33	48	13	13	13	2	3	2
	2 [d]	12.9	14	11.6	11.5	11.1	11	11.9	12.1
	3 [%]	57	56	66	65	66	68	61	62
ed & A-Rep	1 [%]	34	48	14	14	14	14	3	3
	2 [d]	12	11.9	10.8	10.8	10.3	10	9.8	9.9
	3 [%]	62	63	70	69	69	71	73	72

The lower the average storage time, the higher the immediate release and the other way around. Moreover, the higher the inventory levels, the more extra effort; however, the better the performance on the storage time and immediate release. When there are more goods in the system, the top locations (outbound or production facility) are full. Hence, the products are often picked up from these warehouses instead of the less preferred intermediate locations, which leads to more improvements on the storage time and immediate release. When the stock levels are lower, it takes more time to pick the products up, as there are less products released at a certain time step. As a consequence, there is more time required to pick the products in order to fulfil the demand. Therefore, the inventory levels have a high impact on the performance.

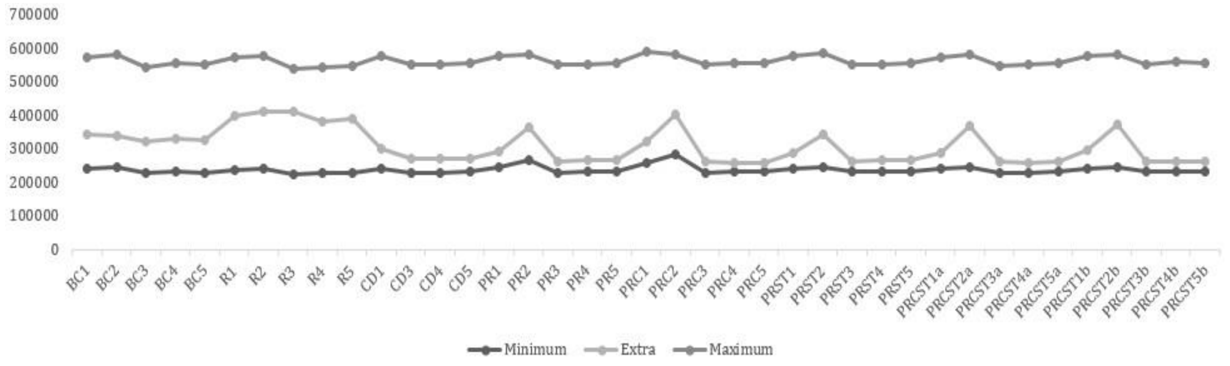

Figure 4. Bounds on unit of effort.

6.4. Value of The Disruption

This section shows the results of a comparison between two runs, one with and one without disturbances. Thus, the sensitivity of the system is tested when disruptions occur. The differences between these two runs are examined on all performance measures. The first run is the PRSTC2a (PRSTCa with the second input file) since the performance of this run is significantly high. The second run consists of this heuristic, although with 14 days of disruptions in the production. A uniform distribution has been used to extract 14 draws in which sometimes the production facilities are completely down (production is 0) or part of the day (production is lower). When incorporating these disruptions in the input, the production is reduced with 5736 goods over the entire run length and the fulfilled demand with 1253.

In these results, all the colors and SKU types are presented; though, only the important classes of the combinations are depicted. The overall percentage of extra effort has been reduced with 27% (see Figure 5). All categories have less effort, since less products are generated, which results in more space at the outbound warehouse.

The overall average storage time is decreased with approximately one day, as shown in Figure 6. Nevertheless, not all categories have an improvement. The less relevant SKU types have a lower performance. The disturbances have a high impact on the performance of B-Repeaters. However, the amount of B-Repeaters in the system is not even 0.08%. Therefore, this class is not a critical category.

On all the products, a 3% increase in immediate release is achieved (see Figure 7). However, not all categories have an improvement. The relevant groups with a reduction are the A-Runners, and black and red with A-Runner. Although the impact on A-Runner is low with a reduction of 1%, the effect on the combinations is higher, respectively 8% and 4%.

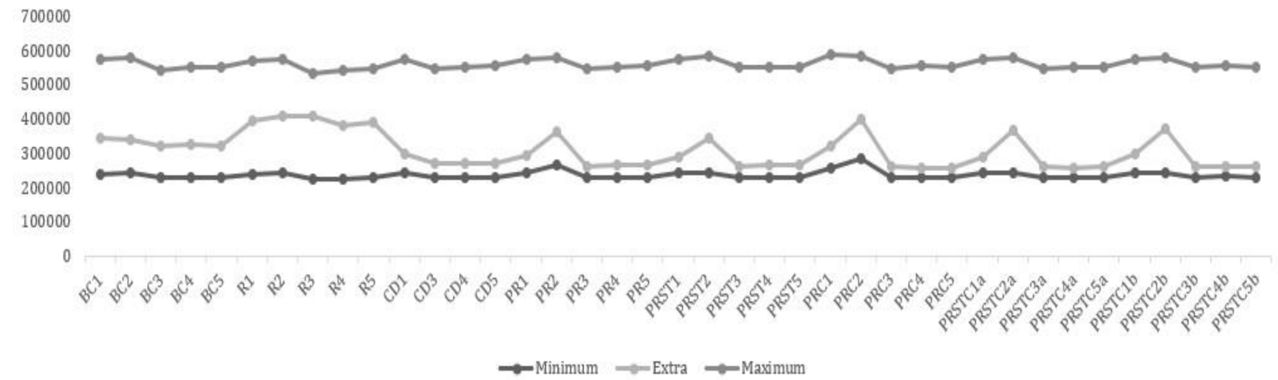

Figure 5. Differences between PRSTC2a and disruption – effort.

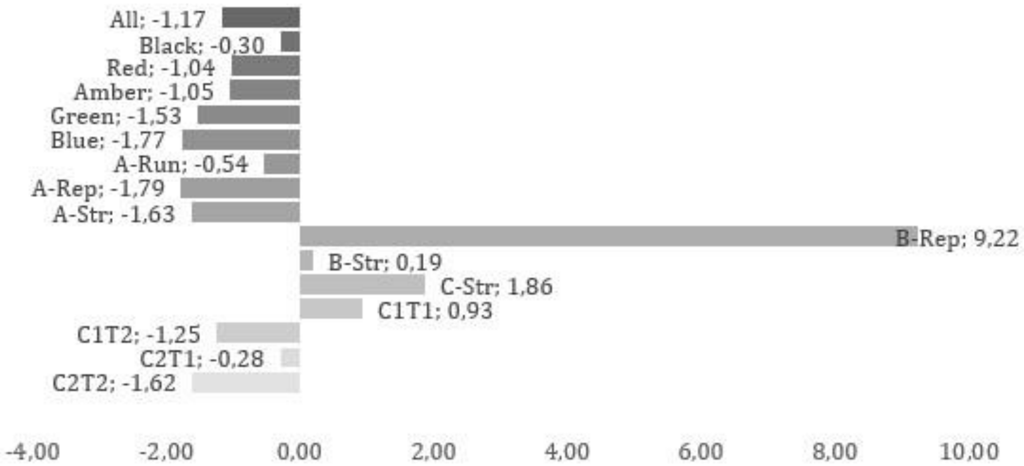

Figure 6. Differences between PRSTC2a and disruption - storage time.

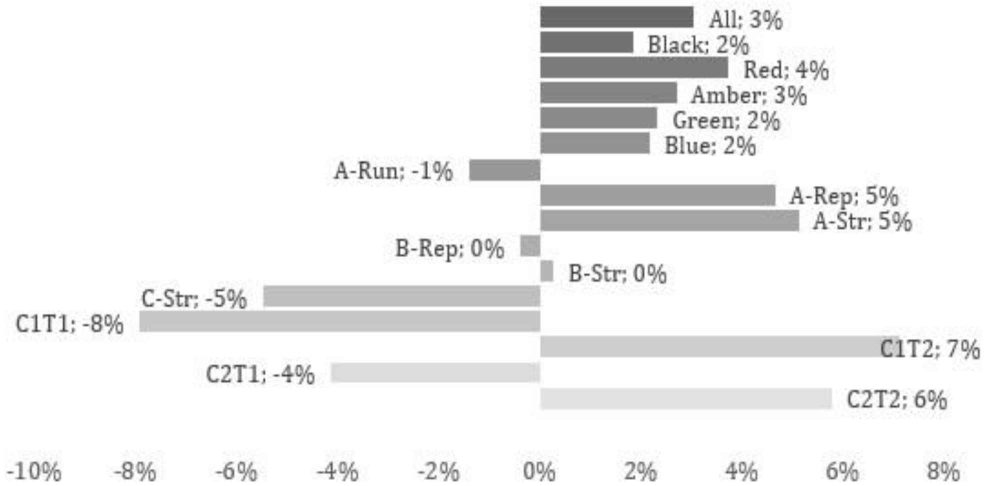

Figure 7. Differences between PRSTC2a and disruption - immediate release.

7. Conclusion

In this paper, we have implemented a priority-based heuristic and its variants for the storage assignment of various (semi-)finished goods among multiple plants and warehouses, also accounting for different production and demand patterns. The performance of these heuristics is tested in an event-based model, considering the unit of effort, the storage time, and immediate release. The product attributes and storage requirements are taken into consideration.

Particularly the priority-based heuristic using the attributes production route and color, and possibly the SKU type incorporate the highest achievements on the KPI's compared to the current state. There are huge improvements on the performance of the whole system as well as on the important and critical products. When testing this priority-based policy with disruptions, the outcomes suggest that the performance of the overall system increases, although less demand is now fulfilled.

There are some potential future research directions. First of all, the input files of production and demand patterns highly affect the performance. Also, existing literature indicate this effect (Petersen 1999), and therefore the need to account more for stochastic demand (De Koster et al. 2007). Secondly, storage assignment is associated with picking. The pick-up decisions in this research are fixed. A combination of optimal assignment and pick-up rules should be constructed, as these influence each other and will provide better results (Petersen 1999, Ong and Joseph 2014). Thirdly, the availability of resources (e.g., crane, forklift truck and train) should be taken into account. The model considers a "continuous" flow: when a product is produced or requested, it can be directly moved while equipment's are required to perform the movements. Next, in practice of the steel industry re-assignments occur to other warehouses. These re-assignments also has been neglected mostly in literature (Gu et al. 2007). A new module should be added with rules to provide a possibility for relocation. Finally, a look-ahead strategy could be used for demand requests entering in the near future and the assignment decisions.

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