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Optimization of an Automated Storage and Retrieval Systems by Swarm Intelligence

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Abstract

Automated storage and retrieval systems (AS/RS) need to execute complex combinatorial and sorting tasks. In this study we have shown how to plan AS/RS using multiple objective ant colony optimisation (ACO). The distribution of products in the AS/RS is based on the factor of inquiry (FOI), product height (PH), storage space usage (SSU) and path to dispatch (PD). The factor of inquiry for any product can be adjusted during the storage process in regard to actual market requirements. In order to reduce space consumption and minimise investment costs we chose an AS/RS with no corridors and one single elevator for multiple products. Results show that the expected distribution of products was reached and that ACO can be successfully used for planning automated storage systems.

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Keywords: automated storage and retrival system; automatisation; multi-objective optimisation; swarm intelligence

1. Introduction

Today, more than ever, the evolution of automatic storage and retrieval systems (AS/RS) is accelerating. Due to steadily growing economic and logistic needs and the fact that more goods need to be stored, AS/RS constantly call for further optimisations. Advanced storage systems allow automatic storage and retrieval of goods with

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management and control of all automated processes from one place. The two more used approaches for AS/RS design and study in present days are analytical optimisations and simulations. Optimisation of the AS/RS operation using modern algorithms was studied by authors such as Lerher, Šraml, Borovišek, Potrč [1] and Yang, Miao, Xue and Qin [2]. Studies which present general overviews of warehouse design and control were presented by de Koster, Le-Duc and Roodbergen [3], Gu, Goetschalckx and McGinnis [4] and Baker and Canessa (2009) [5]. Design of a compact 3D AS/RS was proposed by de Koster, Le-Duc and Yugang [6], Kuo, Krishnamurthy and Malmborg, proposed computationally efficient design conceptualization models for unit-load AS/RSs based on autonomous vehicle technology (AVS/RS) [7] and Manzini, Gamberi and Regattieri presented a multi-parametric dynamic model of a product-to-picker storage system with class-based storage allocation of products [8]. More specific research was presented by Fukunari, Malmborg, Hur, Nam, Yin, Rau, Dooly, Lee and others. Fukunari and Malmborg invented the term ''interleaving'', which refers to the pairing of storage and retrieval transactions on the same cycle to generate DC cycle cycles [9]. Hur and Nam presented stochastic approaches for the performance estimation of a unit-load AS/RS [10], Yin and Rau studied the dynamic selection of sequencing rules for class-based unit-load AS/RS [11]. Dooly and Lee presented a shift-based sequencing problem for twin shuttle AS/RS [12]. In an overall state-of-the-art review authors Roodbergen and Vis [13] found that the strength of simulation could be better exploited in AS/RS researches by comparing numerous designs, whilst taking into account more design aspects, especially in combination with different control policies. They proposed that sensitivity analyses on input factors should also be performed such that a design can be obtained which can perform well within all applicable scenarios.

For our research we chose a non-traditional, unit-load, deep-lane type AS/RS. The unit-load AS/RS is typically a large automated system designed to handle unit-loads stored on pallets or within other standard containers. The system is computer controlled and the stacker cranes are automated and designed to handle unit-load containers. The deep-lane AS/RS is a high density unit-load system that is appropriate when large quantities of stock are stored but the number of separate stock types is relatively small. The loads can be stored to greater depths. Load identification is the primary role for automatically identifying AS/RSs. The scanners are located at the inlet location, to scan a product's identification code. The data is sent to the AS/RS computer which, upon receipt of load identifications, assigns and directs the load to the storage location [14]. Based on the fact that corridors (aisles) use a lot of the available storage space and stacker cranes costs can reach up to 40% of the complete AS/RS investment, we decided to plan an AS/RS completely without corridors and with one major stacker crane with multiple loading sites, able to supply the complete AS/RS. Planning the layout of our AS/RS was based on a table of inquiry and the frequencies when manufacturing individual products. Distribution of products during an AS/RS operation is dependent on factor of inquiry (FOI), product height (PH), storage space usage (SSU) and path to dispatch (PD). Another boundary condition included within our optimisation algorithm is that the factor of inquiry may change dynamically during AS/RS operation regarding actual market requirements. Considering all the parameters resulted in a multi-objective optimisation problem. We chose the particle swarm intelligence (PSO) algorithm for the optimisation as it promises good results for complex combinatorial tasks similar to ours [15, 16, 17].

2. Used methods

Swarm intelligence (SI) is the collective behaviour of decentralised, self-organised systems, natural or artificial. The expression was introduced by Gerardo Beni and Jing Wang in 1989 within the context of cellular robotic systems. SI systems typically consist of a population of simple agents or bodies interacting locally with one another and with their environments. The inspiration often comes from nature, especially biological systems. The agents follow very simple rules and although there is no centralised control structure dictating how individual agents should behave local, and to a certain degree, random interactions between such agents lead to the emergence of intelligent global behaviour, unknown to the individual agents. Examples in natural systems of SI include ant colonies, bird flocking, animal herding, bacterial growth, and fish schooling. The definition of swarm intelligence is still rather unclear. In principle, it should be a multi-agent system that has self-organised behaviour that shows some intelligent behaviour [18].

Particle swarm optimisation (PSO) is a global optimisation algorithm for dealing with problems in which a better solution can be represented as a point or surface within an n-dimensional space. Hypotheses are plotted within this space and seeded with an initial velocity, as well as a communication channel between the particles. The particles then move through the solution space, and are evaluated according to some fitness criterion after each time-step. Over time the particles are accelerated towards those particles within their communication grouping that have better fitness values [19, 20]. A similar approach is the gravitational search algorithm (GSA) presented in [21, 22].

Ant colony optimisation (ACO), as introduced by Dorigo in his doctoral dissertation, is a class of optimisation algorithms modelled on the actions of an ant colony. ACO is a probabilistic technique useful in problems that deal with finding better paths through graphs. Artificial ants (simulation agents) locate optimal solutions by moving through a parameter space representing all possible solutions. Natural ants lay down pheromones directing each other to resources whilst exploring their environments. The simulated ants similarly record their positions and the quality of their solutions, so that in later simulation iterations more ants locate better solutions [23].

3. Parameter definition and optimisation set-up

The discussed AS/RS was planned for the storage of home appliance devices (Fig. 1). Four types of home appliance devices were used during our study, additionally classified based on their heights (PH), model and factory of inquiry (FOI). Each product is available within five different models and each of them has a different FOI. A product's data will be read by the AS/RS when it enters the storage area and processed by the optimisation system, to determine its optimal path to a temporary storage position. The storage position of any product in the AR/RS may change during system operation regarding a newly-entered products FOI level or a possible FOI level change of the product itself.

The following products were used within the optimisation:
Type:

- Cooling box – CB
- Washing machine – WM
- Dishwasher – DW
- Fridge – F

Height (PH):

- A - Height less than 1500 mm – CB
- B - Height less than 900 mm – WM and DW
- C - Height less than 600 mm – F

Model: 1-5
Factor of inquiry (FOI): 1-5

Different types of products with different individual properties require a distribution strategy, which we have defined as follows:

$$SSU>FOI>PH$$

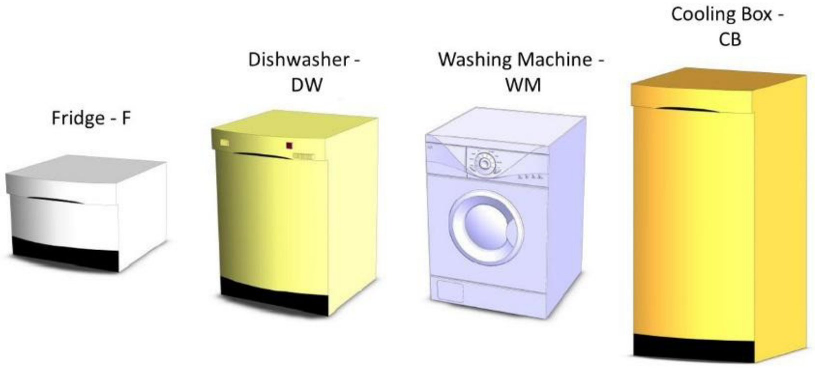


Fig. 1. Home appliance devices used in our study.

Starting condition strategy for the optimisation:

- Products with greater FOI moved closer to the dispatch position
- Possibility of changing FOI during storage planning and storage operation
- Optimal distribution of products based on their heights
- Distribution of higher/heavier products to lower levels
- Number of empty storage cells required by the distribution process would be 1/8 of the total number of storage cells

Table 1 defines the frequencies of manufacturing and the factors of inquiry for different types and models of the discussed home appliance devices. No. of prod. for any of the four product types and models indicates how many of these products are being manufactured while FOI is the products' factor of inquiry.

Table 1. Frequencies of manufacturing and factors of inquiry (FOI) for individual products.

	CB		WM		DW		F	
	No. of prod.	FOI	No. of prod.	FOI	No. of prod.	FOI	No. of prod.	FOI
Model 1	3	1	12	5	4	1	12	4
Model 2	15	5	11	4	6	2	3	2
Model 3	7	3	20	3	7	3	2	1
Model 4	5	2	4	2	9	4	4	3
Model 5	9	4	2	1	11	5	20	5

For easier result evaluation we designed a simulation. The simulation automatically adds storage rack cells (Fig. 2) in three directions as specified by the optimisation algorithm. The maximum construction size of our AS/RS was evaluated based on the frequency of product input and outlet. The maximal possible required measurements of our AS/RS are 10m in length, 10 m in width, and 10m in height.

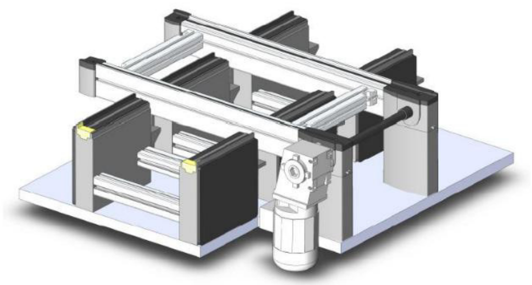


Fig. 2. Basic storage rack system cell (Rexroth Bosch Group).

The optimisation process is initiated by starting the input conveyor. The height of a product is determined at the storage entrance point. After the measurement, the height of the first storage level is set and the product is placed in the AS/RS. With the arrivals of new products, the height of the first level is adjusted accordingly to the requirements of the highest product. Product distribution based on FOI is performed simultaneously. Products with greater FOI are directed closer to the dispatch position. As AS/RS is constantly filled with products of different heights and types, the swarm intelligence algorithm has to define the steps for their distribution. Every product can move left/right or front/back only if the adjacent cell is empty, otherwise all products have to move one position backwards first. This way products with greater FOI are constantly moving closer to the dispatch position (Fig. 3).

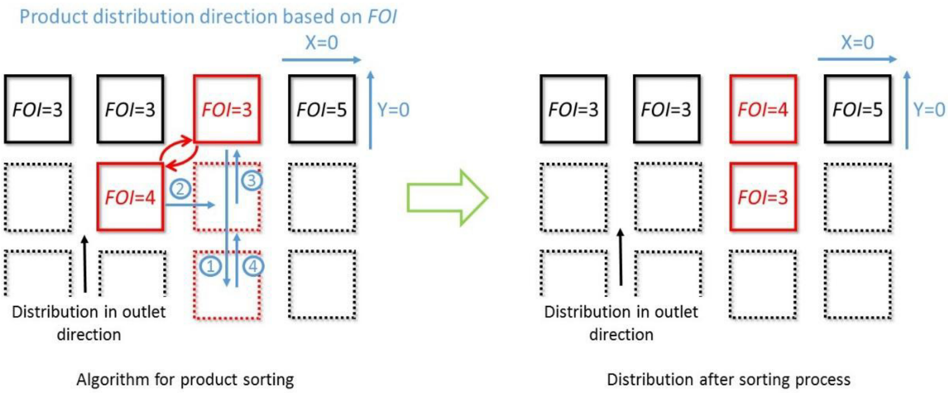


Fig. 3. Sorting algorithm in the AS/RS based on FOI.

If numerous products with height C have consecutively entered the storage, the threshold value for storage space usage (SSU) may be reached. In this case, the optimisation algorithm adds a new storage level to the AS/RS. The input conveyor stops until the products have been distributed on both levels. As SSU has greater priority than FOI, products with smaller height PH = C are moved towards and loaded onto the stacker crane. When the stacker crane is full or if there are no products with PH = C left, the crane lifts the loaded products to the second level. On the second level a height measurement is performed and products are distributed based on their FOI. The results of height measurements and all executed product moves are stored in the MySQL database. This data is used for the analysis of optimisation convergence. After all the products have been optimally distributed, the input conveyor starts delivering new products to the AS/RS. Products are now being distributed on two levels.

The optimisation process stops after the deviation in AS/RS construction regarding the frequency of product inlet/output is less than 5%. The swarm intelligence algorithm for product distribution based on FOI is included within the process of AS/RS planning and operation. During the system's operation, the optimisation algorithm is able to react on FOI change so that it rearranges products in the AS/RS. This way, accessing products in the shortest time is ensured, which is most important for the final customer.

4. Results and discussion

Ant colony optimisation (ACO) is recognized as the most suitable method for solving complex combinatorial and sorting tasks, which is the reason that we chose ACO for our AS/RS optimisation. We designed the optimisation algorithm so that it determines the path and the final position for each product entering the AS/RS. The shortest path for a product is found based on a current vacancy of the AS/RS. If a product with a higher FOI enters the AS/RS, the algorithm for sorting based on FOI is included in the search for the shortest path. For each product entering the AS/RS its path and position are determined based on its height (PH) and factor of inquiry (FOI).

At the start of the optimization process each artificial ant moves with a random value of "rule of transition states" along the paths of the AS/RS. The artificial ant in cell (r), chooses the cell it moves to next (s) based on the "rule of transition states":

$$s = \begin{cases} argmax_{u \in J_k(r)} \left\{ [\tau(r,u)] \cdot [\eta(r,u)]^{\beta} \right\}, & \text{if} \quad q \le q_0 \\ s, & \text{else} \end{cases} \tag{1}$$

Where q is a random number between 0 and 1, q_0 is the relative importance of exploitation based on research: every time the ant in position r has to take position s to move to next, it randomly selects a number ($0<q_0<1$), s is a random parameter, $J_k(r)$ is the group of cells connected with r which are left for ant k to visit and β is the relative importance of pheromones. This way we ensure that the ants use paths with shorter distances and higher quantities of pheromones more often. When all ants have found their way, a global "update rule" is initiated and pheromones on all generated paths are updated:

$$\tau(r,s) \leftarrow (1-a) \cdot \tau(r,s) + \sum_{k=1}^{m} \Delta\tau_k(r,s) \tag{2}$$

Where:

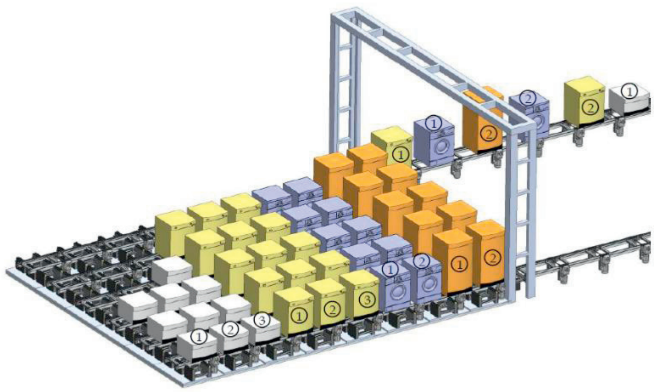
$$\Delta\tau_k(r,s) = \begin{cases} \frac{1}{L_k}, \text{if } (r,s) \in \text{path to ant } k \\ 0, \text{else} \end{cases} \tag{3}$$

Where a is the parameter of pheromone evaporation ($0 < a < 1$), L_k is the path length of ant k and value m is the total number of ants. The quantity of pheromones on connections between the storage cells of the AS/RS is conversely proportional to the path length. Information about the shortest paths is passed from iteration to iteration. In Fig. 4 the distribution can be seen of the first 45 products with different FOI on one level with the ACO algorithm.

After a new level has been added to the AS/RS a much slower optimisation progress can be noticed. In order to accelerate the process we have changed the "update rule", so that it only updates pheromone tracks on globally better paths.

$$\left(L^1(t) \le L^2(t) \le \cdots \le L^M(t)\right) \tag{4}$$

With the new rule the quantity of pheromone that can be secreted by ants is defined by their positions. Only (w-1) best ants are allowed to leave pheromone tracks behind. Weight factor w is used for the best solution. This means that the best ant r of the current iteration secretes pheromone with weight factor w, relative to max. (0, w-r).



RESULTS OF OPTIMIZATION	
Type of artificial group intelligence:	ACO
Iteration:	5647
Swarm size:	350

Fig.4. Partial solution of the AS/RS ACO optimisation with FOI indication.

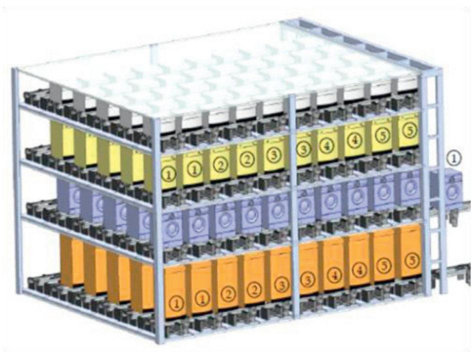
The final form of the "update rule" is:

$$\tau_{ij}(t+1) = (1-\rho)\cdot\tau_{ij}(t) + \sum_{r=1}^{w-1}(w-r)\cdot\Delta\tau_{ij}^{r}(t) + w\cdot\Delta\tau_{ij}^{gb}(t) \tag{5}$$

Where:

$$\Delta\tau_{ij}^{r}(t) = \frac{1}{L^{r}}(t) \quad \text{and} \quad \Delta\tau_{ij}^{gb}(t) = \frac{1}{L^{gb}}(t) \tag{6}$$

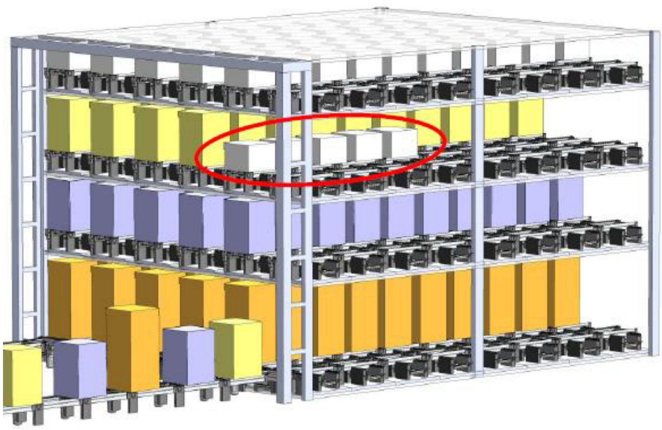
Where ρ is the parameter of the pheromones' evaporation ($0< \rho <1$) and L^{gb} is the length of the best path since the start of the optimisation process. Evaporation of pheromones helps the ants to abandon bad paths. In order to improve convergence of the optimisation it was decided to raise the number of ants in our colony from 350 to 450 thus achieving the results presented in Fig. 5 [24]:



RESULTS OF OPTIMIZATION	
Type of artificial group intelligence:	ACO
Iteration:	238974
Swarm size:	450
Length of AS/RS:	8032 mm
Width of AS/RS:	6696 mm
Height of AS/RS:	5360 mm
Volume of AS/RS:	288.272 m^3
Surface area of one level:	53,782 m^2
Capacity of AS/RS:	200
Length of stacker crane:	6000 mm (9 products)

Fig. 5. Final results of the AS/RS ACO optimization with FOI indication.

The optimal distribution of products based on their heights and FOI can be easily seen in the graphical simulation. The smaller products are stored at higher levels and products with greater FOI are stored closer to the front of the AS/RS and nearer the stacker crane. As the optimisation algorithm distributed products with lower weight and height to the top of the AS/RS, optimal space usage (SSU) can be achieved of the available storage area.



RESULTS OF OPTIMIZATION	
Type of artificial group intelligence:	ACO
Iteration:	205931
Swarm size:	450

Fig. 6. Partial solution of the AS/RS ACO optimisation at iteration 205931.

An interesting situation occurred at iteration 205931 as presented in Fig. 6. Due to maximum occupancy, the system started storing products with height C one level lower, where products with height B should be stored. Product outlet from the AS/RS is performed with a stacker crane (Fig. 7). The frequency of product outlet for each product is defined in the starting conditions of the optimisation. During the outlet process the input conveyor stops because of the boundary conditions defined within the optimisation system.

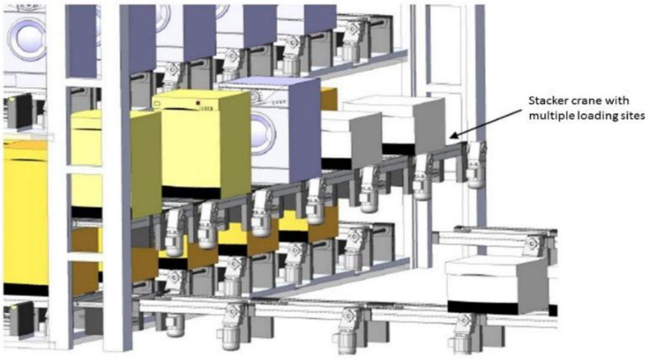


Fig. 7. Outlet of products using stacker crane.

5. Conclusion

Our study provides a solution for AS/RS planning and operation. It simultaneously addresses structural, operational and control features of the AS/RS. Automatic storage and retrieval systems are highly complex and expansive and need to be well planned to avoid problematic behaviour during their operation, which can be best solved with the help of computer-supported optimisation and simulation processes. We developed a swarm intelligence optimisation algorithm and implemented it within the AS/RS planning and control process. The optimisation system is supported by simulation exclusively designed for an easy to evaluate result presentation. The current structural layout and the systems operational state, based on internal control algorithms, are linked with a commercial CAD software package and presented in the form of a CAD model. The obtained results predict structural and operational requirements prior to AS/RS construction. After construction the same optimisation algorithm can be used to control an AS/RS operation. This way we successfully covered the complete structural, operational and control AS/RS design. A lot of storage space can be saved with an unconventional design such as ours but as investment cost is often the most important factor in warehouse design, a cost factors must be included within our future optimisation models.

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