Exploring the Concurrent Impact of Costs, Travel Time and CO2 Emissions Within a Hybrid Aisle-Line Warehouse Through Genetic Algorithm

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Abstract

Effective management of warehouse operations is critical not only for reducing response time and inbound costs, but also for its potential impact on energy consumption and CO2 emissions. This case study fronts location allocation problem is fronted using an evolutionary Genetic algorithm to explore the mutual impact of travel time, total inbound costs and CO2 emissions. The research is developed within the finished products warehouse of an automotive industry, analyzing the operations for the whole warehouse cycle, including the arrival of dirty containers/component-boxes, storage, cleaning, re-storage and delivery of cleaned containers/boxes. The solutions are explored by solving the integer programming model developed for travel time, inbound costs and CO2 emissions. Then, within the location allocation problem the study is augmented with the priorities' options for the containers, to explore the three different perspectives of optimizing travel time, inbound costs or CO2 emission. Results highlight the possibilities of concurrent improvement for these objectives with significant decreasing of all three parameters, i.e. time, cost and CO2 emissions. There is a reduction in costs of 54.43%, a reduction in time of 79.49% and a reduction in CO2 emissions of 54.16%. A sensitivity analysis is further carried out to assess how the variation of these parameters impacts on the optimal solution.

Keywords
Location-allocation; Green design; Warehouse layout; Lead time; CO2 emissions; Genetic algorithm

1. Introduction and literature review

Warehouse is one of the important parts of logistics and supply chain management of today's competitive market, playing the key role of a buffer between customers and the producer. Albeit warehouses usually store components or products for a short time-period, their operations involve almost 20% of the total logistics cost (Ene & Öztürk, 2012). Among warehouse operations, the location/allocation of the inventory plays a critical role in inventory management and picking operations. According to (Tompkins et al., 2010), more than 50% of the time is involved between location of the goods in warehouse and arrival/departure points.

The efficiency of the inventory-placement/order-picking operations of a warehouse can be enhanced by improving location assignment and storage strategy. The frequency of replenishment and order may vary from one product to another. In such a scenario, the location assigned to the products determines the distance travelled during placement and picking operations, thus impacting on lead time and total costs. The typical approaches used to minimize distance travelled, lead time, and energy consumption during placement/picking operations are: (i) optimizing placement/picking route, (ii) zoning, (iii) storage placement allocation considering optimized shelves usage, and (iv) batching.

Warehouse design and management has been discussed in extant literature also with focus on storage assignment (SA) – (Gagliardi et al., 2012). SA refers to the procedure used to determine storage location of each type of product in a warehouse to optimize operational performances (De Koster et al., 2007). For the same problem, (Gu et al., 2007) presented a framework for efficient and effective warehouse design and operations management. SA affects performances both in manual and automatic warehouse management systems. Interestingly, storage location has greater impact on automated storage/retrieval system as compare to manual (Gu et al., 2010).

Past authors found that an important target in solving storage location assignment problem is to minimize travel distance/time and order retrieval time (Chan & Chan, 2011). Few existing studies aimed to decrease order picking time by increasing operational efficiency through planning models (Calzavara et al., 2016). The solution to this is achieved by placing most frequently moving goods at easily accessible points (Bortolini et al., 2017).

Another relevant aspect of warehouse operations management is energy efficiency, leading to sustainable and eco-friendly environment (Meneghetti & Monti, 2013). Then, SA has been discussed by Ene et al. (2016) who fronted the objective of minimizing energy consumption and service time. The allocation focusing minimization of CO2 emission in environment would lead to the deployment of green warehousing/manufacturing.

The storage assignment with the objective of minimizing total inbound costs is another important aspect in the extant body of literature. In fact, minimization of the operational cost of the warehouse fulfilling the requirements of minimum travel time and eco-friendly environment is important both in automatic and manual warehouse operations management.

As regards the multi-objective storage location allocation in a warehouse, Ene & Öztürk, (2012) fronted the minimization of warehouse transmissions and total travel costs. Another study of SA problem considering multi-criteria is discussed by Da Silva et al. (2015), while a bi-objective study of SA model for minimization of travel time and energy consumed by the cranes for single rack automatic warehouses has been recently discussed by Bortolini et al. (2017). This study was conducted in two steps relative to i) identifying best places in the warehouse, and ii) ranking of the products based on multiple criteria using a dedicated approach. Fontana & Cavalcante (2014) proposed preference ranking method which is a multi-criteria method to solve storage assignment problem in a warehouse. Yan et al. (2018) solved a multi-objective storage location problem of stochastic inventory in a stereoscopic warehouse using Matlab simulation. In this last case the multi- objectives problem solution is converged to optimal using changing weight method.

To the best of the authors' knowledge, the extant body of literature does not front properly SA allocation problem with the objectives of minimizing travel time, CO2 emission and total inbound costs during inventory placement and order picking operations.

Addressing the above mentioned lacks, this paper deals with multi-objective storage location allocation problem in a warehouse of an automotive industry for inventory placement and order picking operations. The study is performed with three major objectives. First, we attempt to solve the storage location allocation problem with focus on minimizing travel time, intended as the time taken in inventory-placement/order-picking from arrival/departure point to allocated location in the warehouse. Then, we optimize the storage allocation by minimizing CO2 emissions of forklifts. These emissions are calculated from the energy consumed by the travelling forklift during inventory placement and order picking operations. As third objective, we solve the storage allocation problem to minimize total inbound costs occurred during placement, cleaning and picking operations. Being this study focused on a warehouse for boxes/containers for finished products, the lead time has been given the initial priority, because delay in supply can stop the outbound of finished products. As a further extension of this study, the optimal solution is explored also by considering priority options among the three single objectives.

The paper is organized as follows. The review of the extant literature relative to warehouse location assignment is presented in section 2. Research questions, case study and the development of the mathematical models are presented in section 3. The evolutionary genetic algorithm to solve the developed models is presented in section 4. Case application and results are presented in section 5. Sensitivity analysis is presented in section 6. Discussion of the results and implications are discussed in section 7. The conclusions and recommendations for future research are presented in the last section 8.

2. Research questions and methodology

2.1 Research questions

From review of existing literature, there are some gaps in research on warehouse management considering operational performance along with green manufacturing principles. This paper intends to fill some of these gaps by developing multiple objectives models for storage assignment problem within an hybrid aisle-line warehouse of an automotive industry. The main purpose is to reach an optimum storage allocation, fulfilling the requirements of green principles and sustainability without increasing travel distance/time and operational costs.

Based on the literature review and on the above considerations, the first Research Question (RQ1) of this study deals with the assignment problem for this type of warehouse on the basis of sustainability and green manufacturing principles. RQ1 aims at exploring the possibility of multiple objectives modeling for warehouse storage allocation problem focusing on i) travel distance/time, ii) CO_2 emissions, iii) and total inbound costs.

RQ1: For an hybrid aisle-line warehouse can we model the storage assignment problem in the context of the Green economic warehouse optimization system (GEWOS)?
The second question (RQ2) aims to assess the impact on the optimal solution by relaxing the constraints related to the cost and CO_2 emissions of forklifts, along with the mean lead time to clean the containers.

RQ2: How does the variation in emissions, costs and lead time impact the optimal solution?
After the review of the literature, travel time/distance, energy consumption, CO_2 emissions, and total inbound costs are identified as the main issues which need to be focused. Firms tend to follow sustainability and green manufacturing principles subjected to economic impact. Warehouse managers should make right approach in identifying and implementing sustainability principles. These scenarios, in which one objective can be improved by compromising another one, are fronted through concurrent optimization by using mono-objective approach.
The different elements of the research have been structured and detailed in the research framework of Figure 1.

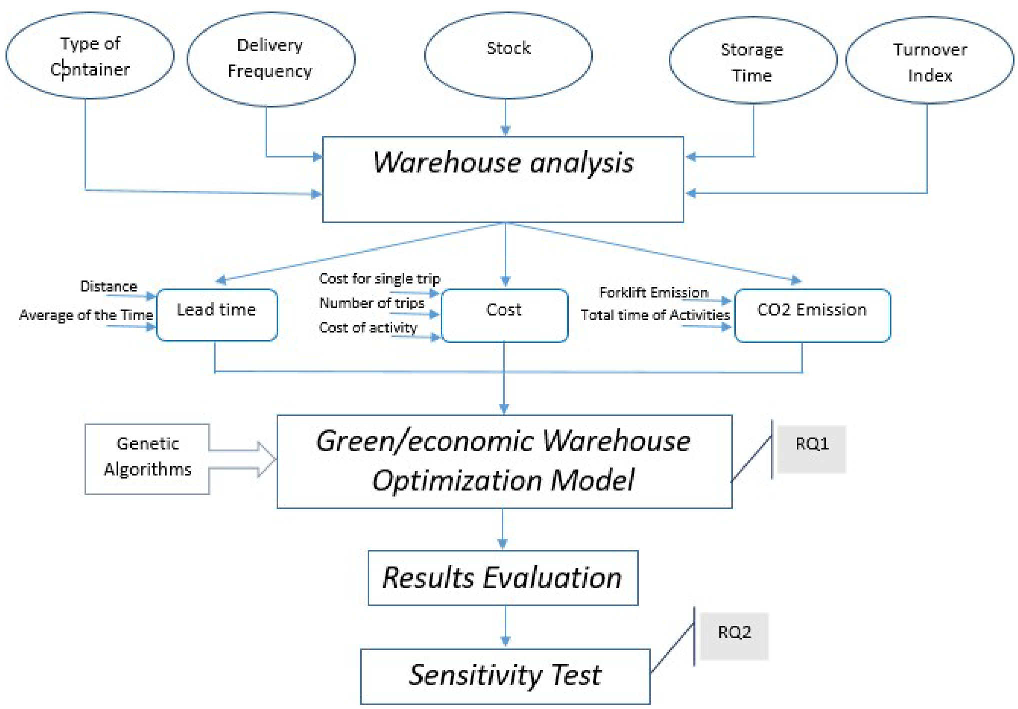

Figure 1. Research framework

1. Analyze the entire logistics process carried out in the as is state

In this phase, modeling and analysis focused on the identification of the most important parameters that allow to evaluate the organization of activities within a warehouse.

2. Define a combined green and economic optimization model for the warehouse

Based on the above considerations, we can argue that an efficient measurement model should include not only economic and time-related indicators, but also an environmental point of view. With this objective we have conceived a green/economic warehouse optimization model (GEWOM), specially developed for this warehouse, with the aim of assessing the correct allocation of products that will allow a much faster management of the picking and shipping phase, allowing have numerous benefits, including:

- Less energy consumption of the trucks used to move the pallets, and therefore regarding the cost of fuel and electricity inside the plant
- A substantial decrease in the total execution time of the whole process, leading also to minor interferences between the work means, lower expectations and greater customer satisfaction The decrease in CO2 emissions considering the mechanical vehicles used within the area.

3. Define the impacts of the optimal solution according to the variations of the input parameters

In this portion of the research, we evaluate how a variation of certain parameters or of certain assumptions within the problem can have repercussions on the optimal final solutions. This analysis allows improving the decision-making process, above all by evaluating the robustness of the decisions taken. It may also highlights the factors whose value is better estimated, and those that it is appropriate to keep under strict control during the execution of the project.

2.2 The warehouse

The research methodology has been applied is an hybrid aisle-line warehouse within a plant producing 600,000 petrol and diesel automotive engines per year. The warehouse includes one aisle with 42 storage lines, able to allocate an equal number of ten different types of containers.

The layout of the warehouse (figure 2) is organized into three main areas. The central area is the cleaning area (CA) where dirty containers are cleaned. The pallets containing cleaned containers are directly moved from arrival to the storage area (STA). The dirty containers may i) either stored in a dedicated area called dirty area (DA) or ii) moved to the CA if the area is full. After cleaning, the containers are then transferred to the STA. Each row is allocated for a specific type of container. The containers are arranged in pallets for shipment and storage. Each storage line is also an aisle due to the length and forklift travels in the line to pick or place the containers, that allows to consider this warehouse as an hybrid aisle-storage.

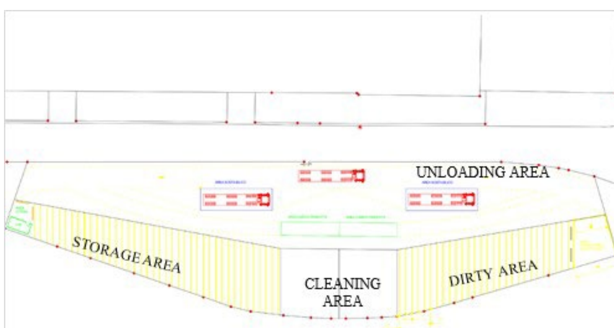

Figure 2. Warehouse layout

Table 1 gives the average values of turnover, average stock, storage time and delivery frequency for all the types of containers.

Table 1. Warehouse performance for the types of containers.

Type of Container	Delivery Frequency	Stock	Storage Time	Turnover Index
1	7.60	13.80	1.80	2.70

2	12.40	5.00	0.40	12.40
3	5.60	5.60	1.30	6.30
4	2.20	25.10	1.80	4.40
5	36.50	29.60	0.80	9.80
6	0.90	5.40	6.10	1.30
7	2.00	4.60	2.30	3.50
8	1.75	7.0	4.0	2.0
9	2.50	5.60	2.30	3.60
10	8.90	12.60	1.40	5.60

When the containers get empty, they are moved to the warehouse where they are cleaned and sent back to the plant, following the demand of each type of container. The allocation of each type of container plays a crucial role in minimizing travel distance/time, energy consumption and CO2 emissions. In this specific case the SA depends on turn-over rate (demand). The containers with high turn-over rate should be placed in a way that inventory placement and order picking requires less effort and time.

The as is storage process is described with the following steps:

i. The truck with containers, arrive at the unloading area (UA) of the warehouse, where the unloading process is accomplished by an electric forklift. In this phase the containers are put in the DA without a particular criteria. There are even some types of containers that are directly stocked in STA, as they do not need to be cleaned and are ready for shipment (for example iron containers).
ii. The containers that require a cleaning activity are placed either in DA, or directly moved to the CA by a forklift.
iii. The shipment and storage of each type of container is made with pallets. However, the cleaning process takes place for each container, which is picked up and inspected individually and placed again in the pallet. The forklift picks up the pallets with the clean containers and places them in the STA to be shipped.
iv. The truck arrives with demand for cleaned containers. The pallets with the containers are uploaded using diesel forklift following the demand. The maximum capacity of a truck is 52 pallets.

The problem of the optimal location allocation of containers in storage before and after the cleaning process has been fronted considering the following main tasks

- Minimize energy consumption of the trucks used to move the pallets;
- Minimizing the total execution time of the whole process, leading also to minor interferences between the means of work, lower expectations and greater customer satisfaction;
- Decreasing CO2 emissions of mechanical means used within the area.

Tables 2a,2b 2c report the main parameters for the assessment of costs, lead time and CO2 emissions, respectively, in the as is state.

Table 2a. Lead Time

Lead Time	**From UA to DA**	**From DA to CA**	**From CA to STA for each line**	**From STA to truck for each line**	**From UA to CA for each line**

Distance [m]	43.48	57.60	23.90; 26.50; 27.00; 30.20; 30.80; 31.90; 32.50; 32.80; 34.90; 37.90; 40.70; 41.00; 41.80; 44.00; 44.50; 46.70; 47.90; 48.70; 49.20; 49.70; 52.40; 53.20; 53.50; 54.30; 56.00; 57.10; 58.70; 61.20; 62.10; 63.30; 64.40; 65.70; 67.70; 68.60; 71.40; 71.60; 73.20; 73.90; 61.70; 62.80; 63.40; 64.60	34.30; 33.90; 33.00; 33.00; 29.90; 28.60; 26.00; 25.70: 24.20; 22.50; 20.30; 19.30; 18.70; 16.70; 15.30; 14.30; 16.80; 14.00; 16.30; 13.80; 14.40; 15.90; 18.30; 20.30; 20.90; 22.00; 22.50; 23.90; 24.50; 26.00; 28.70; 29.30; 31.00; 31.50; 33.70; 34.50; 36.20; 37.60; 86.60; 87.70; 88.00; 89.20	25.20; 25.80; 28.30; 30.90; 32.70; 34.90; 35.00; 38.20; 40.20; 40.50; 42.50; 44.00; 47.00; 49.00; 50.00; 51.20; 52.00; 52.50; 53.00; 54.00; 55.00; 56.50; 57.00; 57.50; 58.00; 58.50; 59.00; 60.00; 60.50; 61.00; 62.00; 62.50; 63.00; 64.00; 65.00; 66.00; 67.00; 68.00; 50.50; 51.00; 52.00; 52.50
Average of the Time [h]	0.0072	0.0096	0.0085	0.0050	0.0086
Lead Time [m]	6517.66				

Table 2b. Cost

Costs	**From UA to DA**	**From DA to CA**	**From CA to STA**	**From STA to truck**	**From UA to CA**
Cost [€/h]	0.89	3.55	3.55	2.32	0.89
Cost for single trip [€/h]	0.01	0.05	0.06	0.03	0.01
Number of trips [day]	317	544	544	780	109
Cost of activity [€]	3.59	27.47	34.46	27.54	1.27
Total cost [€]	94.33				

Table 2c. CO2 Emission

CO2	**From UA to DA**	**From DA to CA**	**From CA to STA**	**From STA to truck**	**From UA to CA**
Total time of Activities [h]	4.03	7.73	9.71	11.87	1.43
Forklift Emission	4.29	7.51	7.51	4.96	4.29

[KgCO2/h]					
Total Emission[Kg]	213.33				

The research is conducted with the following main steps:

i. The critical objectives in SA problems are identified.
ii. The mathematical models are developed for multiple objectives of travel time/distance, energy consumption, CO2 emissions, and total inbound costs.
iii. The optimized SA results are obtained using Genetic algorithm for travel distance/time, CO2 emissions, and total inbound costs.
iv. The developed models are then solved considering possible management priorities. In this step the possibility of concurrent optimization is also explored.
v. The results obtained through the models are compared with results of the existing SA mechanism.
vi. Sensitivity analysis are also conducted to find out the impact of various parameters.

3. Genetic algorithm for optimal location allocation

In this section an implementation of genetic algorithm (GA) is presented to solve the location allocation problem. Evolutionary optimization approach of the genetic algorithm is the reason behind selection of GA in solving this case study.

GA is a search method introduced by Holland based on biological evolution. The practical implementation of genetic algorithm requires two basic issues to be addressed: (1) encoding the potential solutions in the form of chromosome (string) comprising genes (parts of the solution), and a fitness/objective function.

The initial solution (chromosome) is generated randomly or with some specific initializing criteria to evaluate the quality of solution and the measuring fitness. Then, the quality of the solution is improved by generating chromosome (offspring) from matching (crossover) the chromosomes giving probabilities according to the fitness. The selection of parent chromosomes is based on a specific criteria and the process continues until stopping criteria is fulfilled.

The length of the chromosome depends on the number of slots/lines for placing containers. There exist 42 types of containers with high turnover rate. Hence, a chromosome is designed with 42 genes. It is important to mention here that the problem is simultaneously solved for (1) the location allocation in placing dirty containers and (2) location allocation in placing cleaned containers. The flow chart presented in figure 3 describes the flow of optimization process. The followings steps are performed to solve storage location allocation problem

Step 1: The representation of the feasible solution in the form of a chromosome (genetic). The length of the chromosome depends on number of storage lines (genes).
Step 2: Generation of an initial population for starting iterative process (set t=0).
Step 3: Development of fitness/objective function which would be used to evaluate each solution (chromosome). The fitness function is separately defined for each objective. For instance, the fitness function for time taken by the container is defined in terms of time taken by the container for travelling and cleaning. By proper allocation of the location for each type of container, the distance travelled can be minimized which will help in minimizing travel time. Similarly, the fitness functions for cost and CO2 emissions are defined.
Step 4: Determination of reproduction probability for each chromosome depending on fitness value. The roulette wheel selection mechanism is used.
Step 5: Crossover and mutation.
Step 6: Stop if criteria is met, else continue until specified criteria is achieved.

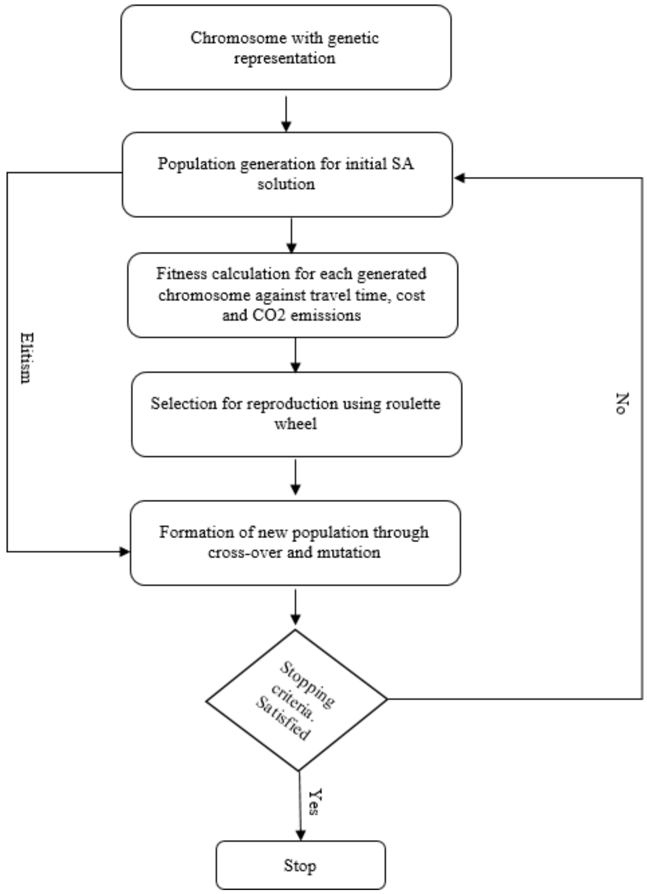

Figure 3. Flow chart of the algorithm

4. Case application and results

This study uses an evolutionary genetic algorithm (GA) to front the problem of optimal storage allocation (Figure 4).

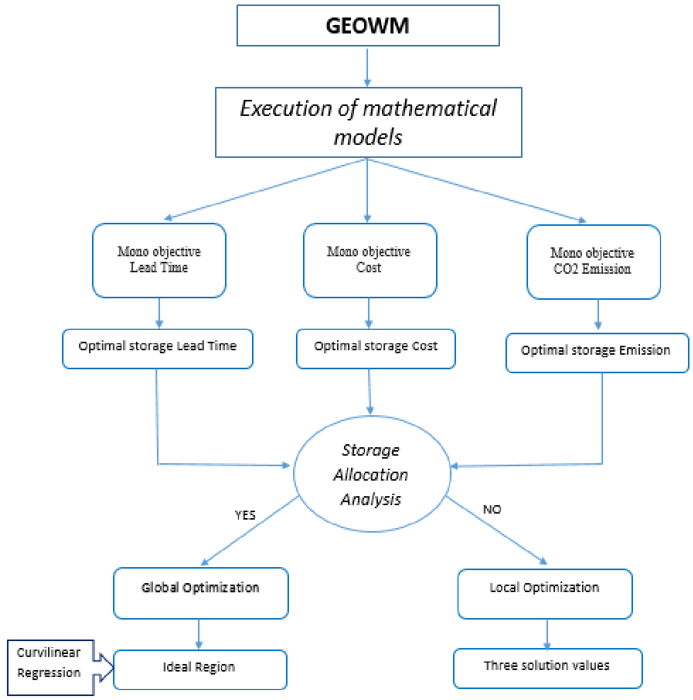

Figure 4. Research Methodology

Because of the mono objectives, it is important to consider the impact that one parameter can have on the other two ones. Then, to evaluate the consistency of the results obtained by the mono objective approach, these results are compared with the parameters of the other two mono objectives. The same procedure is iterated for all the objectives and for the same iterations. The results are presented in Table 3 in which the optimal storage location allocation is shown.

Table 3. Optimal storage location allocation

Storage Line	**Optimal SA**								
	Cost			**CO2**			**Time**		
	Iteration			**Iteration**			**Iteration**		
	1	100	1000	1	100	1000	1	100	1000
1	40	8	24	40	8	24	40	8	24
2	15	19	18	15	19	18	15	19	18
3	8	28	2	8	28	2	8	28	2
4	17	22	1	17	22	1	17	22	1
5	3	13	16	3	13	16	3	13	16
6	19	23	32	19	23	32	19	23	32
7	32	3	12	32	3	12	32	3	12
8	22	11	36	22	11	36	22	11	36
9	42	12	10	42	12	10	42	12	10
10	2	34	7	2	34	7	2	34	7
11	13	7	5	13	7	5	13	7	5
12	20	4	34	20	4	34	20	4	34
13	5	39	9	5	39	9	5	39	9
14	34	40	29	34	40	29	34	40	29
15	25	25	27	25	25	27	25	25	27
16	16	2	13	16	2	13	16	2	13
17	12	17	30	12	17	30	12	17	30

18	35	16	6	35	16	6	35	16	6
19	30	36	8	30	36	8	30	36	8
20	26	14	37	26	14	37	26	14	37
21	6	27	38	6	27	38	6	27	38
22	31	18	25	31	18	25	31	18	25
23	36	41	21	36	41	21	36	41	21
24	1	10	17	1	10	17	1	10	17
25	24	9	33	24	9	33	24	9	33
26	27	37	28	27	37	28	27	37	28
27	33	1	26	33	1	26	33	1	26
28	41	38	4	41	38	4	41	38	4
29	38	20	42	38	20	42	38	20	42
30	21	31	41	21	31	41	21	31	41
31	4	26	35	4	26	35	4	26	35
32	10	32	3	10	32	3	10	32	3
33	29	24	40	29	24	40	29	24	40
34	39	29	39	39	29	39	39	29	39
35	7	21	23	7	21	23	7	21	23
36	9	33	22	9	33	22	9	33	22
37	11	30	19	11	30	19	11	30	19
38	14	5	31	14	5	31	14	5	31
39	18	42	15	18	42	15	18	42	15
40	28	6	14	28	6	14	28	6	14
41	23	35	20	23	35	20	23	35	20
42	37	15	11	37	15	11	37	15	11

From this table 3, we may notice that the storage allocation is the same for all three objectives, indicating that there is a strong correlation between the three functions.

To evaluate the convergence of the results and the consistency of the algorithm, we consider a larger number of executions (Sathya and Radhika, 2013). The results of this portion of the study shows a great stability of the values obtained for the individual optimizations when the initial population varies as indicated in figures 5a, 5b and 5c, showing the variations of CO2, Costs and Lead Time, respectively.

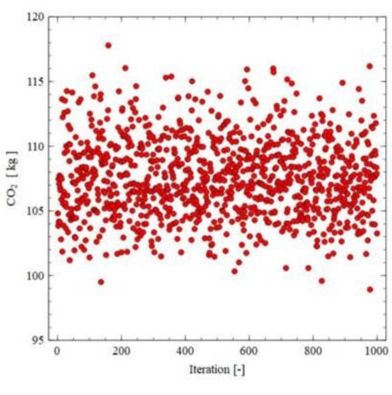

Figure 5a. CO2 emission value

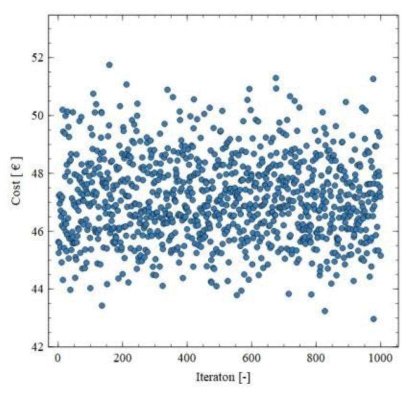

Figure 5b. Cost value

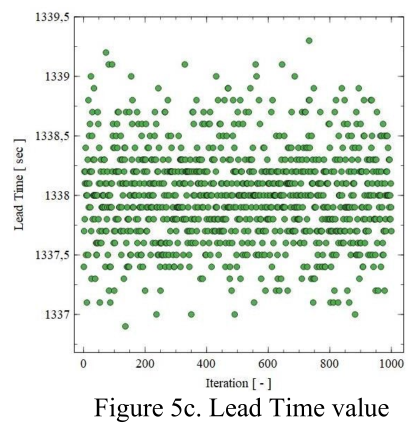

Figure 5c. Lead Time value

Since the results are consistent and the minimum value of the single function is global, the three solutions are tested with curvilinear regressions (Figure 6 and 7).

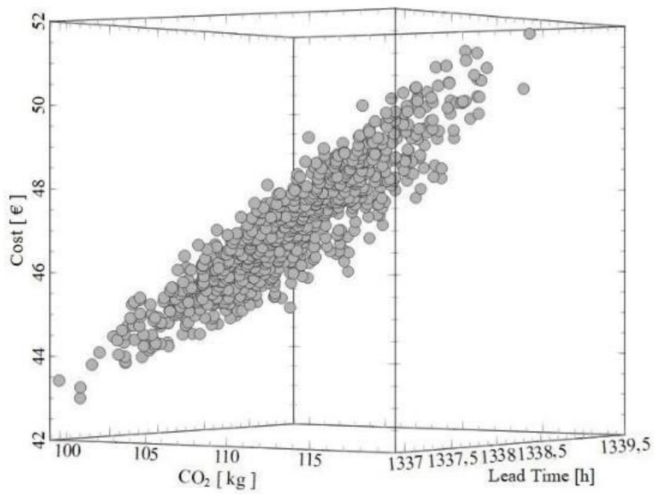

Figure 6. Correlation between Cost, CO2 and Lead Time

From Figure 6 we have determined, through the curvilinear regression, a region in which the optimal solutions for storage allocation are located, fulfilling the requirements of green principles and sustainability without increasing travel distance or time and operational costs.

To appreciate the performance of the proposed models, the existing systems of storage allocation is compared with the proposed one. The comparison between optimized and existing SA set ups is presented in table 4. The results are evaluated as the average of the optimal values of all iterations, showing that there is a considerable improvement in all three objectives, i.e. time, cost and CO2 emissions. A reduction in costs of 54.43%, a reduction in time of 79.49% and a reduction in CO2 emissions of 54.16% can be seen, despite the existing configuration casually allocating the storage position to the containers.

Table 4. Comparison between the existing and the proposed SA mechanisms

Paramete r	**Arrival to dirty storage area**	**Dirty storage to cleaning area**	**Cleaning area to cleaned storage**	**Cleaned storage to the truck**	**Truck to cleaned area**	**Total (Existing)**	**Optimized**	**Savings (%)**
Time [s]	45.81	51.21	64.24	54.78	47.3			
Time [h]	0.013	0.014	0.018	0.015	0.013			
Cost [€/h]	0.89	3.55	3.55	2.32	0.89			
cost/trip	0.01	0.05	0.06	0.04	0.01			
# of trips	317	544	544	780	109			
Activity cost	3.59	27.47	34.46	27.54	1.28	94.33	42.99	54.43
Total time [h]	4.03	7.74	9.71	11.87	1.43	6517.66	1336.74	79.49
Emissions [Kg/h]	4.29	7.51	7.51	4.96	4.29			
Emissions[Kg]	17.30	58.11	72.90	58.87	6.14	213.34	97.79	54.16

*Ave. time in dirty and cleaned storage area=6482.88

5. Discussions

The effects of the input variables on the optimal solutions have been assessed through a sensitivityanalysis, with the prime task to highlight the factors whose value is better to estimate, which is appropriate to keep under strict control during the execution of the project (Sudret, 2008; Koller, 1999).

Since the problem under examination deals with the right allocation of containers in this area, the parameter considered is the number of containers stored inside the STA. Then, we evaluate the parameters concerning the hourly consumption of the forklifts, the values of their CO2 emissions andthe mean time for cleaning.

This evaluation is carried out by increasing the number of containers to be stored by 5%, 10% and 15% to give greater homogeneity to the increase itself. All other parameters are equal to their default value. Figure 7 shows of this portion of the study. We can see that variations in the optimal values of the objective functions face an increasing change, even if not too high as it was expected. The curve of the lead-time assumes a practically linear behavior along the entire interval, which is partially true also for the graph of emissions and costs.

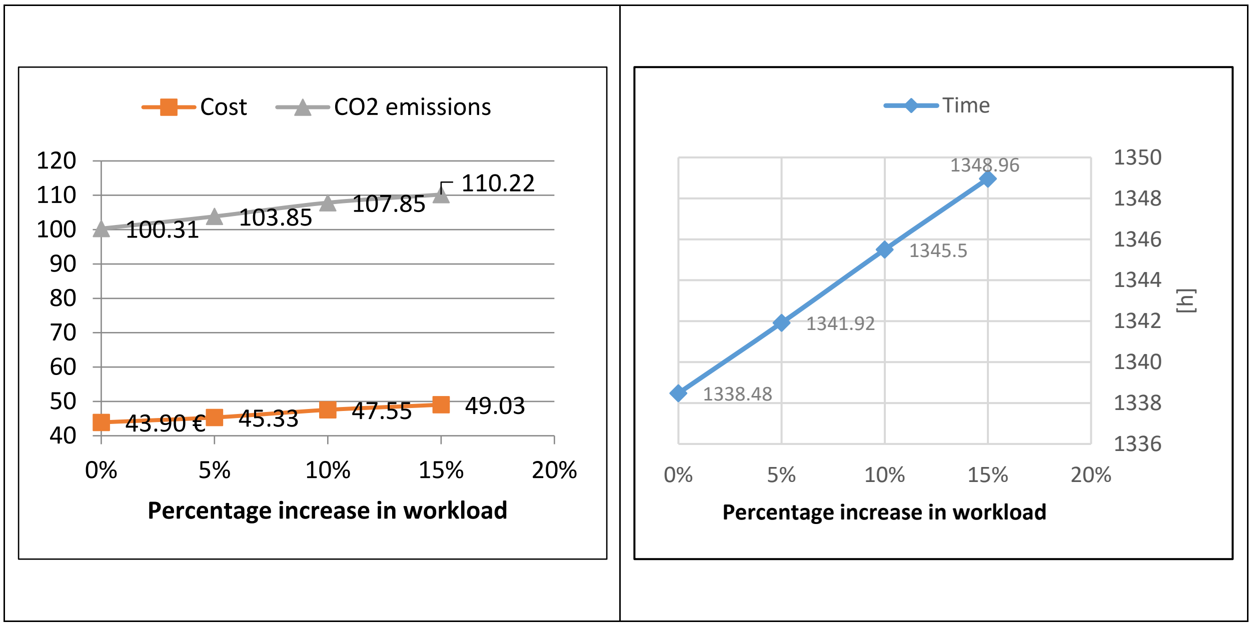

Figure 7. Impact of increase in number of containers

For a more accurate interpretation, we calculate the sensitivity coefficients with respect to the standard values:

$$\frac{\frac{\Delta cost}{Co}}{\frac{\Delta Nadd}{Naddo}} = 0.10 \quad (1)$$

$$\frac{\frac{\Delta lt}{lto}}{\frac{\Delta Nadd}{Naddo}} = 6.82 \times 10^{-3} \quad (2)$$

$$\frac{\frac{\Delta CO2}{CO2o}}{\frac{\Delta Nadd}{Naddo}} = 0.086 \quad (3)$$

Where:

- Δcost, Δleadtime, Δemissions are the differences between the maximum value obtained and the standard value of the objective function;
- ΔNadd is the difference between the maximum increase in the number of containers and their default value;

- C0, lt0 and CO20 are the initial values of the interval;
- Nadd0 is the standard value of stored pallets.

The highest relative sensitivity value is given by the cost function (with an increase of 10%). Equation (2) represents the function related to CO2 emissions, with a coefficient equal to 8.6%, while equation (3) shows that the impact on the lead time is lower (about 0.7%).
From the layout analysis, we know that forklifts operate inside this warehouse. Knowing the data of their hourly cost, the purpose of the analysis is to verify the impact that their variation would have on the final results. Figure 8 shows the graph relating to a variation of the optimal values with respect to a variation of the costs of 5, 10 and 15%.

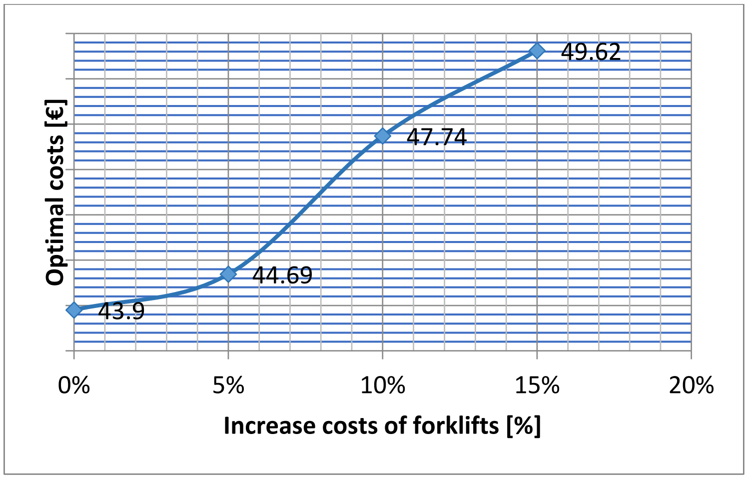

Figure 8. Trend of the optimal cost value increasing the cost of the forklifts

Based on Figure 9, we calculate the sensitivity coefficient:

$$\frac{\frac{\Delta cost}{C0}}{\frac{\Delta ctot}{ctot\_rif}} = 0.87 \qquad (4)$$

Where:
- C0 is the default cost value;
- ctot_rif is the standard value of the forklift's hourly costs.

From equation (4) we see that a 15% increase in costs leads to a change in the sensitivity coefficient of around 87%.
Similarly to the previous case, the behavior of the objective function is analyzed when the emissions of forklifts change. In this case, the range of variability that we consider will extend from -10% to 15%, having evaluated how the forklifts can also be able to emit less carbon dioxide, if good maintenance is performed. Figure 9 shows the results:

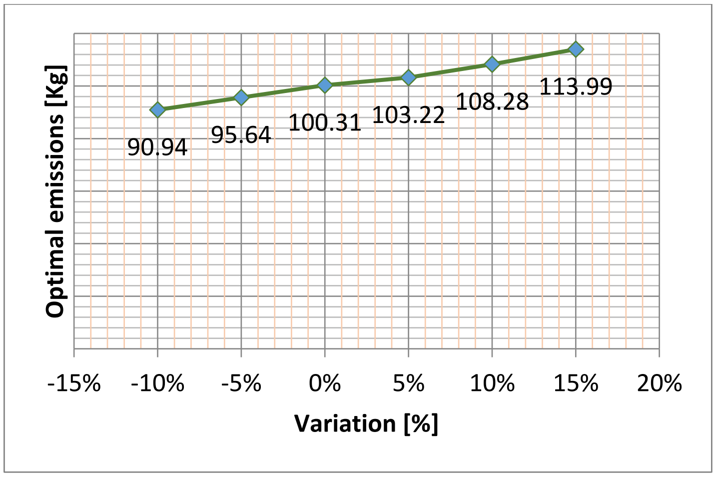

Figure 9. Evolution of the optimal emission values when the hourly emissions of the forklifts change

In this case, the sensitivity coefficient is calculated with the following equation:

$$\frac{\frac{\Delta emissions}{CO2rif}}{\frac{ctot\_em}{ctot\_em\_rif}} = 0.91 \qquad (5)$$

Where:
- C02rif is the default value for total emissions;
- ctot_em_rif is the standard value of hourly emissions related to forklifts.

The results show that an increase from -10% to 15% of the hourly emission values of the forklift returns a relative sensitivity coefficient of approximately 91%.
Another important parameter to consider is the lead time needed to clean a pallet of containers. From Figure 10 and equation (6) shown, we may see how the increase or decrease of this time in the considered interval does not have significant repercussions on the values of the process lead-time.

$$\frac{\frac{\Delta leadtime}{leadtime0}}{\frac{\Delta T\_cl}{T\_cl0}} = 0.04 \qquad (6)$$

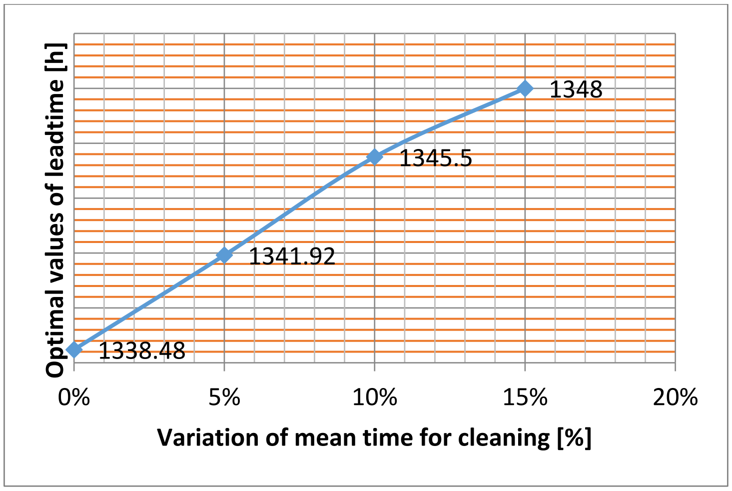

Figure 10. Trend of optimal lead-time values when the pallet cleaning time varies

Warehouse management is crucial and it may affect the value chain to a high extent. The scope of optimal storage location allocation further increases considering green principles and environmental protection and assume on an increasingly important role within industries.

The results of SA shown in table 4 answers to RQ1 which the optimization of warehouse operations not only minimizes the cost but also the negative impact on environment by reducing CO2 emissions in the environment. In addition to cost and CO2 emission, the time taken by a product in a warehouse also becomes critical if selected warehouse deals with components and/or containers used to carry these components as delay may lead to stoppage of production and ultimately, production loss.

The developed models for travel distance/time, CO2 emissions and cost of the not automated warehouse operations allow us to optimize SA fulfilling all three objectives simultaneously. As CO2 emissions calculation is done based on energy consumption, the minimization of CO2 emissions would also lead to minimization of cost of fuel used for handling operations and ultimately, lower energy consumption. Furthermore, the alignment of objectives allows the managers for improvement without compromise on other objectives, i.e. concurrent optimization.

The results from the sensitivity analysis presented in Figures 8, 9, 10 respond to RQ2, highlighting how the variation in cost, CO2 emissions and cleaning time impact on optimal solutions. The impact of increase in workload, i.e. number of containers per unit time (both dirty and cleaned) on cost, time and CO2 emissions is depicted in Figure 7. Increase in number of containers per hours to be handled increases number of trips of the forklifts, leading to an increase in fuel consumption, and consequently costs and CO2 emissions. Increase in number of containers per hour also increases the cleaning workload and, with the same resources, average time taken by each palette for cleaning and movement.

Figure 6 presents the results of the simultaneous optimization considering the priorities of the management and shows that the developed models optimize all three objectives at the same time. The results may vary if the conditions of the input parameters are different.

From managerial perspective, the developed models can also be implemented in warehouses used for finished goods inventory. As SA plays a major role in optimizing (i) travel distance/time, (ii) energy consumption, (iii) cost, and (iv) CO2 emissions, the developed mono-objectives can be used individually or in combination, according to the requirements.

6. Conclusions

This study considers a multiple objectives of minimizing cost, time and CO2 emissions in a warehouse used for storage and cleaning of products' containers. These objectives are achieved by optimizing storage allocation to minimize travel distance. The storage allocation models are derived based on cost, time, and CO2 emission. The proposed models are solved using Genetic Algorithm to find optimum storage allocation. The models are implemented on an automotive industry for case application. The results depict that the proposed mechanism can be implemented to find optimal storage allocation in any warehouse of an automotive industry. This study contributes to extant body of literature by minimizing cost, time and CO2 emissions at the same time.

The results show that substantial can be achieved using proposed mechanism. It also helps in minimizing time taken by the pallet in warehouse. In addition, the decrease in travel distance decreases fuel consumption which leads to reduced CO2 emissions in the environment.

The developed models are implemented on a warehouse containing empty containers. The implementation can be extended to a warehouse used for storage of components or finished products. The implementation to an automated warehouse will also be interesting. In addition, the considered warehouse comprises only storage lanes and no picking aisles.

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Matteo Mario Savino is a Professor of Industrial Operations and Industrial Management at the University of Sannio. He received a PhD in Industrial plants in 1999 at the University Federico II of Naples, Department of Design and Industrial Engineering. Among his research interests there are Project Management, Risk Assessment, Quality aspects related to industrial production. He has managed several National and EU Funded research and educational projects. Since 2008 he has been a Delegate of the Rector for Quality Assurance and is the President of the University Quality Centre. He is the author of more than 50 Scientific Publications and participates in International Journals and International Peer Review proceedings.

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