OPTIMIZATION OF THE LOGISTICS PROCESS IN WAREHOUSE OF AUTOMOTIVE COMPANY BASED ON SIMULATION STUDY

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ABSTRACT
The paper focuses on solving complex warehouse simulation to achieve effective solution. Most attention is mainly paid to optimization of the warehouse operation, especially logistics process of warehouse. The aim of the simulation study is to verify if inbound and outbound deliveries are optimal to cover all the requirements of the warehouse in time and in the right amount. Subsequently, experiment with the simulation helps to formulate recommendation which would improve the processes and reduce total cost. The Witness simulation environment is used for modeling and experimenting. The simulation experiments are evaluated per the total cost for stock transfers and storage costs. Description of the proposed simulation experiments and evaluation of achieved results are presented.

Keywords: warehouse, optimization, modelling, simulation, computer simulation, optimization methods, Witness

1. INTRODUCTION
Warehouses are constantly referred to as cost centers and rarely adding value in the best. Operations efficiency is the key to the success of every company that processes inventories. Management is under constant pressure to reduce the time between customer order and customer delivery. A customer use order-to-delivery time as factor in deciding on a vendor. Therefore, companies must use effective inventory management process to reduce this time to minimum (Curcio and Longo, 2009). When efficiency is low, material may not arrive at customer warehouse on time, orders can get lost, and low stock levels can result in shortage. Companies constantly strive to increase the performance and reduce the costs of production. Here are some recommendations on how to optimize production processes. The functional optimization encounters and accomplishes efficiency and effectiveness of a warehouse process.
The concept of supply chain management entails the consideration and management of logistical processes along the entire supply chain, which includes suppliers, customers, and consumers. Despite the implementation of new enterprise resource planning programs, e-commerce, just-in-time delivery, Kanban, efficient both direction electronic communication aims on shortening the supply chain downtimes. The goal of stock optimization is to harmonize and optimize the processes within the supply chain to reduce the stocks in the entire supply network. Functional optimization inquires to improve efficiency and effectiveness of a warehouse process.
Warehouses are still a typical and central feature in most supply chain due to the partial implementation of lean and agile philosophies. Organizations need to discover ways to effectively manage and perform the operations inside a warehouse with much efficiency and in turn reduce the storage time and costs involved in the storage. There is a need to optimize the technology, operation and the manpower to get good results and high efficiency (Kare et al., 2009). An overview related to warehouse optimization problems presents (Karasek, 2013). Author shows the current state of the art in optimization in three groups of interest in logistic warehouses and distribution centers.
There are many picking, storing, or routing policies. The research (Petersen and Aase, 2004) examines several picking, storing, or routing policies simultaneously to determine which process decisions affect performance the most. Storage policies, which assign stock keeping units (SKUs) to storage locations, generally fall into three broad categories. SKUs may be assigned randomly, grouped into classes with similar SKUs that are placed in the same area of the warehouse, or assigned to a location based on demand or volume.
Inventory classification using ABC analysis is effective way managing materials. ABC classification allows an organization to partition stock keeping units (SKU) into three groups: A, the most important; B, important; and C, the least important (Muppani et al., 2010). The major advantage of ABC analysis is the simple usability of this method. For inventory items, the criterion is frequently the annual cost. In this paper, we are concerned with the ABC classification stock aimed to facilitate inbound deliveries optimally (Bottani et al., 2015).
Recent investigations also reveal that about 33 per cent of logistical costs can be attributed to the costs arising

in inventory management and therefore, a proper investigation of savings that might be achieved within this part of supply chain is necessary and is in many cases profitable (Raidl&Pferschy, 2010). An extensive review on warehouse operation planning problems is presented in (Gu, Goetschalckx, McGinnis, 2007). This paper provides a detailed discussion on warehouse operation-planning methods together with warehouse design, computational systems, and case studies. Moreover, in the work (Baker, Canessa, 2009), the current literature on the overall methodology of warehouse design is explored, together with the tools and techniques used for specific areas of analysis. The output is a general framework of steps, with specific tools and techniques that can be used for each step. This is intended to be a value to practitioners and to assist further research into the development of a more comprehensive methodology for warehouse design.

2. PROBLEM FORMULATION

The aim of the paper is to create a simulation study of the warehouse operation in an automotive company with usage of the computer simulation. Purpose of this simulation is finding the optimal solution of a logistics process control in the warehouse. The warehouse is based on the ABC method. The well-known optimization methods are used for searching the effective solution as quickly as possible.

The simulated model is based on the ABC warehouse management. The ratio 70:20:10 is assumed. The aim is to determine the effective values of inter arrival time of truck loaded part of type A (IAT_A), inter arrival time of truck loaded part of type B (IAT_B) and inter arrival time of truck loaded part type C (IAT_C). It is considered the constant time of unloading units from all parts of the warehouse. Therefore, the inter arrival time of truck loaded part of type A and B can be considered in accordance with the ratio A:B:C (70:20:10) and can be expressed on the base of IAT_C in the form (1).

$$\begin{aligned} IAT_A &= \left(C \cdot IAT_C\right)/\ A \\ IAT_B &= \left(C \cdot IAT_C\right)/\ B \end{aligned} \qquad (1)$$

At the same time, it is necessary to determine the minimum initial number of SKUs in each part of the warehouse to avoid the removal of some parts in the warehouse.

The objective function is total cost of warehouse and this function is possible to define in the form (2). Total cost consists of the storage cost, the transport cost and cost penalty for the removal of some parts in the warehouse.

The storage cost is possible to define in the form (3), where $T_i^{storage}$ is the storage time of i-th SKU. Cost price for storage of one SKU is one CZK per each unit time. The transport cost is possible to express in the form (4), where N_x^{load} is number of unloaded truck with particular type of part and CR^{truck} is cost rate of used type of truck. The amount of the penalty is considered in the form (5). It is dependent on the number of times - N^{zero} that part of the warehouse has been emptied.

$$Cost^{total} = Cost^{storage} + Cost^{transport} + Cost^{penalty} \qquad (2)$$

$$Cost^{storage} = \sum_{i=1}^{N} T_i^{storage} \qquad (3)$$

$$Cost^{transport} = \left(N_A^{load} + N_B^{load} + N_C^{load}\right) \cdot CR^{truck} \qquad (4)$$

$$Cost^{penalty} = 0.1 \cdot N^{zero} \cdot Cost^{storage} + Cost^{transport} \qquad (5)$$

3. MODEL CONSTRUCTION IN WITNESS SIMULATION ENVIRONMENT

For building up the model and subsequent implementation of the proposed experiments, it is possible to use a wide range of simulation programs and systems (Banks 2005). The Witness system environment was available in this case. This system is offered by the Lanner Group and it contains many elements for discrete-part manufacturing. Witness models are based on template elements. These may be customized and combined into module elements and templates for reuse. The standard machine elements can be single, batch, production, assembly, multistation or multicycle. Other discrete modelling elements include multiple types of conveyor, tracks, vehicles, labor and carriers. The behavior of each element is described on a tabbed detail form in the Witness user interface. The models are displayed in a 2-D layout animation with multiple windows and display layers.

The simple model is created for simulation study of our problem. Supply of individual parts of the warehouse is modelled in the Witness environment with help of the element Machine of Production type. The truncated normal distribution is used for modelling of cycle time of each machine. The parameters are set up according to Table 2. The element buffer is used to model individual parts (A, B, C) of the warehouse. Capacity of each buffer is 5000.

The module Witness experimenter is used to search the best solution. In Witness the objective function is set inside the simulation model. The objective function is set according the form (2). This module offers simple analysis of the experiments to determine the variability of typical runs or optional tracking for any other parameters that may be of interest in the results set from the simulation. The experimenter offers a wide choice of options (methods) for experimentation. Some methods are used to experiment in our simulation study. The results according random solution, Min/Mid/Max method, Hill Climb simple algorithm and Adaptive Thermostatistical SA algorithm are compared.

4. DESCRIPTION OF THE SIMULATION EXPERIMENTS

The inter arrival time of truck loaded with part of *x*-type (IAT_x) is not constant. Time of truck arrival is modeled by truncated normal distribution. This distribution has four parameters (mean, standard deviation, minimum, maximum). Three real situations are considered.

1. The inter arrival times of trucks are kept very strictly.
2. The arrival delay of the truck is not more than 20% of the inter arrival time.
3. The delay of arrival of the truck can reach up to 50% of the inter arrival time.

Setting the truncated normal distribution parameters for experiments defined above is clearly shown in the Table 1. The probability density function of truncated normal distribution with parameters of experiment no.3 and for IAT_x=50 is presented in the Figure 1.

Table 1: Parameters of the truncated normal distribution

Parameter	Experiment No.1	Experiment No.2	Experiment No.3
Mean	IAT_x	IAT_x	IAT_x
Standard deviation	$0.05*IAT_x$	$0.1*IAT_x$	$0.15*IAT_x$
Minimum	$IAT_x - 0.2*IAT_x$	$IAT_x - 0.2*IAT_x$	$IAT_x - 0.2*IAT_x$
Maximum	$IAT_x + 0.2*IAT_x$	$IAT_x + 0.2*IAT_x$	$IAT_x + 0.5*IAT_x$

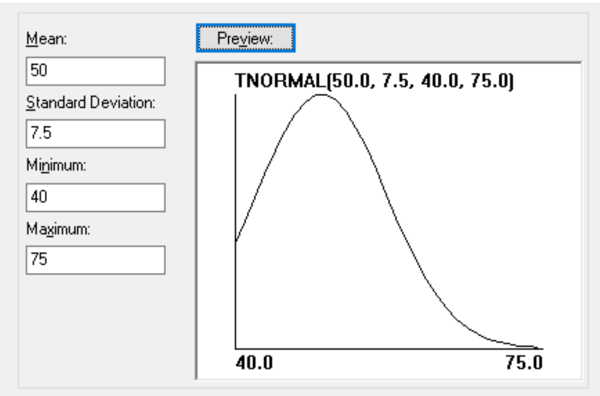

Figure 1: Sample of the probability density function of truncated normal distribution

Each of the above experiments is applied to different types of transport. The goal of this simulation study is to select the best means of transport for given conditions. Three different vehicles are assumed in the experiments. There is a small truck, a standard truck and a jumbo truck. Each of these vehicles has a cargo capacity. This capacity is measured by SKU. Each of the vehicles has its own cost rate per kilometer. Cargo capacity and cost rate for assumed type of vehicle are presented in the Table 2. These parameters are specified based on reality. Distance for all the vehicles is determined as an average value of 100 km.

Table 2: Parameters of assumed vehicles

Type of vehicle	Cargo capacity [SKU]	Cost Rate [CZK/km]
Small truck	50	15
Standard Truck	100	18
Jumbo Truck	150	19

5. RESULTS OF SIMULATION EXPERIMENTS

The model created in Witness environment was verified so it could be used for simulation experiments. The module Witness experimenter is used for analysis of the experiments.

The main goal is to find suitable warehouse parameters to minimize warehouse operation costs. The inter arrival time of truck loaded with part of type C (IAT_C) and initial number of SKUs in each part (A, B, C) of the warehouse ($N_A^{initial}, N_B^{initial}, N_C^{initial}$).

Various optimization methods are used for searching the best solution. The results according Min/Mid/Max method, Hill Climb simple algorithm and Adaptive Thermostatistical SA algorithm are compared. Especially the possibilities of using the random solution algorithm are outlined. This algorithm provides a fast, very good solution that is not optimal, but very close to effective solution. For each method except Min/Mid/Max method, 250 scenarios are generated. The model is running for 5 replications (with 5 different datasets). Model is simulated for stock time units (STU). The stock time units' value is 1000 items. Adapt into real world, its one working month.

The minimal value of the total costs of warehouse is searched during the simulation experiments. This value is calculated according to the formula (2). In addition to the objective function's value, other parameters are further measured. The value of maximum number of SKUs in the warehouse (N^{max}) is measured.

Also, the number of the empty warehouse times (N^{zero}) is measured.

5.1. Simulation experiments for small truck

Firstly, the experiments for small truck are carried out. The cargo capacity of this truck is 50 SKUs. It is considered the constant time (0.1 STU) for unloading one unit from any parts of the warehouse as mentioned above. It means that the 50 SKUs are picked from the warehouse part C for 50 STU while respecting 70:20:10 ratio and maintaining the sufficiency of the given warehouse part. Therefore, the constraint for parameter of IAT_C is set to a very small interval $\langle 48,52 \rangle$ for all experiments with small truck.

The constraints for initial number of SKUs in specific part of the warehouse are set for each experiment separately. The constraint intervals have been set based on simple model experiments. Specific settings for individual experiments are specified in the Table 3.

Table 3: Constraints for initial number of SKUs in specific part of warehouse for small truck

Part of warehouse	Constraints interval		
	Experiment No.1	Experiment No.2	Experiment No.3
A	⟨100,250⟩	⟨150,350⟩	⟨200,500⟩
B	⟨70,150⟩	⟨70,150⟩	⟨70,200⟩
C	⟨50,100⟩	⟨50,100⟩	⟨50,150⟩

The results of experiments defined above are presented in the Table 4, Table 5 and Table 6. The three best results searched by random method and the best result found according the other methods are shown in the tables. The presented results represent the average values of the five replications that are performed within the simulation experiment. Therefore, the values in the last two columns are not integers. The best result for each experiment is highlighted.

Table 4: The results of experiment No.1 for small truck

Optimization method		$Cost^{total}$ [CZK]	IAT_C [STU]	$N_A^{initial}$	$N_B^{initial}$	$N_C^{initial}$	N^{max}	N^{zero}
Random	1	515 534,41	50	130	82	82	373,8	0
	2	525 115,38	50	132	88	84	383,8	0
	3	537 428,11	50	158	78	80	395,8	0
Hill Climb		523 959,33	50	126	70	60	353,8	0,8
Adaptive Thermostatistical SA		513 848,01	50	136	80	76	371,8	0
Min/Mid/Max		550 303,96	50	174	70	74	397,8	0,2

Table 5: The results of experiment No.2 for small truck

Optimization method		$Cost^{total}$ [CZK]	IAT_C [STU]	$N_A^{initial}$	$N_B^{initial}$	$N_C^{initial}$	N^{max}	N^{zero}
Random	1	557 918,25	50	198	74	86	451,6	0
	2	592 959,68	50	230	70	80	476,4	0,2
	3	598 447,65	50	194	104	76	473,0	0,4
Hill Climb		594 623,75	50	194	70	60	455,2	1
Adaptive Thermostatistical SA		559 686,46	50	194	74	92	453,6	0
Min/Mid/Max		618 319,48	50	250	70	100	513,6	0

Table 6: The results of experiment No.3 for small truck

Optimization method		$Cost^{total}$ [CZK]	IAT_C [STU]	$N_A^{initial}$	$N_B^{initial}$	$N_C^{initial}$	N^{max}	N^{zero}
Random	1	598 782,97	49	220	106	104	504,4	0
	2	604 173,34	49	202	100	122	498,4	0,2
	3	623 961,29	49	236	110	110	530,4	0
Hill Climb		629 728,27	48	200	68	70	529,6	0,2
Adaptive Thermostatistical SA		591 224,07	49	218	94	98	484,4	0,2
Min/Mid/Max		672 237,37	48	200	100	100	587,4	0

5.2. Simulation experiments for standard truck

Secondly, the experiments for standard truck are carried out. The cargo capacity of this truck is 100 SKUs. The constraint for parameter of IAT_C is set to a very small interval ⟨95,105⟩ for all experiments with standard truck based on the same considerations as for a small truck. The constraints for initial number of SKUs in specific part of the warehouse are set for each experiment separately. Specific settings for individual experiments are specified in the Table 7. The results of experiments are presented in the Table 8, Table 9 and Table 10.

Table 7: Constraints for initial number of SKUs in specific part of warehouse for standard truck

Part of warehouse	Constraints interval		
	Experiment No.1	Experiment No.2	Experiment No.3
A	⟨150,300⟩	⟨250,500⟩	⟨400,700⟩
B	⟨80,200⟩	⟨80,200⟩	⟨100,200⟩
C	⟨70,150⟩	⟨70,150⟩	⟨100,200⟩

Table 8: The results of experiment No.1 for standard truck

Optimization method		$Cost^{total}$ [CZK]	IAT_C [STU]	$N_A^{initial}$	$N_B^{initial}$	$N_C^{initial}$	N^{max}	N^{zero}
Random	1	469 753,05	100	182	136	118	542,6	0,8
	2	469 884,19	100	208	132	126	556,4	0,2
	3	472 265,32	101	232	142	138	569,6	0,4
Hill Climb		612 431,54	102	266	124	90	657	3,2
Adaptive Thermostatistical SA		459 707,07	100	198	126	144	551,4	0
Min/Mid/Max		503 856,03	100	224	140	150	597,4	0

Table 9: The results of experiment No.2 for standard truck

Optimization method		$Cost^{total}$ [CZK]	IAT_C [STU]	$N_A^{initial}$	$N_B^{initial}$	$N_C^{initial}$	N^{max}	N^{zero}
Random	1	559 444,52	100	308	132	126	720,2	0,4
	2	570 107,47	100	312	122	142	692,8	0,4
	3	578 105,01	100	332	118	116	742,8	0,6
Hill Climb		571 932,04	101	368	132	122	766,2	0,4
Adaptive Thermostatistical SA		556 231,28	101	110	312	120	698,4	1,2
Min/Mid/Max		620 783,38	100	374	140	150	780,8	0

Table 10: The results of experiment No.3 for standard truck

Optimization method		$Cost^{total}$ [CZK]	IAT_C [STU]	$N_A^{initial}$	$N_B^{initial}$	$N_C^{initial}$	N^{max}	N^{zero}
Random	1	663 081,26	100	424	168	154	814	1,2
	2	685 914,67	100	406	194	194	862	1
	3	687 353,25	99	428	198	184	892,2	0
Hill Climb		795 886,91	99	594	170	158	1004,2	0
Adaptive Thermostatistical SA		663 942,21	99	442	176	166	866,2	0
Min/Mid/Max		681 977,55	100	400	200	150	818	1,6

5.3. Simulation experiments for jumbo truck

Finally, the experiments for jumbo truck are carried out. The cargo capacity of this truck is 150 SKUs. The constraint for parameter of IAT_C is set to a very small interval ⟨140,160⟩ for all experiments with jumbo truck based on the same considerations as for a small or standard truck. The constraints for initial number of SKUs in specific part of the warehouse are set for each experiment separately. Specific settings for individual experiments are specified in the Table 11. The results of experiments are presented in the Table 12, Table 13 and Table 14.

Table 11: Constraints for initial number of SKUs in specific part of warehouse for jumbo truck

Part of warehouse	Constraints interval		
	Experiment No.1	Experiment No.2	Experiment No.3
A	⟨150,300⟩	⟨300,600⟩	⟨400,800⟩
B	⟨80,200⟩	⟨100,250⟩	⟨150,400⟩
C	⟨70,200⟩	⟨100,250⟩	⟨150,400⟩

Table 12: The results of experiment No.1 for jumbo truck

Optimization method		$Cost^{total}$ [CZK]	IAT_C [STU]	$N_A^{initial}$	$N_B^{initial}$	$N_C^{initial}$	N^{max}	N^{zero}
Random	1	490 113,08	151	260	192	182	703,2	0,4
	2	500 195,32	151	288	186	192	735,2	0
	3	510 047,46	149	220	156	198	727,2	0,4
Hill Climb		1 051 368,46	149	238	152	84	1235,6	2,8
Adaptive Thermostatistical SA		468 776,35	149	212	168	178	693,8	0,2
Min/Mid/Max		537 129,02	150	274	200	200	764	0

Table 13: The results of experiment No.2 for jumbo truck

Optimization method		$Cost^{total}$ [CZK]	IAT_C [STU]	$N_A^{initial}$	$N_B^{initial}$	$N_C^{initial}$	N^{max}	N^{zero}
Random	1	615 326,55	147	314	184	190	929,2	0
	2	644 866,89	149	370	176	228	933,2	0,2
	3	645 275,34	149	374	212	162	940,2	0,4
Hill Climb		722 028,73	149	486	166	182	993,6	0,4
Adaptive Thermostatistical SA		601 607,40	149	360	172	184	875,2	0,4
Min/Mid/Max		673 186,30	150	450	174	174	947,4	0,6

Table 14: The results of experiment No.3 for jumbo truck

Optimization method		$Cost^{total}$ [CZK]	IAT_C [STU]	$N_A^{initial}$	$N_B^{initial}$	$N_C^{initial}$	N^{max}	N^{zero}
Random	1	703 957,89	149	468	222	210	994	1
	2	781 546,69	147	496	280	212	1120	0
	3	783 095,57	148	404	278	328	1118,2	0,4
Hill Climb		1 015 220,44	151	704	218	174	1232,4	2,2
Adaptive Thermostatistical SA		665 739,39	148	438	244	216	1006,2	0
Min/Mid/Max		841 693,35	150	600	274	274	1231,2	0

6. SUMMARY OF RESULTS

The effective solution for three modeled situation (three experiments) is searched by means of four methods. The results presented in the tables above show that The Adaptive Thermostatistical SA algorithm achieves the best results for most experiments. Furthermore, it should be noted that the Hill Climb method and Min/Mid/Max method are inappropriate for this type of simulation study. The Random Solution achieves relatively good results, sometimes even the best result. The advantage of this method is its simplicity and its calculation speed compared to the Adaptive Thermostatistical SA method. The Random Solution is a fast and efficient algorithm for fast decision making. This algorithm provides a fast, very good solution that is not optimal, but very close to effective solution. The Random method error does not exceed 5% compared to the best simulation result.

The summary Table 15 presents the values of objective function (total costs of warehouse) for assumed type of vehicles and for all performed experiments. It is obvious that a standard truck is the best solution for supply the warehouse for most experiments that are performed. If long delay of loaded trucks is assumed, it is better to use a small type of vehicle.

Table 15: The values of objective function for assumed vehicles and experiments

Type of vehicle	Total costs of warehouse [CZK]		
	Exp. No.1	Exp. No.2	Exp. No.3
Small	513 848	557 918	591 224
Standard	459 707	556 231	663 081
Jumbo	468776	601 607	665 739

At the same time, the simulation study also shows how the total warehouse capacity requirements change when the inter arrival times are extended (the arrival of trucks is much delayed). The summary Table 16 presents the values of maximum number of SKUs in the warehouse (N^{max}) for assumed type of vehicles and for all performed experiments. It is clear that if the delay time of loaded vehicles is extended, it will be necessary to increase the capacity of warehouse by up to 50%.

Table 16: The values of maximum number of SKUs in the warehouse for assumed vehicles and experiments

Type of vehicle	The maximum number of SKUs in the warehouse		
	Exp. No.1	Exp. No.2	Exp. No.3
Small	372	452	484
Standard	551	698	814
Jumbo	694	875	1006

7. CONCLUSION

The paper is focused on increasing the efficiency of warehouse logistics using optimization methods. Different methods are used for searching the best solution. The Adaptive Thermostatistical SA algorithm achieves the best results for all experiments. The Random Solution provides a fast, very good solution that is not optimal, but very close to effective solution. The Random method error does not exceed 5% compared to the best simulation result. Sometimes this method achieves the best result.

Three real situations are considered. Firstly, the inter arrival times of trucks are kept very strictly. Secondly, the arrival delay of the truck is not more than 20% of the inter arrival time. Finally, the delay of arrival of the truck can reach up to 50% of the inter arrival time.

Each of the above experiment is applied to three different types of transport. There is a small truck, a standard truck and a jumbo truck. This simulation study shows that a standard truck is the best solution for supplying the warehouse for the most experiments that are performed. If long delay of loaded trucks is assumed, it is better to use a small type of vehicle. At

the same time, the simulation study also shows that if the delay time of loaded vehicles is extended, it will be necessary to increase the capacity of warehouse by up to 50%.
Simulation study ties together the project of controlled warehouse, which is implemented in these processes by the company. The verified model is subsequently used for simulation experiments.
This paper presents the possibilities afforded by using computer simulation for the design, optimization and identification of reserves in warehouse systems. Using concrete examples, it is demonstrated that the use of the Witness simulation environment – not only for suggestions designed to increase the effectivity of existing warehouses, but also in the initial creation and design is valid and effective.

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