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Determine Selected Delivery Parameters Using Multi-Agent-Based Simulation: A Case Study*

Marcin OLECH and Łukasz PAŚKO

Faculty of Mechanical Engineering and Aeronautics, Department of Computer Science,
Rzeszów University of Technology, Rzeszów, Poland

Correspondence should be addressed to: Marcin OLECH, molech@prz.edu.pl

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Abstract

Establishing warehouse policy parameters is a challenging task that can affect, among others, the retailer's profit. Very few scientific publications deal with the impact of warehouse policy on customer trust in the retailer. The paper focusses on two warehouse policy parameters: *rbs* (retailer's base stock level size) and *dbs* (delivery batch size). The experiments described in the paper ask the question of what values of the parameters provide the retailer with maximum net profit and, at the same time, allow to achieve the assumed level of customer trust in the retailer. To obtain the answer, a multi-agent simulation was used, implemented in the NetLogo environment, in which an appropriate software tool was developed. This tool allows to create simulation models and analyse parameters related to deliveries to the retailer and warehouse policy. The research conducted for the analysed case study determines the optimal values of *rbs* and *dbs*, which ensure maximum net profit and maintain a high level of customer trust. The results also show nonlinear relationships between *dbs* and the retailer's profit and customer trust. The results obtained and the developed tool are important for managers and decision makers in the retail sector, who can use them to adjust their inventory management policy. Research can be continued in many directions. One of them is to consider variable delivery time.

Keywords: multi-agent simulation, supply chain modelling, delivery batch size, base stock level.

Introduction

A key element of the chain that connects a customer with a manufacturer is a retailer. A retailer's task is to maintain an appropriate number of products stored in its warehouse. One of the strategies for inventory management is to constantly keep as many products as possible in stock to satisfy any emerging customer demand. This approach allows minimising the number of unserved customers, but it generates relatively high storage costs and negatively affects retailer's profit. However, maintaining a too low level of inventory will increase the likelihood of a situation in which a customer wants to buy a product and the retailer is not able to meet that demand. This creates the problem of lost sales profits.

The example presented above shows that managing a retailer's inventory is a non-trivial task. It involves determining the appropriate values for parameters such as the retailer's base stock level (*rbs*) and the delivery batch size (*dbs*). The *rbs* (also known as the reorder point) is a threshold that controls the moment of placing an order to replenish the retailer's warehouse. If the current product stock level drops below the *rbs* value, the retailer orders a delivery from the supplier to replenish the warehouse (replenishment delivery). In turn, *dbs* is the number of products ordered from the supplier to replenish the retailer's inventory (the size of the replenishment delivery).

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The task of selecting the appropriate *rbs* and *dbs* values is additionally complicated by the variability of customer demand. Setting a too low value for *rbs* or *dbs* can result in an insufficient level of retailer's inventory. This situation negatively affects customer trust in the retailer. As research shows, trust between supply chain elements is a key issue for the functioning of such a chain. Trust promotes not only building business relationships, but also, among others, innovation (Panayides and Venus Lun, 2009), trade (Kiwala et al., 2023) and supply chain efficiency (Ireland and Webb, 2007). Therefore, customer trust in the retailer can affect the customer's future purchase decisions. The loss of trust discourages customers from buying from the retailer, which causes customer churn.

This paper is a continuation of the publication (Olech and Paśko, 2024), which presents a software tool for modelling and simulating the shopping process of many customers at one retailer. The purpose of this paper is to present an extended version of the developed tool, which has been enriched with the possibility of defining parameters of product deliveries to the retailer. Thanks to this, in the created model it is possible to determine the delivery size (*dbs*), delivery time, fixed cost of delivery, and unit cost (cost of delivering one piece of product). The novelty of this paper is the combination of the analysis of parameters such as *rbs* and *dbs* with the study of their impact on the customer's trust in the retailer. As the Literature review section shows, there is a lack of publications that combine these issues. The paper also shows how *dbs* affects the retailer's net balance and the number of out-of-stock problems.

The conclusions of the paper and the software developed tool can be useful in selecting the best values for stock policy parameters in a given situation. The results described in the paper are addressed primarily to supply chain managers, analysts, and decision makers responsible for optimising warehouse and logistics processes. The software tool will give users the ability to better adapt the warehouse policy to the specifics of their business.

Literature Review

Inventory policy and factors influencing the size of stock in the warehouse

Establishing the appropriate parameters of the inventory policy is made difficult by many factors. One of them is operating under conditions of uncertain demand. An additional difficulty may be the uncertainty of supplies. The retailer's orders may not be delivered in full, depending on the currently available capacity (Jakšič and Fransoo, 2015). The uncertainty of supplies is also influenced by the quality of products. Delivered products of inadequate quality reduce the actual amount of stock in the warehouse, which can be used by the retailer (Wee et al., 2007).

Maintaining low inventory levels is facilitated by a well-developed network of suppliers (high supplier density). However, too long of delivery times can lead to customer loss. In such situations, an appropriate approach to inventory management is also required (Kurata, 2014). In turn, in the case of higher customer density, higher inventory levels are necessary because the number of potential customers is so large that storage costs are less important.

Another factor influencing the amount of inventory is the type of product stored. Determining an optimal storage policy will be more challenging in the case of perishable products with fixed shelf life (Tiwari et al., 2018). The deterioration rate of a product means that the usefulness of the product in stock reaches its minimum close to the expiration date and the stock level of the product can be considered zero. Relationships with product recipients (customers) are also important. Information about product demand obtained from customers in advance allows for better planning of warehouse stocks, thus reducing storage costs (Özer and Wei, 2004).

In summary, achieving the right inventory level in a warehouse requires establishing an inventory policy and its parameters such as reorder point (*rbs*) and delivery volume (*dbs*). Lam and Ip underline that most inventory management models only consider independently varying demand patterns, volume discounts, inventory costs, or lead time changes, but only a few models focus on customer relationships (Lam and Ip, 2011). To fill this gap, in our research we considered the relationship between the retailer and the customer expressed as customer trust in the retailer, and we attempted to examine the relationship between inventory policy parameters and customer trust.

Determining the optimal dbs value

A determination of the optimal *dbs* value is discussed in the literature in different contexts. First of all, researchers consider *dbs* in the context of multi-stage supply chains. In (Chaharsooghi and Sajedinejad, 2010), an attempt was made to develop an algorithm that can be used to optimise the number of kanbans and the size of the batch to minimise the cost in the supply chain. In turn, (Cheng and Kovalyov, 2001) used methods based on dynamic programming that allow for simultaneous optimisation of production and logistics decisions, which in effect affects the determination of the optimal size of the delivery batch. Research on the size of the delivery batch is also conducted in the context of deliveries to the customer. In (Raj et al., 2024), the optimal *dbs* was determined for fast retail deliveries, where costs and risk of delays are important. An open queue network was used to model the order fulfilment process. In (Anufriyeva et al., 2023), a simulation model based on discrete-event principles and a multi-agent approach was used, which considers the minimum allowable batch size transported to a given destination in a transport network.

However, from the point of view of this paper, the most important is retailer's context. To find publications that treat *dbs* in this context, the Scopus database was used. The focus was on publications in English that are scientific papers, chapters, or conference papers. A query was considered that lead to finding publications with the *dbs* term but also with alternative terms, such as "order batch size", "shipment batch size", "delivery lot size", "batch delivery quantity", "batch order quantity", "delivery lot quantity". Additionally, the query narrows the results to only publications that mention "determination" or "optimisation", as well as "retailer" or "store". The query allowed finding 99 publications, of which 19 are in open access mode. After the analysis of the publications found, it was noticed that only one of them refers to the searched context of *dbs* (Fradinata et al., 2018). The authors use three methods (Wagner–Whitin algorithm, Silver–Meal heuristic, balanced holding, and ordering costs heuristic) to determine the batch size under conditions of demand uncertainty.

Furthermore, it was checked whether publications on *dbs* address the issue of examining the dependency between *dbs* and the number of out-of-stock problems, as well as the dependency between *dbs* and the trust of customers in the retailer. For this purpose, the previous query was augmented with terms "out-of-stock" and "customer trust". The first one allows find one publication that addresses the problem of lost sales (Pauls-Worm et al., 2016). The authors focus on establishing a production and replenishment plan for a perishable product, assuming non-stationary demand and using stochastic programming to model the analysed decision problem. However, the second one does not find any publication that addresses the problem of customer trust.

To sum up the literature review, it can be stated that it is possible to find many publications on *dbs*, but the vast majority of these publications treat "batch size" in the context of production or in a batch of goods transported in transport networks. A very small part of the publications concerns the context of deliveries to retailers considered in this paper. In particular, there are no publications examining the relationship between *dbs* and customer trust in the retailer.

Applied methodology and model's characteristics

Introduction to the case study

Presented case study is an extension of the conducted research described in details in (Olech and Paśko, 2024). The retailer sells products to the customers, and the average sales is equal to 7.5 pcs of chosen product per day. The average number of customers per month is equal to 80. If the product is out-of-stock, the sale transaction is aborted, and the customer will return on the other day. But if the product is not be still available, the customer loses trust to the retailer and buys the product from competitors. If, on the other hand – the product is available, the trust level of the specific customer to the retailer raises by approximately 25%. Product's sales price is equal to \$150 and the production costs are estimated to be 70% of the sales price. Because the retailer is using the warehouse space at its logistics partner, the storage cost consists of:

- fixed costs equal to \$8.31 / 1 ft2 / year where: 1 pc. of the product requires 10.5 ft sq. – due to renting warehouse space at logistics partner,
- variable costs equal to \$3.18 / day / 1 pc. of product – due to handling the products at logistics partner.

The innovation in the current version of the model is the ability to model the deliveries between the retailer and the supplier. The most important parameter are as follows:

- delivery time is equal to 3 business days,
- delivery fixed cost is equal to \$500 per delivery,
- delivery variable cost is equal to \$10 per 1 shipped pc of the product,
- *dbs* is initially set to 5 pcs.

The results of previous research suggested that *rbs* value should be set to 13 pcs.

The problem: the retailer wants to know what *dbs* will be the optimal one. The optimal in the case means the retailer will get the highest possible net profit, which takes under consideration production, storage, and delivery costs. What is more, the optimal *dbs* should be set simultaneously to ensure average customers trust level in population high enough – the threshold is proposed at 95% by the retailer.

To conclude, the retailer wants to test the set of proposed *dbs* values between 5 and 80 pcs and their influence on the most important metrics.

Research problems solving process

The research work consisted of the following activities:

1. Extension of the base simulation model by: incorporating deliveries and its parameters into the conceptual model of the system, developing graphical user interface (GUI) control elements connected to various deliveries parameters, modification of the source code of the software to incorporate new features, and testing developed software.
2. Prepare simulation experiments according to the case study description by setting appropriate simulation and model parameters, conducting the simulation processes, and storing final values of metrics.
3. Analyse simulations result as well as visualise them to answer the case study problem.

The detailed specification of what activities were performed is presented in the "Experimental research" section.

Model assumptions

The proposed model is based on the following assumptions concerning specific areas of the problem domain:

- general assumptions area:
    - one simulation cycle means business day,
    - there is a population of customers and one retailer,
    - the general way, how the simulation model works is depicted in Figure 1,

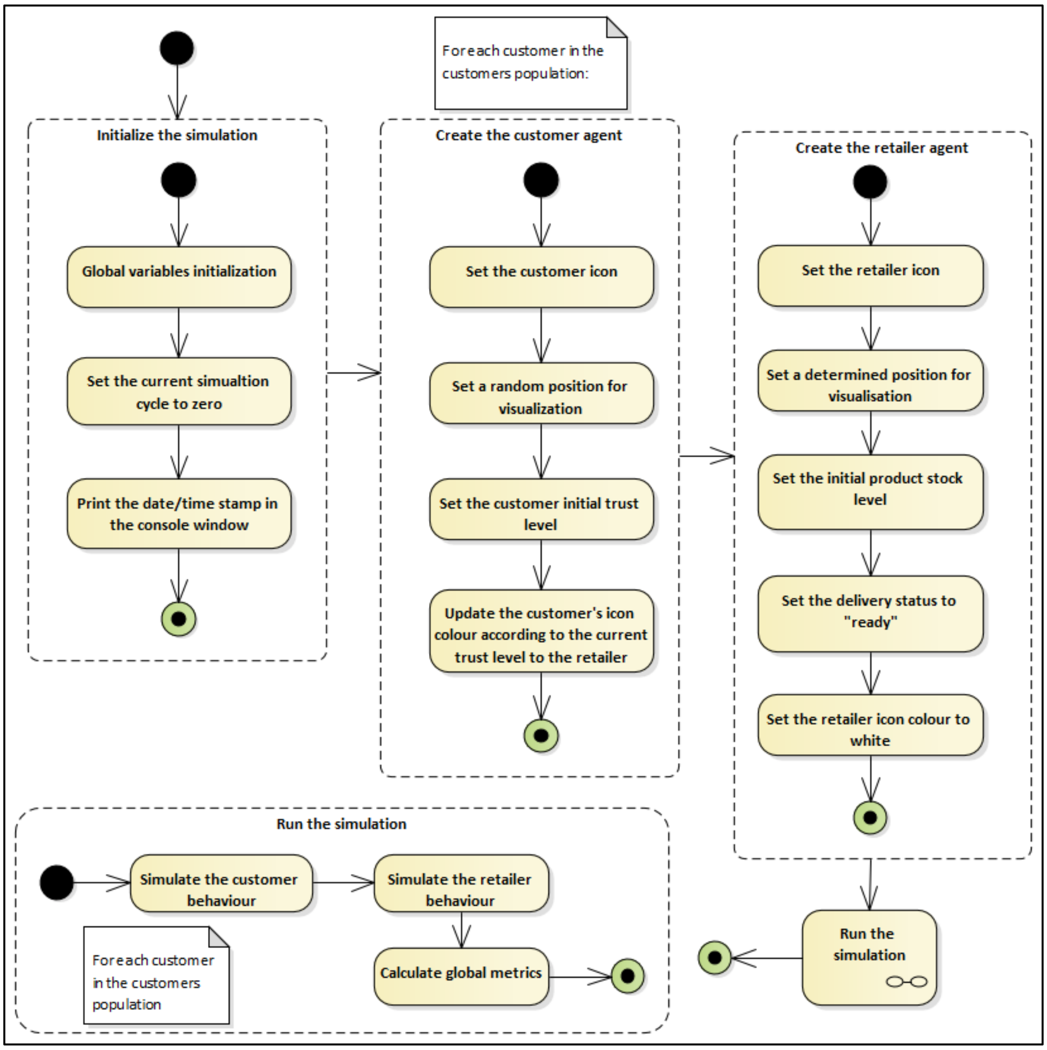

Figure 1. Overview of the simulation model

- customers population area:
  - the number of customers in whole population can be set up using GUI elements,
  - each customer in the population wants to buy the product at the retailer,
  - each customer in population has initial level of trust to the retailer set up, as well as probability of buying at the current simulation cycle,
  - the way in which customers act during the simulation run is depicted in Figure 2,
- the retailer area:
  - the retailer starts with initial stock level of products,
  - the retailer sells products to customers who engage in sales transaction,
  - the way how the retailer acts during the simulation run is depicted in Figure 3.

During running the simulation, the last activity is connected to the storing and/or calculating process of the proposed set of metrics, where total net profit/loss and average customer trust level to the retailer are crucial.

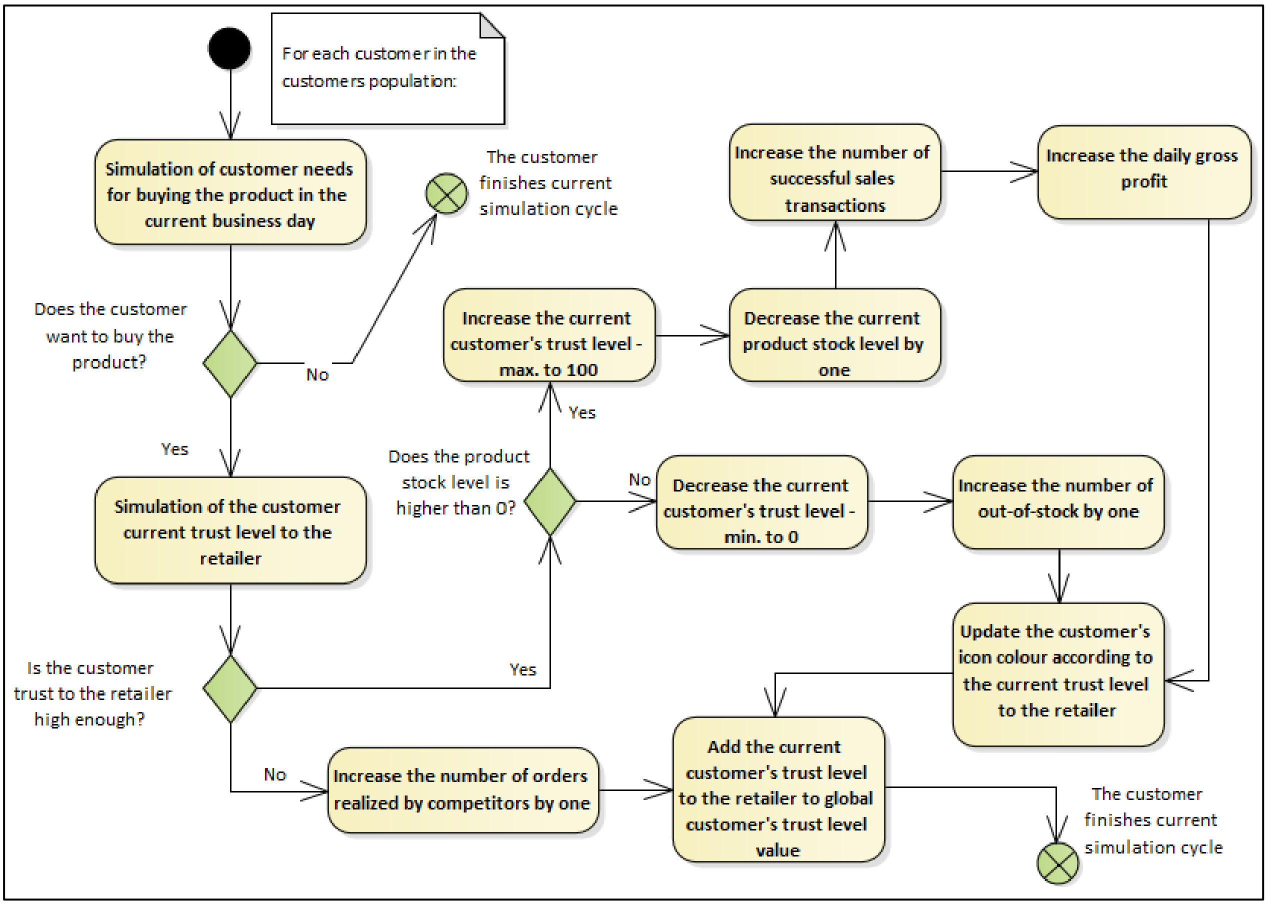

Figure 2. Simulation of the customer behaviour

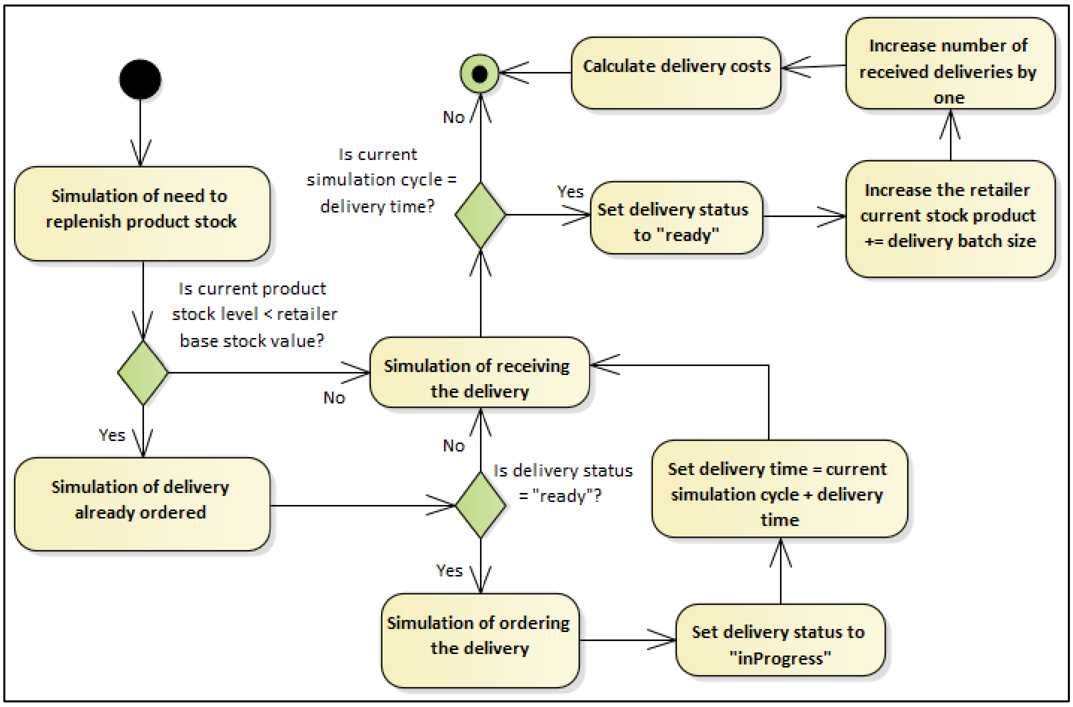

Figure 3. Simulation of the retailer behaviour

Model simplifications

Of course, there are some simplifications and limitations in the current version of the proposed model:

- the customer population is homogenous, so all customers:

- have the same initial trust level to the retailer,
  - have unlimited budget,
  - have the same frequency of buying the products at the retailer,
  - react in the same way to out-of-stock events, as well as successful purchase at the retailer,
  - try to buy the product maximum once per business day,
  - their consumption of bought product is not simulated, so they can return the next day for another piece of product,
- the products offered by the retailer:
  - are sold by one unit per sales transaction per one customer,
  - are homogeneous to the products offered by the competitors in case of features and sales price,
  - belongs to only one type of the product,
- deliveries:
  - all have the same and constant time of completion,
  - fixed and variable cost are constant during the whole simulation run,
  - supplier always has a required number of ordered products,
  - there can be only 1 active delivery from the supplier – the new delivery is possible if the previous delivery is finished.

Some of the restrictions presented are planned to be released in the future version of the model and software tool as described in the Conclusion section.

Software Graphical User Interface (GUI)

Figure 4 presents the GUI of the tool developed. The whole GUI consists of a few sections, where the user can set parameters according to the customer's population and the retailer's stock policy. Moreover, the GUI is composed of several monitor components, which show the current value of different metrics. To give the tool's user possibility to perform an initial analysis of the results, the plot components were prepared as well to illustrate how the value of different metrics evolves over time according to different simulation and model parameters.

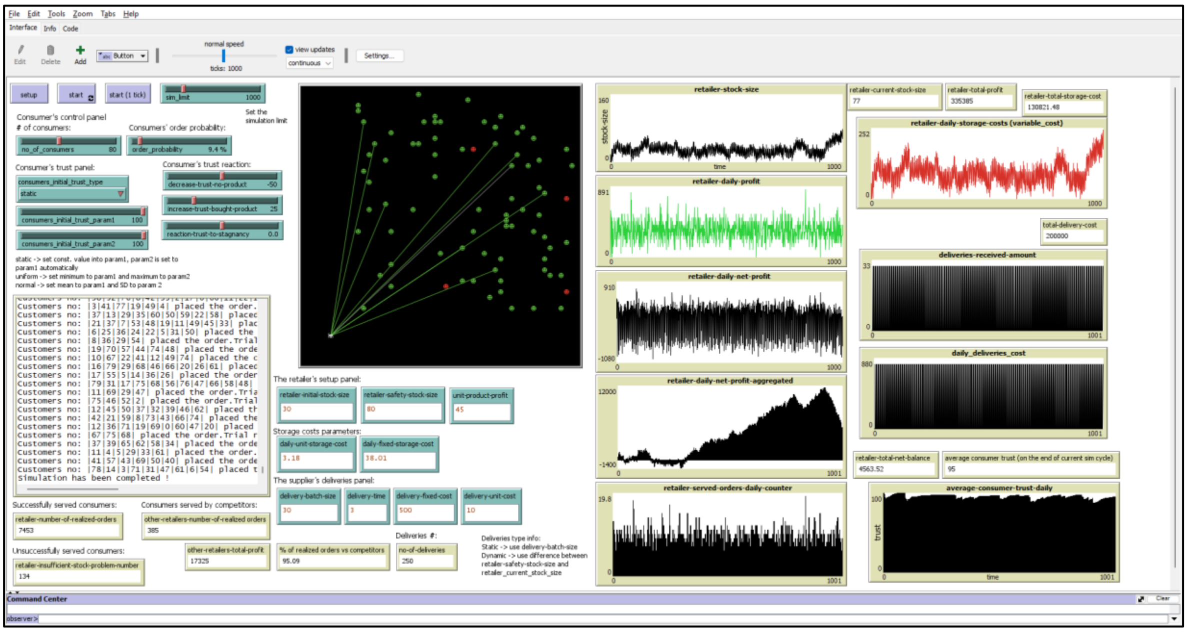

Figure 4. GUI of the developed software tool

What is important to mention, in the current version of the model, a new section has been developed to allow the user of the tool to set the deliveries, what is depicted in Figure 5.

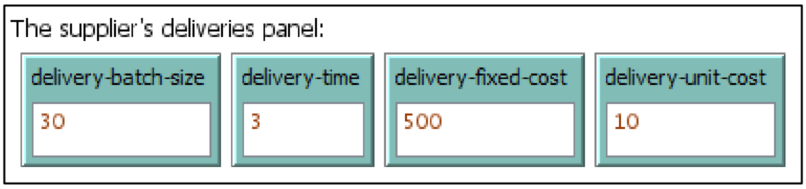

Figure 5. Deliveries modelling section

Experimental Research

Experimental research was conducted by using the developed tool, i.e. a multi-agent-based simulation tool. The research questions were formulated as follows:

1. Due to the elimination of simplification according to the delivery parameters: what *dbs* value will be optimal according to the formulated metrics if the other model's parameters stay the same?
2. Are the results between the simplified and current model according to the formulated metrics different? Is it possible to use the extended version of the model to find the best value of the stock policy parameters in the given case? How to do this process and what values for the stock policy parameters should be finally used?

Figure 6 shows the research plan, which is divided into four experiments. Experiment A considers the optimal value of *rbs*, which was determined in the previous studies. The result of this experiment is the determined value of *dbs*, which answers the first research question. This value is the input to experiment B, which, together with the subsequent experiments, answers the second research question.

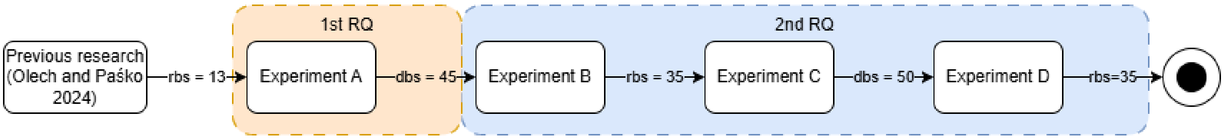

Figure 6. The plan of experiments during the study, indicating the research questions as well as the input and output values of each experiment

According to the first formulated research question and the description of the case study, the simulation model parameters were set up (<u>experiment A</u>) using GUI of the developed software.
To answer the first question, 20 simulation experiments were performed, each with 5 runs in which the values of *dbs* were tested between 5 and 80 pcs. The length of the run was limited to 1000 cycles (business days). The *rbs* was established at 13 pcs. The results are presented in the Results section of the paper.

During analysing the results connected to the first research question it was noticed that *rbs* was set to the optimal value obtained from simplified model, which could be wrong in the extended version of the model. To verify this, another series of simulation experiments (<u>experiment B</u>) was prepared. Almost all of the model parameters were the same as in the first research question despite:

- *dbs* = 45 pcs.

In that case 12 simulation experiments were performed, each with 5 runs where values of *rbs* were tested between 13 and 50 pcs. The length of the single run was the same as before. The results are presented in the Results section of the paper as well.

Analysing the results obtained from experiment B, a new optimal value of *rbs* was established. It meant that a new series of experiments is needed to check if optimal *dbs* determined in experiment A will change if we use new value for *rbs* as suggested by experiment B. Once again almost all simulation parameters in <u>experiment C</u> were the same as in experiment A in exception of:

- *rbs* = 35 pcs,

Proposed *dbs* values were almost the same like in experiment A.

The experiment C suggests slightly different optimal *dbs* equal to 50 instead of 45 pcs. Because of this, it was needed to check if the proposed *rbs* equal to 35 pcs is still optimal in that situation. So, this time only the change in the simulation model in experiment D was:

- *dbs* increased to 50 pcs.

The tested *rbs* values were the same as in experiment B.

During all of simulation experiments (A to D), the set of metrics were obtained or calculated. Two of them were crucial and were used to evaluate the potential solution.

Results of the simulation experiment

Experiment A: determining optimal dbs – 1st research question

To solve the first research question, 20 simulation experiment – each with different proposed *dbs* – were conducted. Every experiment was repeated 5 times to ensure the random distribution will be realised. Figure 7 shows the dependency between generated retailer's net balance according to the proposed *dbs*. The analysis of the result is quite simple. *Dbs* below 25 pcs is not enough to generate net profit, because there is insufficient number of products in retailer's stock, so sales cannot cover costs. The most stable and high net profit is generated if *dbs* is equal to 45-50 pcs. The overall value of the profit in this case is considered as small, but it can be connected to the high storage cost as well as delivery cost. Using higher *dbs* (more than 50 pcs) causes higher costs and, due to market saturation effect, lack of higher profits generated from sales transactions.

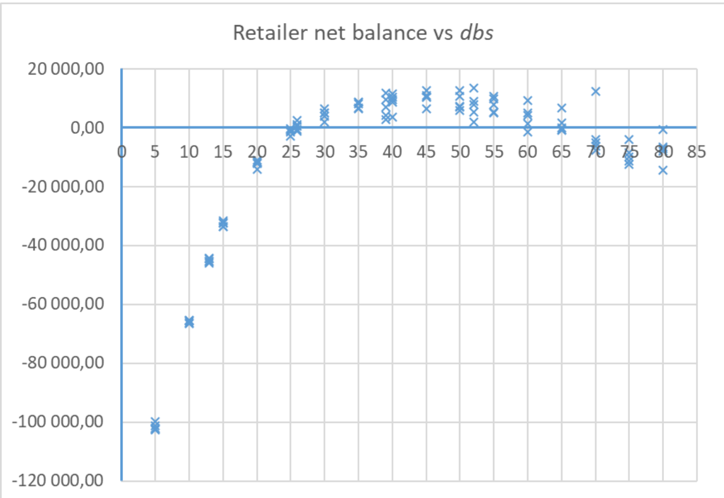

Figure 7. Dependency between net profit / loss according to the *dbs*

To check if the solution is optimal, Figure 8 has been prepared to check if proposed *dbs* equal to 45 or 50 pcs will generate average customer trust in population which exceeds threshold set by the decision-maker to 95%.

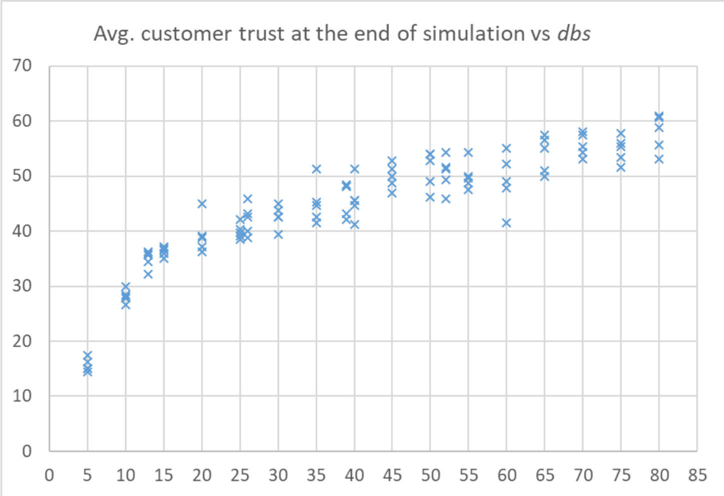

Figure 8. Average customer trust at the last cycle according to *dbs*

The optimal *dbs* equal to 45 or 50 pcs does not allow us to reach the required threshold. Instead of 95%, the average trust in the customer population is about 50%. What is more, even if we choose very high *dbs* equal to 80 pcs, we are unable to reach more trust than 60%. It seems that getting higher *dbs* is not connected to the higher availability of products to the customers, what causes low value of the trust in supply chain. To check, if this is the issue, we have prepared Figure 9, where the number of out-of-stock problems according to *dbs* is presented. Figure 9 confirms our suspicions; the number of out-of-stock problems is getting slightly higher if we use higher *dbs*. In the normal situation the relationship should be contrary, high *dbs* causes the bigger deliveries and higher products stock level, what cause less of stock ruptures, as well as higher average customer trust. So, we have started to examine other parameters in the model to find which is responsible for the situation. We have found that only one other factor was connected to the availability of products and it was *rbs*.

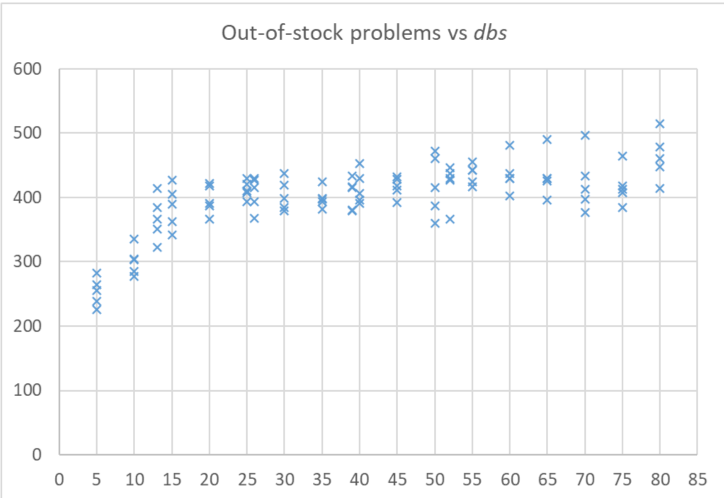

Figure 9. Number of out-of-stock problems according to the *dbs*

Experiment B: determining new optimal rbs – 2nd research question

Because the results of experiment A were not satisfied, we have noticed that there is another key factor – *rbs* – that is directly connected to the availability of products in the retailer. As we have seen before, if the *rbs* value is too low, even the deliveries are high, they are simply made too late, so the products stock is empty for a few days until the delivery is received. The *rbs* value was initially set to 13 pcs, because it was optimal in where case the deliveries were instant. The current version of the model allows to set the delivery time to the desired value and according to the case study it was set to 3 business days. So, we had to do another experiment B to check which *rbs* will be optimal if we assume that the *dbs* will be set to 45 pcs as results in experiment A suggested.

This time 12 simulation experiments were conducted and each of them were repeated 5 times. The results are presented in Figure 10.

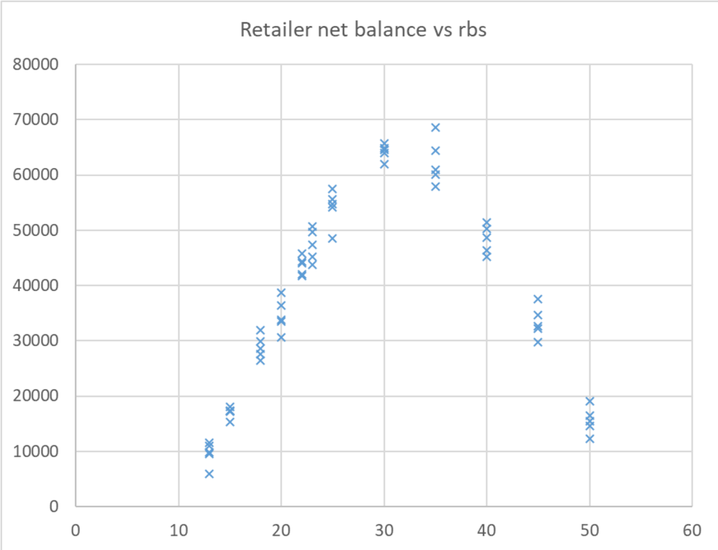

Figure 10. Dependency between net profit / loss according to the *rbs* at *dbs* = 45 pcs

As can be seen, the optimal value of *rbs* is equal to 30 pcs if we choose more stable net profit or 35 pcs if we prefer riskier but sometimes more profitable solution. Of course, we need to check how these two values influence the average customer trust. Because we need detailed information about the average trust, this time Figure 11 was prepared.

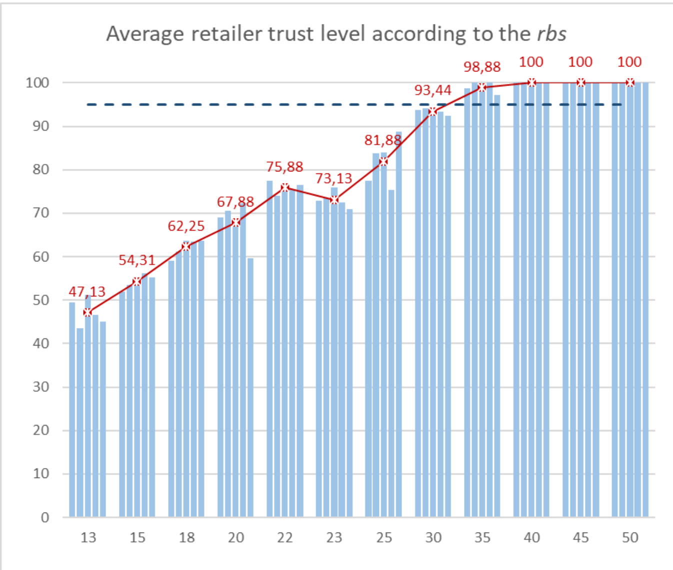

Figure 11. Dependency between average retailer trust according to the *rbs* at *dbs* = 45 pcs

As we can see, according to the minimal average trust threshold indicated in the case study specification, we are forced to choose *rbs* equal to 35 pcs instead of 30 pcs. It is because the total average trust level at 35 pcs is above desired threshold, as the well as average trust level in each simulation run also exceeds that value.

Experiment C: determining new optimal dbs – 2nd research question

Because we have determined the new *rbs* equal to 35 pcs, the results generated during experiment A are no longer valid, so we have performed another series of simulation experiments to obtain new results according to the optimal *dbs*. The retailer net balance according to the *dbs* was depicted on Figure 12.

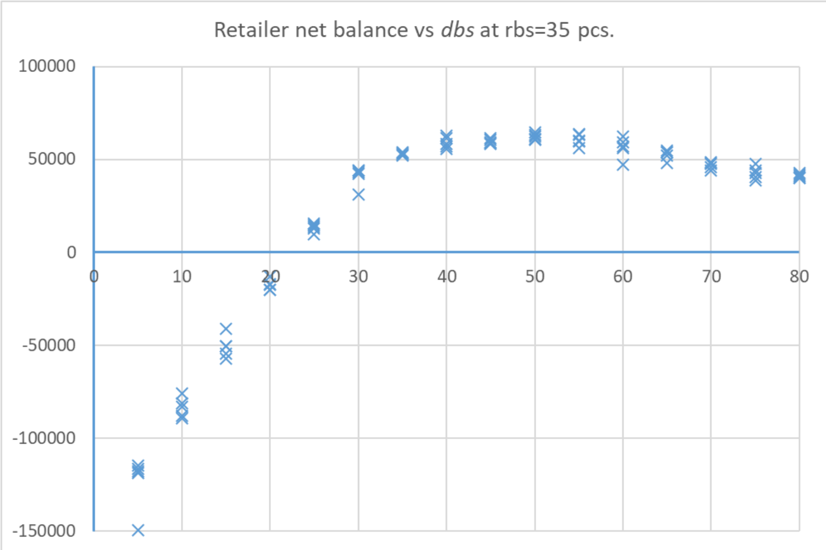

Figure 12. Dependency between net profit / loss according to the *dbs* at *rbs* = 35 pcs

As can be seen, the net profit starts from *dbs* = 25 pcs and the highest and stable value is reached if the *dbs* is equal to 50 pcs. Making *dbs* higher than that value causes a lower net profit because of the market saturation effect, as well as higher storage costs and possibly higher delivery costs.

Of course, the proposed value of *dbs* should be evaluate according to the average trust level. This dependency is presented in Figure 13.

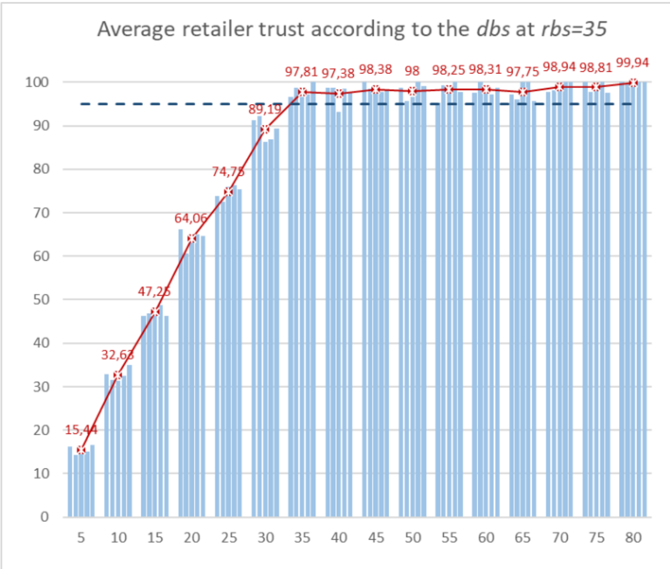

Figure 13. Dependency between average retailer trust according to the *dbs* at *rbs* = 35 pcs

We can see that, in terms of total average trust, *dbs* must be selected equal to or greater than 35 pcs. We have proposed 50 pcs, because that *dbs* generates the highest retailer net profit. According to the trust requirement, proposed *dbs* ensures average total trust level equal to 98%, but also average trust in each run exceeds the threshold as well.

Experiment D: determining updated optimal rbs – 2nd research question

Before we have formulated final answer, we were particularly interested in the issue of does the *rbs* stay the same optimal and equal to 35 pcs, if we try to use *dbs* equal to 50 pcs and try to find optimal *rbs* once again. The results of all 60 simulation runs were analysed and Figure 14 was prepared. As can be seen, two values of *rbs* can be considered as optimal:

- *rbs* equal to 30 pcs generates the highest possible net profit (average: $62,205.48) with some variability (standard deviation: 3.72% of average generated net profit),
- *rbs* equal to 35 pcs where the net profit is smaller by $646.45 (average: $61,559.03) with lower variability (standard deviation: 1.67% of the average generated net profit).

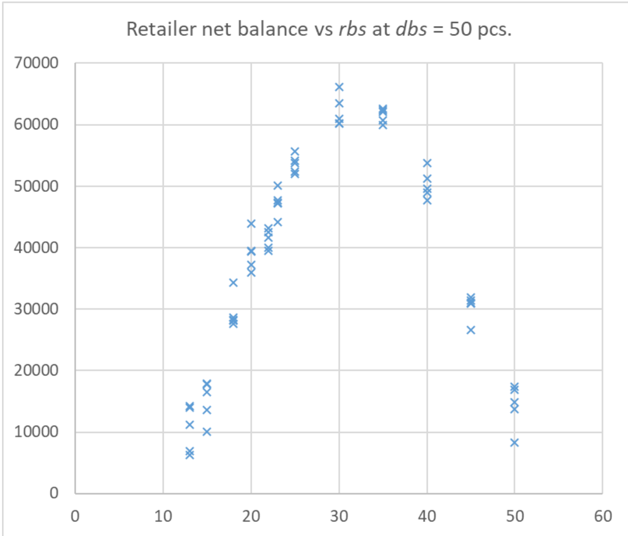

Figure 14. Dependency between net profit / loss according to the *rbs* at *dbs* = 50 pcs

To select optimal *rbs*, the second metric must be evaluated – average trust in the customer population. To check the issue, Figure 15 was prepared. Now it is clear that *rbs* value equal to 30 pcs must be rejected because only 1 of 5 runs exceeds the threshold 95%. Furthermore, the total average trust in the population in this case is equal to 92.88%, which is below the required value. Instead, *rbs* equal to the 35 pcs allows to generate average trust value high enough not only according to the total average but also in any single simulation run – the lowest value in the case is 98.75%.

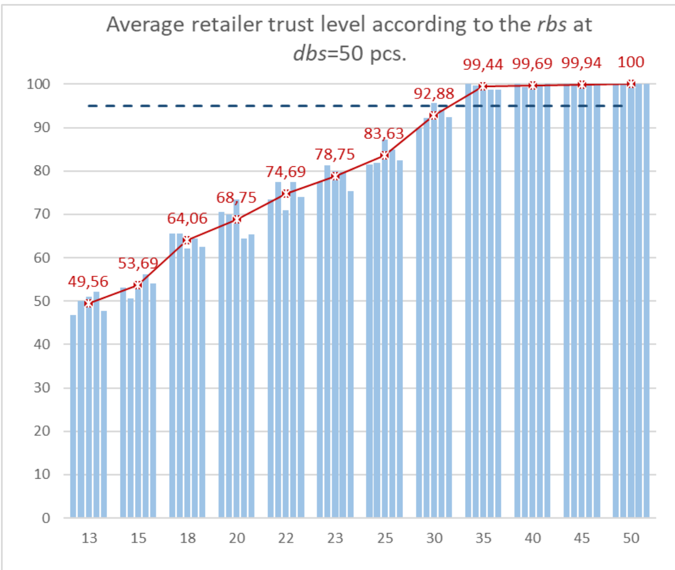

Figure 15. Dependency between average retailer trust according to the *rbs* at *dbs* = 50 pcs

Discussion

To conclude, we need to answer: if optimising the stock policy parameters is important and how it affects the final results. To provide the answer, comparison of results between experiment A and C have been prepared.

According to Figure 16, it is easy to notice that optimal selection of both parameters: *rbs* and *dbs* is crucial to generate high net profit. When the *rbs* value was set to 13 pcs, the highest average net profit was $10,092.25 (at *dbs* = 45 pcs), but if *rbs* value has been increased to 35 pcs, the highest average net profit reached $62,310.77 at *dbs* = 50 pcs.

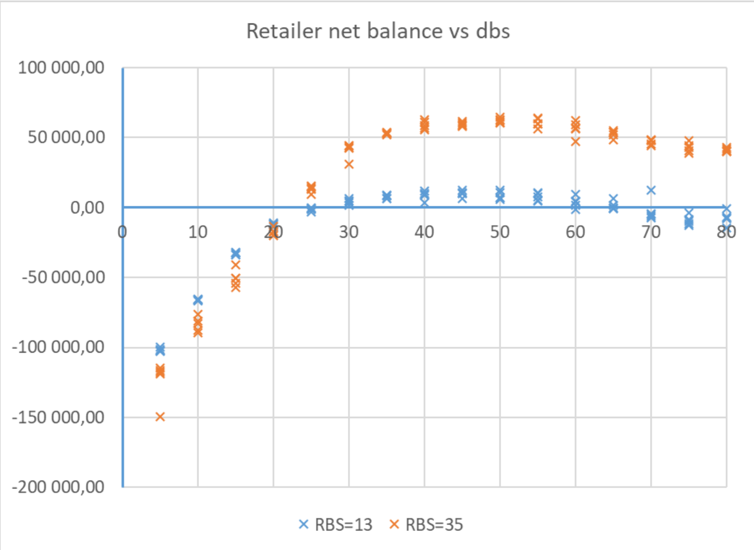

Figure 16. Retailer's generated net profit / loss according to the *dbs* if *rbs* = 13 and *rbs* = 35

To check the second important metric – the average customer trust in population, Figure 17 was prepared. As can be seen, using too low *rbs* causes high limitation of the average customer trust despite of high value of the *dbs*. The best possible average trust value is 57.82% at *dbs* = 80 pcs, but as we can see in Figure 16 that *dbs* together with *rbs* = 13 pcs, cause net loss. Contrary, using appropriate *rbs* equal – in the case – 35 pcs allows to reach required threshold (95%) starting *dbs* just from 35 pcs. If we take into consideration the optimal *dbs* as net balance analysis suggested (*dbs* = 50 pcs) we can see that this time each single run exceeds the threshold, as well as average calculated value.

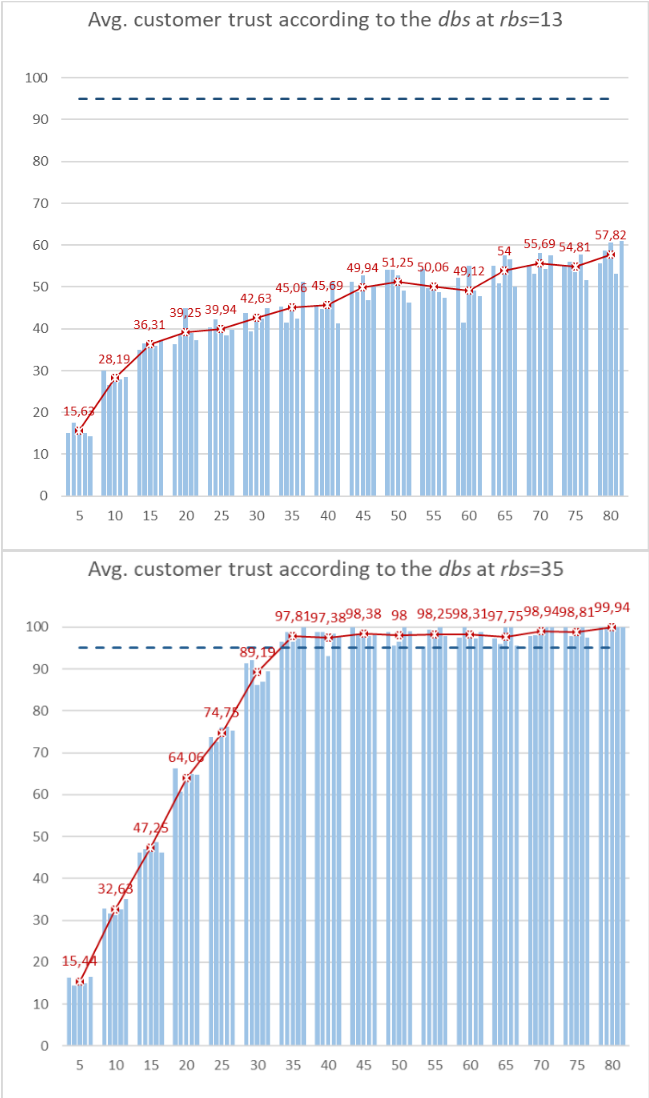

Figure 17. Average customer trust according to *dbs* at *rbs* = 13 pcs and *rbs* = 35 pcs

Finally, we can compare the best results from the simplified and current extended simulation model, but it doesn't really make sense. Why do the results from the simplified model (average net profit equals $312,618.29 and average trust 99.31%) look better than the metrics calculated according to the current simulation model (average net profit equals to $62,310.77 and average trust 98%)? The results obtained using the simplified model are impossible to obtain in reality because the omitted parameters according to the time and costs of deliveries and the chosen batch size are very important. Even if the company will find a very fast supplier, the market's changes cause delays and force to introduce some safety margin, so deliveries will not always be instant. In addition, such a supplier will be quite expensive, so at least delivery costs should be incorporated into the model in the case.

Conclusions

Managing the supply chain in a proper way has to be based on the right and accurate simulation model, where the sweet spot between realism and simplification of the model needs to be carefully balanced. The use of a model with too much simplification can lead not to the optimal decision, but of course – as was stated in (Olech and Paśko, 2024) – it is still better than using just guesses and intuition. The research conducted using the developed tool based on multi-agent simulation allowed to determine the optimal values of key parameters of the warehouse policy – *rbs* and *dbs* – considering their impact on the level of customer trust in the retailer. A set of simulation experiments allowed analysing the relationship between the size of deliveries, retailer net balance, and customer trust, which confirmed the importance of precisely setting the parameters of the inventory policy. The presented tool turned out to be a practical support in the decision-making process, allowing the testing of various scenarios to select the right warehouse strategy.

Future work on the development of the tool will be focused on implementation of variable delivery time by using random distribution generators instead of static delivery time.

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