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DEVELOPMENT OF SPREADSHEET SIMULATION MODELS OF GAS CYLINDERS INVENTORY MANAGEMENT

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Abstract

The solution of the problem of managing the inventory of an enterprise whose activities are related to the purchase and sale of gas cylinders is considered. To solve the problem, it was necessary to investigate and choose the best inventory management strategy that provides the minimum value of the average inventory balance in the warehouse with the established upper limit of the average deficit. The problem of determining the best strategy is presented as a discrete programming problem, the required variables of which depend on the replenishment method. With a periodic replenishment strategy, the controlled variables are the volume of the delivery line and the delivery interval, with a threshold one, the minimum inventory level and the volume of the delivery line. Let's also consider replenishment with a predicted inventory level, where the delivery level and the minimum inventory level are used as control variables. Three tabular simulation models with a given delivery time and random demand are proposed. Using the Chi-square test, it was found that the quantity demanded has a normal distribution law. By carrying out computational experiments, the optimal values of controlled variables were determined. The best objective function values were obtained using a model with a predicted inventory level and a threshold replenishment strategy. Experiments conducted on the basis of historical data have shown the advantage of the two model strategies compared to the strategy currently used in the enterprise. The use of a model with a predictable inventory level would reduce the average inventory balance by 46 %, and, consequently, save working capital. The results of the study can be useful for managers of enterprises whose activities are related to inventory management.

Keywords: simulation, inventory management, optimization problem, tabular model, random demand.

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1. Introduction

The activity of any enterprise is associated with the use of resources (financial, material, etc.), due to the limited number of which there is a need for the rational use of available funds. At the same time, the method of organizing the replenishment of resources has a significant impact on the efficiency of the economic object. In conditions of risk and uncertainty, it becomes necessary to form management decisions regarding such characteristics as the volume of replenishment of resources, the frequency of replenishment, the condition of replenishment, etc. Among the tasks related to resource management, the most common is the problem of inventory management, which consists in choosing the replenishment strategy resources to ensure the minimization of costs associated with delivery, storage, inventory deficits. Thus, a balance level of inventory should be ensured, which does not lead to «overstocking» of the warehouse and ensures that demand is met to the maximum extent. Let's consider some of the existing works devoted to solving such problems.

With constant demand and supply interval, the classical Wilson model can be used to solve the inventory management problem. In published studies, there are various modifications of it, taking into account the presence of several nomenclatures [1], the possibility of deferred payment [2], wholesale and differential discounts [3], the costs associated with the purchase, order, storage, delivery delay, fines, operating costs [4]. In [5], the solution of the problem of inventory management is considered, taking into account the restrictions on the working capital of the enterprise, in work [6] – on the scope of supply. The option of having several suppliers of goods can also be considered [7].

The work [8] considers multi-stage inventory management models that involve dividing the studied interval into periods, each of which has different conditions for the purchase of one product and requires a decision at each stage.

In the simplest case, in inventory management models, demand is assumed to be constant over time, but most often in a real system, demand is stochastic. In this regard, models are being developed that take into account the random nature of demand, in particular, the normal distribution law is quite common [9]. The work [10] searched for a solution to the problem in the case of a stochastic dependence of demand on the price, time and frequency of advertisements, in articles [11, 12] the demand depends on the inventory level. The authors of [13] solved the inventory management problem for seasonal demand. In [14], the perturbation method was used to take into account fluctuations in demand and costs.

The structure of an enterprise may include several distribution and storage points, forming an associated multi-level logistics system [15–17]. The main methods for solving such problems are mathematical programming and simulation, which can also be used together [18].

Thus, the variety of models is determined by the specificity of inventory management tasks associated with different rules for the functioning of economic objects and methods for calculating economic indicators. This leads to the need to modify existing models or develop new ones.

Analyzing the research results presented in the literature, it is possible to conclude that two main approaches are used to solve inventory management problems: the use of analytical models and simulation modeling. The use of analytical models makes it possible to obtain an unambiguous solution based on the initial data. However, there are a number of limitations to this approach:

1. Analytical models do not allow taking into account complex rules for the functioning of the system, as well as some parameters (for example, the initial inventory level). At the same time, taking into account individual rules in the model usually makes such models difficult for computer implementation, understanding and application in practice.

2. The result obtained using analytical models cannot always be applied in practice, for example, the delivery period of 0.16 days obtained using the classical Wilson model will not be appropriate for the enterprise.

3. Analytical models, unlike simulation models, are not dynamic, they do not allow to determine «bottlenecks» and monitor the change in the state of the object over time, collect intermediate statistics on the performance of the system.

The disadvantages of simulation models include the random nature of the output value, due to which the solution may differ in different implementations and it is necessary to run the model multiple times to obtain statistical data and process them. This requires the implementation of a special simulation program. In this regard, the development of easy-to-implement tabular models that take into account the features of the functioning of the object under study and provide the ability to view the dynamics and formulas for calculating indicators is an urgent task.

2. Materials and methods

The aim of research is to develop simulation models and study the best strategy for inventory management for the enterprise LLC Research and Production Complex «Electro-thermal Technologies» (Tomsk, Russian Federation), which activities are related to the purchase and sale of gas cylinders.

To solve the problem, data were obtained from the warehouse of gas cylinders for each working day for the last 15 months (from 09.01.2020 to 24.03.2021). The data for modeling were provided by LLC RPC «Electro-thermal technologies».

Table 1 shows a fragment of data on the balance of cylinders in the warehouse. Here «Incoming» is the number of full cylinders supplied to the warehouse, «Expenditure» is the number of full cylinders shipped from the warehouse to the client. Thus, at the beginning of each working day there is a balance of full gas cylinders for each type of gas, cylinders arrive at the warehouse every day and shipments from the warehouse take place every day.

Delivery time depends on the type of cylinder and is 2 days for acetylene, oxygen, propane, acid and 3 days for argon and nitrogen. The results of modeling the management of inventory of gas cylinders with oxygen are presented.

Table 1

The rest of the cylinders in inventory as of 02.03.2021

Gas	Balance at the beginning of the day 01.03.2021	Incoming	Expenditure	Balance at the beginning of the day 02.03.2021
Acetylene	728,00	18	0	746,00
Oxygen	126,00	200	43	283,00
Propane	49,00	0	34	15,00
Argon	90,00	0	2	88,00
Carbon dioxide	11,00	31	4	38,00
Nitrogen	60,00	0	0	60,00

According to the initial data, demand is a random variable. Pearson's Chi-square test was used to determine its characteristics and type of distribution. **Fig. 1** shows a histogram of the distribution of demand for oxygen gas cylinders. According to the Chi-square test, the hypothesis of a normal distribution is not rejected. The average value of demand is 75 units, the standard deviation is 35 units.

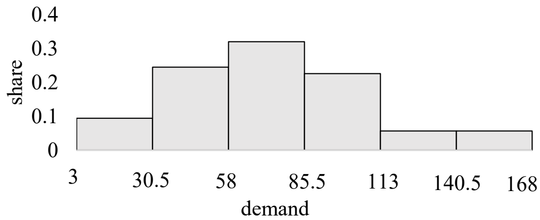

Fig. 1. Histogram of demand distribution

Thus, the input data of the model will be the values of the variables:

– initial level of inventory in the warehouse;

– average value of demand;

– standard deviation of demand;

– time of delivery of the goods;

– simulation period.

Based on the initial data, it is necessary to determine an inventory management strategy that will ensure the least «overstocking» of the warehouse and deficit. The optimization problem can be represented as follows:

$$\begin{aligned} & f(u_p) \to \min, \\ & d(u_p) \le d_{\max}, \end{aligned} \quad (1)$$

where u_p – controlled variables; $f(u_p)$ – average level of inventory in the warehouse (balance at the end of the day); $d(u_p)$ – average deficit level; $d_{\max}$ – maximum value of the average deficit.

Controlled variables depend on the inventory management strategy and will be discussed further for each specific model.

Thus, in contrast to classical models, this model does not include the costs associated with the storage of a unit of goods per unit of time and the delivery of goods. This version of the model can also be considered for solving problems in other areas, for example, in the case when it is necessary to determine the inventory of funds for the implementation of current activities (points for the collection of waste paper, metal, etc.).

To implement the model, universal modeling languages, programming languages, standard mathematical packages can be used. To solve the problem under consideration, tabular modeling was chosen [19, 20], since the tools of the Excel mathematical package provide the ability to store data, step-by-step calculations, and also process data using the built-in VBA language. As a result, such a model is visual for the user: calculation formulas can be viewed and intermediate results analyzed. Tabular models are described by a set of related formulas for calculating indicators and have become widespread in solving problems of economics, queuing, optimization, etc.

To solve the problem, simulation models with a threshold and periodic strategy were used, presented in [20] and implemented in the Excel package, which were modified in terms of calculating the output value and modeling demand. These models are classical; they are given, for example, in [21, 22]. To solve the problem, these models were adapted taking into account the specifics of the object of study.

The periodic strategy is to deliver the goods to the warehouse in accordance with the specified interval – the frequency of delivery. It has the advantage of not having to monitor the current inventory level, but this strategy is less resilient to increased demand, resulting in deficit situations. The controlled variables, by changing which the specialist can determine the optimal strategy, are: the volume of the delivery lot and the delivery interval.

To count the specified frequency of delivery in the tabular model, a counter (periodicity indicator, *PI*) was used, the values of which decrease down to zero, which reflects the moment of delivery, after which the counter is set to its original value (i is the ordinal number of the day, P is the frequency of delivery):

$$PI_i = \begin{cases} PI_{i-1} - 1,\ PI_{i-1} \neq 0, \\ F - 1,\ PI_{i-1} = 0. \end{cases}$$

The inventory balance at the beginning of the period (*SB*) is equal to the balance at the end (*SE*) of the previous period if delivery is not carried out on this day, and otherwise it increases by the specified value of the schedule line (*LV*):

$$SB_i = \begin{cases} SE_{i-1},\ PI_{i-1} \neq 0, \\ SE_{i-1} + LV,\ PI_{i-1} = 0. \end{cases}$$

The generation of a random quantity of demand with a normal distribution law is carried out according to the formula:

$$Demand_i = M + \sigma \cdot \eta,$$

where M – average value of demand; σ – standard deviation of demand; η – value obtained by subtracting the number 6 from the sum of twelve random numbers evenly distributed over the interval from 0 to 1.

In this case, a truncated distribution is used: if the demand value is less than zero, a new value is generated. The balance at the end of the period is:

$$SE_i = \begin{cases} SB_i - Demand_i,\ \mathrm{SB}_i > Demand_i, \\ 0,\ \text{otherwise}. \end{cases}$$

Output values based on simulation results for a given period: average inventory balance at the end of the period, total deficit, deficit probability.

It should be noted that only delivery periods are reflected in the model with a periodic strategy; in order to determine the application periods, taking into account the delivery time, it is necessary to subtract the delivery time from the delivery period.

The simulation algorithm for a periodic strategy is shown in **Fig. 2** (here n – the simulation period, D – the deficit). In the tabular model, each iteration of the cycle corresponds to one row of the table, the columns correspond to the calculated indicators: day number, periodicity indicator, inventory balance at the beginning of the period, demand, balance at the end of the period, deficit.

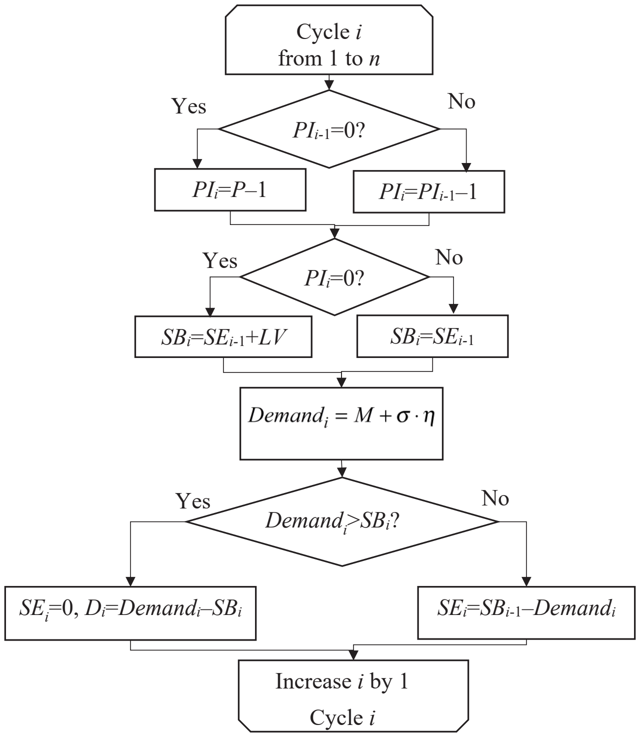

Fig. 2. Simulation algorithm for a periodic strategy

Frequency indicator (cell C8 stores the value of the frequency of delivery):

[C12] = C8-1, [C13] = IF(C12<>0;C12-1;$C$8-1).

Balance at the beginning of the day (cells C4 and C5 contain the values of the initial inventory level and batch volume, respectively):

[E12] = IF(C12<>0;C4;C4+C5), [E13] = IF(C13<>0;G12;G12+$C$5).

Balance at the end of the period:

[G12] = IF(F12<E12;E12-F12;0).

The amount of the deficit is:

[H12] = IF(F12>E12;E12-F12;0).

Demand is generated in column I according to the normal random variable simulation gauge:

[I12] = ROUND(($C$6+$C$7*((RAND()+RAND()+RAND()+RAND()+RAND()+ +RAND ()+RAND ()+RAND ()+RAND ()+RAND ()+RAND ()+RAND ())-6));0).

Since the quantity demanded is positive, a truncated normal distribution is used. To do this, the macro checks the value simulated in column I and copies it to column F if the constraint is met (otherwise, cells are recalculated).

To obtain the average values of the output quantities, the simulation is performed using a macro for the number of iterations specified in the cell. Thus, the macro operation scheme includes the following stages (the current iteration number is equal to one):

Step 1. Fill in the demand value, taking into account the constraint.

Step 2. Calculation of the sheet, placing the output values of the quantities in the variables-adders.

Step 3. If the current iteration number is equal to the number of iterations, then the macro execution ends, the adder values are divided by the number of iterations to obtain average estimates, and the values are written to the cells, otherwise, increase the number of the current iteration by one, recalculate the sheet, go to Step 1.

When using the threshold strategy, the inventory level is monitored in each period, an order for the supply of a batch of a given volume is submitted if the current inventory is less than the minimum level. The controlled variables in this model are: the volume of the delivery lot and the minimum inventory level.

The difference from the model with a periodic control strategy lies in the way the warehouse is replenished. To do this, application (*AI*) and delivery (*DI*) indicators are determined:

$$AI_i = \begin{cases} 1, SE_{i-1} < O_{\min} \text{ and } DI_{i-1} \le 1, \\ 0, \text{otherwise}; \end{cases}$$

$$DI_i = \begin{cases} DT + 1, AI_i = 1, \\ DI_{i-1} - 1, DI_{i-1} > 0 \text{ and } AI_i = 0, \\ 0, DI_{i-1} = 0 \text{ and } AI_i = 0, \end{cases}$$

where $O_{\min}$ – minimum inventory level; DT – delivery time.

The modeling algorithm for the threshold strategy is shown in **Fig. 3**.

The disadvantages of the presented model with a threshold strategy include the impossibility of making a new order before the completion of the delivery of the previous one. Therefore, a model was developed that allows such an operation to be performed and, in addition, for its greater adaptability, the delivery volume is not a constant value, but depends on the forecast inventory level. For this, the value of the level of delivery is determined, the achievement of which must be carried out with the help of the delivery.

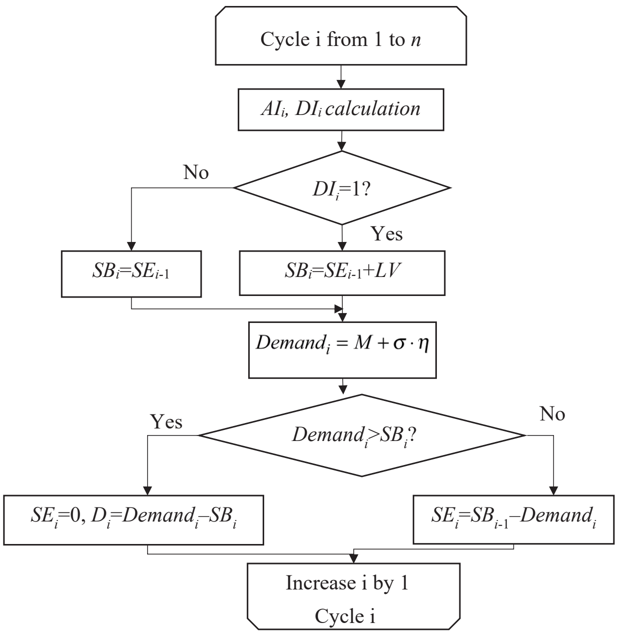

Fig. 3. Simulation algorithm with the threshold strategy

Let's consider this model with a predicted inventory level. A request for delivery is submitted if the inventory level predicted for the delivery date is less than the minimum level. The predicted inventory level is defined as the current inventory balance minus the average demand over the two days plus expected deliveries over the given period. In this case, the volume of the delivery lot is equal to the difference between the level of delivery and the forecast inventory.

In the case of oxygen cylinders, the delivery time is two days, therefore, in this model, three consecutive moments included in the delivery interval are examined in order to determine the need for an application. To do this, for each moment, the forecast level of inventory on the delivery date is determined (in **Fig. 2**, this period is indicated by an arrow) and the indicator for filing an application. At the time of application, the indicator is equal to the delivery time increased by one, and then it decreases by 1 every day until the moment of delivery. So, **Fig. 4** shows an example when a delivery request is submitted on the first day, but there is no request on the second and third days, the values and indicator change are shown in the arrow.

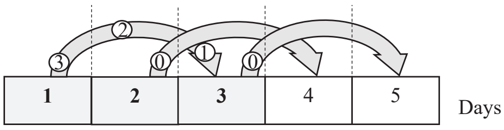

Fig. 4. Study of periods

Thus, the predicted inventory level (PS) for the delivery date is calculated by the formula for each point in time:

$$PS_i = SE_{i-1} - 2 \cdot M + \sum_{j=0}^{2} LV_{i+j}.$$

Depending on the forecast inventory level, the delivery indicator (DI) and the delivery volume are calculated. The algorithm for generating these indicators for moments k is shown in **Fig. 5** (L – delivery level). The increase in the balance in the warehouse at the beginning of period i by the amount of delivery LVi is carried out similarly to the previous models.

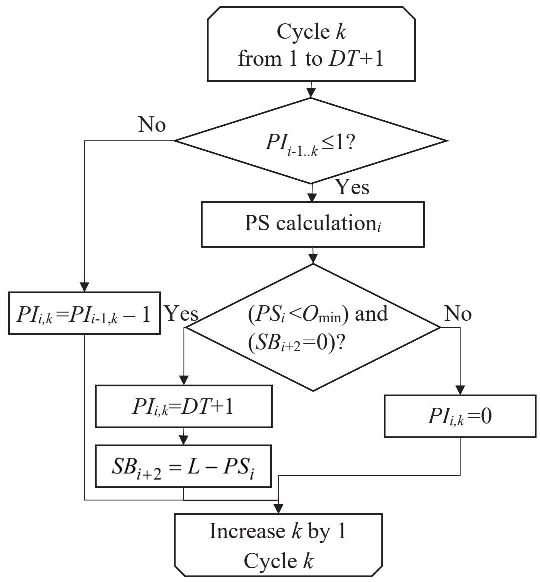

Fig. 5. Algorithm for the formation of indicators and the scope of supply

The controlled variables are: delivery rate and minimum inventory level. A fragment with the simulation results is presented in **Tables 2–4** (delivery level is 300 pieces, minimum inventory level is 300 pieces).

The tabular model processing macro for a given number of iterations includes the following steps (the current iteration number is equal to one):

Step 1. Clearing the cells of the «Waiting» and «Delivery» columns.

Step 2. Fill in the demand values, taking into account the constraint. The current period number is equal to one.

Step 3. Sheet calculation. If the attribute of the application is located in the «Indicator» column (value 3), then the columns «Waiting» are filled with the value of the delivery volume. Filling occurs several lines before the delivery period, while the column «Delivery» is also filled in this period.

Step 4. Check: if the current period number is less than the simulation period, then go to the next period (line) and Step 3.

Step 5. Calculation of the sheet, placing the output values of the quantities in the adders.

Step 6. If the current iteration number is equal to the specified number of iterations, then the macro execution ends, the adder values by the number of iterations to obtain average estimates, the values of which are written to the cells. Otherwise, the number of the current iteration is increased by one, the sheet is recalculated, and the transition to Step 1 is performed.

Table 2

Modeling at predicted inventory levels (Part 1)

Period, days	Prediction 1	Indicator 1	Prediction 2	Indicator 2	Prediction 3	Indicator 3
1	150	3	–	–	–	–
2	150	2	256	3	–	–
3	150	1	256	2	213	3
4	270	3	256	1	213	2
5	270	2	240	3	213	1

Table 3

Modeling at a predicted inventory level (Part 2)

Expectation 1	Expectation 2	Expectation 3	Delivery 1	Delivery 2	Delivery 3
150	–	–	–	–	–
150	44	–	–	–	–
150	44	87	150	–	–
30	44	87	–	44	–
30	60	87	–	–	87

Table 4

Modeling at a predicted inventory level (Part 3)

Balance at the beginning	Demand	Balance at the end	Deficit
300	44	256	0
256	87	169	0
319	30	289	0
333	60	273	0
360	80	280	0

The average value of demand was used to determine the forecast demand in this option, but other methods can be considered, for example, the use of a regression function. **Table 5** presents the values of the determination index and errors calculated on the basis of the initial data for the linear, autoregressive model and the model with a seasonal component. The error value m is calculated by the formula:

$$m = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t - \tilde{y}_t}{y_t}\right|,$$

where T – the number of observations; y – observed value of demand; $\tilde{y}$ – model value of demand.

Thus, the implementation of the algorithm and the presentation of the results in tabular form made it possible to obtain a simple tool for conducting computational experiments and studying intermediate and final statistics. To validate the models, intermediate results were used, which are displayed in the table, and the compliance of the events that occurred during the simulation with the given behavior strategy was checked.

Table 5

Model evaluation results

Indicator	Linear model	Autoregressive model	Extraction of the seasonal component
Determination index	0.05	0	0.24
Average error	0.82	0.93	0.72

To solve the optimization problem, computational experiments were performed during 500 random implementations with a change in the controlled variables ($d_{\max}$ in problem (1) is 0.5). At the same time, the change in the controlled variables was carried out with a step equal to 1. The initial inventory level is 487 units, the average demand value is 75 units, the standard deviation of demand is 35 units.

The best results for each of the control strategies are presented in **Table 6**.

Table 6

Results of computational experiments

Model name	Controlled variables	Value of the controlled variable	Values of output variables		
			Average inventory level, pcs.	Average deficit, pcs.	Deficit probability
Model with periodic replenishment strategy	Lot volume, pcs.	82	388.93	0.33	0.0005
	Delivery frequency, days	1			
Model with a threshold strategy	Lot volume, pcs.	404	315.9	0.27	0.0003
	Minimum inventory level, pcs.	350			
Model with a predicted inventory level	Delivery level, pcs.	257	178.33	0.49	0.001
	Minimum inventory level, pcs.	250			

Experiments were also carried out with historical data. So, as an example in **Fig. 6** shows the value of the average inventory level using demand data for the last 30 days (shortage is zero). It can be seen that the use of a threshold control model and a control model with a predicted level of inventory would make it possible to obtain a lower value of the average inventory compared to the real value, and thus save working capital. In particular, the use of a threshold management model would reduce the average inventory level by 10 %, models with a predicted inventory level by 46 %. The change in the inventory level when using these strategies is shown in **Fig. 7**.

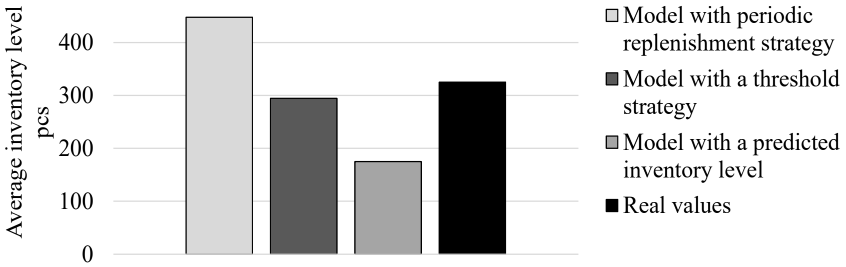

Fig. 6. Average inventory values

According to the values presented in **Fig. 7**, it is possible to conclude that the model with a periodic strategy and the model with a predicted inventory level provide the smallest amplitude of fluctuations in the average inventory level in the warehouse. Thus, these models provide support for its value at a certain level.

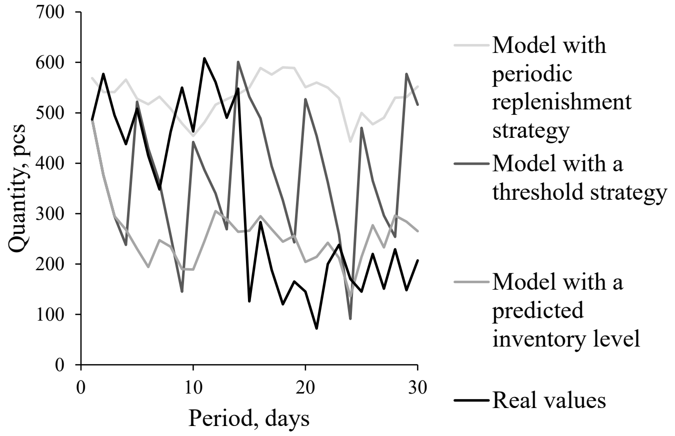

Fig. 7. Change in inventory level

Modeling based on real historical data of the object of study made it possible to conclude that the models are adequate.

3. Results and discussion

Three tabular inventory management simulation models have been developed to determine the best replenishment strategy. Analyzing the results obtained in the course of computational experiments, it is possible to draw the following conclusions:

1. In most experiments, the periodic strategy showed the worst result, because it is not adaptive and does not take into account the current inventory level. However, this strategy is easier to implement in practice due to the lack of the need to monitor the inventory level.

2. The model with the predicted inventory level in most experiments showed the minimum value of the average inventory level. This is due to taking into account the inventory level when placing an order and the possibility of a new order, regardless of the delivery time of the previous one.

Unlike existing models, the developed models take into account the specifics of the object under study, in particular, the absence of costs for the supply and storage of the inventory. In addition, by modifying the model with a threshold strategy, a model with a predicted level of inventory was developed, the use of which provided the best indicators of the output value. The use of tabular modeling reduced the model implementation time, made it possible to take into account the necessary conditions and present the results in an accessible form for statistical data analysis and modification.

The main disadvantage of simulation modeling is the use of random numbers that affect the output value and make it difficult to analyze the result due to its variability. Conducting computational experiments with multiple runs of the model allows to obtain some average estimate suitable for analysis.

The limitation of the approach used is the specificity of the developed model; its application to the study of other economic objects may require significant modification. In order to simplify this modification, a tool can be developed that automates typical scenarios when implementing a tabular model (for example, copying cells until a specified condition is met). The development of such a tool is one of the directions for further research.

4. Conclusions

The solution of the problem of inventory management of an organization selling gas cylinders is considered. For this, two tabular simulation models presented in the literature were modified, and a new tabular model based on the threshold strategy was developed. Its main difference is the possibility of filling out a request for supply regardless of previous requests and the dependence of the supply volume on the forecasted inventory level. Conducting experiments based on historical data showed the advantage of the two models compared to the current management strategy (the decrease in the average inventory level was 10 % and 46 %). As a result of multiple computational experiments, it was concluded that the minimum value of the average inventory level was obtained using a model with a predicted inventory level.

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