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Print ISSN 1727-6209
On-line ISSN 2312-5381
International Journal of Computing

DEVELOPMENT OF AN EVOLUTIONARY OPTIMIZATION METHOD FOR FINANCIAL INDICATORS OF PHARMACIES

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Paper history:
Received 12 May 2020
Received in revised form 29 June 2020
Accepted 08 July 2020
Available online 27 September 2020

Keywords:
genetic algorithm;
evolutionary algorithm;
financial indicators optimization;
C #;
SQL Server Analysis Services;
minimization of stock in warehouse time.

Abstract: The work is devoted to the problem of optimizing the financial performance of pharmacies. To solve this problem, a genetic method of multicriteria optimization was developed with a mutation operator modification to study the degree of influence of factors on the financial performance of pharmacies and the choice of optimization model. The fundamental difference between the developed genetic algorithm and its existing counterparts is the ability to control the mathematical distribution of the values of the solution, which prevents premature convergence of the genetic algorithm and uses all proposed genes in fractions according to the chosen distribution model. A comparative analysis of the work of classical GA and modified versions shows that the best results are achieved in the cognitive-style determination. Three modifications of the mutation operator were developed.
The application of the developed methods will lead to a more effective use of the pharmacy area, to reduce unmet demand and, ultimately, to reduce the retail cost of drugs by reducing the costs of storing and servicing the suboptimal loading of the pharmacy.

1. INTRODUCTION

In a modern competitive environment, the speed and correctness of decision making is a key factor in the success of the retailer, which has a pharmacy network. The main indicators of the success of the pharmacy are its financial performance: profit and turnover.

Influence on these indicators can be different methods, but one of the most effective methods is to optimize the range of pharmacy.

The question of the optimal range is important both for a long-time pharmacy and for a pharmacy that will only be opened.

The choice of the range is influenced by factors such as the area of the pharmacy, the cost of medicines, the turnover of assortment positions, marketing factors, factors of seasonality, environmental factors, factors of the geographical location of the pharmacy in relation to local infrastructure, etc.

The optimization of the range will result in more efficient use of the pharmacy area, reduction of unsatisfied demand and, ultimately, reduction of the retail cost of medicines by reducing the costs of storing and maintaining non-optimal downloaded pharmacy planes.

In the course of work, a genetic method of multicriteria optimization with modification of the mutation operator was developed to study the degree of influence of factors on the financial indicators of pharmacies and the choice of optimization model. The paper investigates problems and existing methods of optimizing financial indicators of network pharmacies, develops a genetic method with the modification of the mutation operator to solve the problem of managing the range of pharmaceutical products based on evolutionary methods. As a result, the use of the proposed methods and tools leads to an increase in efficiency of decision-making processes in the assortment management system.

2. TASK SETTING

The profit of a pharmacy depends on such basic factors:

- Sale amount.
- Gross profit.
- Length of the warehouse.
- Indicators of the morbidity of the population by illnesses.

Mathematically, this can be expressed as a function of two variables (1):

$$F(x)=f(x_1, x_2, x_3, x_4), \quad (1),$$

where $F(x)$ – conditional financial indicator; x_1 – the value of the sales amount; x_2 – is the value of gross profit; x_3 – the value of the length of the pharmacy; x_4 – is the value of health indicators from the amount of pollutant emissions into the air.

This paper synthesizes a model of the dependence of financial indicators on the influence of the range of pharmacy network products. The hypothesis concerning the influence of the percentage ratio between the groups of goods in the assortment and the profitability of the pharmacy is checked.

3. ANALYSIS OF LITERARY DATA AND PROBLEM STATEMENT

Optimization of the assortment in the pharmacy is a complex of measures aimed at quantitative and qualitative changes in its structure in order to increase the rationality and efficiency. The main goal is to harmonize the range that will minimize costs and increase pharmacy profits.

A widespread way to optimize the range is to analyze the defect, which allows you to identify the demand for missing drugs by fixing the demand of buyers in the primary system, in the accounting system or on paper (a magazine of dissatisfied demand or defect accounting). However, it also has its disadvantages, since data corruption may be due to an inadequate defect tracking system. In addition, it is not always possible to obtain objective data, since the study of consumer preferences in only one outlet is often not representative [1].

In the paper [2] an ABC-analysis was proposed for a thorough analysis of the assortment. Quite often in pharmacies for research of assortment the ABC-analysis is used. The idea of the ABC analysis method is based on the Pareto principle: "for most of the possible results there is a relatively small number of reasons", now more commonly known as "the rule is 20 to 80". This method of analysis has received great development due to its versatility and efficiency.

With this analysis, goods are broken down by the degree of influence on the overall result. And the principle of grouping can be the value of revenue derived from a particular group of products, sales or any other parameters. Often revenue is more indicative as a grouping criterion. Grouping by volume of sales may be adequate in the case if the analyzed goods are homogeneous in terms of composition and price.

Thus, by studying retail sales, we allocate the group "A" (positions, the sum of shares with a cumulative result of which is the first 50% of the total amount of parameters), the group "B" (goods, the sum of shares with a cumulative result of which is from 50 to 80 from the total amount of parameters) and the group "C" (the remaining goods, the sum of the shares with a cumulative result of which is from 80% to 100% of the total amount of parameters). After conducting the ABC analysis of product groups, the same analysis is selectively conducted within the groups, for example, only within those included in the groups "A" and "B" or selectively.

Obviously, it is necessary to control the presence in the assortment of commodity positions of the class "A". In relation to the commodity positions of the class "B" control can be current, and in relation to the positions of class "C" – periodic. Thus, in the course of ABC analysis ABC-rating of goods is formed.

Paper [3] provides a description of the used XYZ analysis, which helps to evaluate and compare the stability of sales of product groups or individual products of different types of demand or different price categories. It is used to optimize inventory and determine the frequency of ordering a product.

The XYZ analysis uses an indicator that characterizes pharmacy needs in the inventory.

The XYZ analysis algorithm includes the following steps:

- Selection of analysis objects (product group, commodity unit, suppliers, clients, etc.).
- Determination of parameters of analysis (sales units, sales, income, average stock, number of orders, etc.) and the analysis period (week, month, quarter, half year, year).
- Determination of the coefficients of variation for the analyzed resources.
- The grouping of resources in accordance with the growth of the coefficient of variation.
- Division by categories X, Y, Z.

• Graphical representation of the results of the analysis.

The result of the XYZ analysis is the selection of 3 groups of products:

• Category X – groups of goods with a stable consumption and, therefore, high potential for forecasting demand;

• Category Y – groups of goods with known seasonal fluctuations and average forecasting capabilities;

• Category Z is a group of goods with unstable demand and, as a result, a low accuracy of forecasting demand.

The distribution of goods in categories X, Y and Z is determined by the value of the variation factor. According to the classical approach to the category X, products with a coefficient of variation of 0-10%, to a category Y – 10-25%, and to a category Z – more than 25% are included. However, it is expedient to use large intervals in pharmacies, because the use of the classical approach often leads to the fact that a significant number of goods unnecessarily falls into category Z. That is, in relation to the pharmacy range, category X should include goods with a coefficient of variation of 0-15%, category Y – 15 -40%, category Z – more than 40%.

Paper [4] gives a description of the used assortment analysis using the Dibba-Simkin method. The analysis of the Dibba-Simkin assortment is carried out for the classification of goods and allows us to determine the main directions of development of separate commodity groups, to identify the priority positions of the range, to evaluate the effectiveness of the structure of the range and ways of its optimization. For analysis data on sales dynamics and cost of production were used. On the basis of the ratio of sales in value terms and the contribution to cover costs, the product belongs to one of the 4 groups.

Classification of selected groups by this method shows the following:

• Group A. This is the most significant for a pharmacy group. Products included in this group can serve as a benchmark when choosing a new product for inclusion in the range. It is necessary to strive to increase the number of commodity positions in this group, since the growth of sales of these goods has the greatest impact on the profit of the enterprise.

• Group B1. This is a group of products for which there should be ways to increase the profitability of these products (the possibility of rising prices, search for more profitable suppliers to reduce the cost, etc.).

• Group B2. Need to look for opportunities to increase sales of products of this product group (promotional campaigns, advertising, etc.). Due to the high profitability of this group, the profit growth rate of the company will be higher than the growth rate of sales of these goods.

• Group C. These are the least valuable goods for the company, therefore, it is necessary to consider the possibility of replacing a number of goods from this group, as well as assess the effectiveness of the exclusion of the least profitable goods.

Paper [5] provides a description of the method used to analyze the check. The task of analyzing the structure of checks is the receipt of information necessary for making decisions on correction or change of the assortment structure depending on the location of the pharmacy, seasonality of sales, and other factors affecting the assortment policy.

During the analysis of the structure of the checks, changes in the structure and the amount of checks are determined depending on the time of day, day of the week and season. The main indicator for such an analysis is the amount of the average check, which is calculated as the ratio of total sales to the number of checks for a certain period of time.

In addition to the size of the average check, analyzing the structure of checks, one should consider the change in the number of buyers, the amount of purchases and turnover of the pharmacy on average by days of the week, as well as analyze the change in the number of positions in checks for different ranges of the sum, etc.

With the help of differentiated analysis of checks the most frequent positions (goods) in checks; the biggest checks; checks of different groups of buyers; checks at different times of day are revealed. Differentiated analysis also allows us to divide pharmacy buyers into groups and evaluate their shopping baskets (the composition of checks of different groups of buyers); to discover co-acquired goods. The size of the maximum, average and minimum check in the pharmacy is an indicator of the solvency of the main purchasing contingent. The results of the analysis of checks allow you to determine the range and price of pharmacy policy and compare the size of the average check with that one of the competitors'.

Direct examination of the structure of checks is carried out in order to analyze the current activity of the pharmacy to determine the main trends in its work, which will help you to prepare for seasonal fluctuations in demand and changes in this regard and determine consumer preferences. Analysis of the structure of checks allows you to identify the strengths and weaknesses of the pharmacy institution, to successfully compete and meet the needs of the buyer.

Stochastic (probabilistic) models [6] are widely used in cases where one or the other factors are uncertain. Such situations are typical for the most diverse areas of human activity, for example, weather conditions in a few years, the demand for some products, etc. Stochastic (probabilistic) inventory management models assume that the intensity of consumption of the corresponding type of material resources is a random variable, the distribution of which can be described by one or another statistical legislation.

It is necessary to present the problem so that its solution could be written in the form of a genotype, that is, a vector of values (genes). The optimal strategy will be to manage the range, which minimizes the amount of all costs associated with the creation, storage, and lack of inventory, per unit time or for a certain (including infinite) time span. In the most general form, the task of managing the assortment is to find such an assortment size xt at time t, which minimizes the general cost function (2):

$$F(xt) \to \min . \quad (2)$$

Assortment management aims at finding such a strategy of replenishment and cost of inventory, in which the cost function becomes minimal. A simple inventory management model is presented in this way. Let the functions A (t), B (t) express respectively the replenishment of stocks, their expense for the time interval [0, t]. The stock level at time t is determined by the basic stock equation (3):

$$F(t)=F_0+A(t)-B(t), \quad (3),$$

where F_0 is the initial stock at the time t=0 [7].

Analysis of [2-7] in the subject area suggests that the development of methods for optimizing financial indicators is a rather topical task. The problems and existing methods of management of the assortment of network pharmacies are investigated. On the basis of the investigated methods of assortment analysis it can be concluded that the complex methods of assortment analysis show the necessity of considering an entire group of indicators of the assortment's effectiveness. The composition of these indicators and their impact on the final evaluation varies depending on the characteristics of the range, the pharmacy itself and the current market conditions. Therefore, the methods in [2-5] should not only be chosen, but also adapted based on the current situation in a particular pharmacy. Having analyzed the methods of [6-7] assortment management, one can conclude that linear models do not have a full set of possibilities for choosing variants of the assortment structure, since they allow us to obtain the optimal solution for only one planning period and do not consider its connection with the indicators of the previous and next period. Therefore, in order to optimize the financial indicators of network pharmacies and increase the efficiency of their activities, it is advisable to use more complex nonlinear, in particular neural network models, which will allow us to approximate complex multidimensional nonlinear dependencies with high accuracy.

4. PURPOSE AND TASKS OF THE RESEARCH

The purpose of the study is to create a genetic method of multicriteria optimization with the modification of the mutation operator to optimize the financial performance of network pharmacies.

To solve the problem of optimizing the financial indicators of pharmacies, as functions of distribution of product groups in the range of pharmacy, it is necessary to determine the percentage distribution of groups of goods, which will fulfill the following conditions:

• Maximizing the profit of the pharmacy;

• Minimizing the time of stay of the goods in the warehouse ("length of the warehouse");

• Improvement of the forecast indicators of the pharmacy's profit.

• Variability of the range of pharmacy, which ensures the representation of the maximum number of product groups in the range of pharmacy.

5. DEVELOPMENT OF THE MODIFICATION OF THE MUTATION OPERATOR IN SOLVING THE PROBLEM OF OPTIMIZING THE FINANCIAL INDICATORS OF PHARMACIES

The problem of optimization that has arisen and is solved in this paper is characterized by a large number of variables, and, as a result, a large volume of search space, which prevents the ability to explore all variety of solutions at an acceptable time. In connection with this, there was a problem of the practical possibility of solving this optimization problem: to find an effective or at least very simple in practically important cases an algorithm for its solution. To solve this problem, it was decided to use evolutionary methods [8], which, compared to full-fledging methods, would reduce computing costs and solve the optimization problem faster and more efficiently.

Genetic algorithms [8] are currently the most prominent representatives of evolutionary methods of optimization.

Genetic algorithms (GAs) are the direction of the theory of evolutionary algorithms, based on the principle: "each biological species is purposefully developed and varies in order to best adapt to the environment."

One of the drawbacks of known evolutionary algorithms [8] is the lack of a mechanism for taking into account the limitations of the optimization problem.

Therefore, in order to eliminate this shortcoming, in this work a genetic method of multicriteria optimization with modification of the mutation operator is proposed for solving the optimization problem.

Consider a system consisting of two subsystems that are described by many extreme equations:

$$z_1 = z_1(x_1, y_1), \tag{4}$$

$$z_2 = z_2(x_2, y_2), \tag{5}$$

where x_1, y_1, x_2, y_2 – system parameters; z_1, z_2 – target functions of its functioning [9].

We formulate the problem of solving the problem of multi-purpose optimization of such a system:

$$P^* = P(z_1^*, z_2^*) = \max P(x_1, y_1, x_2, y_2), \tag{6}$$

where P is a complex target function; $x_{1min} \le x_1 \le x_{1max}$; $x_{2min} \le x_2 \le x_{2max}$; $y_{1min} \le y \le y_{1max}$; $y_{2min} \le y_2 \le y_{2max}$. In this case, the function P is, in essence, a component of the multi-purpose indicator of quality $P\ \{z_1, z_2\}$ and converts the set of such components into a scalar target [10].

One of the most common approaches to taking into account restrictions is the method of penalty functions [9], the main idea of which is that the suitability of the individual is calculated not only depending on the value of the target function corresponding to it, but also on the extent of violation of the restrictions:

$$fitness\ (x) = f(x) + \delta \cdot \lambda(t) \cdot \sum_{j=1}^{m} f_j^{\beta}(x), \tag{7}$$

where t is the generation number; δ = 1, if the problem of minimization is solved; δ = -1, if the problem of maximization is solved; $f_j(x)$ – penalty for violating the j limit; β is the real number $\lambda(t) = (C \cdot t)^{\alpha}$ [11].

In the chosen method of penalty functions, the calculation of $f_j(x)$ occurs dynamically, depending on the degree of violation, according to the formula for t – and iteration, and the value $\lambda(t) = (C \cdot t)^{\alpha}$:

$$f_i(x) = \begin{cases} \max\{0, g_i(x)\}, \ j = \overline{1, r} \\ \left| h_j(x) \right|, \ j = \overline{r+1, m} \end{cases}, \tag{8}$$

where $g_i(x) \le 0$, $h_j(x) = 0$ is the restriction of the problem [12].

Consequently formula (7) suitability of the individual has the form:

$$fitness\ (x) = f(x) + \delta \cdot \lambda(C \cdot t)^{\alpha} \cdot \sum_{j=1}^{m} f_j^{\beta}(x). \tag{9}$$

The advantage of the method of dynamic fines [13] is that it requires much less parameters than other methods of penalty functions. Instead of choosing from a set of fixed levels of violation of the restrictions in this method, the fine is calculated dynamically.

Modified mutation operators were developed to improve the quality of the algorithm and expand its capabilities.

The first modification of the mutation operator is as follows: the new values of the genes for modification are chosen not as a random number, but from a number of random numbers that are subject to the law of normal distribution [14].

The cognitive-style determination algorithm is performed in the following sequence:

• Chromosome selection for mutation.

• Generation of a conditionally random number array according to the law of normal distribution, which in size is equal to the size of the chromosome and the median point and the mean square deviation of the distribution coincides with the median point of the series.

• Selection of genes for random mutation.

• Replacement of genes by values from a normalized random series.

• The return of the chromosome to the population.

In the chromosome $A = a_1a_2...a_n$, k position (bit) is randomly selected $1 \le k \le n$. Next, inversion of the value of the gene in the k position is performed: $a_k' = a_k$ [15].

In the cognitive-style determination, the value of the gene after the mutation operator is calculated by the formula:

$$c_i^* = \begin{cases} c_i + \delta(t, b_i - c_i), by\ x = 0 \\ c_i - \delta(t, b_i - a_i), by\ x = 1 \end{cases}, \tag{10}$$

$$\delta(t, y) = y(1 - r^{\left(1 - \frac{t}{\varepsilon_{\max}}\right)^b}), \tag{11}$$

where x is an integer random number that accepts values 0 or 1; $r \in [0,1]$ is a random real number; ε_{max} – maximum number of algorithms; b is the parameter given by the researcher [16].

In addition, if for a sufficiently large number of generations there is no increase in adaptability, then "small" and "large" mutations of the generation are used. In the "small" mutation of the generation to all individuals, except 10% of the best, the mutation operator is used. In the case of "large" mutations, each individual is either mutated or replaced by accidentally generated [17].

The Noetic (Intelligent) Mutation algorithm consists in using SNNs in the mutation process. One of the objectives of the proposed modification is to provide only a "positive" mutation, that is, one that improves the phenotype of the chromosome. Such an operator is executed in the following sequence:

• Selection of chromosomes for mutation.

• Application of standard mutation.

• Use of previously trained ANN to predict profitability by passing the "original" chromosome and "mutated" to the network input.

• Compare the ANN (artificial neural networks) responses and only if the "mutated" chromosome provides better profitability, add it to the population. Otherwise, the "original" chromosome is returned to the population [18].

Mathematically, an artificial neuron is usually represented as some nonlinear function from a single argument – the linear combination of all input signals. This function is called an activation function or a function of operation, a transfer function [19].

Functioning of the neuron can be described by the formula:

$$y = \begin{cases} 1, \sum\limits_{i=1}^{N} w_i u_i \ge \upsilon \\ 0, \sum\limits_{i=1}^{N} w_i u_i < \upsilon \end{cases}, \qquad (12)$$

where y is the output signal of the neuron; $w_1...w_N$ – synaptic weight coefficients; $u_1...u_N$ – input signals of the SH; v – threshold value [20].

The model (13) can be represented as:

$$y = f(\sum\limits_{i=0}^{N} w_i u_i), \qquad (13)$$

where $w_0 = v$, $u_o = 1$.

The third type of modification of the mutation operator is a combination of the previous two methods.

The Merger (unifying) mutation algorithm is executed in the following sequence:

• Selection of chromosomes for mutation.

• Application of "normalizing" mutation.

• Use of previously trained ANN to predict profitability by passing on the "original" chromosome network and "mutated ".

• Compare the ANN responses and only if the "mutated" chromosome provides better profitability, add it to the population. Otherwise, the "original" chromosome [21] returns to the population.

For formula (13) the condition (14) holds.

$$f(x) = \begin{cases} 1, x \ge 0 \\ 0, x < 0 \end{cases}. \qquad (14)$$

As an activation function f, not only a single function (14), but also other threshold functions [22] of the form (15) and (16) can be taken:

$$f(x) = \begin{cases} 1, x \ge 0 \\ -1, x < 0 \end{cases}, \qquad (15)$$

$$f(x) = \begin{cases} 1, \ x > 1 \\ -1, x < -1. \\ x, |x| \le 1 \end{cases} \qquad (16)$$

The genetic method of multicriteria optimization with the modification of the mutation operator, which prevails over reliability and speed in comparison with methods of full-fledging, is developed. In addition, a modified genetic algorithm, endowed with methods for taking into account constraints, is an effective tool for solving the optimization problem of the range in the pharmacy. This, in turn, will lead to a more effective use of pharmacy areas, to reduce unmet demand and, ultimately, to reduce the retail cost of drugs by reducing the costs of storing and servicing the sub-optimal loading of the pharmacy.

6. EXPERIMENTS ON INITIALIZATION METHODS FOR THE INITIAL POPULATION OF THE EVOLUTIONARY ALGORITHM

The sample data contained information on the checklist structure of the pharmacy network. The structure of the check is characterized by information about the presence of certain goods in it. The main features (attributes) characterizing the structure of the buyer's check are:

• x_1 – customer Identifier (KeyCustomer) is a unique number that allows uniquely identifying a particular pharmacy network customer.

• x_2 – SKUQTY– number of items in the check.

• x_3 – ATCQty – number of ATC groups.

• x_4 – SalesSum – the total cost of goods in the check.

• x_5 – MarginSum – a trading point that sells goods.

• x_6 – OrderQty – a number of checks of a particular customer at the time of the current purchase.

• x_7 – AvrOrder – average check (monetary value) of a certain customer.

• x_8 – OrderRowsQty – the size of the discount.

• x_9 – AvrPositionsQty – the average number of goods in the check of a particular customer.

• x_{10} – the structure of goods in the check is presented in the form:

$$x_{10} = \{< t_i, C_i, S_i >\} \tag{17}$$

where t_i – the name of the i-th commodity in the check; C_i – number of i-th goods in a check; S_i is the unit cost of the i-th item in the check.

To solve the problem of optimizing the financial indicators of pharmacies, as functions of distribution of product groups in the range of pharmacy, it is necessary to determine the percentage distribution of groups of goods, which will fulfill the following conditions:

• Maximizing pharmacy profits.

• Minimizing the time of stay of the goods in the warehouse ("length of the warehouse").

• Improving the outlook for pharmacy profits.

• The variability of the range of pharmacy, which ensures the representation of the maximum number of product groups in the range of pharmacies.

Typical distribution of product groups in the range of pharmacy is presented in Figures 1 and 2.

Figure 1 shows the distribution of the average monthly share of the product group in the range of pharmacy in terms of length of the warehouse on which one can see that the main percentage of the product is concentrated in the range from 20 to 24 length of the warehouse.

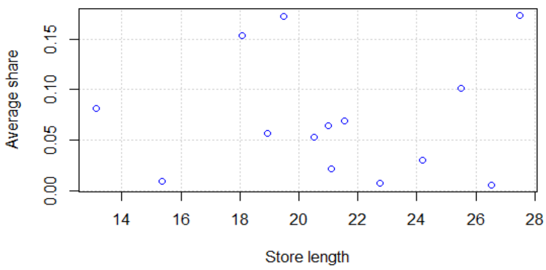

Figure 1 – Distribution of the average monthly share of the product group in the range of pharmacy items of length of the warehouse

Figure 2 shows the statistical distribution of groups of goods in length of the warehouse, where one can see that the most common size of the area occupied by the product is in the range from 20 to 25 m.

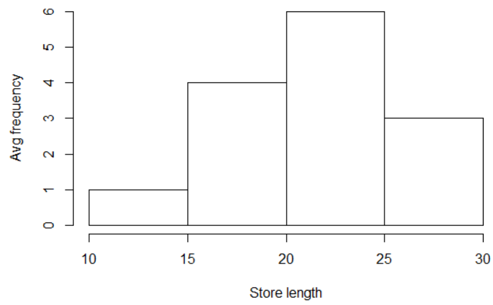

Figure 2 – Statistical distribution of groups of goods in length of the warehouse

The distribution of product groups for profitability is presented in Figure 3, where one can see the dependence that the product with the highest average monthly income has the shortest time of stay in the warehouse.

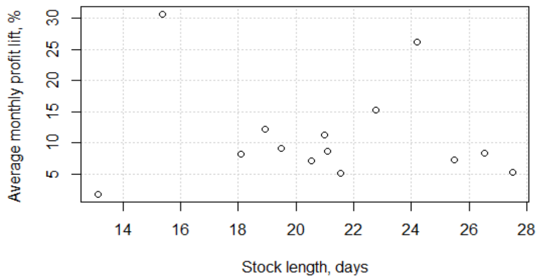

Figure 3 –Distribution of commodity groups by profitability in terms of the length of the warehouse

As a unit of the product group, a classification group for the Morion Medical Device Manual was selected for the active remedy (ATS – classification).

To solve the problem, it is possible to use a combination of methods, the superposition of which results represents a generalized optimization result.

Figure 4 shows a fragment of the input data for all calculations – monthly sales for the period 2013-2019 years. RStudio [23] software was used for data processing and calculations.

KeyCustom...	SKUQTY	ATCQty	SalesSum	MarginSum	OrderQty	AvrOrder	OrderRows...	AvrPosition...
11250	5	2	254,23	234456	6	102,13	6	12
11251	6	4	458,3	234455	7	96,3	4	10
11252	4	5	361,2	234450	2	50,3	4	2
11253	6	4	513,45	234456	8	120,3	3	12
11254	8	4	420,03	234451	5	75,6	5	11
11255	4	3	321,52	234451	4	89,1	6	4
11256	2	4	561,01	234456	7	563,01	7	5
11257	5	5	120,23	234451	4	412,23	4	6
11258	4	5	136,12	234450	7	467,01	5	7
11259	5	4	561,03	234456	4	123,05	4	6

Figure 4 – Sales data per month for the period from 2013 to 2019

These sets of data are basic, they form the following sets of data [24]:

• Profit changes relative to the previous period on a monthly basis.

• Proportions of distribution of groups of goods at the balance.

• "Length of a warehouse" of commodity groups.

• Various averaged data.

An important requirement for data for modeling is their quality. If the data contains the so-called "noise", seasonal component, emissions, gaps – this negatively affects the accuracy of forecasts and the quality of models.

Also, the data intended for use as a training dataset for the ATM should be normalized to reduce the error and improve the quality of the workout.

Processing raw data before submitting the model takes place in the following sequence [25]:

• Clear datasets with indeterminate or empty key fields.

• Processing passes in these predictors.

• Processing of predictors data anomalies.

• Removal of seasonal components from time series.

• Bringing data to the types used in the calculations.

• Normalization of data.

When processing data gaps empty values are replaced by the median value calculated by the formula 18:

$$M_e = X_{Me} + i_M \frac{\frac{\sum f}{2} + S_{Me-1}}{f_{Me}}, \qquad (18)$$

where X_{Me} is the lower value of the median interval; i_M – median interval; S_{Me} is the amount of observations that have been accumulated before the median interval; f_{Me} – the number of observations in the median interval [26].

Thus, a minimum statistical error of the values of a series is provided.

Processing anomalies in the data is the cleaning of a set of variables from anomalous high or low values. This cleaning is done with the InterQuartile Range function [27].

The cleaning from the seasonal component of the time series is carried out using the decomposition method.

To normalize the data, the method of normalizing MinMax [28] is used. The normalized value of the variable x is calculated by the formula 19:

$$z(x) = \frac{x - \min(x)}{\max(x) - \min(x)}. \qquad (19)$$

One of the methods for assessing the effectiveness of the current basket of assortment is to provide profit in the forecast period. To provide such an estimate, it is advisable to use common prediction methods.

Forecasting can be done in absolute terms or in the direction of the trend.

The methods for forecasting absolute values are in [29]:

• Linear regression.

• Polynomial regression.

To predict the direction of the trend, you can represent the trend direction, as a set of discrete classes [30]. In the simplest case of binary classification, condition 20 is fulfilled.

$$P(x) = \begin{cases} 0, \Delta f(x) \le 0 \\ 1, \Delta f(x) > 0 \end{cases}, \qquad (20)$$

where $P(x)$ is the predicted class; $\Delta f(x)$ – change of the value with respect to the previous period.

To increase the accuracy of the forecast for classification, you can increase the number of classes. This allows for more flexible use of forecasting data.

The following methods have been used to predict the classification: [31]:

• logistic regression.

• ANN.

The Bayesian information criterion (BIC), Mean Absolute Error (MAE) and Mean Square Error (MSE) [32] are used to assess the quality of predictive models.

For forecasting the logistic regression model binary classification is used. As a training data model used data on the ratio of ATC groups in the range of pharmacy, as a classifier – the value of 1, if there was an increase in profits, 0 – in the opposite case.

Also, for forecasting a classifier based on ANN is used. As an ANN, MLP was implemented with two hidden layers and one source neuron [36].

To classify the whole range of values of profit growth was broken into 10 equal classes, which were marked by numbers from the set [0; 1].

As a training data model used data on the ratio of ATC groups in the range of pharmacy.

ANN layers are shown in Table 1.

Table 1. ANN Layers for trend movement forecasting

Type of layer	Number of neurons	Activation function
Inbox (first)	14	ReLU
Hidden (second)	27	ReLU
Hidden (third)	20	ReLU
Hidden (fourth)	10	ReLU
Outgoing (fifth)	1	ReLU

The parameters of the study of the University of Agriculture are shown in Table 2.

Table 2. Learning outcomes of the ANN for trends forecasting

Parameter	Value
Number of neurons in the input layer	14
Number of neurons in the original layer	1
Optimizer	SGD
Metrics	MAE, MSE
The size of the training sample	56
% of test data	15%
Size of the batch	25
Number of epochs	250

Figure 5 shows the schedule of training of the ANN on the training data and presents the dependence of absolute error, mean square error and damage from the error, and also compares the training and predicted data.

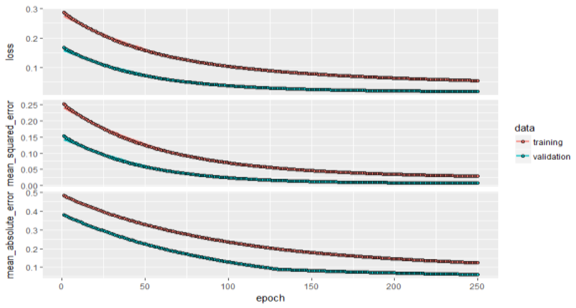

Figure 5 – SCHNM training schedule for forecasting

Table 3 shows the comparative characteristics of forecasting models, calculated on the sales data of the pharmacy for the period from 2013 to 2019.

Table 3. Qualitative characteristics of forecast models

Model	BIC	MAE	MSE
Linear regression	102,81	0,024	0,1055
Polynomial regression	93,57	0,023	0,1067
Logistic regression	84,99	0,025	0,1066
ANN	75,86	0,024	0,1067

The complexity of optimization in this case is that not only one parameter needs to be optimized, but two (profit and turnover of the product), while ensuring the presence of all groups of goods in the range of the pharmacy. If the profit is expressed as P, and the length of the composition through L, then in general, the function for optimization will take the form [37]:

$$f(P,L) = F = \frac{P}{L}, \tag{21}$$

where F is a fitness function.

Figure 6 shows the typical distribution of ATS-groups of goods in terms of length of the warehouse (turnover of goods). This figure depicts the dependence of the average monthly profit per unit of output on the average length of the warehouse. You can see that the volume of pharmacy sales is led by the group ATC406, in particular, has such indicators as average monthly profit of 0.60 and average length equal to 0.4.

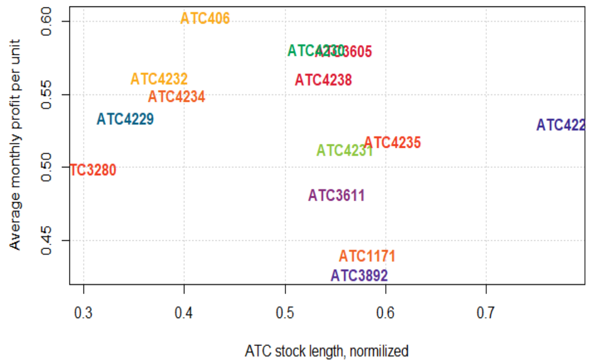

Figure 6 – Typical distribution of ATS-groups of goods in terms of length of the warehouse (turnover of goods)

During the study of the effectiveness of genetic methods, the following initial conditions and parameters were determined: the maximum number of iterations = 1000, population size = 50, minimum value = 0.01, maximum value = 0.99, initialization – random, selection – proportional, crossing – local arithmetic, mutation – proportional random, probability of mutation – 0,2, probability of crossing – 0,8.

We can assume that the classical GA will quickly come up against the obvious decision to distribute a higher percentage to the group that has the highest profitability and a small value of the length of the warehouse. Figure 7 depicts the percentage distribution of classical goods of GA groups. As you can see, GA distributed 94% to ATC406 and ATC 4232 groups, and to other groups only 6%.

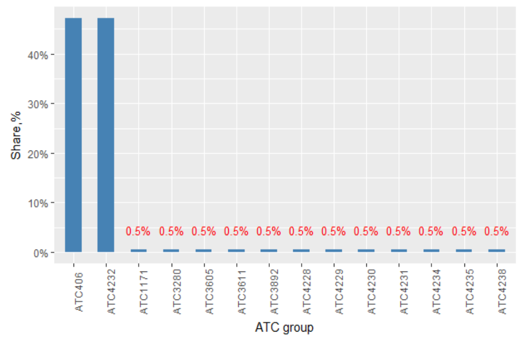

Figure 7 – The result of the classic GA

Figure 8 shows a diagram of the growth of fitness function for classical GA, which shows that the growth of fitness function is quite slow 1000s and the average fitness function is 8.0.

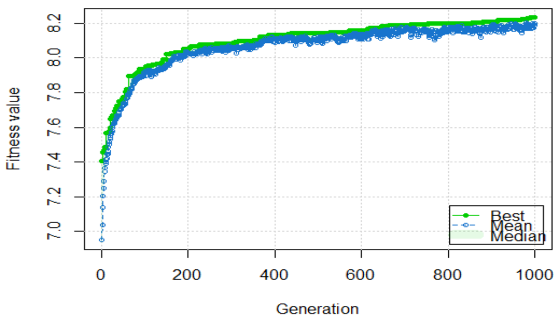

Figure 8 – Diagram of the growth of fitness function for classical GA

But for the pharmacy, such a division is unacceptable, as this will generate a dissatisfied customer request, which will result in a decrease in the number of visitors and, consequently, a decrease in profits.

Therefore, the modified GA must fulfill an additional condition – the distribution of product groups should be close to the normal distribution (Gaussian function) [38].

To solve this problem, the concept of fine algorithm was introduced into the target function. This means that if the estimated population does not correspond to the normal distribution, then the value of the fitness function falls proportionally. We also introduced weight ratios for profit and length of the warehouse, which made it possible to flexibly control the priority of indicators [38].

Equation 21 took the form 22:

$$f(P,L) = \frac{2P + e^{A}}{e^{L}}, \tag{22}$$

where P – expected profit; L – length of the warehouse; A is the degree of proximity of distribution to normal.

The value of A is the result of the Anderson-Darling test, which shows how the distribution of the sample coincides with the normal distribution. The larger this value, the faster the fitness function grows.

After adjusting the fitness function, the GA showed the following results (Figures 9, 10). Figure 9 shows the percentage distribution of groups of goods of classical GA using a fine algorithm, as it can be seen the distribution of the part of commodity groups in the assortment has become more variable.

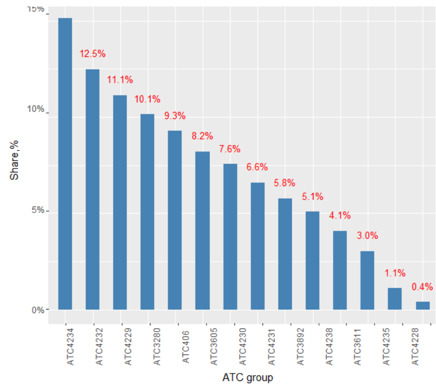

Figure 9 – Distribution of product groups (fine algorithm)

Figure 10 depicts the dependence of the value of the fitness function on the duration of the calculation, which shows that using a fine algorithm, the GA itself went faster to the saturation point, but the duration of the calculation remained unchanged at 1000s.

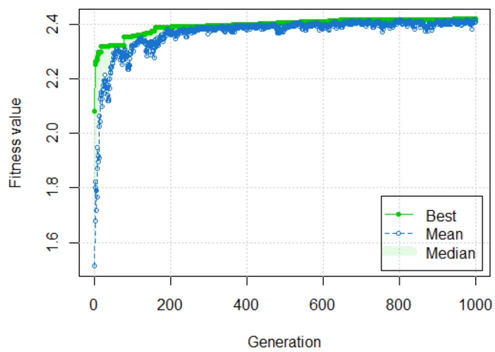

Figure 10 – Diagram of GA (fine algorithm)

Figure 11 presents the results of the proposed method of cognitive-style determination, namely, the percentage distribution of product groups. As can be seen, the distribution of the fate of commodity groups in the assortment became closer to the normal distribution (the function of Gauss).

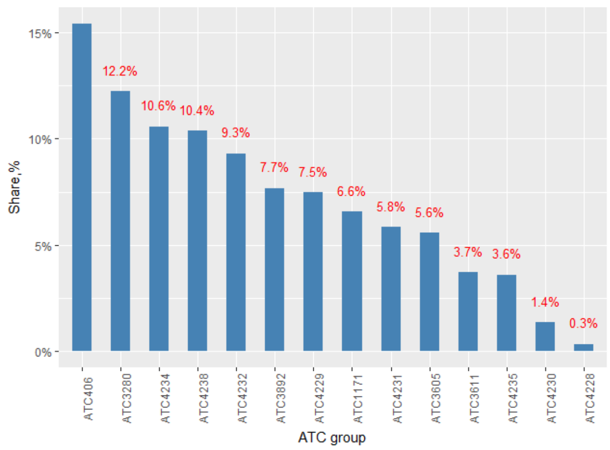

Figure 11 – Distribution of product groups (cognitive-stylistic determination)

Figure 12 shows the result of the operation of the GA due to the law of normal distribution. As can be seen, the normalization of the mutation operator under certain conditions has positively influenced the rate of convergence of the algorithm (in particular, the duration of the iteration calculation using the cognitive-style determination is 994s, which is much less compared with the time of the classic GA, the execution time of which is 1024s).

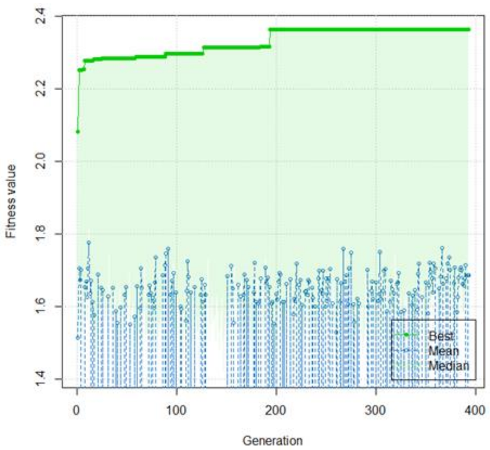

Figure 12 – Diagram of the work of the GA (cognitive-stylistic determination)

The next modification of the mutation operator is to put into operation an operator of the "intelligence" mutation. This modification serves to determine the appropriateness of chromosome mutation, based on knowledge of retrospective and predictive data using a model of ANN as a predictive one. The results of the modified operator are shown in Figures 12 and 13.

Figure 13 shows the percentage distribution of Noetic mutation product groups, which shows that compared to the cognitive-style determination, the distribution of the part of commodity groups in the range of Noetic mutations does not obey the law of normal distribution. But with this modified GA provides quite acceptable parameters of the original set.

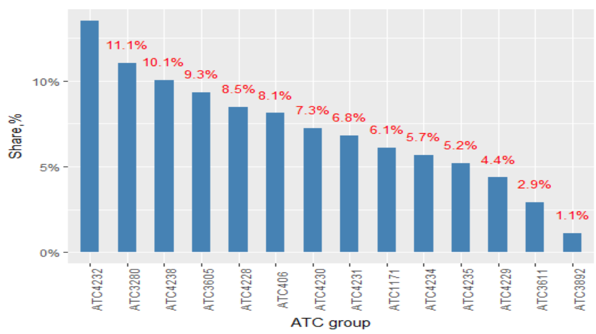

Figure 13 – Diagram of GA (Merger mutation)

Figure 13 shows the diagram of the work of GA (Noetic mutations), by which one can see that compared with the cognitive-style determination, the value of the fitness function of Noetic mutation remains unchanged, but the time of the synthesis of the model significantly increased from 400s to 800s, due to the use of ANN.

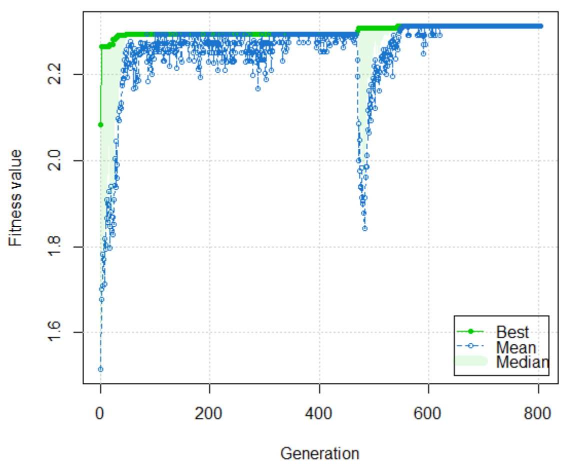

Figure 13 – Diagram of GA (Noetic mutation)

The third modification consists of a combination of the two modifications mentioned. The results of the modified operator are shown in Figures 15 and 16. Figure 15 shows the percentage distribution of the product combining the cognitive-style determination and the Noetic mutation, which shows that the distribution of the part of commodity groups in the assortment became more close to the normal distribution compared with Noetic mutation, but less close than cognitive-style determination.

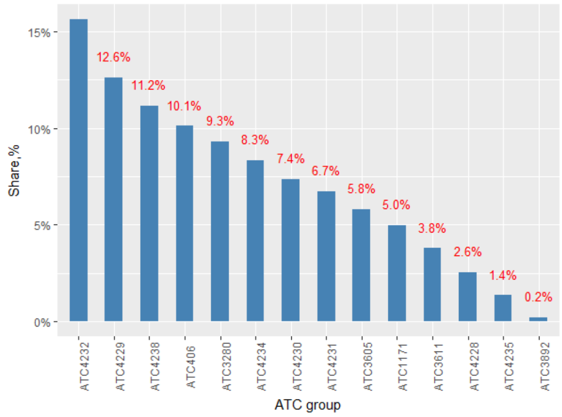

Figure 15 – Distribution of product groups (Merger mutation)

Figure 16 shows a diagram of the work of GA (Merger mutation), by which one can see that the Merger mutation algorithm has quickly reached the saturation point in comparison with the above-mentioned algorithms.

The evaluation of the effectiveness of genetic algorithms was carried out according to the following parameters: the duration of the iteration calculation, the Anderson-Darling test, the mean square error, the expected average profit growth, the average length of the composition is normalized. The Anderson-Darling test [38] is considered as a criterion, which is intended to verify that the distribution of the sample coincides with the normal distribution. The mean square error is the mean square distance between the predicted and actual values. The profitability criterion was calculated as the difference between the level of gross income of the trade and the level of expenses of the transaction.

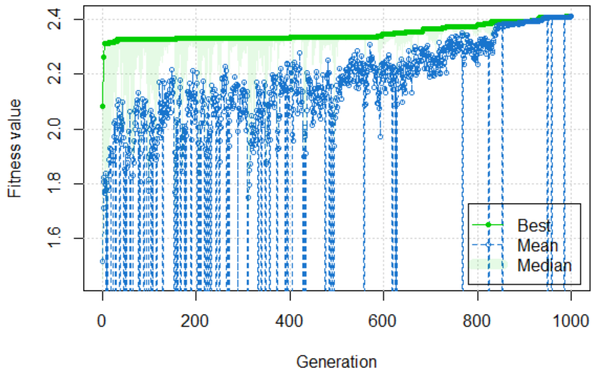

Figure 16 – Diagram of GA (Merger mutation)

Table 4 presents comparative data of classical GA and modified versions.

Table 4. Comparative data of classical GA and modified versions

№ з/п	Type of model	Duration of calculation, iterations, s	Anderson's – Darling Test	Medium-quadratic error	Expected average profit growth,%	The average length of the warehouse is normalized
1	Linear regression	875	0,8878315	0,8080	0,50525923	0,4955
2	Polynomial regression	983	0,8971466	0,998	0,5212312	0,5397
3	Logistic regression	787	0,8772425	0,977	0,509569	0,46345
4	ANN	991	0,8878415	0,967	0,5345789	0,39445
5	Classic GA	994	3,67*10-7	0,9358	0,5217804	0,3964
6	GA with a fine	974	0,9978415	0,754	0,5407766	0,44987
7	Cognitive-stylistic determination	393	0,9837505	0,782	0,5564371	0,4587188
8	Noetic mutation	804	0,9986964	0,638	0,5397302	0,4946176
9	Merger mutation	1024	0,9976742	0,685	0,5438465	0,4544578

7. DISCUSSION

It can be seen that the use of Noetic and Merger mutations increases the duration of the calculation (in particular, when using the Merger mutation, the neurological synthesis time is 1024 s, using Noetic mutation – 804s compared to 787 s when using logistic regression). Such an increase is due to the use of SNN, which is trained on real relationships that do not obey the law of normal distribution. But at the same time the GA provides quite optimal parameters of the output set.

The "Merger mutation" method shows more successful results than logistic regression, namely the Anderson-Darling test (when using the Merger mutation, the test score is 0.9976742, unlike the logistic regression, which has an Anderson-Darling test score of 0, 8772425), it can be argued that the distribution of the sample is more acceptable to normal distribution. So, the fitness function of the

Merger mutation increases faster in comparison with the logistic regression. And this method also provides better profitability (Merger mutation yields 0.5438465%, while logistic regression is 0.509569%), but requires more computational and time-consuming costs (when using the Merger mutation, the neuronal synthesis time is 1024c) due to its basis for the idea of combining Cognitive-Style Determination and Noetic mutation.

Comparing the Noetic mutation with classical GA, one can conclude that Noetic is better than the calculation duration (in particular, when using the Noetic mutation, the neuronal synthesis time is 804s compared with the time of 994s when using the classical algorithm) and the average profit increase (profit indicator in the Noetic mutation is 0,5397302%, and in the classical GA it is 0,5217804%), but inferior in terms of the length of the composition (in particular, when using the Noetic mutation is 0,4946176, and in the classical GA it is 0,3964). Comparing the Noetic mutation with GA with a fine, which is also the development of classical GA, we can say that these algorithms are equal in efficiency.

The best results were shown by a cognitive-stylistic determination, that is, it yields a gain in the calculation time of 393s and an average profit increase of 0.5564371%, which is much larger than its counterparts.

The obtained results allow us to conclude that the proposed approach to solving the tasks of optimizing the financial indicators of network pharmacies enables to increase the average profit growth of the pharmacy by 0.53% and minimize the length of the warehouse to 0.45, taking into account the average square error of 0.685.

Thus, the paper proposes and justifies a new approach to the problem of optimizing the process of work of the drug procurement department, whose main idea is to use a modified genetic method to optimize the parameters of the model with the control of the mathematical distribution of the values of the initial chromosome, in order to increase the efficiency (stability) of the GA as evolving system. The developed algorithm for the efficiency of the solution of the optimization problem on the set of test data exceeds the regression methods and the classical GA.

8. CONCLUSIONS

The scientific novelty of the work is that a modified genetic method for optimizing the parameters of the model with control of the mathematical distribution of the values of the original chromosome is proposed. The fundamental difference between the developed genetic algorithm and its existing counterparts is the ability to control the mathematical distribution of the values of the solution, which prevents premature convergence of the genetic algorithm and uses all proposed genes in fractions according to the chosen distribution model. In addition, three modifications to the genetic operator of mutations are proposed. The first modification is to choose the substitution values for a mutation not in a random way, but from a series that obeys the law of normal distribution. This allows for more "normalized" chromosomes and accelerates the convergence of the genetic algorithm with the law of distribution. The second modification serves to determine the appropriateness of the chromosome mutation, based on knowledge of retrospective and predictive data using as a predictive model of SNM. This allows you to direct the mutation without adding genes to the population that will not improve the initial population. The third modification is the combination of the two modifications mentioned.

A comparative analysis of the work of classical GA and modified versions shows that the best results are achieved in the cognitive-style determination. In addition, the analysis showed that Noetic and Merger mutations are significantly more effective than the average profit growth, despite the long duration of the calculation. Consequently, the obtained results allow us to conclude that the proposed modifications of the mutation operator are appropriate and effective to solve the problem of optimizing the range of the pharmacy. The application of the developed methods will lead to more effective use of the pharmacy area, to reduce unmet demand and, ultimately, to reduce the retail cost of drugs by reducing the costs of storing and servicing the suboptimal loading of the pharmacy.

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