Ekonomski horizonti, Januar - April 2022, Volumen 24, Sveska 1, 57 - 73
UDC: 33 ISSN: 1450-863 X

Original scientific paper
UDC: 658.5:519.2
doi:10.5937/ekonhor2201057N

ENHANCING PRODUCTION AND SALE BASED ON MATHEMATICAL STATISTICS AND THE GENETIC ALGORITHM

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Enhancing production and sale has a very significant effect on the competitive advantage of any production enterprise. In practice, especially in companies with highly diversified production, products have a different impact on generating revenue. Therefore, operational management pay attention to the products of the utmost importance. The Pareto analysis is the most broadly used product classification method. It can be said that the results obtained by this analysis are still very burdened by decision-makers' subjective attitudes. This paper proposes a model for selecting products with the biggest impact on generating revenue in an exact way. In the model's first stage, whether there is a linear relationship between volume demand and a discounted amount is analyzed applying mathematical statistics methods. In the second stage, the Genetic Algorithm (GA) method is proposed so as to obtain a near-optimal set of the most important products. The proposed model is shown to be a useful and effective assessment tool for sales and operational management in a production enterprise.

Keywords: product portfolio selection, enhancing production and sale, descriptive statistics, regression analysis, genetic algorithm

JEL Classification: C40, C61

INTRODUCTION

Due to the frequent changes that occur in the environment, the complexity of operational management in production companies is increasing (Ferdows, 2018). Those problems might be analyzed in different domains, such as the diversification of the production program, the production capacity management, or sales management. All of the foregoing relates to products, where a product (Kotler & Keller, 2016) is everything that can be offered on the market in order to meet customer needs, including a physical product, services (hereinafter ISO 9000: 2016 product), satisfaction, an event, a place, a property, organization, information, and ideas. Given the fact

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that people do not buy products, but they rather buy the expected benefits or solutions according to T. Levitt (1980), it becomes clear that products are becoming increasingly more complex. The fact that the effectiveness of operational management is propagated throughout the company and that it significantly affects the achievement of the most important business goals such as the company's profit, survival, growth, and development should be emphasized.

Starting from the fact that the production program consists of many products, operational management needs to classify products in order to increase the effectiveness of management. Effectiveness is described as the execution of right actions in the right manner, which fact can be applied in different industries (Pakulin, Tsypkin & Pakulina, 2016). In this sense, classification should result in prioritizing products which should be taken into account while executing those actions (Lorenc & Lerher, 2019). Without classification, all products would be treated in the same way, so neither revenue nor the effectiveness of management would be maximized. Several methods developed in the literature are used to classify different items (Chu, Liang & Liao, 2008). The ABC method is the simplest and most broadly used classification method. It is integrated in the literature, together with other methods (Puente, Fuente, Priore & Pino, 2002; Hadi-Vencheh & Mohamadghasemi, 2011; Kefer, Milanovic, Misita & Zunjic, 2016). The sorting problem can be solved by using multicriteria decision-making methods (Alvarez, Ishizaka & Martínez, 2021). Multi-attributive decision-making approaches and the Pareto analysis could be combined for this purpose (Liu, Liao, Zhao & Yang, 2016). It is, however, mathematically more correct to pose the classification problem as the optimization problem of varying complexity. The product classification problem can be considered to be a Nondeterministic Polynomial-time (NP) problem. Numerous metaheuristic methods for solving NP problems have been developed in the literature (Sadigh, Mokhtari, Iranpoor & Ghomi, 2012). Using the Genetic Algorithm (GA), which is the most used method, a near-optimal solution is given (Senvar, Turanoglu & Kahraman, 2013; Nestic, Stefanovic, Djordjevic, Arsovski & Tadic, 2015; Rezoug, Bader-El-Den & Boughaci, 2018; Tadić, Djordjević, Aleksić & Nestić, 2019; Lu, Pei, Liu, Qian, Mladenovic & Pardalos, 2020; Gojković, Djurić, Tadić, Nestić & Aleksić, 2021), as is done in this paper. The fact that the application of heuristic methods provides optimal solutions should be highlighted. NP problems, such as the problem discussed in this paper, cannot be solved using heuristics. In such cases, evolutionary algorithms such as the GA are most often used so as to obtain near-optimal solutions.

The motivation for the research comes from the fact that the literature does not provide us with a significant number of the models treating the relationship between demand and the unit sale price of certain products in a portfolio. The subject matter of the research conducted herein is the analysis of the relationship between demand and a discounted amount, as well as the selection of the products that affect an increase in revenue the most. The goal of the research study is of a complex nature, with the two specific objectives:

- to determine the dependence between demand and a discounted amount, and
- to determine the products whose unit sale price could be decreased to a purposeful level, so that it can significantly enhance the generation of revenue for the company.

In accordance with the mentioned objectives, two hypotheses can be set:

H1: The dependence between demand and a discounted amount can be determined in an exact way.

H2: As the unit sale price decreases while demand increases, it is possible to determine the products in the portfolio the demand for which will generate more revenue than others in an exact way.

The scientific instruments employed in the research are descriptive statistics methods, regression analysis, and the GA. The goal of the research study is achieved through an appropriate research methodology. Real-life data are collected from the representative company, so the analysis-based descriptive statistics are performed. The descriptive statistics method and regression analysis are broadly used as scientific instruments for solving different problems, such as the determination of the statistical dependence between customer trust and a purchase intention when choosing a wellness offer (Kocic & Radakovic, 2019). The analytical relationship between product demand and a decrease in the unit price is performed by regression analysis. The determination of the products that generate the highest revenue is obtained by applying the GA.

New management concepts treat the volume of production as strictly defined according to the demand that comes from end-users and depends on the degree of their satisfaction (Turkyilmaz, Oztekin, Zaim & Demirel, 2013). Customer satisfaction is based on the product attributes that can be both tangible and intangible. Tangible attributes are a functionality, a purpose, quality, the unit sale price, and so on (Gupta, 2018). Intangible attributes are associated with the symbolic characteristics of a product, such as its style, design, status symbol, ability, brand, and so forth (Goode, Davies, Moutinho & Jamal, 2005). The production capacity management, among other things, should be based on the knowledge of the dependence of demand and product attributes (Jiang, Kwong, Ip & Wong, 2012). In this research study, demand dependence and a discounted amount are investigated using mathematical statistics methods.

This paper is organized into the following chapters: after the Introduction, Chapter 2 provides a literature overview; In Chapter 3, the proposed methodology is presented, and in Chapter 4 a case study based on the data from a manufacturing company is given.

LITERATURE REVIEW

This section is dedicated to a detailed review of the literature dealing with the two main research areas:

- demand forecasting, and
- solving the classification problem.

Prediction methods can be of different complexity (Stevenson, Hojati & Cao, 2014). Experts' predictions based on a previous experience might be considered as simple. Complex methods are obtained by developing or using mathematical models and tools (Pinçe, Turrini & Meissner, 2021). Bearing in mind the fact that there are different situations in business when forecasting demand is needed, the models for it can be chosen differently. M. Ulrich, H. Jahnke, R. Langrock, R. Pesch and R. Senge (2021) propose an approach implying a choice of different existing forecasting models in the retailer industry, taking into account different information data that should be incorporated in the appropriate decision tree. The models that can be used for this purpose are linear regression, generalized additive models for the location, the scale and the shape, and quantile regression. Beside the mentioned models, there are also other demand forecasting models that can be used, such as optimization methods (Petrovic, Xie, Burnham & Petrovic, 2008; Mimovic, 2012), machine learning (Tsao, Chen, Chiu, Lu & Vu, 2021), and so forth. The following part is a presentation of the papers describing the models proposed for demand forecasting.

Starting from the generally known approaches, such as linear regression for time series forecasting (Ilic, Görgülü, Cevik & Baydoğan, 2021), demand forecast can be determined. To forecast demand, the formal linear regression model can be enhanced with partially linear additive quantile regression (Lebotsa, Sigauke, Bere, Fildes & Boylan, 2018). Linguistic variables modeled by discrete fuzzy sets can be used to describe customer demand (Petrovic *et al*, 2008). In the mentioned research study, the total costs in the considered supply chain were determined by decomposing the general model into several simpler sub-models. In separate models, costs are represented by linear affiliation functions with a tolerance between acceptable and pessimistic cost values. The constraints set in the coordination model were phase-discrete sets for the sub-model control. The optimal solution was found from the condition that the total costs that represented the function of the goal reached the minimum value, yet simultaneously meeting all the set limits. If rapid changes and vague conditions over time are considered, the problem of demand forecasting is considered in the presence of uncertainty (Mimovic, 2012). Within the scope of the presented research (Mimovic, 2012), the values of the factors influencing demand were estimated by experts. They based their estimates on their knowledge, their experience, and the projected demand trends as well using a predefined measurement scale. The solution to the considered problem was obtained by applying the Analytical Network Process (ANP). Machine learning models can be used to analyze Business-to-Business (B2B) server industry demand forecasting (Tsao *et al*, 2021). The data were collected from the sales departments' historical data. The proposed machine learning models consisted of clustering, classification, and multiple regression. The results were compared with Simple Exponential Smoothing with Seasonality, Holt-Winters Exponential Smoothing, the autoregressive integrated moving average model, the extreme gradient boosting model, and the random forest model. The comparison was based on the Root Mean Square Percentage Error (RMSPE), the Mean Average Deviation (MAD), and the Mean Absolute Error (MAE).

This research study assumes that demand depends on a discounted amount. Demand forecasting is based upon the application of regression analysis. The main difference between this research study and the discussed sources in the literature (Ilic *et al*, 2021) lies in the application domain.

The literature provides no strict definition of or recommendations with respect to how to choose the products characterized by the greatest impact on the achievement of the business goals of a company (Stevenson *et al*, 2014). So, companies choose different approaches. According to the best practice results, product selection is based on the subjective assessments made by operational management. They make their assessments based on the data obtained from records, experience and current information about the changes that have occurred in the company and/or environment. In many industrial companies, the determination of product importance is based on the Pareto analysis. This method is simple, easy to understand and easily applicable. Many authors suggest the integration of the Pareto analysis and other methods for the purpose of increasing the accuracy of the solution (Hadi-Vencheh & Mohamadghasemi, 2011). Furthermore, a brief overview of the papers that can be found in the literature is also given. They propose the methods based on a combination of the Pareto analysis and other methods.

The ABC method could be integrated with the Fuzzy Analytic Hierarchy Process (FAHP) and Data Envelopment Analyses (DEA) (Hadi-Vencheh & Mohamadghasemi, 2011), whose integration leads to a unique presentation of all observed data and their classification in a unique and mutually comparable way. Classification can be made according to the criterion calculated as a product of the defuzzification of two uncertain criteria (Chu *et al*, 2008). Other scholars treated the product classification problem in a similar manner (Puente *et al*, 2002), so the value of classification criteria can be defined as a product of the two uncertain criteria: the volume of demand and the unit sale price. If classification criteria employ uncertainty with different weights (Kefer *et al*, 2016), criteria weights can be obtained by applying the FAHP (Chang, 1996). In compliance with that fact, a classification criterion could be defined as the distance of difficult normalized values from the positive ideal and the negative ideal solutions (Kefer *et al*, 2016). Combining the ABC with the other methods has led to the increased accuracy of classification solutions. No solution to the classification problem, however, has been obtained in an exact way, so its accuracy is still questionable.

In our research, the treated problem is referred to as a discrete optimization problem. Product selection is set as a classical Knapsack Problem (KP). Although filling a knapsack with a given set of objects with associated values and space requirements associated with them have a simple structure, this problem is known to be NP-hard. The KP has very important applications in the financial and industrial domains (Gojković *et al*, 2021), such as resource distribution, investment decision-making, the shipment of items, the budget controlling, production planning (Kellerer, Pferschy & Pisinger, 2004) and so on. According to many authors, the solution to the NP can be based on the application of the GA (Gabaldon, Lerida, Guirado & Planes, 2014; Nestic *et al*, 2015; Metawa, Hassan & Elhoseny, 2017; Tadić *et al*, 2019). E. Gabaldon *et al* (2014) considered the estimation of the task execution slowdown used to guide the GA search process for the Job Scheduling Problem. A slowdown estimation is applied to express the fitness function. The fitness function defined for the slowdown estimation of the ranking of the Key Performance Indicators (KPIs) of the manufacturing process can be presented using the GA (Nestic *et al*, 2015). In this case, the two-goal functions were defined. The first was to maximize the sum of the overall weighted coefficient of the KPIs for the small and medium-sized enterprises (SMEs) and the second was to minimize the sum of the variance of the overall weighted coefficient of the KPIs for the SMEs. Beside manufacturing, other domains could also be analyzed by applying the GA approach. N. Metawa, M. K. Hassan and M. Elhoseny (2017) discussed the problem of bank ranking. In this case, the goal function was set as maximizing the bank's profit and minimizing the costs of crediting. D. Tadić *et al* (2019) discussed the problem of the site selection for the construction of the recycling centers using a two-objective GA. The procedure for determining the fuzzy suitability index was proposed. The goal function was set as maximizing the defuzzified suitability index values and minimizing the total distance between the randomly selected locations and the other nearest locations not selected for building the recycling center.

METHODOLOGY

In this chapter, a methodology for improving the effectiveness of operational management is presented. The production plan consists of the I products formally presented as a set of the indices $\{1,\ldots,i,\ldots,I\}$. The index of a product is denoted as i, $i = 1,\ldots,I$. The total period of the analysis T is divided into the discrete time intervals t. In the case study presented in this paper, that period is a period of one month. At the level of each period $t = 1,\ldots,m$ the data explaining the regular unit sale price, the realized unit sales price, and the sales volume can be obtained. The sales volume and economic revenue per unit are monitored and analyzed in the first half and in the second half of each time period, respectively. Demand for each the discrete time period t, $t = 1,\ldots,m$ can be treated as demand for the first half of that period x_{it}^1, and the demand for the second half of that period x_{it}^2. The unit sale price used for the first half of the time period is denoted as c_{it}^1, and the unit sale price used for the second half of the time period is denoted as c_{it}^2.

The proposed algorithm

A two-stage algorithm was developed (Figure 1). Based on the data obtained from the evidence (the values of demand for each product at each time period and the unit price for each product for each time period) the input data for the stage model were calculated using descriptive statistics (steps 1-4). Those input data included the total mean value of demand for each product at each time period, the total revenue for each product at each time period, and the discounted amount for each product at each time period.

In the first stage (Step 5), the dependence between demand and the discounted amount is described using a regression analysis. In the second stage (steps 6 to 7), the products that are considered as the most important for operational management in terms of increasing the total revenue are identified.

The proposed algorithm can be implemented through the below steps.

Step 1. Let x_{it}^1, x_{it}^2, represent the values of demand for the product i, $i = 1,\ldots,I$. at the level of the first part or at the level of the second part of each discrete time period t, $t = 1,\ldots,m$, respectively. The total mean value of demand when the first part of each time period is taken into account is calculated in the following manner, x_i^1:

$$x_i^1 = \frac{1}{T} \cdot \sum_{t=1}^{T} x_{it}^1$$

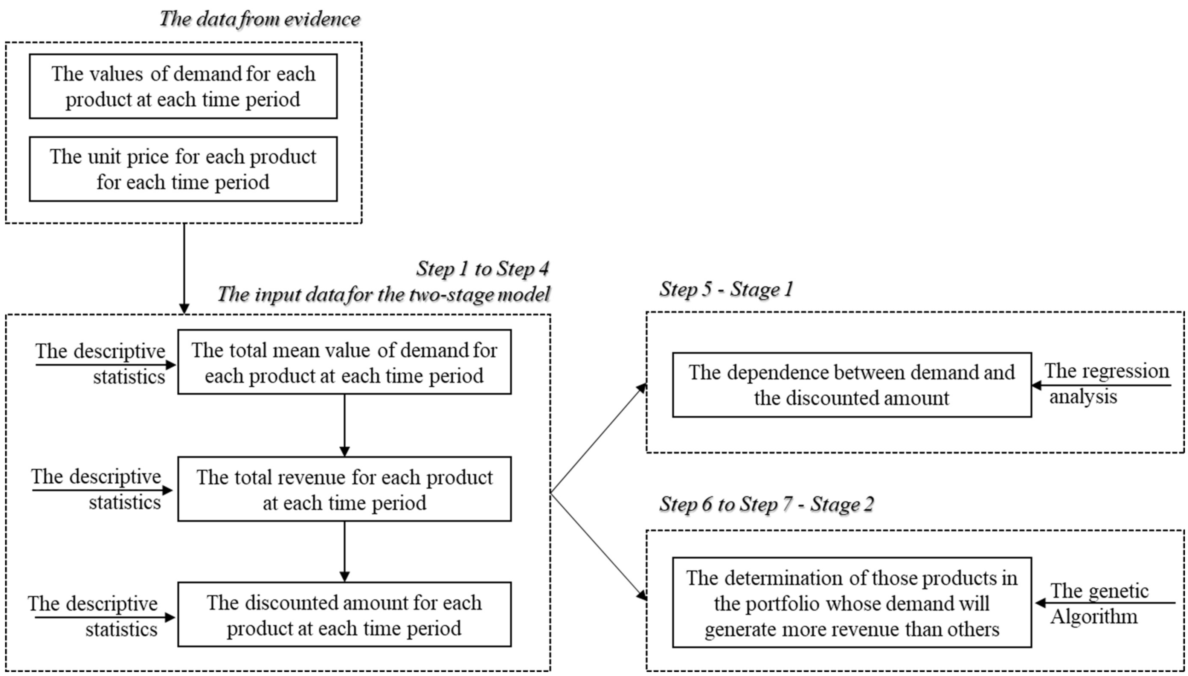

Figure 1 The proposed model

Source: Authors

The total mean value of demand when the second part of each time period is taken into account *t*, x_i^2 is determined in a similar fashion.

Step 2. The total revenue obtained in the total analyzed time period taking into account the first half of each denoted time period d_{it}^1 is obtained as follows:

$$d_i^1 = \sum_{t=1,..,T} x_{it}^1 \cdot c_{it}^1$$

Similarly, the value of the revenue for the second half of the month is calculated, d_{it}^2.

Step 3. The unit sale price is very often reduced by a decision made by the sales management. The value decrease index is marked as z_{it}^1, z_{it}^2, respectively, taking into consideration the first and the second halves of each denoted time period. The discounted amount is calculated as the difference between the regular and reduced unit prices.

Step 4. The mean value of the discounted amount at the level of the total analyzed time period *T* for the first half of each denoted time period z_i^1 is calculated as follows:

$$z_i^1 = \frac{1}{T} \cdot \sum_{t=1}^{T} z_{it}^1$$

The mean value of the discounted amount at the level of the total analyzed time period *T* for the second half of each denoted time period z_i^2 is calculated in a similar manner.

Step 5. The dependence between demand and the discounted amount should be examined by applying the regression analysis method (Black, 2019), in which way sales managers can determine the amount of the price discount while simultaneously generating revenue instead of a loss.

Step 6. The determination of those products whose unit sale price could be decreased to a purposeful level, so that they can significantly enhance the generation of revenue for a company. This is stated as the KP problem:

the fitness function:

$$max \sum_{j=1,..,J} d_j^t, \quad j \in \{1,...,i,...,I\}$$

the objective:

$$\frac{1}{J-1} \cdot \sum_{j=1,..,J} z_j^t \le z^*$$

$$\sum_{j=1,..,J} x_j^t \le x^*$$

The values of the right side of the constraint (z^*, x^*) are defined on the data record and operational management. Those values may vary from one company to another and those are valid for the product selection in the first half of each discrete time period t

and

$$j = \begin{cases} 1 & \text{if the object j is selected} \\ 0 & \text{otherwise} \end{cases}$$

The problem is set in a similar way for the product selection in the second half of each discrete time period t.

Step 7. The near-optimal solution of the treated problem is generated by using the GA. In this case, the near-optimal solution represents those products in the portfolio demand for which will generate more revenue than others.

CASE STUDY

The proposed methodology is illustrated on the data obtained from the supply chain that operates in the Republic of Serbia. In the company, the process of furniture production is being realized with production plans that are defined based on the demand for each product from the product range. A small part of the manufactured products is sold to foreign customers. The operational management of the company strives to implement the Just in Time (JIT) business principle where retail is organized as a chain of 38 retail stores.

Action discounts are carried out monthly. Additional discounts are usually granted at the end of the calendar month. Based on the current production plan, it is determined when it is possible to produce/deliver any model. After confirming the purchase, the demand for the product is confirmed, based on which the production plan is updated. There is a causal link between the sale and the production plan. This is further reflected in the plan for the procurement of raw materials, employment planning, transport, revenue, and expenditure plans. Therefore, each purchase in any of the retail facilities in part affects the determination of the aggregate plan. If they relied entirely on this way of planning without any long-term predictions, it would be very difficult to maintain the profitability of the company as well as plan the development.

The analysis of the product portfolio

The product portfolio includes upholstered furniture: sofas, two-seaters, corner sets, beds, and armchairs. All pieces of furniture are delivered from the factory in several parts which can be assembled very easily, thus reducing the transport space. By packing on pallets, it is possible to load about 80 units into a transport truck, which greatly reduces the share of the transportation costs in the total cost of the product. In this paper, 35 products of the product range of the considered company are included. The data were collected over a period of 12 months. Demand for these products is not continuous. Sales promotions (discounts) are conducted on a monthly basis, and they are aimed at a specific product or a specific group of products. In addition to the monthly shares, there are also the short-term shares carried out at the end of the month or at the times when a change that requires an additional reduction is made on the market. No time periods in which there was no demand for the products were included in the data processing. This assumption was introduced so as to avoid scattering the results.

An application of the proposed model

An illustration of the proposed algorithm (Step 1 to Step 3) is presented on the example of the product I = 30 (Table 1). This product was randomly selected. All other products from the company production program were considered in the same way.

The average value of demand at the level of the entire considered period of time for the first half of each month is as follows:

$$x_{30}^{1} = \frac{1}{11} \cdot (111 + 8 + 4 + 37 + 46 + 25 + 20 + 38 + 16 + 10 + 6) = 29.18$$

The revenue realized by selling the considered product for the first half of the month reads as follows:

$$d_1^1 = 101.93 \cdot 111 + 123.13 \cdot 8 + 75.68 \cdot 4 + 98.18 \cdot 37 + 80.73 \cdot 46 + 76.10 \cdot 25 + 94.66 \cdot 20 + 104.50 \cdot 38 + 132.36 \cdot 16 + 105.20 \cdot 10 + 62.29 \cdot 6 = 31250$$

The average value of the discounted amount at the level of the entire considered period of time for the first half of the month is as follows:

$$z_{30}^{1} = \frac{1}{11} \cdot (0.226+0.125+0.349+0.243+0.326+0.258+0.258 + 0.213 + 0.081 + 0.210 + 0.413) = 0.246$$

The average volume of demand, the total generated revenue, and the average discounted amount are shown in Figure 2. The values of the average volume of demand, the total generated revenue, and the average discounted amount for all the other products are calculated in a similar manner. The results of said calculation are given in Appendix, Table A.

The total average volume of demand for the product I = 30 at the level of each considered time period is presented in the form of a histogram in Figure 2a). The graphic of the total generated revenue for the product

Table 1 The demand values, the unit prices, and the discounted amount for the product I = 30

	c^1_{30t}	x^1_{30t}	z^1_{30t}	c^2_{30t}	x^2_{30t}	z^2_{30t}
t=1	101.93	111	0.226	105.84	284	0.207
t=2	123.13	8	0.125	99.20	13	0.238
t=3	75.68	4	0.349	79.74	26	0.331
t=4	98.18	37	0.243	105.08	358	0.211
t=5	80.73	46	0.326	83.65	41	0.312
t=6	76.10	25	0.258	83.79	26	0.193
t=7	94.66	20	0.258	108.72	30	0.193
t=8	104.50	38	0.213	100.83	26	0.231
t=9	132.36	16	0.081	124.68	17	0.118
t=10	105.20	10	0.210	95.71	12	0.255
t=11	62.29	6	0.413	39.79	2	0.520

Source: Authors

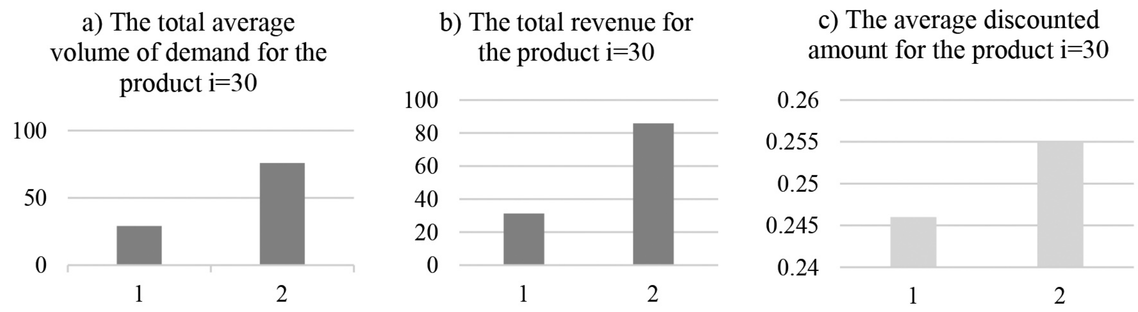

Figure 2 The graphic demonstration of a) the average volume of demand, b) the generated revenue, and c) the discounted amount for the product i=30 at the level of the total time period of 12 months

Source: Authors

I = 30 at the level of each considered time period is presented in the form of a histogram in Figure 2b). The average discounted amount for the product I = 30 is calculated based on the data obtained from the records at the level of each considered time period and the same is presented in the form of a histogram in Figure 2c).

By applying regression analysis, the dependence between the average volume of demand and the discounted amount (the Step 5 of the proposed Algorithm) should be examined.

Let us consider the first half of each time period (the first part of each month) by applying the pspp4windows software (Table 2). The pspp4windows software is a program for the statistical analysis of sampled data. In this case, a regression analysis module was used.

The regression line that describes the dependence between demand and the discounted amount is as follows:

$$\hat{x}_i = -0.18 + 53.89 \cdot z_i$$

The correlation coefficient is r = 0.41. The fact that some products could be described using a more elastic or less elastic demand (Mankiw, 2020) is worth mentioning. It may be considered that elastic demand means that in the case of a small change in the price, change in demand will be significant.

In the second half of each time period, a linear dependence is assumed to be present between demand and the discounted amount (Table 3).

Table 2 The obtained solution by using the pspp4windows software

The model summary

R	*R square*	*Adjusted R square*	*Std. error of the estimate*
0.41	0.17	0.15	9.18

ANOVA

	Sum of squares	*df*	*Mean square*	*F*	*Sig.*
Regression	560.63	1	560.63	6.65	0.015
Residual	2698.95	32	84.34		
Total	3259.57	33			

Coefficients

	Unstandardized coefficients		*Standardized coefficients*	*t*	*Sig.*
	B	*Std. error*	*Beta*		
(Constant)	-0.18	5.15	0.00	-0.03	0.973
	53.89	20.90	0.41	2.58	0.015

Source: Authors

Table 3 The obtained solution by using the pspp4windows software

The model summary

R	R square	Adjusted R square	Std. error of the estimate
0.35	0.12	0.09	17.69

ANOVA

	Sum of squares	df	Mean square	F	Sig.
Regression	1412.26	1	1412.26	4.51	0.041
Residual	10331.51	33	313.08		
Total	11743.77	34			

Coefficients

	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. error	Beta		
(Constant)	-6.19	12.16	0.00	-0.51	0.614
	100.47	47.30	0.35	2.12	0.041

Source: Authors

The regression that describes the dependence between demand and the discounted amount is as follows:

$$\hat{x}_i = -6.19 + 100.47 \cdot z_i$$

The analysis of the correlation coefficient is delivered in a similar way as in the first time period. The value of the correlation coefficient is $r = 0.35$.

Considering the data from Table 2 and Table 3, it can be concluded that the dependence between demand and the discounted amount produces a positive, though not statistically significant. With respect to the hypothesis 1, a conclusion can be drawn that the analyzed dependence is nonlinear, and the type of the dependence should be examined in future research.

Concerning the results of the Pareto analysis, about 30% of the total product development can be said to be of great and medium importance for operational management. Based on this fact, it was determined that 10 products should be selected from the set of the available products that operational management must consider. In compliance with the Step 6 of the proposed algorithm, the company management introduced the value of the constraint $z^* = 0.333$, which is determined according to the statistical analysis since it represents the threshold of the non-loosing revenue below that value. The value $x^* = 250$ was determined according to the information obtained from the market. According to the proposed algorithm (Step 6 to Step 7), the obtained near-optimal solution on an annual basis for the first half of the month was obtained. Figure 3 clearly shows that the near-optimal solution was achieved in about 630 iterations.

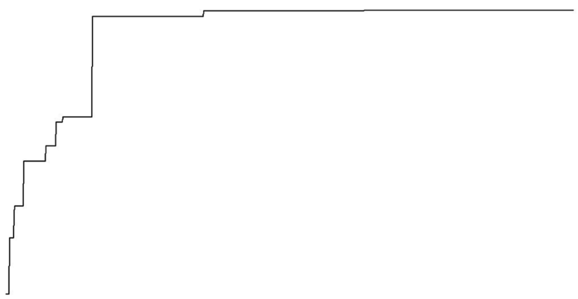

Figure 3 The obtained solution by using the GA at the level of the first half of the month

Source: Authors

The near-optimal solution is (i = 12; i = 16; i = 21; i = 24; i = 26; i = 28; i = 30; i = 32; i = 33; i = 34). The recommendation for management is to consider those products as the most significant for each considered first period of time at the total time interval.

In the same way, the data obtained at the second time period are analyzed on the set of the significant products denoted by applying the GA algorithm.

For the second part of each time period (the second part of each month), the GA search is presented in Figure 4.

The near-optimal solution is achieved in 612 iterations as (i = 6; i = 16; i = 18; i = 21; i = 24; i = 26; i = 28; i = 30; i = 33; i = 34). The recommendation for management is to consider those products as the most significant for each considered second time period at the whole-time interval. In this way, the products contributing to an increase in revenue are identified while the discounted amount and the sales volume are predefined. In this way, the hypothesis 2 is confirmed.

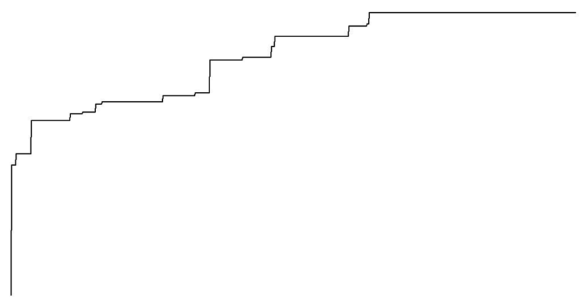

Figure 4 The obtained solution by using the GA at each considered second time period

Source: Authors

DISCUSSION

The model is presented as a two-stage model. The first stage (Step 5) is dedicated to the sales managers with a goal of making a practical contribution, in which way sales managers can determine the amount of the price discount while simultaneously generating revenue instead of making a loss. Stage 2 (Step 6 to Step 7) is dedicated to operational management with the goal to make a practical contribution, in which way operational managers can determine the products in the portfolio demand for which will generate more revenue than others. In that way, the company can pay more attention to the management of those products.

The results of the descriptive statistics indicate the following (Step 1 to Step 4): for 9% of the products, the sales volume and the generated revenue are higher in the first half of the month; for 11% of the products, the sales volume and the generated revenue are approximately the same in the first and the second halves of the month. The sales volume of the largest number of the products (about 80%) is higher in the second half of the month. The generated revenue corresponds to the sales volume. At the same time, the obtained results indicate the fact that, for most products (80%), the sales are higher in the second half of the month for several reasons. The sales shares (discounts) are promoted at the end of the month, which leads to increased purchases. Sellers' motivation in retail stores increases at the end of the month when they are busy working on the implementation of the set sales plans. To equalize demand and the sales volume in all parts of the month, it is necessary to do additional research and define a strategy to reduce this difference. Also, after finding all the reasons for this difference in sales, their analysis should be used as the input in the planning department for procurement planning and the production cycle planning in future time intervals. There are several products with stable demand. For 11% of the products, there is no relationship between the part of the month in which they are sold and the sales volume.

The results of the descriptive statistics are used for the regression analysis. In this way (Step 5), it is shown that there is a linear dependence between demand and the discounted amount. At the level of each product, change in demand can be the subject matter of forecast by an analysis of the value of the discounted amount.

By applying the GA (Step 6 to Step 7), the near-optimal solution is obtained on an annual basis for both time periods under consideration. Production and sales management perceive the near-optimal solution as a list of the products exerting the biggest impact on the revenue generated by the company. The obtained solutions are not identical. This is an important piece of information for both production and sales management since it could serve as an input for production planning, which represents the main managerial implication of the conducted research study. The practical implications refer to operational management, since those products should be treated more carefully from the quality management, transport, and logistics perspectives.

CONCLUSION

The case study analysis performed based upon the actual business results of a production and sales company highlights the most important results of the conducted research. The theoretical contribution of the research study could be summarized as follows:

- the dependence between demand and the discounted amount is determined on a large sample in an exact way;
- it is also shown that it is possible to determine the products in the portfolio demand for which will generate more revenue than others in an exact way as the unit sale price decreases, on the one hand, and demand increases, on the other.

The observed sales results were very suitable for proving the mentioned dependences, because changes in the product prices were often propagated, which clearly and unambiguously reflected on the sales volume and on the revenue as well. There is an evident difference in the sales volume between the two periods of the month, namely the first and the second halves of the month, for about 80% of the products included in the study. This difference in the sales volume in favor of the second half of the month is presumably a result of the campaign discounts propagated most often in the second half of the month. This assumption is also proven.

Practical contribution - The obtained research results should be viewed from the aspect of a practical contribution in sales planning, procurement planning, and production planning. The managers of the named departments should use the obtained regression line to determine the forecast values so that planning can be enhanced in those departments. This confirms the necessity for the cooperation of all the parts of a company. Every, even the smallest change in sales can be said to affect all the aspects of the company's business to a greater or lesser extent. If income and expenses are planned from the economic point of view for a certain period of the proven dependence, they can help to forecast the same most accurately. Since the mentioned dependence was established, when planning a purchase or production, sales plans should be considered. If production wants to achieve a certain production volume, it can use the procurement service to influence increased demand, i.e. to increase the sales volume using a product price discount as a corrective factor. The sensitivity of each product to the corrective price reduction index should serve as the basis for the day-to-day planning of sales campaigns in the future. The main constraint of the proposed method pertains to a relatively great number of the input data and the collection of those, since it is a complex task.

In today's business environment, defining an optimal portfolio is crucial for a market success. To define the optimal portfolio, it is very important to qualitatively evaluate and interpret the existing historical business results. Poorly interpreted information about the previous performance of a certain product on the market may lead to a situation where a wrong strategy may be introduced. In this paper, the importance of the product is determined by the Pareto analysis according to each considered criterion separately, namely according to the sales volume, the total revenue, and the discounted amount. The overall importance of the product is determined based upon the tautology, the conjunction method. In this way, the form of the conventional Pareto analysis is not disturbed. The importance of the product obtained in this way is an unambiguous indicator for the further planning of its development. Future research could be oriented towards a modification of the mathematical model in the direction of the improvement of the defined GA constraint, where the variance of the discounted amount could be performed at the level of each product.

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Received on 18th August 2021,
after revision,
accepted for publication on 13th April 2022

Published online on 20th April 2022

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POSPEŠIVANJE PROIZVODNJE I PRODAJE PRIMENOM MATEMATIČKE STATISTIKE I GENETIČKOG ALGORITMA

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Pospešivanje proizvodnje i prodaje značajno utiče na konkurentsku prednost bilo kog proizvodnog preduzeća. U praksi, posebno u privrednim društvima sa izrazito diversifikovanom proizvodnjom, različiti proizvodi različito utiču na ostvarivanje prihoda. Stoga, upravljanje poslovanjem podrazumeva potrebu da se posveti pažnja proizvodima od najveće važnosti za dato privredno društvo. Pareto analiza je najšire korišćeni metod klasifikacije proizvoda, ali su rezultati dobijeni ovom analizom opterećeni subjektivnim stavovima donosilaca odluka. U ovom radu se predlaže model za odabir proizvoda koji imaju najjači uticaj na ostvarivanje prihoda na egzaktan način. U prvoj fazi modela, analizira se da li postoji linearna veza između tražnje za količinom i eskontovanog iznosa primenom metoda matematičke statistike. U drugoj fazi se predlaže primena genetičkog algoritma (GA), u cilju dobijanja skoro optimalnog skupa najvažnijih proizvoda. Iz priloženog se vidi da predloženi model predstavlja korisnu i efektivnu alatku za procenu koju bi trebalo koristiti u upravljanju poslovanjem i prodajom u proizvodnom preduzeću.

Ključne reči: izbor portfolija proizvoda, pospešivanje proizvodnje i prodaje, deskriptivna statistika, regresiona analiza, genetički algoritam

JEL Classification: C40, C61

APPENDIX

Table A The average volume of demand, the total generated revenue and the average discounted amount

	x_i^1	d_i^1	z_i^1	x_i^1	d_i^2	z_i^2
i=1	16	$3.65 \cdot 10^3$	0.303	22.75	$4.94 \cdot 10^3$	0.335
i=2	10.75	$5.76 \cdot 10^3$	0.211	16.50	$8.80 \cdot 10^3$	0.233
i=3	9.75	$2.92 \cdot 10^3$	0.293	20	$4.91 \cdot 10^3$	0.208
i=4	14.12	$12.76 \cdot 10^3$	0.251	21.50	$18.62 \cdot 10^3$	0.260
i=5	14	$4.48 \cdot 10^3$	0.293	19.33	$6.31 \cdot 10^3$	0.262
i=6	10.14	$8.06 \cdot 10^3$	0.152	8.29	$8.32 \cdot 10^3$	0.191
i=7	7.92	$7.43 \cdot 10^3$	0.304	15.15	$9.55 \cdot 10^3$	0.286
i=8	7.25	$2.36 \cdot 10^3$	0.289	5	$1.66 \cdot 10^3$	0.243
i=9	10.20	$5.19 \cdot 10^3$	0.199	33.33	$16.75 \cdot 10^3$	0.248
i=10	9.25	$3.52 \cdot 10^3$	0.288	19.25	$6.56 \cdot 10^3$	0.365
i=11	5	$1.29 \cdot 10^3$	0.222	7	$1.71 \cdot 10^3$	0.242
i=12	25.09	$41.68 \cdot 10^3$	0.208	29.50	$14.51 \cdot 10^3$	0.219
i=13	1.67	$0.43 \cdot 10^3$	0.067	2.67	$0.52 \cdot 10^3$	0.175
i=14	10.50	$10.45 \cdot 10^3$	0.144	14.12	$14.28 \cdot 10^3$	0.154
i=15	1.20	$0.97 \cdot 10^3$	0.253	3.80	$2.85 \cdot 10^3$	0.284
i=16	11.30	$15.20 \cdot 10^3$	0.179	13.60	$15.33 \cdot 10^3$	0.224
i=17	2.75	$1.84 \cdot 10^3$	0.181	5.25	$3.26 \cdot 10^3$	0.23
i=18	2.50	$1.90 \cdot 10^3$	0.161	2.67	$2.07 \cdot 10^3$	0.148
i=19	6.75	$4.64 \cdot 10^3$	0.279	11	$7.27 \cdot 10^3$	0.301
i=20	13.50	$5.08 \cdot 10^3$	0.453	13.75	$5.21 \cdot 10^3$	0.407
i=21	13.71	$28.49 \cdot 10^3$	0.223	21.86	$40.89 \cdot 10^3$	0.280
i=22	10.20	$4.63 \cdot 10^3$	0.253	12.60	$6.38 \cdot 10^3$	0.195
i=23	16	$11.45 \cdot 10^3$	0.212	15.20	$10.11 \cdot 10^3$	0.239
i=24	30.60	$45.93 \cdot 10^3$	0.220	41.10	$59.47 \cdot 10^3$	0.233
i=25	9.14	$10.44 \cdot 10^3$	0.207	15.86	$16.43 \cdot 10^3$	0.239
i=26	11.43	$12.91 \cdot 10^3$	0.191	14.14	$16.77 \cdot 10^3$	0.199
i=27	4.50	$2.66 \cdot 10^3$	0.289	4.50	$2.85 \cdot 10^3$	0.346
i=28	21.50	$46.24 \cdot 10^3$	0.238	49.81	$71.81 \cdot 10^3$	0.241
i=29	6	$4.04 \cdot 10^3$	0.312	8.50	$5.29 \cdot 10^3$	0.258
i=30	29.18	$31.25 \cdot 10^3$	0.246	75.91	$85.88 \cdot 10^3$	0.255
i=31	4.17	$3.74 \cdot 10^3$	0.242	4.17	$3.47 \cdot 10^3$	0.235
i=32	51.50	$18.64 \cdot 10^3$	0.437	83.83	$30.51 \cdot 10^3$	0.411
i=33	15.62	$18.59 \cdot 10^3$	0.159	11	$10.91 \cdot 10^3$	0.148
i=34	13.55	$13.81 \cdot 10^3$	0.182	11.45	$15.28 \cdot 10^3$	0.234
i=35	3.33	$3.53 \cdot 10^3$	0.151	5	$4.20 \cdot 10^3$	0.192

Source: Authors