UDC 004.855.5(045)
DOI:10.18372/1990-5548.78.18263

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DETERMINATION OF MARKETING PARAMETERS FOR BUILDING A DEMAND FORECASTING MODEL USING NEURAL NETWORKS

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Abstract**—***This article is devoted to finding marketing parameters for building a demand forecasting model using neural networks using real data. The work deals with the problem of modeling product demand on the market in marketing using artificial intelligence and machine learning methods. The main features of existing approaches to building models of products on the market, their advantages and disadvantages are shown. The need for their improvement has been identified. A new methodology for solving the problem is presented. The model's demonstrated ability to predict consumer demand based on a variety of marketing parameters helps businesses plan inventory, production, and personnel more effectively and can lead to significant cost savings and improved efficiency.*

Index Terms—Determination of marketing parameters; forecasting; neural networks; regression models; multilayer perceptron.

I. INTRODUCTION

Demand forecasting in marketing is a critical process in the field of marketing that provides the use of historical data, market trends, and statistical methods to predict future customer demand for products and services [1], [2]. Forecasting allows businesses to make informed decisions about production, staffing, inventory management and financial planning, ultimately aiming to match supply between consumers and demand [3].

Traditionally, demand forecasting has relied heavily on historical sales data and linear projection methods [4]. However, this approach often did not take into account market volatility, changes in consumer behavior, and external factors such as economic changes or competitive actions [5], [6].

Although demand forecasting is a key aspect of strategic marketing planning, current models often face several challenges that can hinder their accuracy and effectiveness. Understanding these issues is essential to developing more reliable forecasting models. One of the main ones is the quality and availability of data. Reliable forecasting depends on access to accurate and timely data.

Demand forecasting models often have to take into account complex and non-linear relationships between various factors such as price, consumer preferences, economic performance and competitive actions [7]. Determining these complex relationships accurately is challenging, especially when using traditional linear forecasting techniques.

As businesses grow and markets evolve, demand forecasting models must scale and adapt. Solving these problems requires a transition to more qualitative and advanced forecasting models based on methods that use machine learning and artificial intelligence. These models can handle complex nonlinear relationships, integrate multiple data sources, and adapt to changing market conditions, offering a more accurate and dynamic approach to marketing demand forecasting.

Focusing on Base Line (BL), Promo Price Impact (PPI) and Base Price Impact (BPI), the study aims to create a demand forecasting model that, although simplified, remains effective for practical use in business. It will serve as a tool for marketers to understand and use the most important factors affecting sales, which will allow them to make better strategic decisions about pricing and sales management.

II. WORK OVERVIEW

As the main approaches to solving the forecasting problem, we will consider: linear regression, Bayesian linear regression, decision trees.

Linear regression is a statistical technique used to model the relationship between a dependent variable and one or more independent variables. The goal is to find a linear relationship between these variables.

The basic form of a linear regression model with several independent variables:

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n + \varepsilon,$$

where y is the dependent variable we are trying to predict; x_i is the independent variable. The vector of parameters $(\beta_0, \beta_1, \ldots, \beta_n)$ is unknown and the task of linear regression is to find these parameters based on some experimental values and ε – error.

Coefficients β are estimated by the method of least squares. This method minimizes the sum of the squared differences between the observed values and the values predicted by the model. Mathematically, the least squares method finds the βs that minimize the sum of squared residuals (SSR), where the residual is the difference between the observed value and the value predicted by the model. The solution to this minimization problem involves taking the partial derivatives of SSR with respect to β, in the case of equating them to zero.

Linear regression has several key assumptions, including linearity, independence of errors, homoscedasticity (constant error variance), and normal distribution of errors.

Linear regression models are among the most popular demand forecasting methods because of their simplicity, interpretability, and ease with which they can be implemented. They provide a clear mathematical relationship between the independent variables (marketing parameters) and the dependent variable (unit sales). This transparency allows business analysts to understand the impact of each parameter on sales, making the model accessible and actionable for making strategic decisions [8] – [10].

In demand forecasting applications, linear regression can effectively identify and quantify trends over time. When historical data is consistent and dense enough, linear regression can serve as a reliable method for predicting future sales based on past performance. This is particularly useful for stable markets with well-known products, where past sales data are a good predictor of future demand [11], [12].

However, the effectiveness of linear regression models is significantly challenged by the realities of marketing data, which are often sparse due to market fluctuations. Researchers may only have access to a limited set of data, typically covering a period of about three years, as data may become less relevant after that point due to rapid changes in the nature of the market and consumer behavior [11].

In addition, marketing reports are usually collected on a quarterly basis. This aggregation further reduces the data points available for analysis. For example, only twelve data points are available over a three-year period if reporting is done only quarterly. This deficiency is exacerbated when considering noise, outliers (punctured points) and their uneven distribution on the time scale, which can distort the predictive accuracy of the model.

The presence of noise and outliers in the data can significantly affect the coefficients of the regression model, leading to inaccurate predictions. Outliers can be particularly problematic because they can distort the results, making the model less reliable. In the context of demand forecasting, where decisions can have significant financial consequences, these inaccuracies are not trivial.

In addition, the assumption of linearity in the relationship between variables can be a critical limitation. Marketing data often contains non-linear relationships that a basic linear regression model cannot capture. This simplification can lead to suboptimal solutions if the underlying patterns in the data are more complex than the model predicts.

Given the sparsity of the data, the risk of overtraining also increases. Overtraining occurs when a model is too fine-tuned to a limited data set, including its anomalies and noise, causing it to perform well on historical data but poorly on future, unseen data.

Bayesian linear regression is an approach that combines linear regression with the principles of Bayesian probability. It differs from traditional linear regression in that it provides probabilistic statements about estimated parameters and predictions. Bayesian inference involves updating our beliefs in light of new data. In Bayesian linear regression, we start with prior beliefs about the parameters (coefficients) of the linear model and update those beliefs to obtain the posterior distribution of the parameters after the observation. The Bayesian regression equation has the same form as the regular one, but ε is usually assumed to be normally distributed with mean zero and standard deviation σ. In Bayesian regression, we define prior distributions for the parameters β and σ. They represent our beliefs about the parameters before observing the data. After receiving the data, we use Bayes' theorem to update our beliefs and obtain the posterior distribution of the parameters.

$$P(\beta | y, X) = \frac{P(y | X, \beta) P(\beta)}{P(y | X)},$$

where $P(\beta | y, X)$ – is posterior distribution of parameters; $P(y | X, \beta)$ – is the probability of the data given the parameters (which are based on the model); $P(\beta)$ – is the a priori probability distribution; $P(y|X)$ – evidence of the model.

Bayesian regression does not provide any best estimate of the parameters, instead it provides distributions. Predictions are made by integrating these distributions, often using techniques such as Markov Chain Monte Carlo (MCMC) to improve computing power.

Bayesian linear regression provides a more complete statistical picture, taking into account the uncertainty in parameter estimates. This is particularly useful when dealing with limited data or when prior information is available that can be quantitatively incorporated into the model.

In the context of demand forecasting, Bayesian models stand out by recognizing and quantifying uncertainty in forecasts. They deal particularly well with outliers, or "puncture points", by treating these data points as part of a probability distribution rather than as fixed inputs. This characteristic makes it possible to obtain a more reliable forecast, which is less sensitive to anomalies in the data [13].

For marketing data that often contains few data points due to market changes and is reported quarterly, Bayesian linear regression offers a framework that can assimilate prior knowledge or expert opinion to reinforce the data.

Bayesian linear regression overcomes some of the limitations of traditional linear regression by providing a more flexible model structure that can adapt to the inherent uncertainty in the data. While traditional regression can be overly affected by outliers or noise, Bayesian methods naturally moderate this effect by treating these cases probabilistically.

However, Bayesian linear regression is not without limitations. The effectiveness of the model depends on the quality of the previous information. If the prior distributions are chosen incorrectly, they can lead to biased results. In addition, Bayesian methods can be computationally intensive [14] – [16].

Despite its strengths in dealing with uncertainty and outliers, Bayesian linear regression still struggles with the fundamental problem of data scarcity in marketing. A small number of data points can lead to wide credible intervals (the Bayesian equivalent of confidence intervals), indicating high uncertainty in predictions. This can be especially problematic when making business decisions that require precision and certainty.

In addition, the choice of prior probability can have a significant impact on the results, especially when the data are limited. In the absence of strong, informative prior data, the Bayesian model may not offer significant improvements over traditional methods [17]. The dependence of the model on the previous period becomes a critical factor when historical data is scarce, as it can lead to over-reliance on subjective judgments or assumptions.

Neural networks represent a leap forward in demand forecasting methodology. As state-of-the-art computational models, they have the ability to handle and identify complex nonlinear relationships that are often missed by traditional statistical methods. The fundamentals of neural networks lie in their structure consisting of interconnected nodes or "neurons" that mimic the processing in the human brain, thus allowing them to learn from data in a complex way [18] – [21].

Neural networks excel at dealing with complex patterns and making predictions based on data of complex structure. This ability is of primary importance in marketing, where consumer behavior and preferences are multifaceted and depend on many factors [13]. In practice, neural networks can provide accurate predictions and offer insight into consumer demand trends, even despite the inherent volatility and noise in marketing data.

However, the implementation of neural networks and decision trees in practice, especially among marketers, is hindered by their complexity. Despite their performance, neural networks are often perceived as "black boxes" because it is difficult to understand how they arrive at a particular prediction. This lack of transparency is a significant obstacle for marketing professionals, who need not only forecasts, but also interpretable models that can inform strategy and decision-making processes [22].

The impenetrability of neural networks means that marketing experts cannot easily validate the model's reasoning or explain it to stakeholders. Such opacity can lead to skepticism and reluctance to trust model results, regardless of their accuracy. For industries where explainability is as important as performance, such as marketing, the nature of neural networks is a significant obstacle.

III. Problem Statement

The main objective of this study is to develop a simplified but reliable model for forecasting unit sales (US) using a reduced set of marketing parameters. This model is aimed at accurate forecasting of the US, taking into account the most influential factors on the volume of sales and provides a simplified and practical application in business analytics.

This equation:

$$US = BL \times PPI \times BPI \times ACVI \times FI \times DI \times FDI,$$

where $US(\text{Unit Sales})$ is the total number of sold units of the product; $BL(\text{Base Line})$ is the determined value of the product outside of marketing efforts; $PPI(\text{Promo price impact})$ is a influence of the promotional price; $BPI(\text{Base Price Impact})$ is a influence of the base price; $ACVI(\text{All-commodity volume impact})$ is the impact of the annual sales volume of retailers; $FI(\text{Feature Impact})$ is the influence of marketing offers; $DI(\text{Display impact})$ is the impact of visual marketing; $FDI(\text{Feature+Display Impact})$ is the impact of both types of marketing together.

However, due to the limitations of this study, the equation simplifies to:

$$US = BL \times PPI \times BPI. \tag{1}$$

The study focuses on quantifying the effect of base sales, promotional price, and base price on unit sales. The model aims to provide a clear and quantified understanding of these factors, which are considered to be the main levers affecting sales volume. The simplified model does not take into account the effect of product volume, features or display strategies, which may also have some effect on sales. The study assumes that BL, PPI, and BPI are independent of each other, which may not always be true in real-world scenarios.

This model is best suited for scenarios where the impact of ACVI, FI, DI and FDI is minimal or can be assumed to be constant and therefore does not require explicit modeling.

The methodological core of the research is the multi-layer perceptron neural network model. Its role is to examine inputs that encode marketing parameters and predict likely demand outcomes. The model will be trained on a real data set that includes historical sales figures and relevant marketing parameters during those sales periods.

IV. Methodology for Determining Marketing Parameters. Building a Product Model on the Market

The proposed methodology includes the following stages.

1) Data pre-processing.

2) MLP model training.

3) Extraction of elasticity from data.

4) Calculation of the coefficients of the equation.

The initial stage of the proposed method includes an innovative data preprocessing methodology designed to increase the number of data points available for analysis. Given the time-series nature of marketing data, pre-processing will include the technique of expanding the data set by creating correlations from existing time points. For every two points in time, we will calculate the ratio and its inverse across all metrics, effectively synthesizing new data points that represent increases or decreases in marketing parameters over time. This approach will not only increase the size of the data set, but also capture the dynamic relationships between different time periods.

Preprocessing will continue with standard practice of data cleaning and normalization to ensure uniformity and reduce the potential for bias in model predictions. The data will be segmented into training and validation sets to facilitate model training and subsequent performance evaluation. In addition, categorical data will be transformed into a numerical format using coding techniques, and any missing values or outliers will be properly addressed to maintain the integrity of the data fed into the neural network.

After preprocessing the data, the study will continue with the training of the multilayer perceptron (MLP) model. This step involves choosing the MLP architecture, including the number of hidden layers and nodes, and the type of activation functions to be used. The training process will involve feeding the pre-processed data to the MLP and using back-propagation with the chosen optimization algorithm to adjust the weights and network biases to minimize the prediction error.

After training and validating the MLP model, the next step is to extract the elasticity from the data. Elasticity in this context means the response of demand to changes in marketing parameters. The ability of the MLP model to predict demand fluctuations based on different parameter values will be used to calculate the elasticity of each parameter. This involves slightly changing the value of each parameter individually and observing changes in the model output to understand the sensitivity of demand to each marketing variable.

The final stage of the proposed research method is the calculation of the coefficients of the simplified equation (1) of demand forecasting: BL, PPI, BPI. The ratios represent the relative impact of each marketing parameter on unit sales. Using the elasticities derived from the MLP model together with the demand forecasts, coefficients will be calculated using regression techniques that relate changes in the input parameters to changes in demand predicted by the model.

The parameter extraction procedure using the multilevel perceptron (MLP) model plays a crucial role in approximating the impact of various marketing factors on demand forecasting. After training the MLP model, the first step in parameter extraction is to analyze the importance of each product characteristic (in this work: Promo Price Impact, Base Price Impact, Base Line) for demand forecasting. This involves estimating the weights and biases assigned to each input function within the MLP.

The model undergoes a sensitivity analysis (calculation of elasticities) to understand how changes in each marketing parameter affect forecasted demand.

IV. Assessment of Forecast Quality

A. Rationale for using WMAPE

When evaluating the effectiveness of an explicit model in demand forecasting, the weighted average absolute percentage error (WMAPE) is used as the main indicator. The choice of WMAPE is particularly appropriate given the varying scale of unit sales for different products: within the data set, unit sales for different products vary widely, with some products selling in the millions and others only in the hundreds. This large discrepancy can distort measures such as MAE or RMSE, which do not take into account the relative scale of sales figures. WMAPE removes this variability by providing a normalization effect. It calculates the absolute error as a percentage for each data point, thus providing a more balanced view of the model's accuracy for products with significantly different sales volumes. This makes WMAPE a more suitable metric for data sets where the target variable, in this case unit sales, spans a wide range.

Weighted average absolute percentage error is calculated by dividing the sums and absolute differences between the actual and predicted values by the total actual values. This gives a percentage error weighted by actual sales volume, ensuring that errors in forecasting high-performing products do not disproportionately affect the overall error metric.

$$\text{WMAPE} = \sum \left| \frac{A_t - F_t}{A_t} \right|,$$

where A_t is the actual volume of product sales at time t; F_t is the forecasted volume of product sales at time t.

B. Interpretation of WMAPE results

A lower WMAPE value indicates higher model accuracy because it means that the predicted values are closer in percentage to the actual values for all product categories. It provides a clear and uniform measure of accuracy that is applicable to all products, regardless of their individual sales volumes.

In summary, using WMAPE as the primary measure to evaluate the accuracy of the MLP model in demand forecasting is a strategic choice that takes into account the different scales of product sales in the data set. It offers a fairer means of evaluating model performance across a range of products, thereby providing a more accurate representation of the model's overall predictive capabilities in a diverse and dynamic market environment.

C. Forecast discussion

The figure (Fig. 1) shows a comparison of the time series of actual sales (blue solid line) with forecasted sales (red dashed line) for the period from the beginning of September to mid-November 2022.

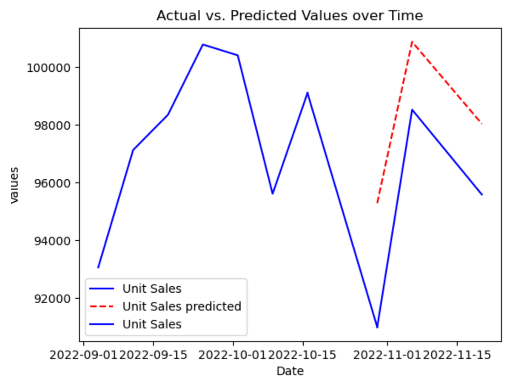

Fig. 1. Forecast of the model on the time series

In summary, the graph shows that while the model has learned the overall sales trend, there is room for improvement in accurately predicting exact unit sales, especially in terms of the timing and magnitude of changes. Further refinement of the model and the inclusion of additional explanatory variables may improve the accuracy of the predictions.

D. Comparison with existing analogues

Table I presents a comparison of the WMAPE for different demand forecasting models, including the model presented in the thesis and widely used alternatives such as linear regression, Bayesian regression, multilayer perceptron, and decision trees.

The model presented in this paper (9.46% WMAPE) significantly outperforms others with a WMAPE of 9.46%. This indicates a relatively very accurate model, as lower WMAPE values mean closer agreement between predictions and actual values. Performance indicates that "This Model" effectively captures the dynamics and variability of the data, resulting in more reliable predictions.

The linear regression model shows the highest WMAPE (38.95%), which means that it is the least accurate among those compared. This may be due to the limitations of linear regression in capturing the complex nonlinear relationships often present in sales data.

Bayesian regression performs similarly to linear regression in this context with a slightly lower but still high WMAPE (38.83%). Although Bayesian approaches can handle uncertainty and incorporate prior knowledge, the result shows that it may not provide significant improvements over linear regression for this particular data set or prediction task.

The multilayer perceptron model shows a marked improvement over both regression models, with a WMAPE of 23.45%. This performance reflects the neural network's ability to model nonlinear relationships and potentially handle a more complex feature space.

Decision trees perform better than regression models and neural networks (19.17% WMAPE), but not as accurate as the model presented in the thesis.

TABLE I. COMPARISON OF MODELS ACCORDING TO THE WMAPE METRIC

Model	WMAPE, %
The model is presented in this paper	**9.46**
Linear regression	38.95
Bayesian regression	38.83
Multilayer perceptron	23.45
Decision trees	19.17

In summary, the model presented in the work demonstrates high accuracy of forecasting using WMAPE as a metric. This indicates that the proposed model approach is well suited to the features of the data set and the demand forecasting task. This indicates a successful application of the methodology outlined in the thesis, providing a potentially valuable tool for practitioners in the field. The results also confirm the need to select the right model based on the specific characteristics of the data set and business context to achieve the most accurate predictions.

V. CONCLUSION

A methodology for determining marketing parameters for building a demand forecasting model using neural networks is proposed, which is used to create a regression model but with coefficients that have a marketing essence. Using this approach will allow businesses to plan inventory, production and staff more effectively and can lead to significant cost savings and improved efficiency.

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Received September 29, 2023

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В. М. Синєглазов, М. С. Новіков. Визначення маркетингових параметрів для побудови моделі прогнозування попиту за допомогою нейронних мереж

Статтю присвячено знаходженню маркетингових параметрів для побудови моделі прогнозування попиту за допомогою нейронних мереж з використанням реальних даних. У роботі розглянуто проблему в області моделювання попиту товару на ринку в маркетингу за допомогою методів штучного інтелекту та машинного навчання. Показано основні особливості існуючих підходів до побудови моделей товарів на ринку, їх переваги та недоліки. Виявлено потребу у їх вдосконаленні. Представлено нову методологію для розв'язання задачі. Продемонстровано здатність моделі успішно прогнозувати споживчий попит на основі різноманітних маркетингових параметрів, що допомагає підприємствам ефективніше планувати запаси, виробництво та персонал і може призвести до значної економії коштів та підвищенню ефективності.

Ключові слова: визначення маркетингових параметрів, прогнозування, нейронні мережі, регресійні моделі, багатошаровий персептрон.

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Освіта: Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського», Київ, Україна, (2022).
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