Досліджено тенденції розвитку промислових ринків та стан наукової думки щодо визначення поняття «система управління маркетинговою інформацією». Встановлено необхідність модернізації класичної концепції побудови системи управління маркетинговою інформацією промислового підприємства. Розроблені класифікація інформації, яка надходить у підсистему прогнозування та типів прогнозів, які можуть бути отримані в підсистемі прогнозування системи управління маркетинговою інформацією промислового підприємства

Ключові слова: маркетингова інформація, система управління маркетинговою інформацією, типи прогнозів, методи прогнозування

Исследованы тенденции развития промышленных рынков и состояние научной мысли относительно определения понятия «система управления маркетинговой информацией». Установлена необходимость модернизации классической концепции построения системы управления маркетинговой информацией промышленного предприятия. Разработаны классификация информации, поступающей в подсистему прогнозирования и типы прогнозов, которые могут быть получены в подсистеме прогнозирования системы управления маркетинговой информацией промышленного предприятия

Ключевые слова: маркетинговая информация, система управления маркетинговой информацией, типы прогнозов, методы прогнозирования

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DEVELOPMENT OF THE SUBSYSTEM OF FORECASTING FOR THE SYSTEM OF MARKETING INFORMATION MANAGEMENT AT AN INDUSTRIAL ENTERPRISE

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1. Introduction

A market is a social phenomenon. The availability of valuable marketing information reduces uncertainty, ensures promptness of managerial decision-making, makes it possible to avoid threats and creates a basis for an increase in the efficiency of production process and competitiveness. Therefore, control over changes in the marketing environment requires creation of a marketing information management system based on effective methods of collection and analysis. Markets of industrial enterprises provide a possibility to form and test progressive marketing mechanisms of adaptation to the dynamics of the marketing environment.

Marketing is an integral part of the system of management of an industrial enterprise with strategic and operational directivity. In the first case, it provides determining market objectives of an enterprise and the choice of ways to achieve them. In the second case – it forms a mechanism of management activity. Therefore, the market position of an enterprise directly depends on the effectiveness of marketing activities, which is very risky.

The following trends in the development of industrial markets increase business risks:

– a life cycle of goods is reduced;

– a need appears to take into account consequences of internationalization of markets;

– effectiveness of advertising campaigns decreases;

– importance of traditional media diminishes;

– a role of a complex of Internet communications, social networks, blogs, forums is growing;

– a number of producers decreases;

– a number of marketing intermediaries decreases, intermediaries dictate terms of cooperation to a manufacturer;

– a process of interaction with consumers is accelerated.

The effectiveness of information provision of marketing solutions is of particular importance under conditions of adverse business climate. Forecasting is a source of necessary and reliable information for making managerial decisions. The relevance is explained by the need to overcome a high degree of uncertainty in the management of an enterprise on a basis of evaluation of probability to achieve a planned result. The development of a subsystem of forecasting of the marketing information management system at the industrial enterprise can reduce a level of uncertainty and assist to achieve competitive advantages.

2. Literature review and problem statement

The state of scientific thought regarding the definition of "marketing information management system" indicates the absence of discussions on this subject (Table 1).

Table 1

The state of scientific thought regarding the definition of "marketing information management system" (marketing information system)

Source	Definition
Malhotra N. K., Birks D. F. [1]	Marketing Information System is a formalized procedure of actions of obtaining, analyzing, storing, dissemination of necessary information for those who is responsible for marketing decisions on a regular basis
Churchill, G. A., Iacobucci D. [2]	Marketing Information System (MIS) is a set of procedures and methods for regular, systematic collection, analysis and distribution of information for a preparation and adoption of marketing decisions
Evans J. R., Berman B. [3]	Marketing Information System (MIS) is a set of procedures and methods developed for creation, analysis and distribution of information for proactive marketing decisions on a regular constant basis

Thus, a system of marketing information management is a human-machine system, a hardware-software complex. Functions include search, receiving, collection, accumulation, processing, analysis, storage, issue, distribution of marketing information. The marketing information management system is a part of the enterprise information system. It combines manufacturing resources with information manipulation technologies.

A modern information system of an enterprise is called "electronic nervous system". It performs two main functions in the formation of corporate intelligence [4]:

1) it extends analytical abilities of people; similarly, mechanical devices expand their physical abilities;

2) it combines abilities of many individuals and forms an aggregate intelligence of a whole organization and collective readiness for action.

The "electronic nervous system" should combine efforts of individuals and form corporate actions in interests of clients. The "electronic nervous system" can also be considered at the following aspect: it provides employees information, which is usually prepared for external consultants within special projects, for everyday business use "[4].

The professional community considers the following concept of a marketing information management system as classic (Fig. 1).

A classical marketing information management system of an enterprise consists of four subsystems:

1) internal reporting;

2) collection of external marketing information;

3) marketing research;

4) analysis of marketing information.

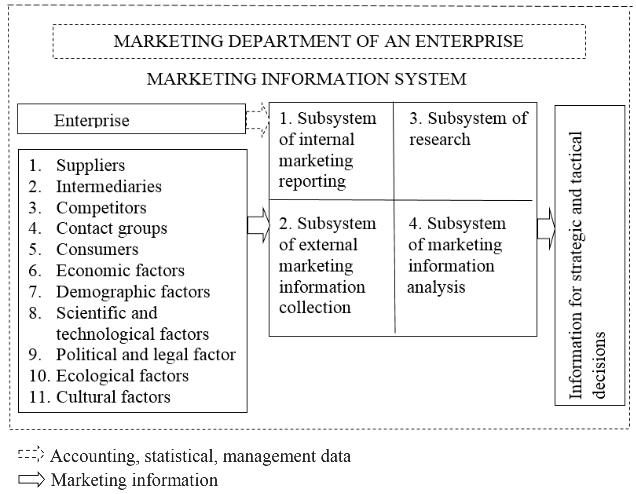

Fig. 1. Structure of classic marketing information management system of an enterprise [5]

A need to restructure the classical marketing information management system is conditioned by the following:

– division of sub-systems of marketing information collection into internal and external is not substantiated;

– separation of the subsystem of marketing information analysis is inappropriate as analysis is an integral part of other subsystems;

– there are no subsystem of risk assessment and subsystem of forecasting.

A modern forecasting toolset contains a large number of methods, techniques and tools. Advantages and disadvantages of a use of different levels of time aggregation of data, their combinations, and a use of a time hierarchy for forecasting have been analyzed in modern studies. It has been proven in paper [6] that an application of one optimal level of time aggregation leads to a decrease in the accuracy of the obtained model, and an application of several levels of time aggregation is reliable for modeling of uncertainty, but is not optimal by parameters. Study [7] suggests a use of a time hierarchy to obtain forecasts of time series. Authors propose to combine forecasts obtained at different levels of a time hierarchy to get more accurate, reliable and adequate models. A combination of individual forecasts is essential for obtaining of an accurate aggregated forecast according to [8].

Traditional statistical models remain relevant to the research and forecasting of economic indicators. Questions about a number of model parameters, due to which it is possible to achieve the highest accuracy of forecasts is debatable [9]. It is proved [10] that the use of econometric models with a large number of variables is effective for obtaining complex forecasts, for example, a forecast of inflation. The Bayesian approach is also relevant for forecast of demand. Authors of paper [11] prove that it has an advantage over traditional approaches to forecasting for obtaining a partial forecast.

Genetic methods and methods of neural networks are widespread in addition to traditional statistical and Bayesian approaches. Thus, a two-stage method of classification based on a genetic method is proposed to be used to predict bankruptcy [12], and in combination with neural networks, it is used to forecast demand in the services sector [13].

A combination of neural networks and ridge regression is effective for short-term forecasts of price changes [14]. A multi-purpose approach with a use of different forecasting methods is effective for obtaining forecasting of exchange rates [15]. A research [16] develops a genetic algorithm based on a fuzzy neural network (GFNN), which makes it possible to formulate a knowledge base of fuzzy rules of output that can measure a qualitative effect on a stock market.

Of special importance are the studies that highlight problems of forecasting under conditions of uncertainty. Thus, approaches to obtain a fuzzy regression model for evaluation of functional relationships between dependent and independent variables in a fuzzy environment are used [17]. An industrial environment, as an object of the research, relates to such environment, it requires the development of an effective marketing information management system. In paper [18], a technology of artificial orthogonalization of results of a passive experiment is proposed based on a complex use of fuzzy clustering and a technology of solution of fuzzy systems of linear algebraic equations. Solutions obtained are usually used in decision support systems for management systems that exist at enterprises. For example, study [19] describes an approach used to select an appropriate decision support system (ERP) for the textile industry. Authors of this work identified the following factors that create uncertainty: width of product structure, product diversity, unskilled human resources. A fuzzy method of hierarchy analysis and a multicriteria approach for fuzzy decision-making expansion are used to analyze such a system. The use of methods of fuzzy logic and fuzzy set theory in the system of decision making support for the implementation of forecasting estimates of production processes can be found in [20]. Attention should also be paid to the coverage of relevant issues related to multicriteria decision making with the use of fuzzy sets in decision making support systems in industrial production [21].

It is impossible not to ascertain the following conclusion taking into account described state of the problematic. Despite the existence of a wide range of forecasting methods, problems of their specific application dependent on the nature of data, the type of information, and sources of obtaining are debatable.

3. The aim and objectives of the study

The aim of present study is to systematize classes of forecasting methods for obtaining forecasts in a management system of marketing information of an industrial enterprise and to provide recommendations for their application depending on the characteristics of information.

To achieve the study objective, the following tasks have been solved:

– improvement of the classical management system of marketing information of an enterprise through development of methodical principles of a forecasting subsystem;

– development of a classification of information which comes into a forecasting subsystem of a management system of marketing information of an industrial enterprise;

– development of a classification of forecasts types which can be obtained in a forecasting subsystem of a management system of marketing information of an industrial enterprise.

4. Methodology of marketing information management system

The methodological toolset includes a theory of systems, a theory of marketing information, a theory of making managerial decisions. Methods and models of these theories are used to form a marketing information system of industrial enterprises under conditions of an increase of risks of entrepreneurial activity of the information economy. Growth of these risks is facilitated by trends of globalization, informatization and social changes. In addition, external factors – fiscal, banking, foreign trade policy do not contribute to positive forecasts related to the improvement of macroeconomic indicators. There is a threat of demand falling due to political uncertainty, negative expectations of the development of financial and economic situation, high volatility of the national currency rate. Risks of entrepreneurial activity increase. Risks of target audiences become determinant. Therefore, it is not enough for marketing information systems to be defined as mechanisms of collection, analysis, processing and storage of information now, under conditions of free movement of finances, goods, personnel and information.

Necessity of the development of a theoretical foundation of a new configuration of a management information system of an industrial enterprise determined the choice of theme, purpose, task, logic and directions of the study.

5. Subsystem of forecasting of a modernized marketing information management system

A structure of the modernized marketing information management system of an enterprise is proposed (Fig. 2).

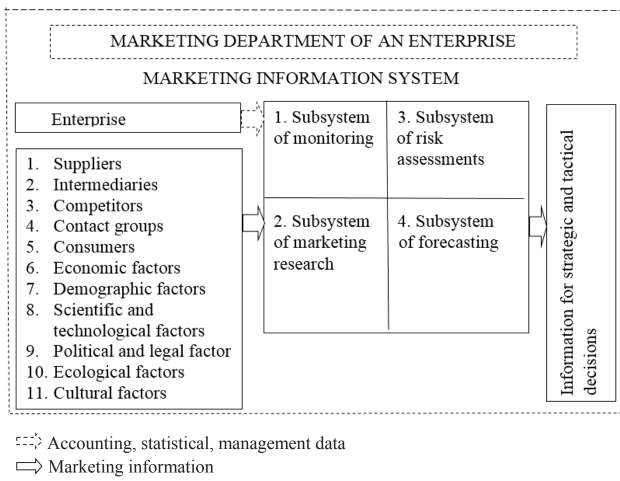

Fig. 2. Structure of a modernized marketing information management system of an enterprise

In contrast to the structure of classical system, it consists of four following subsystems:

1) a subsystem of monitoring;
2) a subsystem of marketing researches;
3) a subsystem of risk assessment;
4) a forecasting subsystem.

The subsystem of forecasting of a modernized marketing information management system receives data from subsystems of monitoring and marketing research. Data that arrive in the subsystem of forecasting can be categorized as follows:

1) data received from the monitoring subsystem or data received from the subsystem of marketing research;

2) dynamic or static arrays of information;

3) dynamic data, changes of which have a trend in time or dynamic data, changes of which are similar to stationary processes;

4) data which are hypothetically related to each other or data which is not characterized by bonds;

5) expert assessments or factual data;

6) retrospective data or forecasts of industry-relevant indicators.

When data come from the monitoring subsystem to the forecasting subsystem, they are not systematized, analyzed or processed by software products. These data are "raw", they are collected and recorded in the monitoring system only. That is, they need further systematization, classification, analysis and interpretation of certain procedures, methods and techniques. If data come from the subsystem of marketing research, then they already have a certain interpretation, they have been a subject to qualitative or quantitative analysis procedures and patterns revealed in them have verbal, graphical, analytical interpretation. Such data are considered as ready for further deeper analysis.

Data from subsystems of monitoring and marketing research, which were collected or investigated for some time, are dynamic – these are time series. Data collected to solve a particular management problem and not characterized by time changes are static. Different procedures, methods, and analytical techniques are commonly used for dynamic and static data. This is explained by different objectives: dynamic data is analyzed in order to identify patterns of changes in time; static data is analyzed in order to identify links between them.

Dynamic data, in turn, can show a clear tendency for growth or decline in time (trend) or characterized by fluctuations that can not be explained by analytical models. In the case of dynamic data fluctuations around a certain level, such processes are stationary. In the case of growth or decline of dynamic indicators that are far from a certain level, such processes are non-stationary.

An important task is to establish bonds between dynamic or static data sets in the forecasting system. An establishment of bonds between these mathematical and statistical methods must be preceded by a complex economic analysis of the hypothetical bond of the studied features. It is possible to move on to obtaining of models of these bonds and forecasts for them only in the case of proving of the existence of economic bonds or the validity of the hypothesis of their existence.

Researchers seek for assistance of experts in the case of a deficit of factual data or the impossibility of obtaining them. Expert evaluations are a category of data that is analyzed by special methods and techniques. These approaches are usually different from the analysis of factual data, as expert surveys are important to evaluate a degree of consensus of expert opinions, a level of reliability of information they receive, a probability of forecasts by their estimates.

Retrospective data from monitoring subsystems and marketing studies, as well as forecasts, may be received in the subsystem of forecasting. Forecasts usually come from the subsystem of marketing research as a result of systematization, classification and data analysis. Forecasts that arrived at the forecasting subsystem, and were received to solve managerial problems, can be used to explain other patterns and to solve other problems.

Classification of information coming into the subsystem of forecasting of a modernized marketing information management system of industrial enterprises can be presented in the following form (Fig. 3).

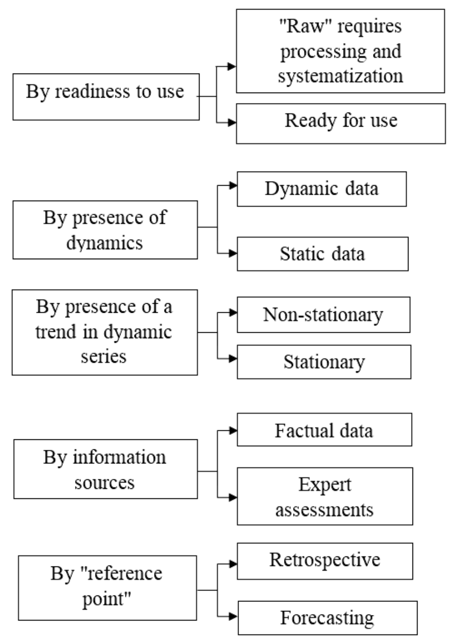

Fig. 3. Classification of information entering the subsystem of forecasting of a marketing information management system of an industrial enterprise

A choice of forecasting method depends not only on the type of information that comes to the subsystem, but also on the needs for forecasts. They can be divided into three groups by the demand of administrative structures of industrial enterprises in forecasts (Fig. 4).

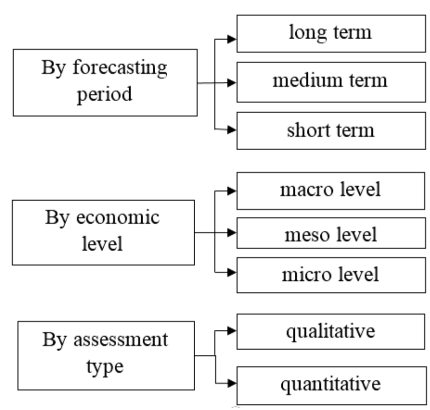

Fig. 4. Classification of types of forecasts that can be obtained in the subsystem of forecasting of a marketing information management system of an industrial enterprise

Top-level managers of an enterprise make decisions about determination of its development for the future period of 5–10 years. Long-term forecasts, which should be provided to a management by a subsystem of forecasting, are important for making such decisions.

Long-term forecasts are forecasts for periods of more than five years. A management develops and approves strategic plans according to long-term forecasts. Medium-term forecasts, from 2 to 5 years, are also important for determining strategic plans for development of an enterprise, but they cover standard activities without taking into account prospects provided by the introduction of innovative technologies, materials and processes – this is the priority of long-term forecasting. Short-term forecasts – up to 2 years – are a source of information for a development of tactical plans.

Global macroeconomic forecasts are obtained using complex models with more than 200 variables. They are developed by leading world banks and research organizations. Thus, forecasts of the gross domestic product of the world countries are provided by the European Bank for Reconstruction and Development, the World Bank, the International Monetary Fund. Among national institutions, GDP forecasts are provided by the International Center for Economic Research, Institute for Economics and Forecasting. It is too difficult to obtain such forecasts at the enterprise level, but these forecasts are widely available and can be a benchmark for enterprises.

Microforecasts – forecasts of performance indicators of an enterprise in a short, medium or long-term perspective. They relate to forecasts of sales, prices, demand for finished products.

Forecasting procedures can be classified as qualitative and quantitative. There are results of a thinking process of experts at one pole – qualitative assessments, and on the other – quantitative data.

All of the above factors need to be taken into account when choosing a forecasting method. It is necessary to determine a level of detailing: whether a forecast, which determines certain details (micro forecast), is required or whether there is a need to get a future state of certain generalized factors (macro forecast). It is also important to define whether it is necessary to determine a state of a certain indicator in the near (short term forecast) or in the distant future (long term forecast). And to what extent are qualitative or quantitative forecasting methods acceptable?

A modern scientific and methodological basis of forecasting encompasses a system of methods, techniques and procedures. Methods of forecasting, which can be applied in a subsystem of forecasting of the marketing information system of an enterprise, can be divided into two groups: quantitative and qualitative. As noted, qualitative assessments are provided by experts, and quantitative forecasts are obtained by different methods of analysis of factual information.

Let us consider what quantitative forecasting methods should be used in the subsystem of forecasting of a marketing information system of an enterprise. It is proposed to divide quantitative forecasting methods into three groups:

– forecasting of time series;
– causal methods;
– other specific methods.

The following mechanism for selection of a forecasting method can be proposed depending on the kind and type of time series data (Table 2).

Table 2

Choosing a forecasting method depending on the kind and type of time series

Data kind	Data type	Forecasting methods
Stationary data series without seasonality	1. Sales volume of enterprise's products that fluctuates around a certain level 2. Prices for raw materials or components that fluctuate around a certain level 3. Indicators of demand for products of an enterprise that fluctuate around a certain level	1. Simple average 2. Slippery average 3. Exponential smoothing 4. Box-Jenkins Models (ARIMA)
Seasonal data series without trend	1. Monthly or quarterly volumes of sales that fluctuate around a certain level 2. Monthly or quarterly volumes of production in a country or a region that fluctuate around a certain level.	1. Seasonal exponential smoothing 2. Method of decomposition of time series without a trend 3. Box-Jenkins models (ARIMA)
Trend data series	1. Annual sales volumes of enterprise products 2. Prices of components or raw materials that rise or fall 3. Annual indicators of demand for enterprise products 4. Annual volume of capital investments to industry, annual GDP or other indicators	1. Trend models 2. Adjustment by S curve 3. Gompertz model 4. Linear exponential smoothing: Holt's method 5. Box-Jenkins models (ARIMA)
Trend data series with seasonality	1. Monthly or quarterly sales volumes of an enterprise with a growing or declining trend 2. Monthly or quarterly volumes of production in a country or region with a growing or declining trend	1. Time series decomposition 2. Exponential smoothing based on a trend and seasonal variations: Winters method

We systematize methods of application of time series forecasting methods.

1. Simple average. The method should be used in cases where processes that generate a time series are stabilized, and the environment, where this series exists, mainly stays unchanged. As a rule, time series is divided into two parts by this method: the first one – after which a forecast is obtained; the second one – for which it is checked. A forecast for future periods is defined as an average value of past observations in the method of simple average:

$$\hat{Y}_{t+1} = \frac{1}{t}\sum_{i=1}^{t} Y_t, \tag{1}$$

where $\hat{Y}_{t+1}$ – forecasted value; Y_t – value at a t time period.

A forecast error is calculated by the formula:

$$e_{t+1} = \hat{Y}_{t+1} - Y_{t+1}. \tag{2}$$

Forecasted values can be taken into account in formula (1) in the case when forecasts are needed not for one period, but for several.

Disadvantages of this method: all previous observations are taken into account in obtaining a forecast, and all of them have the same effect on a forecasted value.

2. Slippery average. The method of slippery averages does not take into account all observational data, but only

a few of the latter. This eliminates disadvantages of the previous method and makes possible to use "fresh" data to get a forecast. An amount of data k to calculate a forecast is determined by a researcher. A simple slippery average of the average order k ($SA(k)$) includes k of previous observations and is calculated by the formula:

$$\hat{Y}_{t+1} = \frac{(Y_t + Y_{t-1} + \ldots + Y_{t-k+1})}{k}. \quad (3)$$

The disadvantage of this method is that it does not take into account a trend and seasonal fluctuations.

3. Exponential smoothing method. This method is based on averaging of data, where older data is given less weight, and data that is closer to a forecasted value is given greater weight:

$$\hat{Y}_{t+1} = \alpha Y_t + (1-\alpha)Y_{t-1} + (1-\alpha)^2 Y_{t-2} + \ldots + (1-\alpha)^k Y_{t-k+1}, \quad (4)$$

where α – constant of smoothing ($0<\alpha<1$).

Constant α is chosen by considerations of the importance of the "freshest" data (the more important they are, the more is α), as well as on the basis of an error that will be obtained from the data for validation of a model. The technique of the exponential smoothing method is as follows: forecasts are made with several α values and compared with factual data determined for testing of a model. The value of α, which gives the lowest error, is optimal for forecasting.

The disadvantage of this method is that it is used in cases where a level of data changes slightly. If there is a trend in the data, then simple exponential smoothing is constantly lagging behind real data.

4. Exponential smoothing based on trend: Holt's method. Time series are rarely characterized by a fixed linear trend in economics and business. The method of exponential smoothing takes into account a local linear trend in exponential smoothing [22]. This method is called "two-parameter method of Holt". It is based on three equations:

a) An exponentially smoothed series or an estimate of a current level:

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}); \quad (5)$$

b) Trend assessment:

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}; \quad (6)$$

c) Forecast for p periods ahead:

$$\hat{Y}_{t+p} = L_t + pT_t, \quad (7)$$

where L_t – new smoothed value; α – constant of smoothing for data ($0<\alpha<1$); Y_t – value of series at t period; β – constant of smoothing for trend assessment ($0<\beta<1$); T_t – trend assessment; p – forecasting period; $\hat{Y}_{t+p}$ – forecast for p periods ahead.

The technique of method application can be as follows: a first estimate is equal to a first observation and the trend is zero. Or the initial value is defined as an average of the first five or six observations, then the trend is characterized by the inclination of lines formed by these observations.

5. Exponential smoothing based on trend and seasonal variations: Winter's method. The method contains a three-parameter, linear and seasonal model of exponential smoothing [23]. This approach is an extension of the Holt's method. An additional equation is used to estimate seasonal variations in this method. The Winter's multiplicative model is determined by four equations.

a) Exponentially smoothed rows

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} - T_{t-1}); \quad (8)$$

b) Trend estimation:

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}; \quad (9)$$

c) Seasonality estimation:

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s}; \quad (10)$$

d) Forecast for p periods ahead:

$$\hat{Y}_{t+p} = (L_t + pT_t)S_{t-s+p}, \quad (11)$$

where L_t – new smoothed value; α – constant of smoothing for data ($0<\alpha<1$); Y_t – value of series at t period; β – constant of smoothing for trend estimation ($0<\beta<1$); T_t – trend estimation; γ – constant of smoothing for seasonality estimation ($0<\gamma<1$); S_t – seasonality estimation; p – forecasting period; S – duration of seasonal fluctuation period; $\hat{Y}_{t+p}$ – forecast for p periods.

The technique of method application can be as follows: the first estimate is equal to the first observation, with the trend equal to zero, and the coefficients of seasonality are equal to one. Or the initial value is defined as an average for the first season (s values), then the trend is characterized by the inclination of lines formed by these observations. Coefficients of seasonality in this case are determined by the formula:

$$S_t = Y_t / L_s. \quad (12)$$

6. Trend models. In the case when the output data shows a tendency that is close to the type of analytic functions, forecasting is used according to the trend. Reference functions here can be:

a) linear trend $\hat{Y}_t = b_0 + b_1 t$;
b) parabolic trend $\hat{Y}_t = b_0 + b_1 t + b_2 t^2$;
c) hyperbolic trend $\hat{Y}_t = b_0 + b_1 / t$;
d) logarithmic trend $\hat{Y}_t = b_0 + b_1 \ln(t)$;
e) exponential trend $\hat{Y}_t = b_0 + b_1 e^t$;
f) degree trend $\hat{Y}_t = b_0 t^{b_1}$.

Coefficients of models are estimated using the least squares method (LSM), an estimate is made usually in special software products Excel or Minitab.

7. Adjustment by S curve. S-curve or logistic curve, or Pearl-Reed curve characterizes processes with saturation of the market. Equation:

$$\hat{Y}_t = \frac{k}{1 + ab^t}, \quad (13)$$

where k –horizontal asymptote of a function graph (saturation line of the market); a, b – added parameters and $b<1$.

To determine parameters of a logistic model, it is sufficient to have two initial conditions and a market saturation point. Other modifications of formula are possible (13).

8. Grompertz model. It also relates to saturation models of the market. Equation:

$$\hat{Y}_t = k * a^{b^t}. \tag{14}$$

There are other modifications of the Gompertz curve. Parameters are determined in the same way as for the Pearl-Reed curve.

9. Model of decomposition of time series. In the case when data have a clear tendency (trend) and seasonal fluctuations, the time series decomposition model is used. The method of obtaining a model has five stages:

a) we smooth seasonal fluctuations in the output data by a slippery average;

b) we obtain seasonal indices for each quarter or month by averaging the ratio of output data to a slippery average;

c) we obtain output data adjusted for a season by dividing the source data into seasonal indices;

d) we get a trend and a season-adjusted forecast according to the data adjusted for a season;

e) we obtain a trend and a forecast adjusted to a season by multiplying a forecast with a season adjustment for relevant seasonal indices.

In the case when data contains only seasonality without a trend, it is enough to complete the first three stages. The forecast is obtained by multiplying the average level of output data by corresponding seasonal indices.

10. Box-Jenkins method. Common models for time series forecasting are models of autoregression and slippery average (the AutoRegressive Integrated Moving Average (ARIMA)). These models show reliable results in forecasting for both stationary and non-stationary time series. ARIMA models are based on the autocorrelation data structure. In the forecasting methodology of Box-Jenkins there is no any special structure in given time series, for which the forecast is carried out. An iterative method for determination of a model among a general class of models is used (Fig. 5).

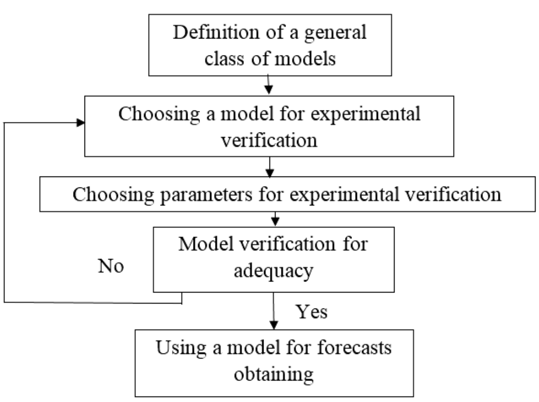

Fig. 5. Diagram of strategy for choosing of a model by the Box-Jenkins method [24]

The autoregression model of p order takes the form:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_p, \tag{15}$$

where Y_t – response (dependent variable) at time t; $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}$ – response at time intervals $t-1$, $t-2$, ..., $t-p$ respectively; $\phi_0, \phi_1, \phi_2, \ldots, \phi_p$ – coefficients of the model to be evaluated; ε_p – errors that determine the influence of factors not considered in the model.

The model with a slippery average order q is given by the following equation:

$$Y_t = \mu + \varepsilon_t - \omega_1\varepsilon_{t-1} - \omega_2\varepsilon_{t-2} - \ldots - \omega_q\varepsilon_{t-q}, \tag{16}$$

where Y_t – response (dependent variable) at time t; μ – constant average of a process; $\omega_1, \omega_2, \ldots, \omega_q$ – coefficients of the model to be evaluated; ε_t – errors in previous periods of time that were included in the response Y_t at time t.

In the combination of the autoregressive model (15) with the model of the slippery average (16) we obtain a mixed model of autoregression-sliding-average (17), which is denoted by ARMA (p, q), where p is the order of the autoregressive part of the model, q is the order of the slippery average part:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \\ + \varepsilon_t - \omega_1\varepsilon_{t-1} - \omega_2\varepsilon_{t-2} - \ldots - \omega_q\varepsilon_{t-q}. \tag{17}$$

The ARMA model (p, q) (17) provides a description of a broad spectrum of behavior of stationary series.

The output series Y_t is replaced by its first or second (sometimes third) differences for non-stationary time series. For example, the first difference is $\Delta Y_t = Y_t - Y_{t-1}$, the second difference

$$\Delta^2 Y_t = \Delta(\Delta Y_t) = Y_t - 2Y_{t-1} + Y_{t-2}.$$

Differences are taken until a number received is not stationary.

Models for non-stationary reries are called autoregressive integral models with slippery average and are denoted as ARIMA (p, d, q). Here the parameter p is the order of the auto-regression part of the model, the parameter d defines the difference order, and the parameter q determines the order of components of the slippery average. The implementation of the Box-Jenkins method is developed in such software products as Minitab, SPSS and Statistica.

Several series, not a one separate time series, or several parameters, which are not time series, are considered to obtain causal (cause-effect) models. The methods for determination of causal relationships between variables include regression models (pairwise or multiple regression), as well as multidimensional statistical methods (Table 3).

Other specific methods of forecasting include the method of fractals and the method of maintaining of lag correlation. Let us consider in detail.

1. The method of fractals. One of the specific methods for time series forecasting is the method of fractals. The method of fractal analysis of time series is one of the directions of the analysis of the financial market, which is intended to study nonlinearities in the dynamics of time series, including financial [25–27].

Fractal analysis, as a new trend in the analysis of the dynamics of financial indicators, was formed on the basis of the theory of fractal markets. It states, unlike the theory of effective markets appeared in the early XX century, states that the development of market processes in the future, as well as future time series values that reflect these processes, depend on retrospective changes. It is believed that the pricing process is generally globally deterministic and depends on the initial conditions, but locally it is random.

Table 3

Methods for determining the causal relationships between variables

Method	Application
1. Cluster analysis. Cluster analysis is a class of methods used to classify objects or events in relatively homogeneous groups called clusters	Segmentation of the market. For example, consumers can be divided into clusters based on benefits they expect from a purchase of a product. Understanding of customer behavior. Cluster analysis is used to identify homogeneous groups of customers. Determination of capabilities of a new product. Clustering of brands and goods can be determined by competitive kits within the market. Trademarks in the same cluster compete more rigorously with each other than with brands of other clusters.
2. Correlation-regression analysis. Multi-factor correlation-regression analysis makes possible to estimate the extent of influence of each factor introduced into the model at a fixed position on the researched productive parameter on the average level of other factors	Determination of the optimal price for goods and services. The influence of several factors on the price is studied and the optimal price is determined according to available competitor's supply and prices, or other factors. Determination of the cost effectiveness of advertising and sales promotion. The correlation coefficients between sales volumes and promotional costs give possibility to determine how closely sales changes and increase in costs for promotional activities are connected. The regression equation makes possible to predict necessary advertising costs to get the desired sales volume.
3. Factor analysis is a class of methods used to reduce a number of variables and their generalization. Factor is a latent (hidden) variable that explains a correlation between a set of variables	When segmenting the market to determine latent variables for the purpose of consumers grouping. When developing a commodity strategy, factor analysis is used to determine characteristics of a trademark that affects the choice of a consumer. When designing a pricing strategy, factor analysis determines characteristics of consumers who are sensitive to prices
4. Variance analysis – statistical method of study of differences between sample averages for two or more sets	For example: – are the segments of the market different in terms of the volume of consumption of goods? – does the intention of consumers to buy the goods of this trademark depends on the difference in price levels?

According to the principles of fractal analysis, time series have a fractal dimension $1<D<2$, endowed with properties of scale invariance (self-similarity) and memory of its initial conditions. It is believed that time series, which reflect the development of economic processes, have a fractal structure. The fractal dimension indicates a degree of "crenation" of time series. For example, a straight line has a fractal dimension $D=1$, if D=1.5, then the time series is a Gaussian random process [27].

It is possible to receive forecasts of prices for components and components with the help of fractal analysis in the subsystem of forecasting of the marketing information system of enterprises.

2. Method of preservation of lag correlation. Specific methods for forecasting of time series, in which time series are forecasted in the interconnection, include the method of preservation of lag correlation. For example, forecasting of sales volumes of the company in connection with other market factors gives opportunity to get a forecast that is balanced with the determining factor of sales.

It is recommended to apply methods for preservation of lag correlation in order to obtain balanced projections [28]. This method determines the relationship between two rows of time parameters x_1 and x_2, which are related to a certain lag η in the prehistory period (model definition). Connection is determined by the lag correlation coefficient $R_{x_1x_2}(\eta)$. It is believed that the connection between these parameters should be maintained also during the forecast period. Therefore, forecasts are firstly obtained for each parameter by the method of preservation of lag correlation, and then the coefficients of lag correlation of the time series, to which the forecasted values $r_{x_1x_2}(\eta)$. are added. According to the criterion that shows the deviation of the lag correlation coefficient calculated on the factual points from the same coefficient, but calculated with the addition of forecasting points, the following value is accepted:

$$K=\left|R_{x_1x_2}(\eta)-r_{x_1x_2}(\eta)\right|, \quad (18)$$

where $R_{x_1x_2}(\eta)$ – coefficient of lag correlation calculated on the factual levels of the series of economic parameters; $r_{x_1x_2}(\eta)$ – coefficient of lag correlation, calculated on the actual levels of series of economic indicators with the addition of forecast points.

The value K is called a criterion of the deviation of lag correlation. The best pair of trends for forecasting of economic indicators is proposed to consider the one that has a minimum deviation criterion of lag correlation.

It is necessary to pay attention to the general disadvantage of the listed methods of forecasting which are dynamically developing: traditional technologies of their implementation are oriented on the processing of the observed process values in the assumption that they are accurate. In practice, they are not. The inaccuracy of observations, as a rule, is a consequence of not only errors of measurements, but also the possible influence of any factors of the environment. The problem of choosing an adequate approach to the description of the real uncertainty that arises is a key problem. The usual way of use of theoretical probabilistic methods for these purposes cannot always be applied, since there is no possibility of an adequate restoration of the unknown density of the distribution of random errors of observations in the limited sample of observations. For the same reason, it is not entirely reasonable to consider the hypothesis of the normal distribution of these errors, which follows from the central limit theorem. An acceptable direction of solving the problem of forecasting under conditions of uncertainty of the initial data is the use of methods of fuzzy mathematics [29, 30].

Emerging difficulties are not trivial and require discussion. Let's consider the essence of these problems and possible ways to overcome them on the example of construction of a multi-factor regression model (Table 3) under uncertainty of the initial data described in terms of fuzzy mathematics. Let us introduce the formal model of the problem in the following way.

Let us suppose $F=(F_1, F_2,...,F_m)$ is a set of factors that affects the value of any indicator $y(F)$, the dynamics of change that needs to be forecasted.

As a result of a series of experiments, sets of measurements of values of variables were obtained – explaining $\{F_{ij}\}$ and explained (y_j), where F_{ij} – a value of i-th explanatory variable in j-th experiment, $i=1, 2,...,m,$ $j=1, 2,...,n,$ y_j – a value of the explanatory variable in j-th experiment.

In a situation when there is no information about the nature of trustworthy distribution laws of observational errors, we assume that the observed values of variables are fuzzy numbers given by their membership functions. In this case, an analytical description of these membership functions is chosen in the class of functions (L-R)-type, i. e.

$$\mu_i(F_i)=\begin{cases}\exp\left\{-\dfrac{(m_i-F_i)^2}{2\alpha_i}\right\}, & F_i\le m_i,\\ \exp\left\{-\dfrac{(F_i-m_i)^2}{2\beta_i}\right\}, & F_i>m_i.\end{cases} \tag{19}$$

$$\mu(y)=\begin{cases}\exp\left\{-\dfrac{(m_y-y)^2}{2\alpha_y^2}\right\}, & y\le m_y,\\ \exp\left\{-\dfrac{(y-m_y)^2}{2\beta_y^2}\right\}, & y>m_y.\end{cases} \tag{20}$$

Here m is a modal value of the corresponding fuzzy number; α is a left coefficient of fuzziness; β is a right coefficient of fuzziness.

The choice of the analytical description for membership functions of fuzzy numbers is dictated by the following remarks. Firstly, a very simple statistical evaluation of parameters of these functions. Secondly, these functions have broad approximation capabilities. And, finally and most importantly, algebra is introduced [31] for functions of this type, it defines simple rules for execution of operations with corresponding fuzzy numbers. These rules are as follows.

Let us suppose A_{LR} and B_{LR} – arbitrary fuzzy numbers of (L-R)-type given in the form:

$$A_{LR}=<m_A,\ \alpha_A,\ \beta_A>,\quad B_{LR}=<m_B,\ \alpha_B,\ \beta_B>.$$

Then the basic algebraic operations (addition and multiplication) are realized as follows

Expectation.

$$A_{LR}+B_{LR}=C_{LR}=<m_c,\ \alpha_c,\ \beta_c>,$$

and

$$m_c=m_A+m_B,\quad \alpha_c=\alpha_A+\alpha_B,\quad \beta_c=\beta_A+\beta_B. \tag{21}$$

Multiplication.

$$A_{LR}*B_{LR}=C_{LR}=<m_c,\ \alpha_c,\ \beta_c>$$

and

$$m_c=m_A\cdot m_B,\quad \alpha_c=m_A\cdot\alpha_B+m_B\cdot\alpha_A,$$

$$\beta_c=m_A\cdot\beta_B+m_B\cdot\beta_A. \tag{22}$$

A traditional technology of systems research by the method of multi-factor regression analysis is realized with a use of the least squares method (LSM). The regression equation is introduced in this case

$$y(F)=a_1F_1+a_2F_2+...+a_mF_m, \tag{23}$$

values of explanatories and explanatory variables, as well as a set of unknown coefficients of the regression equations united in the matrix H, and vectors Y and A:

$$H=\begin{pmatrix}1 & F_{11} & F_{12} & ... & F_{1m}\\ 1 & F_{21} & F_{22} & ... & F_{2m}\\ . & . & . & . & .\\ 1 & F_{n1} & F_{n2} & ... & F_{nm}\end{pmatrix},\ A=\begin{pmatrix}a_1\\ a_2\\ ...\\ a_m\end{pmatrix},\ Y=\begin{pmatrix}y_1\\ y_2\\ ...\\ y_n\end{pmatrix}.$$

The desired vector is calculated by formula

$$\hat{A}=(H^TH)^{-1}H^TY.$$

In the real situation of a deficiency of the output data, the use of this reliable statistical analysis may be incorrect (for example, if $n<m$), and also in view of possible violation of one of the fundamental prerequisites of regression analysis (normality of distribution of observational errors). The following multi-stage regression analysis procedure is proposed due to this fact.

Stage 1. Parameters of the corresponding membership function are calculated for each explanatory variable:

$$\hat{m}_i=\frac{1}{n}\sum_{j=1}^{n}F_{ij},\quad \hat{\alpha}_i=\frac{1}{G_i^-}\sum_{j\in N_i^-}(F_{ij}-\hat{m}_i)^2,$$

$$\hat{\beta}_i=\frac{1}{G_i^+}\sum_{j\in N_i^+}(\hat{m}_i-F_{ij})^2, \tag{24}$$

$$N_i^-=\{j\in(1,2,...,n):(F_{ij}\le\hat{m}_i)\};$$

$$N_i^+\{j\in(1,2,...,n):(F_{ij}>\hat{m}_i)\},$$

$G_i^-(G_i^+)$ – number of elements of a multiplicity $N_i^-(N_i^+)$.

Similarly, the parameters of the membership function of the explanatory variable are determined

$$\hat{m}_y=\frac{1}{n}\sum_{j=1}^{n}y_j,\quad \hat{\alpha}_y=\frac{1}{S_y^-}\sum_{j\in N_y^-}(y_j-\hat{m}_y)^2,$$

$$\beta_y=\frac{1}{S_y^+}\sum_{j\in N_y^+}(y_j-\hat{m}_y)^2, \tag{25}$$

$$N_y^-=\{j\in(1,2,...,n):(y_j\le\hat{m}_y)\},$$

$$N_y^+=\{j\in(1,2,...,n):(y_j>\hat{m}_y)\},$$

$S_y^-(S_y^+)$ – number of elements of a multiplicity $N_y^-(N_y^+)$.

Stage 2. Calculation of coefficients of the regression equation. The proposed approach to the solution of the problem of regression analysis in this case, coincides in principle with the approach implemented in the traditional LSM. In this case, the "model" function of the membership of the fuzzy value of the resulting index is constructed on the basis of partial descriptions (19) of the membership functions for each factor with the use of rules (21), (22) of performing operations on fuzzy numbers. This function is compared with the membership function (20) determined by the experimental data. The sought set of coefficients of the regression equation is sought so that these functions differ in minimum from one another. The problem of mathematical programming, which thus arises, can be solved, for example, by the method proposed in [32]. According to this method, the modal value of the forecasted result is calculated (23)

$$y_M = \sum_{i=1}^{m} a_i m_i.$$

After that, the function of the fuzzy value of this indicator

$$\mu\left(a_0 + \sum_{i=1}^{m} a_i F_i\right)$$

by this way.

Since taking into account (19), (21), (22),

$$\mu(a_i F_i) = \mu(u_i) = \begin{cases} \exp\left\{-\dfrac{(a_i m_i - u_i)^2}{2a_i^2 \alpha_i}\right\}, & u_i \le a_i m_i \\ \exp\left\{-\dfrac{(u_i - a_i m_i)^2}{2a_i^2 \beta_i}\right\}, & u_i > a_i m_i, \end{cases}$$

then

$$\mu\left(\sum_{i=1}^{m} a_i F_i\right) = \mu(v) = \begin{cases} \exp\left\{-\dfrac{\left(\sum_{i=1}^{m} a_i m_i - v\right)^2}{2\sum_{i=1}^{m} a_i^2 \alpha_i}\right\}, & v \le \sum_{i=1}^{m} a_i m_i, \\ \exp\left\{-\dfrac{\left(v - \sum_{i=1}^{m} a_i m_i\right)^2}{2\sum_{i=1}^{m} a_i^2 \beta_i}\right\}, & v > \sum_{i=1}^{m} a_i m_i. \end{cases} \quad (26)$$

Now a complex criterion is formed

$$J = S^2\left[\mu\left(a + \sum_{i=1}^{m} a_i F_i\right)\right] + \left(a + \sum_{i=1}^{m} a_i m_i - \hat{y}\right)^2, \quad (27)$$

which is minimized by A.

The first term of the criterion is a quadrate of the square under the curve, which corresponds to the membership function and determines a level of compactness of this function. The second term describes a degree of proximity of the modal value of the predicted result (23) to its experimental value.

In a simple particular case, when the fuzzy factor of (L-R)-type functions are equal, that is $\alpha_i = \beta_i = \sigma_i^2$, then the minimization problem (27) can easily be solved analytically. Thus

$$\mu(F_i) = \exp\left\{-\frac{(F_i - m_i)^2}{2\sigma_i^2}\right\},$$

$$\mu(a_i F_i) = \mu(u_i) = \exp\left\{-\frac{(u_i - a_i m_i)^2}{2a_i^2 \sigma_i^2}\right\},$$

$$\mu\left(a_0 + \sum_{i=1}^{m} a_i F_i\right) = \mu(v) = \exp\left[\frac{v - \sum_{i=1}^{m} a_i F_i}{2\sum_{i=1}^{m} a_i^2 \sigma_i^2}\right]^2,$$

$$S\left[\mu\left(a_0 + \sum_{i=1}^{m} a_i F_i\right)\right] = \int_{-\infty}^{\infty} \exp\left\{-\frac{\left[v - \sum_{i=1}^{m} a_i m_i\right]^2}{2\sum_{i=1}^{m} a_i^2 \sigma_i^2}\right\} dv =$$

$$= \sqrt{2\pi}\left(\sum_{i=1}^{m} a_i^2 \sigma_i^2\right).$$

Now the problem is reduced to the following: to find

$$A = (a_0\ a_1 \ldots a_m)^T,$$

vector, which minimizes

$$L(A) = \sum_{i=1}^{m} a_i^2 \sigma_i^2$$

and satisfies the constraints

$$\sum_{i=1}^{m} a_i m_i = \hat{y}.$$

Let us introduce a Lagrangian function

$$\Phi(A) = \sum_{i=1}^{m} a_i^2 \sigma_i^2 - \lambda\left(\sum_{i=1}^{m} a_i m_i - \hat{y}\right).$$

Further

$$\frac{d\Phi(A)}{da_i} = 2a_i \sigma_i^2 - \lambda m_i = 0, \quad a_i = \lambda \frac{m_i}{2\sigma_i^2},$$

$$\sum_{i=1}^{m} a_i m_i = \frac{\lambda}{2} \sum_{i=1}^{m} \frac{m_i^2}{\sigma_i^2} = \hat{y}.$$

From here

$$\frac{\lambda}{2} = \frac{\hat{y}}{\sum_{i=1}^{m} \dfrac{m_i}{\sigma_i^2}}.$$

Then

$$a_i = \frac{\dfrac{m_i}{\sigma_i^2}}{\sum_{i=1}^{m} \dfrac{m_i^2}{\sigma_i^2}} \hat{y},$$

$$i = 1, 2, \ldots, m.$$

The result obtained is easily and naturally perceived: the contribution of each factor that affects the result is higher, the higher its modal value and the less a variance.

Stage 3. Forecasting of the value of influential factors and the resulting indicator.

Forecasting of the values of each of the factors can be done by any of the above one-factor methods. Let us consider, for example, the procedure of forecasting by the Holt's method taking into account the possible uncertainty of the measurement results. Suppose, for example, that the membership functions of the smoothed value until the time t are described by triangular numbers at moment $t-1$

$$\mu(L_{t-1})=\begin{cases}0, & L_{t-1}<a_{t-1}^{(L)},\\ \dfrac{L_{t-1}-a_{t-1}^{(L)}}{b_{t-1}-a_{t-1}}, & a_{t-1}^{(L)}\le L_{t-1}<b_{t-1}^{(L)},\\ \dfrac{c_{t-1}^{(L)}-L_{t-1}}{c_{t-1}^{(L)}-b_{t-1}^{(L)}}, & b_{t-1}^{(L)}\le L_{t-1}\le c_{t-1}^{(L)},\\ 0, & L_{t-1}>c_{t-1}^{(L)}.\end{cases}\qquad(28)$$

The membership function of the trend estimation at moment $t-1$

$$\mu(T_{t-1})=\begin{cases}0, & T_{t-1}<a_{t-1}^{(T)},\\ \dfrac{T_{t-1}-a_{t-1}^{T}}{b_{t-1}^{(T)}-a_{t-1}^{(T)}}, & a_{t-1}^{(T)}\le T_{t-1}<b_{t-1}^{(T)},\\ \dfrac{c_{t-1}^{(T)}-T_{t-1}}{c_{t-1}^{(T)}-b_{t-1}^{(T)}}, & b_{t-1}^{(T)}\le T_{t-1}\le c_{t-1}^{(T)},\\ 0, & T_{t-1}>c_{t-1}^{(T)}\end{cases}\qquad(29)$$

and a fuzzy measurement of the factor at time t

$$\mu(Y_t)=\begin{cases}0, & Y_t<a_t^{(Y)},\\ \dfrac{Y_t-a_t^{(Y)}}{b_t^{(Y)}-a_t^{(Y)}}, & a_t^{(Y)}\le Y_t<b_t^{(Y)},\\ \dfrac{c_t^{(Y)}-Y_t}{c_t^{(Y)}-b_t^{(Y)}}, & b_t^{(Y)}\le Y_t<c_t^{(Y)},\\ 0, & Y_t>c_t^{(Y)}.\end{cases}$$

Then the membership function of the exponentially smoothed factor value has the form

$$\mu(L_t)=\begin{cases}0, & L_t<a_t^{(L)},\\ \dfrac{L_t-a_t^{(L)}}{b_t^{(L)}-a_t^{(L)}}, & a_t^{(L)}\le L_t<b_t^{(L)},\\ \dfrac{c_t^{(L)}-L_t}{c_t^{(L)}-b_t^{(L)}}, & b_t^{(L)}\le L_t\le c_t^{(L)},\\ 0, & L_t>c_t^{(L)},\end{cases}$$

where

$$a_t^{(L)}=\alpha a_t^{(Y)}+(1-\alpha)\left(a_{t-1}^{(L)}+a_{t-1}^{(T)}\right),$$

$$b_t^{(L)}=\alpha b_t^{(Y)}+(1-\alpha)\left(b_{t-1}^{(L)}+b_{t-1}^{(T)}\right),$$

$$c_t^{(L)}=\alpha c_t^{(Y)}+(1-\alpha)\left(c_{t-1}^{(L)}+c_{t-1}^{(T)}\right).$$

The function of membership of the trend at time t

$$\mu(T_t)=\begin{cases}0, & T_t<a_t^{(T)},\\ \dfrac{T_t-a_t^{(T)}}{b_t^{(T)}-a_t^{(T)}}, & a_t^{(T)}\le T_t<b_t^{(T)},\\ \dfrac{c_t^{(T)}-T_t}{c_t^{(T)}-b_t^{(T)}}, & b_t^{(T)}\le T_t<c_t,\\ 0, & T_t>c_t,\end{cases}\qquad(30)$$

where

$$\begin{aligned}a_t^{(T)}&=\beta\left(a_t^{(L)}-a_{t-1}^{(L)}\right)+(1-\beta)a_{t-1}^{(Y)},\\ b_t^{(T)}&=\beta\left(b_t^{(L)}-b_{t-1}^{(L)}\right)+(1-\beta)b_{t-1}^{(Y)},\\ c_t^{(T)}&=\beta\left(c_t^{(L)}-c_{t-1}^{(L)}\right)+(1-\beta)c_{t-1}^{(Y)}.\end{aligned}\qquad(31)$$

Finally, the function of the factor membership p periods ahead

$$\mu(Y_{t+p})=\begin{cases}0, & Y_{t+p}<a_{t+p}^{(Y)},\\ \dfrac{Y_{t+p}-a_{t+p}^{(Y)}}{b_{t+p}^{(Y)}-a_{t+p}^{(Y)}}, & a_{t+p}^{(Y)}\le Y_{t+p}<b_{t+p}^{(Y)},\\ \dfrac{c_{t+p}^{(Y)}-Y_{t+p}}{c_{t+p}^{(Y)}-b_{t+p}^{(Y)}}, & b_{t+p}^{(Y)}\le Y_{t+p}\le c_{t+p}^{(Y)},\\ 0, & Y_{t+p}>c_{t+p}^{(Y)},\end{cases}\qquad(32)$$

where

$$a_{t+p}^{(Y)}=a_t^{(L)}+pa_t^{(T)},$$

$$b_{t+p}^{(Y)}=b_t^{(L)}+pb_t^{(T)},$$

$$c_{t+p}^{(Y)}=c_t^{(L)}+pc_t^{(T)}.$$

The relations obtained with the use of (28)–(32) for the functions of membership of the forecasted values of factors make possible, taking into account (23), to obtain the function of membership with the forecasted value of the resulting indicator.

6. Discussion of the essence and significance of the forecasting subsystem of the marketing information management system

The forecasting subsystem is a set of methods, techniques, algorithms for processing various types of input information and obtaining forecasts for them.

An enterprise receives forecasts of sales, prices for finished products and raw materials, sales and competitor prices, sectoral, regional and macroeconomic forecasts by forecasts of time series.

An enterprise receives sales forecasts based on product prices, competitor actions and promotion costs, consumer behavior forecasts, sales volumes by the use of casual methods of forecasting.

An enterprise receives forecasts of prices for raw materials, materials, semi-finished products, components with the help of fractal analysis.

According to the lag correlation method, an enterprise receives forecasted volumes of sales in connection with other market factors using the lag correlation method.

However, it is impossible to deny that the named methods of forecasting need to eliminate their main general disadvantage, which is related to the assumption of accuracy. The inaccuracy of observations, as a consequence of measurement errors and the possible impact of any environmental factors, leads to inconsistencies in expected results. Therefore, the use of methods of fuzzy mathematics is effective under such conditions. Traditional forecasting methods can be successfully upgraded for a case where the source data is unclear as the proposed procedure suggests. Possible continuation of studies of the problem of registration of uncertainty of the source information is to consider the technology of solving this problem, when this information is inaccurate in the sense of Pawlak [33]. One of the possible approaches to overcome the difficulties encountered here is proposed in [34].

Taking all this into account, there are reasons to state that the forecasting subsystem is crucial in the management system of marketing information of an enterprise for the formation of tactical and strategic plans of marketing activity.

7. Conclusions

1. A classical management system of marketing information of industrial enterprises is modernized by identifying the following four subsystems:

a) monitoring;
b) marketing research;
c) risk assessment;
d) forecasting.

Such a structure of the marketing information management system and the principles of interoperability of subsystems can reduce risks of entrepreneurial activity through risk assessment and obtaining of forecasts pool.

2. The information, which comes into the subsystem of forecasting of the marketing information management system, is classified according to the following criteria:

– by the readiness for use;
– by the presence of dynamics;
– by the presence of trends in dynamic series;
– by sources of information;
– by a reference point.

Such a division of information simplifies the process of information flow management and validates a choice of the method of analysis and forecasting.

3. Three types of forecasts are distinguished by three criteria: by a forecast period, by a level of economy, by a type of estimations. This approach involves detailing of methods, techniques, and algorithms used to obtain forecasts for each type of task. The possibility of modernization of known forecasting methods with consideration of possible fuzziness of initial data is considered.

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