ANALYSIS OF MEDIUM-TERM FORECASTING METHODS FOR PROCESSES WITH STRUCTURAL SHIFTS IN FINANCIAL AND COMMODITY MARKETS

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Abstract. Medium-term price forecasting methods for financial and commodity markets are considered. The forecasted processes are nonstationary and nonlinear; they contain structural shifts arising due to systemic changes in the market structure and extreme events affecting the market. The probability of structural shifts grows with increasing the forecasting horizon, so the forecasting problem should be solved considering possible changes in the process of interest on the forecasting horizon. To forecast future changes in the process, it is necessary to expand the information field of the forecast, i.e., include expert judgments and the results of qualitative analysis of the processes, e.g., using the methods of fundamental analysis, cognitive analysis, and their implementation algorithms. Medium-term price forecasting in financial and commodity markets is a necessary element in the planning and management of socio-economic and production systems and investment management. This survey addresses the peculiarities of the forecasted processes determining the requirements for medium-term forecasting methods, their implementation, and the selection of necessary information included in the forecast to detect future changes in the process and their causal factors. Models and methods of statistical forecasting, artificial intelligence, and fractal analysis are considered, in addition to those using information from various sources in the forecasting algorithm: expert judgments, news about extreme events, and search engine data. The results of this survey are summarized in the context of medium-term forecasting. Finally, some promising lines of research in this area are outlined.

Keywords: commodity and financial markets, time series, structural shifts, medium-term forecasting.

INTRODUCTION

Medium-term price forecasts in financial and commodity markets play an important role in the strategic planning of global and regional economic development and management of interdisciplinary complex system development (socio-economic, economic and technical, and other systems).

Market price forecasting for one or two years ahead is a major practical task of medium-term forecasting. Price forecasting for raw materials, components, and food products for one or two years ahead with a monthly breakdown is a necessary element of the procurement planning and inventory management of an enterprise, and improving the accuracy of forecasting is crucial to reduce costs. Medium-term price forecasting is a necessary element of another task, namely, the strategic planning of socio-economic system development, in particular, market forecasting in the planning and management of foreign economic activity [1] and investment management.

Modern financial and commodity markets are a complex system. Due to profound changes in pricing mechanisms in the early 2000s, financial markets have become influential for world commodity prices. Financialization has sharply complexified the causal relations forming world commodity prices. In addition to the usual fundamental factors (stocks, demand, production, technology, geopolitical risks, and cyclicity), financial factors (inflation, exchange rates, supply and demand in financial markets, their correlation, microstructure, etc.) are acting simultaneously [2].

Note that despite numerous numerical data characterizing all these factors, their volume and quality are insufficient for medium- and long-term forecasting. Expert and scenario forecasts are mainly used to assess the long-term perspective, although some empirical studies challenge the value of expert recommendations and qualitative forecasts [3], especially when it comes to longer horizons.

Against the background of near-future forecasting methods widely covered in the literature, there is growing attention to the issues of building medium-term forecasts. Some researchers use short-term forecasting methods to solve this problem; different approaches are proposed to reduce uncertainty under possible structural shifts on the forecasting horizon. However, what should be done if medium-term forecasts become unreliable after a certain time when changes occur on the forecasting horizon? This research problem remains topical.

In addition to financial and commodity markets, the tasks of medium-term forecasting arise in other applications, such as forecasting of network and road traffic, energy consumption, weather (wind strength, solar activity), and the spread of diseases (for example, see [4]). In these applications, the problem of considering related processes and non-systemic parameters is the main challenge when building medium-term forecasts, but the processes are observable and can be structured. In contrast, prices in financial and commodity markets are subjected to the influence of many heterogeneous parameters and, most importantly, events. Hence, it is necessary to include non-systemic process changes in the forecasting model, ranging from changes in related markets to the news background. In other words, the processes under consideration are largely unstructured.

The choice of an appropriate forecasting method depends on several factors: the properties of the forecasted series (a random walk or a fractal process); regular/irregular problem solution (a one-time or repeated process); the forecast form (a particular value, a particular value and/or interval, a trend direction (ascending/descending), or a trend direction and estimation of its duration); the forecasting horizon; the type of information and data on the forecasted process, their availability and completeness; finally, the requirements to the accuracy of forecasting.

Among forecasting methods, there are those based on quantitative time data characterizing the forecasted process, qualitative time data (from search engines and news feeds) characterizing the intensity and tone of information on the subject of the forecasted process, and expert information.

Before applying deep learning in financial and commodity markets, linear Gaussian models were widespread; they use a window of current information to forecast the next time step. This class includes the following models: ARIMA (*AutoRegressive Integrated Moving Average*), VAR (*Vector AutoRegression*), and VECM (*Vector Error Correction Model*). Nonlinear conditional Gaussian models were proposed to describe the clustering of volatility and the deviations of yields from the Gaussian distribution, namely, ARCH (*AutoRegressive Conditional Heteroskedasticity*), GARCH (*Generalized AutoRegressive Conditional Heteroskedasticity*), FIGARCH (*Fractionally Integrated Generalized AutoRegressive Conditional Heteroskedasticity*), and others.

In recent years, artificial intelligence (AI) methods have been actively used for analysis and forecasting besides statistical models. They include machine learning, deep learning, and hybrid models based on combinations of different approaches to forecasting. Machine learning methods, such as random forest, *Support Vector Machine* (SVM), *k*-nearest neighbors, logistic regression analysis, etc., are applied in forecasting; unlike linear models, they can cope well with nonlinearities. However, these methods operate within a general forecasting model that solves the learning problem: e.g., minimizing the forecasting error, decreasing the training time or the amount of calculations, etc. Deep learning methods allow reducing the acceptable model assumptions and improving the solutions by extracting necessary information from data. Currently, neural network models with deep learning are widely used to forecast processes in financial and commodity markets; their high learning ability serves to expand the composition and volume of information about changes in the forecasted process and to extract important characteristics from available data when forecasting market fluctuations and trends. Lately, there has been an increasing trend towards hybrid deep learning models that combine statistical and deep learning components, thereby taking advantage of both.

In addition to quantitative methods, expert methods are used in forecasting: network knowledge representation models for the forecasting object and related factors, events, and explanatory variables; Bayesian networks and belief networks; and *judgment forecasting methods*, when experts announce a particular value or the "probability" of some value on a given horizon [5].

To improve the effectiveness of medium-term forecasts, it is topical to expand the information field of forecasting: employ the results of fundamental and cognitive analysis, the estimated influence of systemic changes in the market, the effects of external events, expert judgments, and qualitative impact factors on the process in the medium term, which are generated using text information.

Ensemble and hybrid models are used to expand the information field by increasing the volume and improving the quality of input information processing in forecasting. The former class includes models yielding a forecast from those generated by ensemble models. Hybrid models combine different forecasting stages, each performed by different methods: along with statistical ones, intelligent computational methods are applied for forecasting in financial and commodity markets, namely, artificial neural networks, fuzzy logic, genetic algorithms, and other evolutionary methods [6–8].

This survey endeavors to analyze the approaches to price forecasting with a monthly breakdown that would be fruitful for medium-term forecasting tasks (one or two years ahead). In the context of improving the accuracy of forecasts, we consider the current state of models, methods, and algorithms applicable to medium-term forecasting of processes with structural shifts, including methods for expanding the information field both by expanding the set of time series and by incorporating expert information and the results of information processing and structuring systems.

The remainder of this paper is organized as follows. Section 1 describes the peculiarities of forecasted objects in commodity and financial markets that determine the requirements for the forecast and its implementation methods. In Section 2, the modeling apparatus used to solve forecasting problems is generally characterized, including various models and methods of price analysis and forecasting in commodity and financial markets: statistical methods, deep learning methods, hybrid models, and fractal analysis methods. Section 3 is devoted to methods for expanding the information field by using quantitative and qualitative information extracted from external sources and included in mathematical forecasts: search engine data, news about external events and their influence analysis, and expert information. The results of this survey are summarized in Section 4. Finally, some promising lines of research into medium-term forecasting methods are outlined in the Conclusions.

1. PECULIARITIES OF FORECASTED OBJECTS AND MAIN IMPACT FACTORS OF DIFFERENT STRUCTURAL SHIFTS

A forecasted object under consideration is described by a nonstationary time series or a group of time series; its dynamics can change due to the influence of exogenous factors (crises, natural disasters, wars, etc.) and endogenous factors (market interdependence, industry and macrofinancial impacts [9], changes in the market price for a particular product due to the rise in transportation costs, bankruptcy or changes in the composition of suppliers, the emergence of a strong competitor, etc.).

Each component of the forecasted object at a time instant t depends on:

– its past values;

– the past values of other process components;

– the past values of other processes that have causal relations with the forecasted one;

– extreme events occurring in the environment (important government decisions, crises, epidemics, wars, and man-made and natural disasters);

– the exogenous and endogenous impact factors of the process, which can be manifested by changes in process dynamics or identified by the results of expert information processing and analysis.

The impact factors of a process can be described by:

• the time series of macro-indicators, world currency exchange rates, world prices for oil and commodities of leading industries, transportation, electricity, etc.;

• various-kind signals obtained when structuring expert knowledge about the state and direction of impact factors on the current state of the environment and the object.

Impact factors result in structural shifts in the market, with the following possible causes [9–11]:

– changes in the dynamics of GDP and other macroeconomic indicators, such as inflation, the key interest rate of the Central Bank, employment, and labor remuneration;

– speculations, changes in investor preferences, and episodic events (catastrophes, pandemics, wars, etc.);

– changes in supply and demand for key commodities and food products: oil, gas, base metals, wheat, and sugar;

– the formation of new market sectors.

Financial and commodity markets are interconnected, and since 2000 there has been an increase in the correlation between them, the growth of financial investors' interest in the commodity market, and the expansion of opportunities to diversify portfolios by placing the products of different markets [12, 13]. The nature of time correlations between commodity and financial markets during the financialization of commodity markets and after the crisis of 2008 was investigated in [14]. As noted, the interest of financial investors in commodity markets is growing, and they participate through direct or indirect investments in commodity futures; the increase in the correlation between the markets is not associated with the financial crisis.

The peculiarities of modern financial and commodity markets (globalization, the improvement of digital technologies, the reduction of state regulation of financial services, the importance of product innovations, etc.) lead to significant changes in their dynamics and cause the need to improve forecasting models.

Various methods are used to identify and analyze the impact factors of the forecasted object as well as to assess their direction and strength:

• Fundamental analysis, which allows identifying the causal relations of macroeconomic indicators and market indicators with the forecasted indicator and assessing the financial condition of companies whose goods or financial instruments are present in the market. Fundamental analysis examines economic factors that can influence market movements, so its results are useful for medium-term forecasting.

• Construction and analysis (scenario modeling) of fuzzy cognitive maps[1] (FCMs) of the situation [16, 17], which serve:

– to systematize and aggregate expert knowledge about the controlled object and its environment reflecting the causal relations of significant impact factors of the object, based on structuring and formalization of expert knowledge and information from heterogeneous sources (in particular, using the results of fundamental analysis);

– organize the directed search of datasets when monitoring heterogeneous information sources.

The forecasting task is complex due to structural shifts in the market processes (jumps in the level or volatility as well as changes in trends and the nature of the interaction between the forecasted object and other processes occurring in financial and commodity markets under the influence of exogenous and endogenous factors). Structural shifts of the forecasted indicator change its dynamics and increase the forecasting error, which can also signal a change and/or the need to correct the forecasting model due to changes in the strength and direction of impact factors of the market. Therefore, when building the forecast and on its horizon, it is necessary to consider changes in the values of the forecasted indicator and, moreover, changes in its impact factors. Examples of such factors can be external regular and extreme events as well as changes in the market structure, investor sentiment, and the nature of the interaction between supply and demand.

The presence of these changes in the forecasted process creates difficulties when applying conventional Gaussian time series models (ARIMA, VAR, or VECM), which are intended to describe linear processes. According to the analysis results, building such models while ignoring structural shifts in the process leads to errors and deteriorates the quality of forecasts. Based on the study of 76 monthly time series in the United States, J. Stock and M. Watson discovered the instability of parameters in a significant part of their models [18]. Their research initiated the development of forecasting methods considering changes in the process properties.

In addition to the standard steps of building a forecasting model, it becomes necessary to include monitoring algorithms in the forecasting procedure to detect structural changes in the process under consideration [19, 20] and, in some cases, to forecast such changes.

Due to the specifics of applying the results of medium-term forecasting in current planning and management processes, the ultimate goal in most tasks is to generate forecasts with monthly or quarterly breakdowns, which necessitates building multistep forecasts.

2. ANALYSIS OF MODELS AND METHODS FOR MEDIUM-TERM FORECASTING

The sample of research works on various methods for analyzing processes in commodity and financial markets and building medium-term forecasts covered by this survey includes about 200 publications over the last 20 years, which corresponds to the emerging boom in the application of data analysis methods for accumulated datasets. Among them, there are no works fully satisfying all the requirements for the medium-term forecasting procedure of nonstationary processes with structural shifts on the forecasting horizon. Therefore, the emphasis is placed on highlighting individual models, methods, and algorithms that increase the accuracy of forecasting or solve particular tasks to improve the forecasting procedure. In addition, we feel it necessary to include results from a longer period with relevant methods for solving individual tasks. The ultimate goal of the study is to select useful and well-tested models, methods, and algorithms for the medium-term forecasting of nonstationary pro-

[1] Proposed by B. Kosko [15], the term “fuzzy cognitive map” is generally accepted in foreign investigations of dynamic systems in the context of soft computing. FCMs represent a graph structure reflecting causal reasoning, where fuzziness is due to the ambiguous degree of causality (strength of impact) between fuzzy causal concepts (factors) [15]. The term “cognitive map” is more widespread among Russian researchers; it has the same meaning. In view of the conceptual content, we use FCMs throughout this survey regardless of the term adopted in the cited publications.

cesses with structural shifts and to specify the conditions of their application.

2.1. The Modeling Apparatus Applied in Forecasting Problems: Historical Excursion and General Characterization

As noted in Section 1, processes in financial and commodity markets are nonstationary due to intra-system changes or the influence of external events; structural shifts are observed in them, both in historical data and on a forecasting horizon. In the case of medium-term forecasting, it is necessary to consider possible changes in the process properties on the horizon as well as use monitoring and correction mechanisms.

The evolution of statistical models for single-step forecasting has a history of over 50 years. The figure below presents the historical development of models and methods for time series forecasting. Such models are based on improving classical models when applied to processes described by nonstationary time series.

For nonstationary processes, statistical uni- and multivariate models, such as the *AutoRegressive Integrated Moving Average* (ARIMA) model and the *Error Correction Model* (ECM), were proposed in the 1970s. After that, the *AutoRegressive Conditional Heteroskedasticity* (ARCH) and *Generalized AutoRegressive Conditional heteroskedasticity* (GARCH) models, the *Vector AutoRegression* (VAR) model, and the *Vector Error Correction Model* (VECM) were proposed.

According to the *Efficient Market Hypothesis* (EMH), stating that prices are described by random processes with the Gaussian distribution, all information is contained in data and available to investors, no sudden events should occur, and the market is stable. Abrupt changes in process properties under the influence of major events, as well as the emergence of crises and structural shifts, *are not consistent* with the EMH. According to the analysis of processes in financial markets conducted by E. Peters and B. Mandelbrot at the end of the last century [21, 22], a considerable part of real price series significantly deviates from the EMH. Peters put forward the *Fractal Market Hypothesis* (FMH): most processes in financial and commodity markets have nonlinear dynamics and self-similarity. A time series possesses fractality if it has the same structure as its separate parts. In the 1980s, the *AutoRegressive Fractionally Integrated Moving Average* (ARFIMA) model was introduced to model processes with fractal properties.

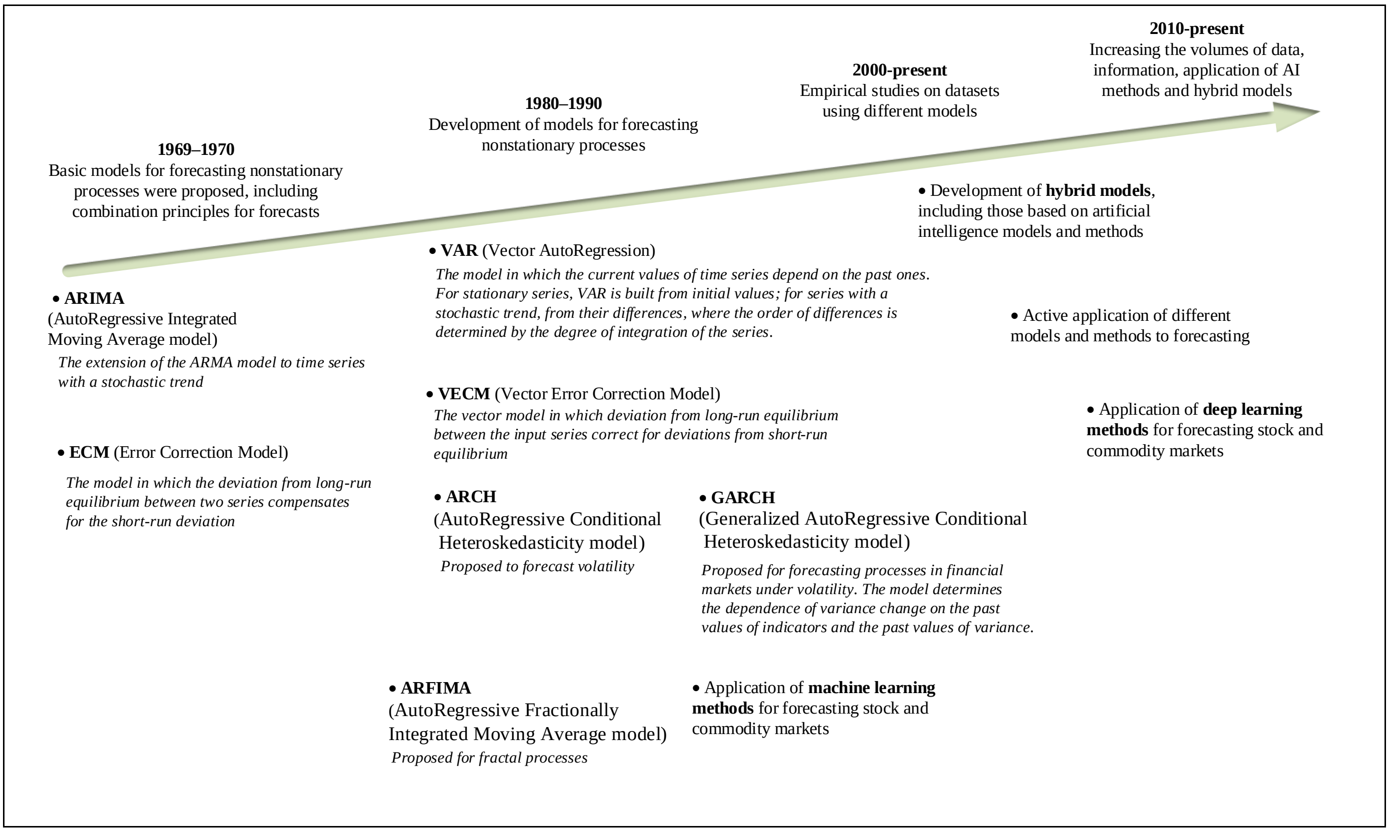

Fig. The historical development of time series forecasting models and methods.

The nonstationary process forecasting models proposed in the 1970s–1990s were the foundation for the medium-term forecasting of nonstationary processes with structural shifts. Nevertheless, the deterioration problem of the forecasting quality was still topical.

The structural shifts of a process on the historical periods of observations complicated the solution of forecasting tasks and, moreover, represented a problem when determining the type of process nonstationarity and identifying cointegration relations.

In the 1990s, P. Perron [23] demonstrated that, due to structural shifts, standard tests for determining the type of process nonstationary (with a stochastic trend or with a deterministic trend) [24] lead to errors and, consequently, erroneous models. He proposed a procedure for determining the type of process nonstationarity under a known date of the trend change and/or jump. Since the date of a structural shift is not always known, algorithms are necessary to identify the moment of its occurrence. Much attention of modern researchers is paid to detecting structural shifts and determining their nature and "precursors." The need to build procedures for determining the type of series nonstationarity under structural shifts complicates the forecasting process [25]. By the present time, many algorithms have been developed to detect structural shifts with a known or unknown date of their occurrence and tests to determine the type of the process [26–28].

When building the VAR models of nonstationary processes by differences (a transformation making the process stationary), a significant part of information is lost. If there exists cointegration between series, then more efficient models—VECM—are built for these series; such models consider long-term relations between the factual values of the series. Therefore, checking cointegration is an important stage of model selection and construction. In the 1980s and 1990s, C. Granger and S. Johansen, the leading applied statisticians, showed that in the presence of structural shifts, standard cointegration tests [29, 30] yield incorrect results. Modern approaches to solving this problem were described in [31].

Multistep forecasting is used to generate a medium-term forecast for one or two years ahead with a monthly breakdown. Three approaches to solving this complex problem are widely known: recursive, based on the repeated application of a single-step model; direct, based on building a set of models at different scales; single-input multiple-output. The latter is a modification of the multiple-input multiple-output approach presented in [32]: in the multistep forecasting model proposed by the author, the forecasted value is not a scalar variable but the vector of future values of the time series. This approach replaces the set of direct models with one multiple-output model to preserve the stochastic dependence inherent in the time series among the forecasted values. The peculiarities of multistep forecasting strategies are discussed in more detail in subsection 2.2.

In recent years, some studies of price forecasting in commodity and financial markets have been based on the extensive empirical verification of large data volumes available for a long period of observations accumulated. Modern researchers use the basic statistical models mentioned above, with different adaptation strategies to changes, as well as demonstrate hybrid algorithms, including the application of artificial intelligence methods.

Below, we analyze in detail modern research into medium-term forecasting in commodity and financial markets with structural shifts.

2.2. Statistical Methods

According to the efficient market hypothesis, price increments are independent and obey the Gaussian distribution. However, many studies do not confirm these assumptions. For a long time, statistical models such as ARIMA, ECM, VAR, VECM, ARCH, and GARCH, as well as their modifications, have been widely used to forecast prices and volatility. However, in today's market, due to nonstationarity, structural shifts, and nonlinearities in the processes, these models do not generate forecasts of the required quality.

The idea of combined approaches, first implemented in [33], is effective because of considering the forecasted process from all sides and expanding its information field. As was shown in [33], the combination of forecasts can give a smaller RMS error than any of its constituents.

Ensemble formation allows considering more factors that affect the forecasting process and reducing the uncertainty about the data and the model form: the forecasts included in the ensemble may contain overlapping but not completely coincident information [34]. Forecast combinations have been the main winners in the M4 competition [35], which is conducted to compare different forecasting methods.

Based on the results of competitive experiments, the reasons for the success of the most effective combinations were analyzed in [36]; the diversity of combination forecasts and the winning strategy of combination formation were named among them. Diversity in forecasts can be achieved by using variables from different sources (e.g., time series, economic indicators, and data from the company's financial statements), combining forecasts at different time scales, and using different models on the same data. A winning combination strategy should include diverse and efficiency-comparable forecasts. Modern publications on forecast combinations were reviewed in [37]; as was underlined, of all forecasting-related papers indexed by the Web of Science, the share of those concerning forecast combinations has increased over the last 50 years and reached 13.8% in 2021. Note that along with the increasing complexity of forecasted objects, combination schemes are changing due to the inclusion of algorithms executing different functions to consider nonlinearities in objects, correlations between components, and cross-training. The algorithms included in a combined forecast may differ in the composition of information, processing methods, and results.

At the end of the last century, *Bayesian model averaging* (BMA) became increasingly popular in forecasting under the changing properties of forecasted series [38]. To generate a BMA forecast, N possible models are built, differing from each other by the composition of their predictors. The forecast at step t is calculated as a weighted average of the forecasts of each model with weights proportional to the probability of correct prediction for it at the forecasting time; the composition and structure of the models remain invariable.

The Bayesian approach was successfully applied to forecast macroeconomic indicators under structural shifts. Bayesian model learning and comparison methods were applied to compute the predictive density of the probability that a rupture will occur before the next observation [39]. A Bayesian procedure was proposed to estimate the probability of new ruptures occurring on the forecasting horizon considering the duration of past ruptures and using a hidden Markov chain model [40].

Depending on the properties of the process under consideration, different ways of adaptation to changes in the process are used in statistical models to improve the forecasting quality: the integration of linear models and expert information [41]; sliding windows, moving regression, and exponentially weighted moving average [42, 43]; the generation of combined forecasts in a sliding window [44]; the construction of adaptive models that change their parameters when changing the properties of the forecasted price series [42, 45]. However, such models do not ensure the necessary accuracy of forecasting under nonlinearities in the object's dynamics and structural shifts on the forecasting horizon.

Dynamic model averaging (DMA) assumes that the properties of the forecasted process are not precisely known and change over time. It combines each of the original models with a Markov chain to produce a correct model. As a result, the "correct" model changes over time. In a special case (where the model and parameters remain invariable), DMA is a recursive implementation of BMA (standard Bayesian model averaging). Pioneered in [46], DMA is being extensively used for forecasting [47, 48], and its first application to econometric problems was described in [49]. As was noted in [48], DMA outperforms linear statistical models and BMA in forecasting gold prices.

Next, we take a closer look at multistep forecasting algorithms using statistical models. The recursive strategy mentioned in subsection 2.1 has low accuracy: prediction errors accumulate due to the growing share of forecasts in the input data. On the other hand, the direct strategy has a high variance of forecasting errors as the data scale increases. The algorithm proposed in [50] combines both strategies and improves the forecasting quality: it reduces the bias of the recursive strategy and the variance of the direct one.

The motivation for the multiple-output strategy is to preserve the stochastic dependence characterizing the time series between the forecasted values. In addition, this forecasting strategy avoids the assumption of conditional independence adopted in the direct strategy and the accumulation of errors in the recursive multistep forecasting strategy. According to the experimental studies [51], multiple-output approaches represent a competitive choice for long-term forecasting.

Nevertheless, the main drawback of this strategy is that a single model must preserve stochastic dependencies and predict all values on the forecasting horizon simultaneously, which usually results in low efficiency [52].

Findings. The strengths of conventional statistical methods lie in their interpretability and strong theoretical basis. They provide insight into the patterns underlying economic variables, which simplifies decision-making. However, these methods may be ineffective under nonlinearities, changes, or deviations from the original models, often encountered in the processes under consideration.

2.3. Deep Learning Methods

Forecasting methods for financial time series have been very popular among researchers in the area of machine learning for over 40 years. Nowadays, along with classical *machine learning* (ML) methods, deep neural networks are widely used in forecasting models. *Deep learning* (DL) in forecasting algorithms allows increasing the volume of input information required to expand the forecasting horizon as well as avoiding overtraining and higher learning errors as the number of network layers grows. According to the surveys [53, 54], the vast majority of studies have demonstrated that DL in forecasting models improves the quality of short-term forecasts.

Over the last few years, various types of DL models have been developed: *deep multi-layer perceptron* (DMLP), *convolutional neural networks* (CNNs), *recurrent neural* networks (RNNs), including their modification known as recurrent networks with *long short-term memory* (LSTM), and others. The LSTM structure is organized so that the network can add or remove information, retaining only relevant information and deleting unnecessary information. To this end, LSTM utilizes three important "gate" structures: a forget gate, an input gate, and an output gate. These control elements determine what information should be discarded/be stored in the cell state/appear at the output data. In financial market forecasting, LSTM can automatically learn and adapt to nonlinear conditions and complex future market behavior, thereby improving the accuracy and reliability of the forecast [55]. By learning the time dependencies and volatility parameters of data, LSTM can capture long-term trends in market indices and stock and commodity prices as well as detect and react to short-term fluctuations and unexpected events. Deep learning neural networks and hybrid models, which are combinations of DL algorithms with other methods, dominate the area of financial time series forecasting.

The high learning ability of neural networks allows expanding the composition and volume of information about changes in the forecasted process and extracting important characteristics from the data when forecasting fluctuations and trends in a financial market. The challenges of their application include the following: the need for a large volume of data for training, the time-consuming training process for large datasets, and the demand for high-performance computing resources.

Building a time series forecast is traditionally treated as a regression problem. However, the attention of many researchers of financial and commodity markets is focused on forecasting the direction of trend changes, and the corresponding problem is posed as a classification one. More than half of the existing implementations of DL algorithms are centered in this area.

Let us consider the application of DL to medium-term forecasting. The corresponding studies currently account for a very small percentage of the proposed short-term forecasts. One reason is the complexity of this problem; another is the absence of structured information about the impact factors of the market and the forecasted process. According to [56], the informativeness of short-term forecasts by analysts has improved in the long run whereas the informativeness of their long-term forecasts has decreased. This fact is explained by the availability of alternative market data concerning short-term future outcomes, which encourages forecasters to shift their attention from long-term to short-term forecasts.

The research works below considered a forecasting horizon of one month. Within developing an investment portfolio formation algorithm, the results of using RNN models with LSTM and a supervised recurrent module for selecting the best predictor in portfolio formation were compared in [57]. According to the experimental results on a set of ten US stocks, the LSTM-based forecasting model outperforms the others in terms of the one-month-ahead prediction matching rate.

In [58], the CNN model was proposed to forecast monthly and weekly price trends. The resulting accuracy of forecasting was 65% for monthly price trends and 60% for weekly price trends.

Findings. Deep learning algorithms allow identifying patterns in the dynamics of the forecasted process using historical data of time series and alternative data on the impact factors of the market and the forecasted process. However, the problems of generating medium-term forecasts are related to the low informativeness of medium-term alternative data, which was confirmed by the results of [56]. Handling process evolution data for terms comparable to the forecasting horizon and their introduction into the forecast should make medium-term forecasts more informative.

2.4. Hybrid Models

Hybrid models combine models of different types: statistical, machine learning, deep learning, and so on. Each algorithm included performs a definite function, and a control algorithm organizes their interaction and generates the solution (a forecast). In [59], an algorithm was proposed for forecasting the closing prices of four stock exchange indices, namely, SP500, NIKKEI 225, AORD, and CSI300, for 30, 60, 100, and 200 trading days. A hybrid model developed by the authors combines *ensemble empirical mode decomposition* (EEMD, the decomposition method of an original series into empirical modes), ARIMA, and *Taylor expansion forecasting* (TEF, first applied in [60]) for forecasting financial time series. The original time series is divided using EEMD into an ensemble of subsets, each containing a collection of functions (series) corresponding to a definite oscillation mode. On the subsets, linear and nonlinear series are forecasted using the linear ARIMA model and the nonlinear TEF model, respectively. The forecasts of the linear and nonlinear models are combined into a forecast on each subset. The final forecast is obtained by combining the forecasts of all subsets. According to empirical evidence for real financial time series, this new hybrid approach improves the results of standard hybrid models discussed in [60, 61].

A "decomposition and ensemble" paradigm combining EEMD and *extreme learning machine* (ELM) was proposed for forecasting complex time series with high volatility and non-uniformity [62]. The main goal of the "decomposition and ensemble" concept is to divide the original complex forecasting problem into several relatively simple subproblems, thereby reducing the complexity of modeling.

The monthly forecasting problem of volatility in the copper market was studied in [63]. To solve this problem, the authors considered various structures from a collection including the following time series models: parametric models (ARIMA and GARCH); nonparametric models from the area of soft computing, namely, *artificial neural networks* (ANNs), *fuzzy inference systems* (FISs), and genetic algorithms. A large number of experiments were conducted on data from 1990 to 2016, and the following conclusions were drawn based on the experimental results: generating forecasts using the adaptive method is crucial to obtain reliable and improved performance; the Adaptive–GARCH–FIS model provides the best forecasting capability.

Findings. The application of hybrid models offers great opportunities for improving the reliability of short-term forecasts and developing medium-term forecasting models: they are able to consider many factors affecting the forecast owing to advanced mechanisms for processing and analyzing quantitative and alternative market data both in the short and medium run.

2.5. Fractal Analysis

As has been mentioned in subsection 2.1, fractal analysis methods and corresponding process models are applied to forecast financial and commodity markets.

Multifractal Detrended Fluctuation Analysis (MFDFA), originally presented in [64], is one of the main tools for analyzing and identifying multifractality in time series.

MFDFA and its modifications are used to determine the presence of long-range correlations, calculate multifractal characteristics of series (the generalized Hurst exponent, scaling exponent, and singularity spectrum), and study degree cross-correlations between different simultaneously recorded (synchronized) time series [65, 66].

An important issue in time series forecasting is to choose an appropriate model for the forecasted object. One parameter of this choice is the fractal structure of the forecasted object. The ARFIMA(p, d, q) model [67] is commonly used to forecast fractal processes:

$$A(L)(1-L)^d Y_t = B(L)\mu_t,$$

where $d \in (-0.5, 0.5)$ is the fractional coefficient related to the Hurst exponent H by $D = 2 - H$; D is the fractal dimension of the series Y_t; $A(L)$ and $B(L)$ are polynomials of degrees p and q, respectively, of the delay operator L; μ_t is a sequence of independent identically distributed random variables with zero mean and a finite variance.

Methods and models of multifractal analysis were considered in detail in the review [68], including the proof of multifractality in financial time series, the quantitative assessment of market inefficiency, and risk management support.

Much attention is paid to studying the effectiveness of the ARFIMA model in financial markets, there exist different opinions on the subject. The forecasts of Russian companies' stocks using the ARIMA and GARCH models and their fractal modifications, ARFIMA and ARFIMA-GARCH, were compared in [69]. According to the experimental results, considering the fractality of financial series gives better forecasts: in most cases, the accuracy of ARFIMA and ARFIMA–GARCH forecasts was higher than that of ARIMA and GARCH.

The effectiveness of the ARFIMA model for forecasting on a horizon of up to 100 steps was analyzed in [70]; the authors considered the cases of a priori known baseline value of the parameter d and an uncertain one. It was demonstrated that, in general, linear models outperform the ARFIMA model under both positive and negative values of d for the modeled series and positive values of d for real time series data. The forecasting results of the Hang Seng index (Hong Kong, a long memory series) with the ARFIMA model were presented in [71]; the model turned out to be ineffective.

The forecasting performance characteristics of the ARIMA(p, d, q) and ARFIMA(p, d, q) models for the stationary series of the GBP/USD foreign exchange rate with long memory were compared in [72]. The comparison performed on two parameters—the *root mean square error* (RMSE) and the *mean absolute percentage error* (MAPE)—showed that the forecasts of the ARFIMA model are more realistic and more accurately reflect the current economic reality in the UK and USA. The obtained results are consistent with the opinion of the authors of [73, 74].

A two-stage approach was used to forecast long memory series in [75]. In the first stage, the long memory parameter was estimated and the long memory operator was applied to the original series to calculate forecasts for several steps ahead. In the second stage, a fractional cumulation operator was applied to the forecasted values to transform them into those of the original series. The proposed approach was applied to real data together with simulation modeling; according to the analysis results, the new method is stable to changes in the mean value of the process and the long memory parameter. Therefore, it can be used in applications under deviations of the true data parameters from the model ones.

The ARFIMA–LSTM hybrid recurrent model was proposed in [76] to forecast prices in commodity and financial markets. In the first step, the ARFIMA model was used to filter data (with better quality than the ARIMA model); in the second step, the filtering results were processed using the LSTM neural network. To investigate the quality of forecasting, the model was tested on commodity market data. According to the experimental results, this hybrid model is effective: the *mean absolute error* (MAE) was reduced by an average of 80% in comparison with the *generalized regression neural network* (GRNN), ARFIMA, and ARIMA models.

Fractal analysis methods can be applied to predict crises. The quality of prediction of the global financial crisis of the late 2000s was evaluated under FMH in [77]. For the three American indices (DJI, NASDAQ, and S&P500) as an example, it was demonstrated that the FMH describes quite well the behavior of indices on different investment horizons before and during the global financial crisis.

Findings. The ongoing studies of financial market processes confirm the validity of the fractal market hypothesis and its usefulness for analyzing the structure of financial series and trends in financial flows, predicting crises, and forecasting [78]. However, there exists no unambiguous opinion on the advantages of a certain hypothesis, and the apparatus for generating forecasts of fractal processes in financial and commodity markets is underdeveloped so far.

3. EXPANDING THE INFORMATION FIELD BY USING INFORMATION FROM EXTERNAL SOURCES

Medium-term price forecasting in financial and commodity markets under nonstationarity and structural shifts due to changes within the system (e.g., investor preferences, the distribution of investors over different horizons, etc.) or external events (man-made and natural disasters, wars, epidemics, drought, etc.) necessitates including possible situation scenarios and impact assessments in medium- and long-term forecasts. To build such scenarios, one needs information about the state of the environment, changes in the structure of financial and commodity markets, government decisions, extreme events, and so on. Therefore, one of the most important lines of improving medium-term price forecasts of financial and commodity markets is acquiring appropriate information to estimate the possibilities of future changes in the environment or the structure of the forecasted object.

Expanding the information field of the forecast only by augmenting the composition of price time series does not yield medium-term forecasts with the required accuracy. For example, a medium-term forecasting model of oil prices with a horizon of 6–8 quarters (18–24 months) was proposed in [79] by combining forecasts based on the following indicators: world oil market prices, the prices of industrial raw materials unrelated to oil, oil futures prices, the spread between spot prices for gasoline and crude oil, the time parameters of gasoline and heating oil spreads, and naive forecast. According to the experimental results, although the proposed forecast combination model systematically shows higher accuracy than naive forecasts on all horizons from 1 to 18 months, its accuracy is low: the RMSE of the forecast relative to the naive one is reduced by only 13%, and the accuracy of trend forecasting reaches 65%; for quarterly forecasts on horizons from 1 to 6 quarters, the reduction of the error and accuracy are 12% and 72%, respectively.

There are two strategies for expanding the information field and including in the forecast not only structured data on different processes but also expert knowledge and information from news and analytical and other sources related to the forecasted object. Both consist in augmenting the forecasting scheme: building a forecast model on a fixed dataset, monitoring changes and correcting the original model, and calculating the forecasted values.

The first strategy enables system analysis by adding the stage of searching and structuring available information about the market and building a knowledge model of the forecasted process and its external impact factors (the existing and potential ones). In practice, the knowledge model is often used for structuring analytical information for experts and less for forming the time series of activity, frequency of requests, and tone of messages, added to the data during modeling.

The second strategy is to incorporate information processing algorithms, knowledge, and inferences in the form of estimated change or direct value judgments of experts into the forecasting model or forecast correction procedures.

3.1. Use of Search Engine Data

With the development of big data technologies, the idea of including search engine data in forecasting has become widespread. *Search Engine Data* (SED) is a powerful factor in assessing the importance and interest of users in this problem. The predictive power of SED has been studied in detail in the literature.

In [80], the *Google search volume index* (GSVI) was used to measure the attention of non-commercial and non-reporting investors (traders) and to investigate the relationship between GSVI and crude oil prices. The dynamics of GSVI and crude oil prices from January 2004 to June 2014 were analyzed; according to the results, there is an inverse relationship between them, and the use of GSVI improves the accuracy of forecasting in recursive weekly forecasts.

A multiscale crude oil price forecasting method was proposed in [81]. The method includes several elements as follows:

– multivariate search engine data processing, dimension reduction, and predictive power evaluation using statistical analysis;

– multiscale analysis to extract consistent common modes at similar time scales from oil price and multifactor search data using multivariate empirical mode decomposition;

– oil price prediction with forecasting at each time scale and ensemble forecasting across all time scales using the selected method.

According to the results of the empirical study, the multiscale method with multivariate SED significantly outperforms all the oil price forecasting methods considered by the authors; the information contained in multivariate SED can have greater predictive power for crude oil price.

Findings. However, as was noted in [56], search engine data are mostly short-term oriented; due to their availability, analysts pay more attention to the collection of short-term information to the detriment of long-term information. As shown in this paper, in the long run, the informativeness of short-term forecasts by analysts improves while that of their long-term forecasts decreases.

3.2. Analyzing the Influence of Extreme Events

Extreme events occurring in the environment are an important element of influence on the prices of financial and commodity markets. In many publications, extreme events are understood as some global events, such as pandemics or sanctions, but the question remains open: which events can be significant for a particular forecasted process?

In other papers devoted to short-term forecasting in financial markets, price movement forecasts are generated by processing the flow of news headlines. The issues of classifying the flow of events to identify significant ones are almost not considered; the main attention is paid to the characteristics of intensity and outbursts in a definite subject area. In this class of methods, a news or post-tone series is often studied: a change in its characteristics also represents an attribute of significant events. Among such research works, it is necessary to emphasize methods for discovering a relationship between this (alternative) information and the change in the forecasted series [82].

The influence of extreme events on crude oil prices was investigated in [84]. To assess their effect on price volatility, the forecasted time series was first decomposed into several internal modes at different time scales and an average trend. The decomposed modes reflect the fluctuations due to an extreme event or other impact factors during a period under consideration. As was established, the total influence of an extreme event appears in only one or a few dominant modes, while the secondary modes are modified by other impact factors. According to the research results, the empirical mode decomposition method provides an acceptable solution for assessing the influence of extreme events on crude oil price changes.

In [84], it was demonstrated that sudden extreme events significantly influence the relations between changes in the volatilities of financial, commodity, and carbon markets in China.

Findings. Research in this area has focused on methods for identifying a relation between event information and series change, in particular, the development of the empirical mode decomposition method.

3.3. Expert Information

In addition to intelligent analysis methods of textual information from various news sources, expert information is used to improve the accuracy of forecasting by expanding the information field.

An approach to improving the accuracy of forecasting by structuring and effectively utilizing expert knowledge was presented in [85]. This approach involves subjective forecast correction: mathematical forecasts are considered a basis, and structured expert knowledge is provided to adjust the initial statistical forecasts. In this case, expert knowledge is structured by using four formalized factors (by the types of dynamics) to identify and classify events that cause different changes in the dynamics (at different time instants) of the forecasted process and could not be considered in the initial forecasts. An expert judges the strength (weights) of the identified impact factors associated with the events for further correction of the statistical forecast at the corresponding time instants.

The effectiveness of this approach was validated by two case studies conducted with forecasters from a plastic bag manufacturer in southern Spain and a distributor operating in the food market in northern France. According to the results, structuring expert knowledge through the identification of events associated with the classification factors leads to a 2% improvement in the accuracy of forecasting. The accuracy of forecasting using this approach was evaluated using the MAE and MAPE measures (the results yielded by mathematical models were compared with those obtained by forecasting, corrected for subjective evaluations).

Findings. Expert judgments are used at the stage of correcting generated mathematical forecasts. However, the issues of end-to-end application of expert judgment algorithms in the forecasting procedure, as well as the verification of expert forecasts, remain poorly developed.

3.4. Cognitive Analysis and Situation Modeling

Nowadays, cognitive analysis and situation modeling, a line of scientific and applications-oriented research, is being actively developed to solve problems of structuring, analysis, classification, forecasting, and management decision support, including time series analysis and forecasting; for example, see the recent surveys [86, 87]. It is based on fuzzy cognitive maps (FCMs).

An FCM of a situation is its formalized model reflecting beliefs about the mutual causal relations of significant factors affecting the situation. As a rule, such a map is the result of structuring and formalizing heterogeneous information about an object of interest for subsequent modeling of possible situation scenarios. Depending on the sources used, there exist direct, indirect, and mixed methods for building FCMs. The first method involves direct interaction with experts to extract the necessary knowledge about the object; the indirect method consists in searching and acquiring relevant information from heterogeneous sources; the mixed method is a combination of the first and second ones.

In several studies, in order to improve the accuracy of forecasting, the formation and/or correction of the forecasting model was based on data regarding events (newsmakers) of the environment extracted from heterogeneous sources and processed using FCMs; for example, see [88–90].

An approach to forecasting financial data series with the joint use of signed FCMs and neural networks was presented in [88]. In a signed FCM, causal relations between concepts (factors) reflect only the sign of the causal influence, i.e., positive (strengthening) or negative (weakening), between any pair of concepts in the map without establishing the weights (degree) of this influence. The authors proposed KBNMiner, an automated system including the following components:

– a prior knowledge base formed from expert knowledge represented by FCMs on various subject areas;

– an information retrieval subsystem for automatic collection of news information about events from the Internet, with the directed search organized using the concepts of the FCMs of subject areas;

– a knowledge application subsystem designed to process the selected positive and negative events based on the structural analysis of the causal influences of the FCMs; the analysis results are inputted into a predictive neural network model in the form of a parameter characterizing the relative strength of the influence (positive or negative) on the forecasted indicator, together with other related financial indicators.

The approach was applied to interest rate forecasting; according to the empirical results, qualitative information significantly influences the efficiency of the neural network when forecasting interest rates on a horizon of 30 days.

A modular time series forecasting system was proposed in [89]. This system includes three main modules as follows. A hybrid neuro-fuzzy network generates a quantitative forecast of a time series, and the results are verified by the criterion of given accuracy. Based on the collected data on the event's influence on the time series, an FCM considers the causal impact factors of the forecasted indicator to generate a forecast with an assessment of the event's influence on the forecasted indicator. The final forecast is produced by a neural network model aggregating the results of the first two modules.

Although the authors declared the effectiveness of the hybrid approach (using FCMs and neural networks) to time series forecasting, no supporting practical or experimental results of its application were provided in the paper.

The problem of forecasting commodity prices on a one-year horizon with a monthly breakdown was considered in [91]. The complexity of this problem is due to the forecast uncertainty, which grows with increasing the forecasting horizon. To reduce the uncertainty, the authors proposed a hybrid model for generating and adjusting the monthly forecast on the one-year horizon. The forecasting model is based on the ensembles of multivariate statistical models of time series at different time scales. The ensemble models include various combinations of series that are Granger causal for the forecasted one. In addition to the forecasted indicator and the influencing time series of prices and macroindicators, the model involves expert analytical information processed using FCMs. This approach is being developed in the vein of combined forecasting methods.

The general medium-term multistep forecasting algorithm for processes with structural shifts caused by environment events has the following elements:

– systematization, structuring, and formalization of expert judgments and information from heterogeneous sources using an FCM that reflects the structure of causal relations (influences) between systemic[2] factors, which characterize the main processes of the situation studied in commodity markets;

– combined price monitoring in commodity markets [91], including:

1) numerical monitoring to identify structural shifts in the time series of the forecasted process (and in the series of related processes);

2) situational monitoring of the environment using heterogeneous information sources and subsequent FCM scenario modeling to generate signals on possible consequences of the influence of significant events of the environment (newsmakers) on the change of the forecasted process and related processes;

3) management of information exchange between items 1 and 2 and generation of aggregated output signals;

– building monthly price forecasts on the one-year horizon based on processing expert knowledge and time series data using an ensemble of VECM, ARIMA, and VAR statistical models; correction of the forecasts in the combined monitoring mode based on the aggregated output signals.

The effectiveness of the proposed approach was tested on the example of forecasting ferrous scrap prices for 2019. The accuracy of the resulting forecast was compared with naive forecasts and those obtained using the ARIMA model. According to the experimental results, owing to the ensembles of models, the accuracy of forecasting is almost doubled compared to the naive forecast and ARIMA, and the average percentage error of the forecast is improved by 10.5 and 3 times, respectively. Correction applied on the forecasting horizon reduces the absolute percentage error by 20% and the average error by 5 times compared to the forecast without correction based on FCMs and monitoring [41].

Findings. The results of expert knowledge processing (FCM scenario modeling) can be used to generate various signals reflecting information about the change of direction and strength of the trend of the forecasted indicator, the weights for forecasts included in the combination, as well as information about new parameters whose data should be searched and added in the initial samples.

4. SUMMARIZING THE SURVEY RESULTS IN THE CONTEXT OF MEDIUM-TERM FORECASTING

• For an object of medium-term forecasting in a commodity or financial market, multistep forecasting is necessary for planning tasks. In many cases, multistep forecasting allows increasing the resulting accuracy by using data at different scales (see subsections 2.1 and 2.2).

• Combining forecasts allows reducing the errors due to market volatility and changes caused by external events (see Section 2).

• Hybrid models are applied by combining different forecast generation stages, and each stage can be performed by different methods (see subsection 2.4).

• To detect in due time and forecast changes, first of all, to identify the attributes of future structural changes (a change in the trend or the set of parameters), it is necessary to expand the information field both by including time series characterizing related processes and by applying qualitative information processing methods (search engine data, news and factual data, and expert information) when performing monitoring in the mode of current observations and forecasting (see Section 3).

• Medium-term price forecasting models based on historical data often fail due to changes in endogenous and exogenous factors on the forecasting horizon: they change the dynamics of the forecasted object and necessitate correction. The peculiarities of the forecasted object and the specifics of medium-term multistep price forecasting in commodity and financial markets require changes in the conventional forecasting scheme, which generally includes:

– data sampling,

– analyzing the properties of the forecasted series and identifying explanatory variables,

[2] The factors are called systemic because, together, they form a system reflecting an integral view of the situation in the problem under consideration.

– selecting the type and parameters of the model,

– generating a forecast and performing its correction on the horizon based on monitoring results.

For different stages, these changes are as follows.

The data preparation stage. In medium-term forecasting, there has been a transition from using available data to building a model of data and information needed to solve the forecasting problem. A knowledge representation model should be built by structuring the knowledge of processes in commodity or financial markets; the model serves as a thematic filter for collecting time series and structuring incoming (unstructured) market information. This allows one to expand the set of different models (operating differently on different periods) for further combination and/or switching and, when using qualitative information processing and analysis methods, to detect the attributes of changes or distinguish important events affecting different parameters.

The stage of choosing the set of parameters and their structure for the forecasting model. To enable the selection of different model ensembles or formation of hybrid medium-term forecasting models for nonstationary processes, the identification stage has included a transition from choosing a limited set of parameters for a given period to forming structured diverse sets of parameters and classifying the types of dynamics periods for the forecasted process. The expansion of the information field for generating forecasts, associated with the complexity of processes in commodity and financial markets and the accumulated data for a large historical period, has involved machine learning and neural network methods in the forecasting procedure for analyzing the properties of causality on a large dataset. They have been discussed in detail in subsection 2.3.

The model formation stage. At this stage, statistical methods, ML, DL, ARFIMA, and hybrid models are applied (see Section 2). Studies show that the level of fractality of processes (the fractal dimension D, see subsection 2.5) is an important criterion for model selection. If the fractal dimension D lies in the interval [1.4, 1.6] and the time series obeys the Gaussian distribution, then the EMN hypothesis holds, and the system behavior is well described by classical statistical methods (ARIMA, VAR and VECM, and other statistical models). Special methods are used to determine the type of the process (stationary, trend-stationary, with unit root) on a given forecasting period, together with algorithms for analyzing cointegration between series (see subsection 2.1). Among the statistical models considered in subsections 2.1 and 2.2, the best quality of forecasting is reached by forming an ensemble of models, applying procedures for analyzing the forecast quality dynamics on different periods, and choosing an appropriate strategy for combining algorithms.

If the distribution of the time series is non-Gaussian and the fractal dimension D lies in the interval [1, 1.4) or (1.6, 2), then the process has long correlations (long memory) and is stable (in the former case) or has an antipersistent, unstable state (in the latter case). In both cases, statistical models may yield unacceptable results; it is advisable to apply fractal analysis and forecasting models considering their fractal properties, e.g., ARFIMA (see subsection 2.5) and AI methods.

In contrast to statistical models, forecasting methods using AI algorithms (subsections 2.3 and 2.4) and their combinations do not require knowledge of the process type and its distribution and remain effective even when these properties change. AI models with self-learning are now widespread to consider nonlinearities in object's dynamics. The application of AI methods increases the accuracy of forecasts in changing financial and commodity markets by studying the nonlinear characteristics of their dynamics using historical data. However, the challenges of their application include the following: the need for a large volume of data for training, the time-consuming training process for large datasets, and the demand for high-performance computing resources.

The monitoring and correction stage. At the monitoring stage in the mode of current observations, it is recommended to use algorithms for detecting and identifying the type of changes, but they are not widely applied in the sample of publications covered by the survey. If a change is detected, the expediency of model correction is decided on. Accordingly, the arsenal of methods and algorithms should include a set of model correction algorithms for a definite type of changes detected. Section 3 has presented several research works with heterogeneous information processing and analysis methods applied to price forecasting in financial and commodity markets. The occurrence of structural shifts on the forecasting horizon necessitates their detection and model correction. To detect structural shifts in the online mode, along with time series monitoring algorithms, it is advisable to use combined monitoring, including the detection of structural shifts and expert analysis of the situation affecting the forecasted object: the resulting influence of environment events and strategies of different groups of market participants.

CONCLUSIONS

This survey has attempted to study medium-term price forecasting methods for financial and commodity markets. Such forecasts are crucial in the strategic planning of global and regional economic development and management of the socio-economic development of objects with different degrees of complexity.

The forecasted objects are processes in commodity and/or financial markets. Such processes respond quickly to changes in exogenous and endogenous factors; for the most part they are nonlinear, changing from stationary to nonstationary and vice versa. A medium-term forecast is understood as a forecast with a monthly breakdown and a forecasting horizon of three months to two years.

On these horizons, there is an increasing probability of structural shifts causing changes in the initially generated forecast. Therefore, on the forecasting horizon, it is necessary to monitor the occurrence of structural shifts and correct the forecast based on the monitoring results.

The findings of this survey are as follows:

• The problem of building medium-term forecasts in commodity and financial markets has been given little attention by researchers; the results on short-term and (less often) monthly forecasting are mainly presented in the literature.

• Medium-term forecasting is more complicated than classical one-step forecasting and requires using more time-consuming procedures for collecting data on the impact factors of the market and their analysis methods and augmenting the solution scheme.

• The problem of forecasting structural shifts and subsequent correction on the forecasting horizon has received little consideration in the literature. The solution of this problem requires forecasting the occurrence of various types of changes in endogenous and/or exogenous factors affecting the process. To build such a forecast, it is necessary to include not only information on market prices but also qualitative information.

• The survey covers publications concerning models, methods, and algorithms that implement individual stages of the augmented medium-term forecasting scheme. In the authors' opinion, the hybrid approach has good prospects for implementing this scheme.

• The following lines seem promising for developing medium-term forecasting methods for processes in commodity and financial markets with structural shifts:

– methods for expanding the possibilities of using quantitative and qualitative information extracted from heterogeneous sources (search engine data, news, analytical studies of causal relations between individual market sectors, expert judgments, and scenario analysis results for the influence of significant events);

– the Bayesian approach for forecasting structural shifts on a forecasting horizon;

– fractal analysis for forecasting crises and events significant for the forecasted object in real time.

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