Forecasting of Key Indicators of the Manufacturing System in Changing External Environment

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Abstract: The management of a manufacturing system faces with the problem of long-term and medium-term forecasting of the system-forming factors of the stable functioning of the system(raw material prices, expected demand, the volume of orders, cost of products), changing due to dynamics of the markets for raw materials and end-products, high competition, as well as other political, economic and global factors. The expected improvement of the forecasting quality has not been achieved even with a large amount of qualitative and quantitative information about the system. The events accompanied by cumulative influences from many factors often lead to rapid changes in prices (structural shifts, changes in trends and price relationships) that are reflected in the quantitative data with a delay. Analysis of the strength and direction of cumulative influences of many factors on prices improves the quality of forecasting. This paper proposes the general scheme of the forecasting algorithm based on a system of models that includes a situation cognitive map and a set of the quantitative forecasting models of changes in the key indicators of a manufacturing system.

Keywords: manufacturing system, quantitative and qualitative forecasting, non-stationary processes, time series, cognitive map

1. INTRODUCTION

When forming multi-step forecasts for the long term for solving the problem of planning a manufacturing system (MS), based on the process dynamics of quantitative information available at the time of forecasting, the required forecast quality may not be achieved. The reason is external environmental events that determine the change in the interval of the horizon of analysis of key parameters of the value chain of the final product. Changes in political, economic, social, geopolitical factors influence on MS through the business-environment factors, for example, through such factors as a resource price, a level of demand, a currency course, a production time, a delivery time. Rapid and frequent changes cause jumps in the level, the direction and inclination of the trend, volatility. These factors influence the value chain of the final production, which is sensitive to uncertainty in the commodity markets and the markets of final products of an MS.

Commodity markets are markets where buyers mostly make large transactions and plan them. The production needs for the commodity, external environment factors and the situation on the domestic market, which determine the volume of orders, prices for raw materials and products, import and export prices determine the transaction price. Price change processes in such markets are processes described by non-stationary time series. Planning options for dates and volumes of transactions requires long-term and medium-term multi-step forecasts, for the formation of which it is necessary to take into account not only the information reflected in the data but also the information about possible options for the situation development.

The different approaches apply when predicting the processes described by non-stationary time series: parametric models design, singular spectral analysis, empirical mode decomposition, support vector machine, neural networks, etc. (Cheng et al. (2015), Bayükşahina (2017)).

However, quantitative methods take into account information about changes in external environment factors only after it reflects in the values of the price series. When constructing long-term forecasts, information about future events changing the dynamics of the target indicator in the forecast horizon interval is not available at the time of its formation in the data.

In addition to numerous random influences, the various heterogeneous external environment factors influence on the commodity markets, which result in shifts and structural change in the forecasted processes. In the presence of changes in the intervals between the points of formation of the quantitative methods don't reflect these changes, since information about them isn't available in the data. Improvement of a long-term forecast is possible through a combination of qualitative and quantitative methods (see for example Makridakis et al. (2009)) by taking into account in the quantitative model corrective signals generated as a result of the analysis of qualitative information.

In the modern methodology of decision-making, the cognitive maps and methods of cognitive mapping are one of the widespread means of qualitative forecasting and analysis ill-structured situation, reflecting the knowledge of the experts and data about the causal influences between the significant factors.

The cognitive maps (CMs), apart from their predictive strength, explicitly structure the knowledge and information. Range of their implementation is continuously increasing (see

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the recent review by Papageorgiou (2013)), including the production sector (Fathian (2009), Groumpos (2014), etc.).

The joint application of cognitive maps and statistical methods or neural networks to generate time series forecasts has been considered, for example, in Hong et al. (2004), Avdeeva et al. (2019). An important distinctive feature of such models is that they are constructed using heterogeneous data (quantitative and qualitative, expert) to identify significant factors and parameters of events that may affect the forecast generated. In this case, the formation and/or correction of the forecasts rely on the results of CM analysis of the event data extracted from heterogeneous information sources.

This paper considers the general scheme of the forecasting algorithm based on a system of models that includes CM of the situation and a set of the quantitative forecasting models of changes in the key indicators of MS: the target indicator and causal factors of influence on it. Considered forecasting technique is the part of the combined approach to forecasting of the manufacturing system target indicators, depending on the key factors determining the functioning of this system and external environment factors (Avdeeva et al. (2019)).

The forming of the system models prescribes structural and parametric identification of models both at the building stage and during the monitoring process, including identification: 1) the structure and parameters of the cognitive map of the situation in accordance with a given type of formal model; 2) structure and composition of quantitative forecasting models. To calculate forecasts, we use a set of models of non-stationary series. Such models describe the relationship between a key indicator and a limited set of factors. The resulting forecast is calculated as the weighted sum of the forecasts of a particular model, the weights of which are determined by the results of cognitive mapping.

2. GENERAL DESCRIPTION OF THE FORECASTING ALGORITHM

Figure 1 shows a general scheme of the forecasting algorithm. The grey bidirectional arrows designate the relationship of the processes of building, analysis and correction of forecasting models with information monitoring. This relationship is that the significant changes in the situation detected by monitoring reflected in the relevant processes.

An object of forecasting is the set of non-stationary series integrated of order r. Series is integrated of order r, denoted by $I(r)$, if it becomes stationary after r differences and is non-stationary after r-1 differences (Engle and Granger, (1991)). A discrete interval for data collection is a week, the forecast horizon is a year, and the month is a step.

Structural changes occur in these processes under the influence of external environment events. We understand structural changes as changes in trends, or volatility and sharp jumps in the level of the target indicators and the factors. Structural changes in time series can lead to a violation of Granger causality and cointegration between them.

If the monitoring results show that the algorithm of current detection (see section 2.3) detects structural changes in the series of quantitative data, a correction of the forecasting algorithm is necessary. The direction of adjustment is determined by the results of expert analysis of the external environment, carried out using cognitive modelling.

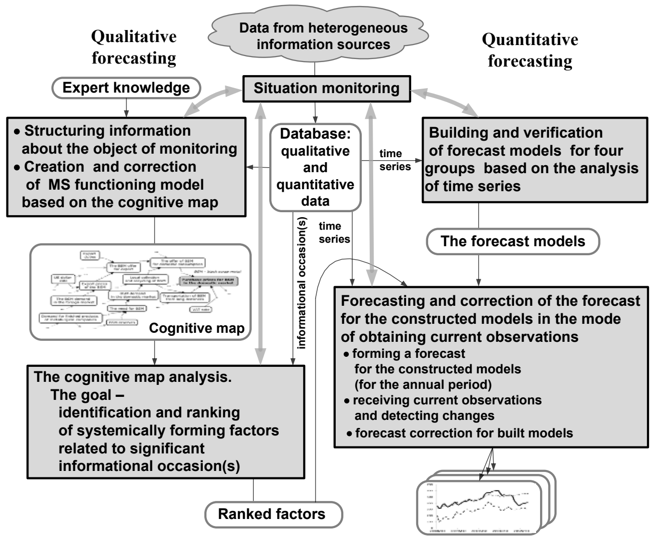

Fig. 1. The general scheme of the forecasting algorithm

The inclusion of cognitive mapping in the procedure of building forecast models and the forecasting procedure aims at achieving the following goals:

– evaluation of the integral effects between factors and the target indicator;

– constructing possible scenarios of the development of the situation, allowing grouping of factors influencing the target indicator;

– selection of the best combination of factors for each of the possible scenarios, for inclusion in the forecasting models, taking into account the division into groups;

– justification for switching between forecast models by signals of a change in the significance of causes.

2.1 CM analysis to identify and rank the system-forming factors of the MS functioning and development

The analysis of CM in the monitoring and forecasting mode aims to identify and to rank important system-forming factors in groups depending on the qualitative change in the situation according to the observed factors and analysis of changes under various events. In the long-term and medium-term, forecasting the key economic components of the MS functioning is the end-product value chains of an MS: the cost of raw materials, production costs and final demand. It is necessary to take into account the inverse relationships between the demand for industrial products and market prices for raw materials. Therefore, the core of the CM of the functioning of MS includes four groups of system-forming factors related to finished products (C1), primary (C2) and secondary raw materials for creating products (C3), and macro and business environments (C4). Within the framework of these groups, forecasting models are built based on time series selected from the database (section 2.2).

It is important to note that the procedures for building forecast models (section 2.2) and forecasting (section 2.3) are common; splitting factors into groups does not affect the sequence of steps in these procedures.

Figure 2 shows a CM fragment associated with the activities of a pipe-rolling plant, where the target parameter is the price of black scrap, which is an essential raw material resource.

Let $K_f(X, A, f)$ be a situation CM, in which $X = (x_1, \ldots, x_n)$ is a set of factors of the situation S; $A = [a_{ij}]$ is the $N \times N$ matrix of factors mutual influence, where $a_{ij} \in [-1; 1]$ is the weight of influence of factor x_i on the factor x_j ([-1; 1] – a discrete scale; f is a function that defines the rule of factor value change at any discrete-time $t \geq 0$ (Avdeeva et al. (2016)).

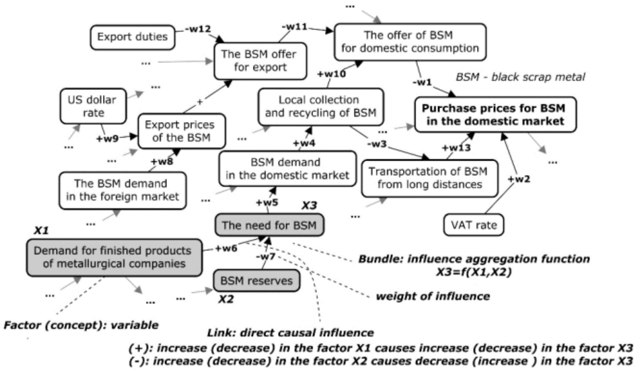

Fig.2. The fragment of a CM associated with the activities of a pipe-rolling plant

The state of the situation at any discrete point of time $t \geq 0$ expressed as follows

$$X(t+1) = Q(t+1)X(0) + Q(t)G(0), \tag{1}$$

where $Q(t) = E_N + A + A^2 + \ldots + A^t = (E_N - A)^{-1}$.
We limit the study of the maps by the ones which matrix A eigenvalue is inside the unit circle on the complex plane. Q is the matrix of cumulative influence; its elements characterise all direct and indirect in the map.

When solving the problem of forecasting a target indicator, y, analysis on the matrix of integral influences allows us to identify the causal-factors, to assess the degree of their impact on the structure, to assess the significance of the influence of any group of factors $\{C\}$. Thus, the set of factors X are divided into classes according to the belonging of factors to the groups $\{C\}$.

Let, $S_y^d(X(0); G(0); K_f; R(r_j = sign(x_j(0)))$ – the d-th qualitative forecast on the map K_f, depending on the values of factors X at the time $t = 0$, is determined by Eq. 1. That is, in each scenario d, we obtain the value of the factor y^* at any discrete point of time $t \geq 0$ and an estimate of the dynamics $r_y = sign\left(y^* - y^0\right)$. Let $\{x_k\}$ be the causal-factors for the target y. All causal-factors are divided into (+)-factors and (–)-factors: $X_y^+ = (x_k : q_{ky} > 0)$ and $X_y^- = (x_k : q_{ky} < 0)$. Submatrices Q_y^+ and Q_y^- are formed and from the matrix Q, where Q_y^+ (Q_y^-) is the submatrix, in which the factors of the X_y^+(X_y^-) and the factor y possess in the columns and in the rows; on the intersections of rows and columns – the corresponding cumulative influence q_{jk}, if there is no influence, then $q_{jk} = 0$. $X_y = X_y^+ \cup X_y^-$ – all causal factors of influence on target indicator y.

The weight of the positive (or negative) influences of the causal-factors from X_y^+(X_y^-) on the target indicator y is equal to the modulus of the sum of the weights of the cumulative influences $q_y^+ = \sum_{k=1}^{l} \left|q_{ky}^+\right|$ and $q_y^- = \sum_{k=1}^{l} \left|q_{ky}^-\right|$, where q_{ky}^+ (q_{ky}^-) is the weight of the cumulative influence of the causal-factor $x_k \in X_y^+$ ($x_k \in X_y^-$) on the target indicator y. Then the total weight of the causal-factors is $q_y^{total} = q_y^- + q_y^+$.

Cognitive map factors serve as the basis for the search for quantitative data (time series), the analysis of which allows us to build the set of the forecasting models $\{M_i\}$ of the key indicator on sets of time series of indicators $f_1, f_2, \ldots, f_{m_1}$.

In this case, the correspondence of the time series of indicators to the factors of the cognitive map is established. Each indicator f_i (time series) is assigned the number no of the causal-factor x_{no} in K_f. Let, $\{M_i\}$ – a set of forecasting models, X^{M_i} – a set of causal factors of influence (on the y) for each forecasting model M_i.

Then the significance of each forecasting model M_i is estimated at K_f by the cumulative influence of causal-factors X^{M_i} related to the corresponding parameters of the model M_i (taking into account the identification of time series by the numbers of causal-factors) $-q_{M_i}^{total} = q_{M_i}^{+} + q_{M_i}^{-}$ (similarly formed q_y^+, q_y^-, q_y^{total}).

In the block of qualitative forecasting of a target indicator for given input conditions for factors X, in addition to assessing their value, an assessment is made of the significance in the change of certain factors-reasons. For this simulation scenario, a Q^R submatrix is formed on the Q, in which the factors of the $X_{R(y)}^{inpS}(x_i : edf_i \neq 0)$ *and those* $x_R^{M_i} : (edf_i \neq 0)$ represented in the rows and the factors { $X_R^{M_i}$ } and the target indicator y in columns; on the intersections of rows and columns – the corresponding integral influence q_{jk}, if there is no influence, then $q_{ij} = 0$.

Then a significance of the M_i for some scenario S_y^d defined as

$$q_{S_y^d}^{M_i} = \sum_{k1=1}^{m1} \sum_{j1=1}^{l1} r_{x_{k1}} \times q_{x_{k1}}^{x_{j1}^{M_i}} + \sum_{j2=1}^{l2} r_{x_{j2}^{M_i}} \times q_{x_{j2}^{M_i}}^{y^{M_i}}, \tag{2}$$

where the first addend is the cumulative influence of the factors from $X^{X^{M_i}}$ on causal factors related to a model M_i on target indicator, y, and the second addend is the cumulative influence of the causal factors related to M_i on target indicator y.

Accordingly, for each qualitative forecast $S_y^d(X(0); K; EDF(edf_i = sign(x_i(0)))$, we obtain the following estimates for the forecasting models

$\{M_i, (S^d_{x_k}; \{q^{M_i}_{S^d_{x_k}}\}; edf_{x_k})\}$. In addition, we can obtain an estimate of a forecasting model M_i in the form

$$q^{*M_i}_{S^d_y} = \sum_{k2=1}^{m2} r_{x^{other_i}_{k2}} \times q^{y^{M_i}}_{x^{other}_{k2}},$$

which estimates a cumulative effect of the causal factors has not been connected with factors from X^{M_i}.

2.2 Building of forecasting models

The building of forecasting models includes: the selection of causal factors for the target indicator, the selection of the structure and type of models, the verification of models

We considered two types of model in this study: Vector error correction model (VEC model), which we build if the cointegration between variables exists and Vector Autoregressive model (VAR model), which we use in the absence of cointegration.

We can perform the model building process only in areas that do not contain structural shifts. The length of such sites due to a sufficiently large horizon of the forecast, as a rule, is small. Since the number of estimated parameters of a multidimensional model has the order $O(p^2)$, where $p=k+1$, k is the number of factors (without a target indicator) included in the model, we limit it to the value $k \le 2$. For changes in the dynamics of the target indicator to take into account the possible effects on its values of all factors affecting it at different times, we build a set of models.

Selection of factor time series for the process of forming models from the database carried out based on the analysis of statistical suitability of factors for the forecast of target indicators. Let, $f_1, f_2, ..., f_m, y$ be series of values of factors and target indicator on a model building interval.

The process of models' building includes a sequence of the following steps:

(i) We analyse the conformity of the factor to the target indicator. All factors involved in the model should have the same integration and seasonality orders as the orders of the target indicator. As a result of the compliance check, we get a set of factors $f_1, f_2, ..., f_{m_1}$, $m_1 \le m$ where m is the total number of factors from the database.

(ii) Testing the Granger causality of the factors $f_1, f_2, ..., f_{m_1}$ relative to the target indicator y (Lütkepohl, 2005).

Check the conditions: 1) "factor f_i is causal by Granger for y" and 2) "target indicator, *y*, is causal by Granger for f_i". If both conditions are satisfied, it means that a common external cause influences on the values of both series. We leave the factor f_i for further analysis if condition (1) is satisfied for it, and condition (2) is not fulfilled.

Since the considered series are not stationary, we test causality by a series of the first differences.

(iii) The formation of model variants. We form variants of the model structure in the form of a set (y, f_{i1}, f_{i2}), where f_{i1}, f_{i2} are factors selected in steps 1 and 2 belong to one of the groups C1, C2, C3, and C4.

(iv) Specifying the type of model (VAR or VEC). If there is a cointegration between the time series of the set (y, f_{i1}, f_{i2}) then we build a VEC model; otherwise, we build a VAR model, i=1... *N*, where *N* is variants number.

(v) Model building. For each variant, according to the structure defined on the step (iv), we evaluate the coefficients and orders of the models.

(vi) Ranking quantitative forecast models. We calculate the mean square error (MSE) of forecasting on the data which the model was built. In each group, we rank models in descending order of the received ratings: the model with the maximum error gets the first rank;

(vii) Ranking models by cognitive map. The significance of the forecasting model $M_i^{y_k}$ is estimated on the CM, K_f, by the combined influence of the reason-factors related to the indicators on which the model was built. As a result, each model is assigned a rank $R_{CM}^{M_i^{y_k}}$ by ranking order $\{q^{M_i}_{x_k}\}$ (section 2.1).

In each group, we select models that have the highest ranks in terms of quantity and satisfy the condition:

$R_{CM} \ge m_{R_{CM}}$, where R_{CM} is the rank of the model by CM; $m_{R_{CM}}$ is the average of the ranks of CM.

(viii) We build an integrated forecast by the formula:

$$YI_t(h) = \sum_{J=1}^{4} \alpha_J \tilde{y}_t^J(h) \mid y_{t-h}, y_{t-2h}, \ldots, f_{it-h}, f_{it-h}, \ldots) \tag{3}$$

where $\tilde{y}_t^J(h) \mid y_{t-h}, y_{t-2h}, \ldots, f_{it-h}, f_{it-h}, \ldots$ is the forecast for the *J*-th model $\alpha_J \ge 0$, $J = 1, ..., 4$ are the weights of the forecasts satisfying the condition: $\sum_{J=1}^{4} \alpha_J = 1$; 4 is the number of selected models.

2.3 Forecasting and forecast correction by built models

In the monitoring mode, we receive new quantitative and qualitative data about the situation.

- Check the properties of the time series included in the models, and adjust the $\{M_i\}$ models and forecasts. Under the influence of environment events that affect prices, both the characteristics of a separate process (level, volatility, autocorrelation) and the relationships between processes (co-integration and/or causality according to Granger is violated) can change. It is necessary to detect both types of these violations promptly for the subsequent correction of the forecasting algorithm.

Necessary steps in monitoring model: (i) calculation of the MSE of forecasts made at moments $t-h, ..., t+k-h$; (ii) checking the Granger causality and co-integration between the target indicator and the factors included in the VEC model for a set of models that form the integrated forecast using formula (3), excluding from it the models for which at least one of the conditions is not met; (iii) Replacing the models removed in step (ii) with models that include factors from the groups from which these models were removed (when selecting a model, follow steps 2-7 in section (2.2)); (iv) forecasting the next step.

Depending on the forecast horizon, the above steps are performed for monthly, quarterly, semi-annual and annual data.

A sequential causality check in the mode of obtaining new observations according to Granger performed in package *R* by implementing the algorithm (Toda & Yamamoto (1995)) on an expanding sample of observations.

The Johansen test (Johansen (1995)) performs the detection of cointegration changes in a fixed-volume sample.

To check the violation of cointegration in the mode of obtaining current observations, we use the algorithm proposed in (Grebenyuk E. (2004)).

• In the block of qualitative forecasting, we build a forecast $S^d_{x_k}$ and obtain the following estimates of the forecast models $\{M_i, (S^d_{x_k}; \{q^{M_i}_{S^d_{x_k}}\}; edf_{x_k})\}$, where $q^{M_i}_{S^d_{x_k}}$ are calculated by equation (2). These estimates are the basis for ranking models for updating the current model of the form (3).

According to the results of the verification, in the quantitative and qualitative forecasting blocks, the forecast model for the next period is updated according to the proposed general forecasting algorithm scheme in the mode of receiving current observations, based on signals received from CM and signals of sequential analysis algorithms applied to quantitative data.

3. DEMONSTRATION

The efficiency of the approach tested as part of a pilot project of the development of a procurement strategy system for the Russian pipe-rolling plant. In the system structure, one of the main is the block of forecasting prices for raw materials. Monthly forecasts of resource prices for the year ahead are needed for the procurement strategy optimization. The algorithm for the formation and correction of long-term digital forecasts of the target indicator, taking into account possible variants for the development of situations in the external environment, is demonstrated by the example of forecasting prices for black scrap metal (BSM).

The algorithm combines a system of models:

1. A Cognitive model of the development of the situation on the key parameters of the value chain: prices for primary and secondary raw materials – the cost of production – final products demand. The model includes 56 factors.

2. A time series models for calculating annual, semi-annual, quarterly and monthly forecasts, which in addition to the target indicator include a number of factors. All factors, by the recommendations of the CM, are divided into four groups: group M1 includes scrap prices; M2 resource prices; M3 product prices; M4 – values of macroeconomic indicators. The forecast is a weighted sum of forecasts for four models.

We used three-dimensional VEC models with two cointegrated variables and two dummy exogenicity variables. The monthly forecast of the BSM price until the end of 2019, based on the model built on data (2015M01-2018M12) is shown in figure 3. Prices for BSN (Rub) are on the Y-axis; the time period (2019M01-2019M12) is on the X-axis.

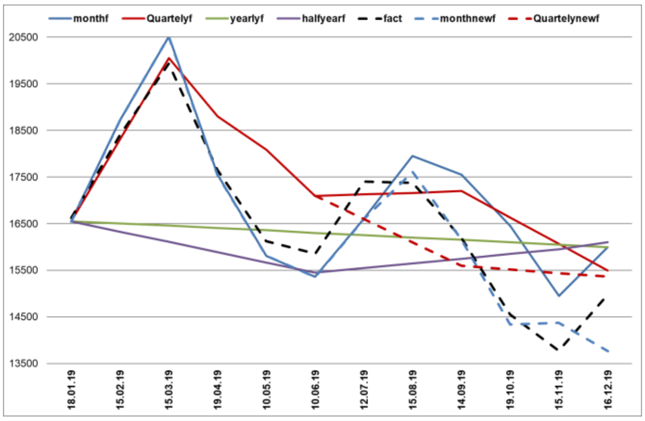

Fig. 3. Long-term forecast 2019 y. (January'19)

Until July 2019, inclusive, the integrated (the formula (4)) had acceptable deviations from the actual values, and although forecasts for individual models from the M1, M2, M4 groups had more significant deviations in April 2019. However, the composition of models did not change, since there were no signals about significant changes in the situation from the external environment, and there were no signals about the need to replace models in groups formed as a result of monitoring quantitative data. The weights of the groups varied according to the signals from the cognitive map, depending on the situation.

In the mode of current observations, monthly forecasts were generated for the selected four models using the steps given in section 2.2. As part of the pilot project, during 2019, we were able to demonstrate the functioning of the algorithm when observing changes of various types. Based on the results of monitoring information on changes of the CM's factors, scenarios of modelling changes in the key indicator (price for scrap) were formed, according to the results of which the significance of the forecasting models $q^{M_i}_{S^d_{x_k}}$ was calculated (see the table 1), and the integrated forecast was corrected.

So, in January 2019 there were changes in the market due to a sharp change in steel prices caused by accident at the largest plant, the quantitative and qualitative forecast data did not match. Therefore, it was performed the correction of the forecast by including a Dami-variable in the model.

A qualitative forecast (March) based on information about changes in the situation with demand for final products and the introduction of import duties in the USA in March showed a drop in scrap prices against the background of the previous growth.

Table 1. CM's Estimates of the significance of causal factors connected with Mi in the change of TI

M_i	$q_{M_i}^{total}$	01'19	02'19	03'19	06'19	01'20
Trend of TI		- → +	+	+ → -	0 → -	+ → --
M1	0,4	0,7	0,6	0,5	0,8	0,7
M2	0,3	0,0	0,4	0,3	0,0	0,1
M3	0,3	0,0	0,0	0,9	0,3	0,0
M4	0,0	0,3	0,0	0	0,0	0,2

The possible negative scenario of the situation development in July had discovered by the monitoring in March. Later in July, the monitoring by the marked factors had confirmed this scenario. Forecasting models were corrected. Models 2 and 4 were withdrawn from the pool of forecasting models by results of the Granger causality check of Model 4 factors and the violation of cointegration in Model 2. In September, the models M1 and M3 were rebuilt, and the forecast was adjusted. Figure 3 shows these changes with a dashed blue line.

As for 2020, the December 19 scenario showed an increase in the price growth rate. Cognitive modelling of the January situation showed a change in trend that reflected in quantitative forecasting (Figure 4).

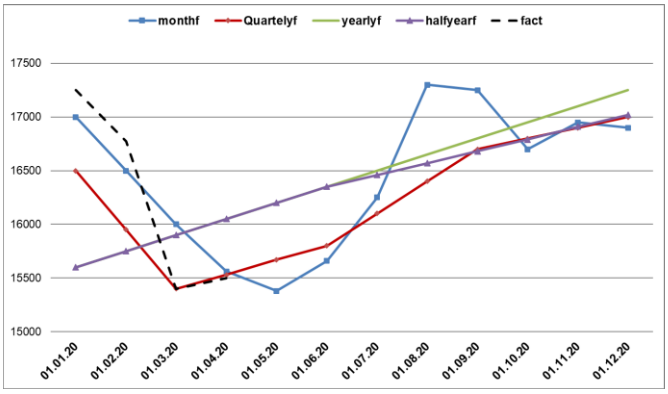

Fig. 4. Long-term forecast on the 2020 year (January 2020)

4. CONCLUSIONS

A new forecast correction algorithm of the models selected at the building stage proposed correction using signals of dynamic modelling of the situation on the cognitive map using qualitative data and detecting changes by sequential analysis on quantitative data. The effectiveness of the forecasting algorithm verified in the problem of forming purchase prices for ferrous scrap metal by metallurgical plants in the secondary market for raw materials. Accuracy of the forecasting increased on month horizon up to 3%, on three months horizon up to до 5%. Initial naive forecasts on these horizons gave 9 and 12%, respectively, which is unacceptable when deciding on a strategy for the procurement of raw materials.

The directions for further research are related to the solution of the discovered problems:

– building a forecast after a structural shift in the absence of sufficient data, which can be solved by the development of methods of interrupted time series to form a scenario for the probable development of the situation.

– the formalisation of the interaction of various types of signals about a possible change in the development of the situation from qualitative and quantitative data.

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