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Contextual Analysis of Financial Time Series

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Abstract: Today, problems of the evaluation of the financial state of small and medium-sized companies are actual. We propose a novel approach for the evaluation of the company financial state, that realized as a module of a decision support system. The proposed component is based on fuzzy logic and knowledge engineering. We present a model of ontology to form the context of data analysis and financial time series modeling. The ontological context allows to represent trends of the analyzed financial state indicators. An expert can add a set of fuzzy rules to the ontology for the creation of the control systems based on the fuzzy inference. The proposed approach allows reducing the time of analysis and interpretation of the results. Experimental results confirm the correctness and effectiveness of the approach proposed in this article.

Keywords: finansial time series; contextual analysis; knowledge base; fuzzy inference

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1. Introduction

We have determined the analysis of the financial time series as a subtask of the company financial state analysis. The major consumer of this development are small and medium-sized companies. Adequate analysis and forecasting of changes in financial indicators trends is relevant for that companies for the following reasons:

- Reducing the number of errors in management decisions.
- More effective resources distribution. Small companies infrequently have abundance resources count.
- Expensive express analysis consulting services are unavailable to small and medium-sized companies.
- Statistical packages for operational analysis and forecasting of time series of financial indicators are expensive for that companies. Also, statistical packages require from managers the qualification in mathematical statistics and significant intellectual and time costs. Existed models and methods for modeling and analyses of time series have high complexity and variety.

Thus, the small and medium-sized companies are required for low-cost and ready-to-use software products for the financial state evaluation, especially an unstable economy.

2. Related Works

Analysis of financial indicators is important for managing various systems [1,3]. This task can be solved based on an analysis of risks and various other factors which influence to the sustainable of company growth and evolution.

Such analysis is based on a variety of approaches. One of the dominant ones is time series analysis, primarily statistical, and also intelligent time series analysis [2]. It is necessary to consider the history of the indicators state [2,3]. Management decisions can be decided to the company financial system and in solving of global management problems.

The following tasks of various nature exist in the financial sector: security issues identifying [7,8], financial audit [9], human resources management [10].

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Currently, the data coming from various payment systems has high heterogeneity. For example: payment processing data, transaction settlement data and many e-commerce platforms that use various payment methods [11,12].

There are many financial planning applications [13]. Users can define financial plans based on personal data [14]. This trend started from the insurance companies needs [15–17], that developed an integrated knowledge-based model for AI-based (artificial intelligence) advisor [18–21] to evaluate stock portfolios and study the negative and positive reactions to portfolio risk management. Also, some applications are used to the mutual fund services evaluation [22].

The following methods are used for the financial data analysis:

- Neural Networks. The paper [9] considers an approach of using an autoencoder to detect unusual entries in a financial transaction log. This approach has an advantage when the data set contains many features, and it is impossible to build simple statistical rules.
- Fuzzy logic methods provide excellent performance comparable or slightly behind neural network models in terms of accuracy. But they outperform all models in terms of explainability. Authors of the paper [23] recommend fuzzy logic methods as a suitable approach for financial services use cases.
- Ensemble learning methods. Modern methods are based on decision trees with gradient boosting. Researchers consider feature selection as important for machine learning models. This not only improves accuracy, but also makes the results more interpretable [24].

There is a need to analyse not only the company indicators in the financial data analysis. It is also important to consider the influence of external objects on the internal company processes. For example, the following studies examine the impact of COVID-19 on the company state [4–6].

The main problem of our research is the creation of an approach that provides a meaningful interpretation of results and based on methods of time series analysis, methods of fuzzy time series modeling, and methods of knowledge engineering. The proposed approach should have the property of adaptation for application for small and medium-sized companies that do not have large arrays of accumulated data. The novelty of the approach is a hybridisation of a time series modeling and knowledge engineering for the financial indicators forecasting and financial state evaluation of a company.

3. Financial Time Series Analysis

Some patterns of behavior of individual objects at specific time intervals can be an indicator for evaluating the state of a system. Also, the preservation of long-term trends at a certain value of the significant indicator can be an indicator of a dangerous situation.

Time series analysis is in constructing a model that describes this series. The resulting model can identify dependencies and can be used for forecasting. However, one of the key points of the analysis is the reflection of the semantic component of the time series.

The semantic interpretation of forecasted trends is important in the financial time series analysis. Semantically important properties are the duration of the trend, intensity, and direction. Expert can formulate statements about technical and financial time series in the following sentences: ”If a long-term intensive growth of some indicator value exists, then ...”, ”If a short small decline in some indicator value exists, then ...”, ”If a long-term stability of some indicator value exists, then ...”. Thus, the problem arises to describe the original series in the specified terms.

The formal model of the time series can be represented as the following expression:

$$TS = \{ts_i\}, i \in N,$$

where $ts_i = [t_i, v_{t_i}]$ is an element of the time series at the moment of time t_i and v_{t_i} is a value.

The proposed approach comprises the following steps:

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1. Identify the piecewise linear trend of the time series by smoothing:
   $Tend_{TS} = Tend(TS), Tend_{TS} = tend_j, j < i.$
   We perform smoothing based on previously developed methods [25].
2. Characterize the levels of trends of a series with semantically significant labels. Experts form the set of labels based on the task conditions. A fuzzy series of trends can be represented as:
   $Tend'_{TS} = Fuzzy(Tend_{TS}).$
3. Forecast the next value of the series trend:
   $tend'_{j+1} = Forecast(Tend_{TS}),$
   where $j + 1$ is the time point for trend forecast.
4. Provide a semantic interpretation of the identified trend and forecast of the time series for the next period based on the knowledge base. This process described in more details in the Section 4.1.

4. Contextual Analysis of Financial Time Series

Our research aims to describe and forecast the financial state of a company by analyzing time series arrays. The task can be divide on the following subtasks:

- Perform identification of the indicators that characterize the financial state of a company. Also, we need to determine the approach for the calculation of the values and trends of company indicators, and the rule set for evaluation of a company state. A list of some indicators is represented in the Table 1. The calculation formulas are based on the values of the regulated financial statements of the Russian Federation: balance sheet (form 1), profit and loss statement (form 2).
- Perform formation of the time series for each of the selected indicators and identify the general trend of each series. This procedure is usually based on the extraction and accumulation of data from databases of information systems of a company. Thus, it is necessary to consider statements of a company for several periods and recalculate the indicators using the formulas.
- Perform evaluation of the financial state of a company using the set of expert rules for the indicators set. Each indicator in the economical context has a specific characteristic of its dynamics and standard value intervals. For example, an increase in the current liquidity ratio has a positive impact on the company financial state, while a decrease has a negative impact. Interval from 1 to 2 is the normal value of this indicator. If the current liquidity ratio is below 1, it is considered that a company does not have enough working capital to cover short-term liabilities. A current liquidity ratio greater than 2 also has a negative impact on the financial condition of the company. A company may invest its funds irrationally and use them ineffectively. It is possible to give a financial state evaluation of a company based on a set of such rules.
- Perform analysis of the current trend and forecast the future trend for each indicator and give interpretation to this forecast based on an economical context. It is needed to know the dynamic of a future state of the indicators to make a correct management decision.

The time series of the selected financial indicators are the input data, and the output data are predicted trends of the selected financial indicators, along with their semantic interpretation.

Table 1. Indicators of a company financial state.

Indicator	Calculation Formula
Current ratio	Current assets/Current liabilities
Quick ratio	(Current assets—Reserve)/Current liabilities
Indebt ratio	Equity/Assets
Cash ratio	Equity/Liabilities
Reserve ratio	Own working capital/ Reserve
Capitalization ratio	Attract capital/Own sources of capital

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4.1. Proposed Rule Base for Financial State Evaluation

The financial state model Φ allows consider the primary indicators of a company. This indicator models allow making predictive and/or descriptive analytics. A set of financial indicators represents any company. Extracting these indicators is possible from the information systems of a company. Some indicators can be calculated based on the values of other indicators. The system of indicators for company financial state evaluation can be considered as a tree. For an I indicator of the proposed model we can express this dependence as $\Phi(I)$.

The dependencies between the model indicators can be described as $\mathbb{D}$. The $\uparrow$ function allows to obtain a set of indicators which values are required to calculate the current indicator if such dependencies are defined. The expression $I^{\mathbb{D}} =\uparrow {}^{l}I$ describes that I is a calculated indicator, and $I^{\mathbb{D}}$ is a set of values for calculation. For two indicators $I, J \in \mathbb{D}$ is defined that I depends on J, which can be written as $I \Rightarrow J$ with $I^{\mathbb{D}} =\uparrow {}^{1}I$. Between indicators may also exist the transitive dependencies $I \Rightarrow \ldots \Rightarrow J \Rightarrow \ldots \Rightarrow K$ when $I^{\mathbb{D}} =\uparrow {}^{l}I$, where $l \geq 2$.

The rules for calculating the indicators are described by the set $\mathbb{R}$. Each rule defines a method for calculating some indicator I considering the dependencies $I^{\mathbb{D}} =\uparrow {}^{1}I$ using arithmetic operations $\mathbb{F} = \langle +, -, \times, \div \rangle$.

The following triplet can represent the rule for calculating the indicators:

$$r = \langle I, \mathbb{A}, I^{\mathbb{D}} \rangle, I^{\mathbb{D}} =\uparrow {}^{1}I, \tag{1}$$

where $I \in \Phi$ is an indicator for calculating the financial state of a company; $\mathbb{A} = \{a_1, a_2, \ldots, a_n\}$ is the set of a rule s, $I^{\mathbb{D}}$ is a set of indicators which needed to calculate the indicator I.

Each atom of the calculation rule can be described as a triplet:

$$a^r = \langle I_i^{\mathbb{D}}, \mathbb{F}_j, I_k^{\mathbb{D}} \rangle,$$

where $I_i^{\mathbb{D}}, I_k^{\mathbb{D}} \in I^{\mathbb{D}}, I^{\mathbb{D}} =\uparrow {}^{1}I, I \Rightarrow I_i^{\mathbb{D}}, I \Rightarrow I_k^{\mathbb{D}}$ are the indicators for calculating the value of the indicator I; $\mathbb{F}_j \in \mathbb{F}$ is an arithmetic operation.

Dependency tree based on $\mathbb{D}$ is used to define the order of the rules execution. Dependency tree also considers transitive dependencies between indicators. Financial state calculation cannot be performed if any rule is missing the required dependencies.

A set of rules $\mathbb{S}$ is used to evaluate the financial state of a company. A each rule from $\mathbb{S}$ defines the condition of some indicator I. It is also possible to build dependencies between indicators for evaluation of a company financial state. The structure of the rule $s \in \mathbb{S}$ is similar to the rule $r \in \mathbb{R}$ (expression 1). The difference between the s and r rules is in the structure of the the s rule atoms:

$$a^s = \langle I_i^{\mathbb{D}}, and, I_k^{\mathbb{D}} \rangle,$$

where the logical operator *and* is used instead of the arithmetic operation. The logical operator *or* is performed by creating additional rules:

$$s_1 \ or \ s_2 \ or \ \ldots \ or \ s_n.$$

Let us consider an example of the proposed approach. We chose Semantic Web technologies as a tool for representing expert knowledge. The OWL 2 language [26] is used to describe the knowledge model. The SWRL language [27] is used to describe the rules. The inference based on the contents of the knowledge base is performed by the Pellet reasoner [28]. The SWRLF reasoner [29] developed by the authors is used to perform fuzzy logic inference.

The Semantic Web technologies allow to reduce the costs of building a knowledge base to solve the problem of evaluation of a company financial state. OWL 2 and SWRL languages and Pellet

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reasoner allows to check the consistency of the ontology content, and obtain new knowledge with the inference. Fuzzy inference allows expert to describe the rules for evaluation the financial state using terms (in verbal form), which allows to reduce the costs of forming a rule base.

We use the $\mathcal{SHOIQF}(\mathcal{D})$ (DL) [30] dialect of description logic (DL) to describe the knowledge model of the proposed knowledge base. Table 2 contains DL operators and axioms for representing the elements of the proposed knowledge base model.

Table 2. DL operators and axioms.

Description	DL	OWL
top (a special class with every individual as an instance)	$\top$	owl:Thing
bottom (an empty class)	$\perp$	owl:Nothing
class inclusion axiom	$A \sqsubseteq B$	A owl:SubClassOf B
disjoint classes axiom	$A \sqcap B \sqsubseteq \perp$	$[A, B]$ owl:DisjointClasses
equivalence classes axiom (or defining classes with necessary and sufficient conditions)	$A \equiv B$	$[A, B]$ owl:equivalentClasses
intersection or conjunction of classes	$A \sqcap B$	A and B
universal restriction axiom	$\forall R.A$	R only A
existential restriction axiom	$\exists R.A$	R some A
cardinality restrictions axiom	$\leq nR.A$	R exactly n A
concept assertion axiom (a is an instance of class A)	$a : A$	a: A
role assertion axiom	$(a, b) : R$	a R b

The $TBox$ terminology of the proposed knowledge base contains a description of the following classes:

- $Finance$ class describes a set of indicators for evaluation of the financial state of a company;
- The $Object$ class describes a company.

The $Finance$ and $Object$ classes are declared disjoint:

$$Finance \sqcap Object \sqsubseteq \perp.$$

An individual cannot belong to several classes at the same time if the classes are declared as disjointed.

Let us consider the indicators classes as an element of the terminology of the proposed knowledge base:

- The $StateIndicators$ class describes a group of indicatoes that are calculated based on numerical indicators from the company balance sheet.
- The $State$ class describes possible states of the company. The state is inferred based on the $StateIndicators$ indicators.

The $StateIndicators$ and $State$ classes are declared as disjointed:

$$StateIndicators \sqcap State \sqsubseteq \perp.$$

The $StateIndicators$ class has the following subclasses:

- $CapitalizationRatio$;
- $CashRatio$;
- $CurrentRatio$;
- $IndebtRatio$;
- $QuickRatio$;
- $ReserveRatio$.

Classes described above correspond to a set of indicators of the financial state of a company from the Table 1. All classes for describing the indicators of the financial state of a company are declared as disjointed:

$$CapitalizationRatio \sqcap CashRatio \sqcap CurrentRatio \sqcap$$
$$\sqcap\ IndebtRatio \sqcap QuickRatio \sqcap ReserveRatio \sqsubseteq \perp.$$

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It is necessary to perform calculations to obtain the values of the financial state indicators of a company. The initial data for the calculation are numerical indicators from the balance sheet of a company. The following properties of the *Object* class are used to consider the values of numerical indicators:

$$
\begin{aligned}
Object \sqsubseteq\ & \exists assets.Double \sqcap \forall assets.Double \sqcap \\
& \sqcap = 1 assets.Double \sqcap \\
& \sqcap \exists attractCapital.Double \sqcap \forall attractCapital.Double \sqcap \\
& \sqcap = 1 attractCapital.Double \sqcap \\
& \sqcap \exists currentAssets.Double \sqcap \forall currentAssets.Double \sqcap \\
& \sqcap = 1 currentAssets.Double \sqcap \\
& \sqcap \exists currentLiabilities.Double \sqcap \forall currentLiabilities.Double \sqcap \\
& \sqcap = 1 currentLiabilities.Double \sqcap \\
& \sqcap \exists equity.Double \sqcap \forall equity.Double \sqcap \\
& \sqcap = 1 equity.Double \sqcap \\
& \sqcap \exists liabilities.Double \sqcap \forall liabilities.Double \sqcap \\
& \sqcap = 1 liabilities.Double \sqcap \\
& \sqcap \exists ownWorkingCapital.Double \sqcap \forall ownWorkingCapital.Double \sqcap \\
& \sqcap = 1 ownWorkingCapital.Double \sqcap \\
& \sqcap \exists reserve.Double \sqcap \forall reserve.Double \sqcap \\
& \sqcap = 1 reserve.Double.
\end{aligned}
$$

Each property of the *Object* class is functional and corresponds to a company balance sheet indicator. *Objects* class properties are used for calculation of the indicators of a company financial state (see Table 1).

The expert formed a SWRL rule ($\in \mathbb{R}$) to calculate the value of the *ownWorkingCapital* property:

$$
\begin{aligned}
& currentAssets(?o, ?ca) \wedge currentLiabilities(?o, ?cl) \wedge \\
& \wedge subtract(?owc, ?ca, ?cl) \rightarrow ownWorkingCapital(?o, ?owc)
\end{aligned} \tag{2}
$$

The rule 2 describes the expression:

$$ownWorkingCapital = currentAssets - currentLiabilities.$$

Also, a set of functional properties is defined for the *Object* class to represent the values of financial state indicators (see table 1):

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$$
\begin{aligned}
& Object \sqsubseteq \exists capitalizationRatio.Double \sqcap \forall capitalizationRatio.Double \sqcap \\
& \quad \sqcap = 1 capitalizationRatio.Double \sqcap \\
& \quad \sqcap \exists cashRatio.Double \sqcap \forall cashRatio.Double \sqcap \\
& \quad \sqcap = 1 cashRatio.Double \sqcap \\
& \quad \sqcap \exists currentRatio.Double \sqcap \forall currentRatio.Double \sqcap \\
& \quad \sqcap = 1 currentRatio.Double \sqcap \\
& \quad \sqcap \exists indebtRatio.Double \sqcap \forall indebtRatio.Double \sqcap \\
& \quad \sqcap = 1 indebtRatio.Double \sqcap \\
& \quad \sqcap \exists quickRatio.Double \sqcap \forall quickRatio.Double \sqcap \\
& \quad \sqcap = 1 quickRatio.Double \sqcap \\
& \quad \sqcap \exists reserveRatio.Double \sqcap \forall reserveRatio.Double \sqcap \\
& \quad \sqcap = 1 reserveRatio.Double.
\end{aligned}
$$

Each of the functional properties described above of forms the $\mathbb{D}$ set.

The calculation of the values of a company financial state indicators is performed in the process of inference. The following SWRL rules from $\mathbb{R}$ set are used to calculate the values of the financial state indicators (see Table 1):

$$
\begin{aligned}
& attractCapital(?o, ?ac) \wedge ownWorkingCapital(?o, ?owc) \wedge \\
& \quad \wedge swrlb : divide(?gr, ?ac, ?owc) \rightarrow capitalizationRatio(?o, ?gr) \\
& equity(?o, ?e) \wedge liabilities(?o, ?l) \wedge \\
& \quad \wedge divide(?wcr, ?e, ?l) \rightarrow cashRatio(?o, ?wcr) \\
& currentAssets(?o, ?ca) \wedge currentLiabilities(?o, ?cl) \wedge \\
& \quad \wedge swrlb : divide(?cr, ?ca, ?cl) \rightarrow currentRatio(?o, ?cr) \\
& equity(?o, ?e) \wedge assets(?o, ?a) \wedge swrlb : divide(?fir, ?e, ?a) \rightarrow indebtRatio(?o, ?fir) \\
& currentAssets(?o, ?ca) \wedge currentLiabilities(?o, ?cl) \wedge reserve(?o, ?r) \wedge \\
& \quad \wedge subtract(?car, ?ca, ?r) \wedge divide(?qr, ?car, ?cl) \rightarrow quickRatio(?o, ?qr) \\
& ownWorkingCapital(?o, ?owc) \wedge reserve(?o, ?r) \wedge \\
& \quad \wedge divide(?rr, ?owc, ?r) \rightarrow reserveRatio(?o, ?rr).
\end{aligned}
$$

The following properties of the *Object* class are used to determine the financial state of a company based on the values of the calculated indicators:

$$
\begin{aligned}
& Object \sqsubseteq \forall hasCapitalizationRatio.CapitalizationRatio \sqcap \\
& \quad \sqcap \forall hasCashRatio.CashRatio \sqcap \\
& \quad \sqcap \forall hasCurrentRatio.CurrentRatio \sqcap \\
& \quad \sqcap \forall hasIndebtRatio.IndebtRatio \sqcap \\
& \quad \sqcap \forall hasQuickRatio.QuickRatio \sqcap \\
& \quad \sqcap \forall hasReserveRatio.ReserveRatio \sqcap \\
& \quad \sqcap \forall hasState.State.
\end{aligned}
$$

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The values of the properties described above are calculated during fuzzy inference using the SWRLF module. The SWRLF module functionality is based on the annotations. Each annotation type is used to define the parameters and settings of the fuzzy inference algorithm [29].

The fuzzy inference consists of the following steps [31,32]:

1. Fuzzification. Fuzzification is used for transition from numerical indicators of object properties to linguistic terms. The values of all input variables are associated with specific linguistic term with some membership value. The input variables for the fuzzyfication are the numerical values of the indicators.
2. Aggregation. A truth degree of antecedents for each rule of $\mathbb{S}$ set is determined at the aggregation stage. If an antecedent of a fuzzy rule contains one atom, then a truth degree of an antecedent is a truth degree of this atom. A truth degree of an atom is calculated based on the membership value of a linguistic term. If an antecedent of a rule contains several atoms, then a truth degree is calculated based on the truth degrees of the antecedent atoms using fuzzy logic operations. The fuzzy logical AND (min) operator is usually used.
3. Activation. A truth degree of each consequent atom of a fuzzy rule is determined at the stage of activation. A truth degree of each consequent atom is equal to the algebraic product of a rule weight and a truth degree of a rule antecedent. If weight of production rule is not specified, then weight is one. Minimum and average functions can be used to calculate truth degree in addition to the algebraic product.
4. Accumulation. A membership function is formed for each linguistic variable from the consequent of a fuzzy rule at the accumulation stage. Accumulation is based on the union of fuzzy sets of all consequent atoms for some linguistic variable.
5. Defuzzification. The result of defuzzification is quantitative (crisp) values for each output linguistic variable based on the results of the accumulation of all output linguistic terms from the consequences of fuzzy rules.

The stages of fuzzy inference can be implemented in various ways. Different bases of fuzzy logic, different approaches to combining sets, different approaches to activation and defuzzification, etc., can be used.

The following properties of the $Object$ class were defined as input variables for the fuzzy inference algorithm using the $fuzzyInputVariable$ annotation:

- $capitalizationRatio$,
- $cashRatio$,
- $currentRatio$,
- $indebtRatio$,
- $quickRatio$,
- $reserveRatio$.

$ABox$ axioms were formed to define linguistic terms for each indicator. For example, for the indicator $CapitalizationRatio$:

$$
\begin{aligned}
&CapitalizationRatio \sqsubseteq \{ \\
&\quad CapitalizationRatioLow, CapitalizationRatioMiddle, CapitalizationRatioHigh \\
&\}.
\end{aligned}
$$

The $fuzzyTerm$ annotation was used to specify the connection between the input variable and corresponding linguistic terms and membership functions. The Table 3 contains the settings for all linguistic terms.

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Table 3. Fuzzy inference settings.

Fuzzy Term	Input Variable	Membership Function
CapitalizationRatioLow	capitalizationRatio	ZShape (0.33, 0.37)
CapitalizationRatioMiddle	capitalizationRatio	Trapezoid (0.35, 0.4, 0.6, 0.65)
CapitalizationRatioHigh	capitalizationRatio	SShape (0.63, 0.7)
CashRatioLow	cashRatio	ZShape (0.08, 0.15)
CashRatioMiddle	cashRatio	Trapezoid (0.1, 0.2, 0.8, 1.0)
CashRatioHigh	cashRatio	SShape (0.9, 1.1)
CurrentRatioLow	currentRatio	ZShape (0.4, 0.8)
CurrentRatioMiddle	currentRatio	Trapezoid (0.6, 1.0, 1.5, 1.9)
CurrentRatioHigh	currentRatio	SShape (1.6, 2.2)
IndebtRatioLow	indebtRatio	ZShape (0.35, 0.45)
IndebtRatioMiddle	indebtRatio	Trapezoid (0.4, 0.5, 0.6, 0.7)
IndebtRatioHigh	indebtRatio	SShape (0.65, 0.8)
QuickRatioLow	quickRatio	ZShape(0.42, 0.84)
QuickRatioMiddle	quickRatio	Trapezoid (0.83, 0.85, 0.87, 0.91)
QuickRatioHigh	quickRatio	SShape (0.9, 1.2)
ReserveRatioLow	reserveRatio	ZShape (0.3, 0.51)
ReserveRatioMiddle	reserveRatio	Trapezoid (0.47, 0.5, 0.57, 0.61)
ReserveRatioHigh	reserveRatio	SShape (0.6, 0.8)

5. Results

Let's consider examples of fuzzy rules generated by an expert for evaluation of the current liquidity ratio(Figure 1):

1. If there is a long-term growth, this allows to talk about a favorable situation at a company.
2. If there is a long or medium decline, this allows to talk about an unfavorable situation at a company.
3. If there is a short intensive decline, this allows to talk about the fact that a company needs to pay more attention to its cash and assets.

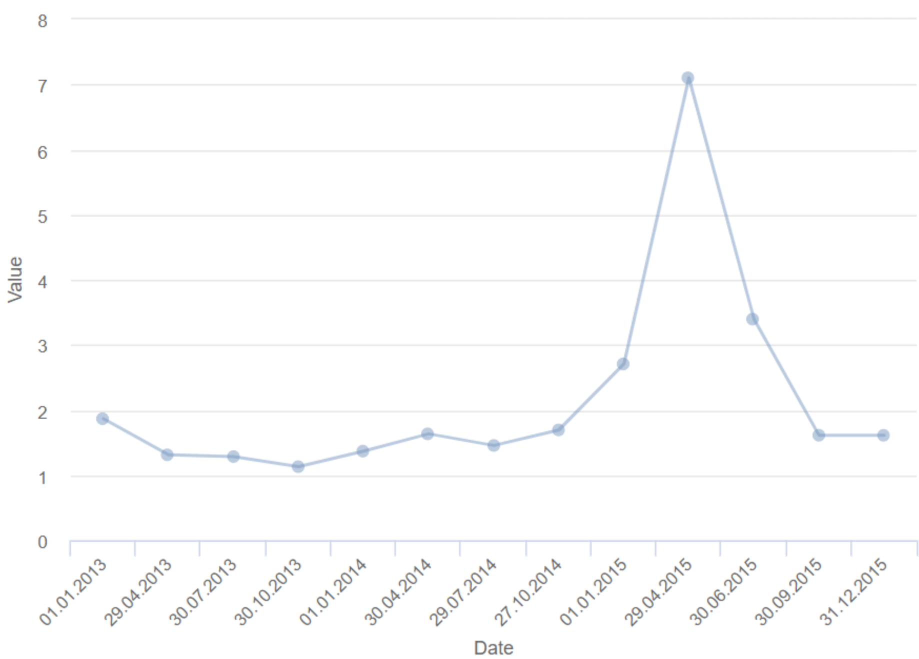

Figure 1. Current liquidity ratio.

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The expert rules presented above were formalized as SWRL rules from the $\mathbb{S}$ set. For example:

$$
\begin{aligned}
&hasCurrentRatio(?o, CurrentRatioLow) \wedge hasQuickRatio(?o, QuickRatioLow) \rightarrow \\
&\quad \rightarrow hasState(?o, StateLow) \\
&\ldots \\
&hasCurrentRatio(?o, CurrentRatioHigh) \wedge hasQuickRatio(?o, QuickRatioMiddle) \wedge \\
&\quad \wedge hasCapitalizationRatio(?o, CapitalizationRatioHigh) \rightarrow hasState(?o, StateHigh) \\
&\ldots \\
&hasCurrentRatio(?o, CurrentRatioMiddle) \wedge hasQuickRatio(?o, QuickRatioMiddle) \rightarrow \\
&\quad \rightarrow hasState(?o, StateMiddle) \\
&\ldots \\
&hasCurrentRatio(?o, CurrentRatioHigh) \wedge hasQuickRatio(?o, QuickRatioHigh) \rightarrow \\
&\quad \rightarrow hasState(?o, StateHigh).
\end{aligned}
$$

Let's consider an example of solving the problem of evaluation of the financial state of a company. Let's define some company as an individual *object* and set the values of its numerical indicators:

$$
\begin{aligned}
&object : Object \\
&(object, 6154721) : currentAssets \\
&(object, 3818380) : currentLiabilities \\
&(object, 7018805) : assets \\
&(object, 7018800) : liabilities \\
&(object, 3818380) : attractCapital \\
&(object, 3622864) : reserve \\
&(object, 3200440) : equity.
\end{aligned}
$$

The values of the following properties of the *object* individuality were calculated after execution the rules from the $\mathbb{R}$ set:

$$
\begin{aligned}
&(object, 2336341) : ownWorkingCapital \\
&(object, 1.63) : capitalizationRatio \\
&(object, 0.46) : cashRatio \\
&(object, 1.61) : currentRatio \\
&(object, 0.46) : indebtRatio \\
&(object, 0.66) : quickRatio \\
&(object, 0.64) : reserveRatio
\end{aligned}
$$

The $\uparrow$ function is already implemented in the SWRL library to calculate dependencies between rules and the order of their execution [33].

The results of the fuzzification stage for the defined input variables are present in the Table 4.

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Table 4. Fuzzification results.

Fuzzy Term	Membership Degree
currentRatio	
CurrentRatioLow	0.0
CurrentRatioMiddle	0.72
CurrentRatioHigh	0.00078
capitalizationRatio	
CapitalizationRatioLow	0.0
CapitalizationRatioMiddle	0.0
CapitalizationRatioHigh	1.0
indebtRatio	
IndebtRatioLow	0.0
IndebtRatioMiddle	0.56
IndebtRatioHigh	0.0
quickRatio	
QuickRatioLow	0.65
QuickRatioMiddle	0.0
QuickRatioHigh	0.0
cashRatio	
CashRatioLow	0.0
CashRatioMiddle	1.0
CashRatioHigh	0.0
reserveRatio	
ReserveRatioMiddle	0.0
ReserveRatioLow	1.0
ReserveRatioHigh	0.1

Next, the aggregation and activation steps were performed. The truth degree for the results of the logical rules were calculated as a result. The following rules have a truth degree value greater than 0:

Degree: 0.65

$$hasCurrentRatio(?o, CurrentRatioMiddle) \wedge hasQuickRatio(?o, QuickRatioLow) \rightarrow$$
$$\rightarrow hasState(?o, StateLow)$$

Degree: 0.00078

$$hasCurrentRatio(?o, CurrentRatioHigh) \wedge hasQuickRatio(?o, QuickRatioLow) \rightarrow$$
$$\rightarrow hasState(?o, StateMiddle).$$

As a result, we have two decisions about the state of a company:

- $StateLow$ with a confidence level of 0.65;
- $StateMiddle$ with a confidence level of 0.00078.

The proposed approach to contextual evaluation of the financial state of a company can calculate the values of some financial indicators. It is necessary to form a set of fuzzy rules to calculate such indicators. Each fuzzy rule may describe the method for calculating a certain indicator based on the data known at the moment. Crisp (numerical) values of indicators unknown at the moment can be calculated in the process of fuzzy inference.

We were to make forecast the time series using the exponential method with an additive trend without a seasonal component to compare the result from the knowledge base (Figure 2).

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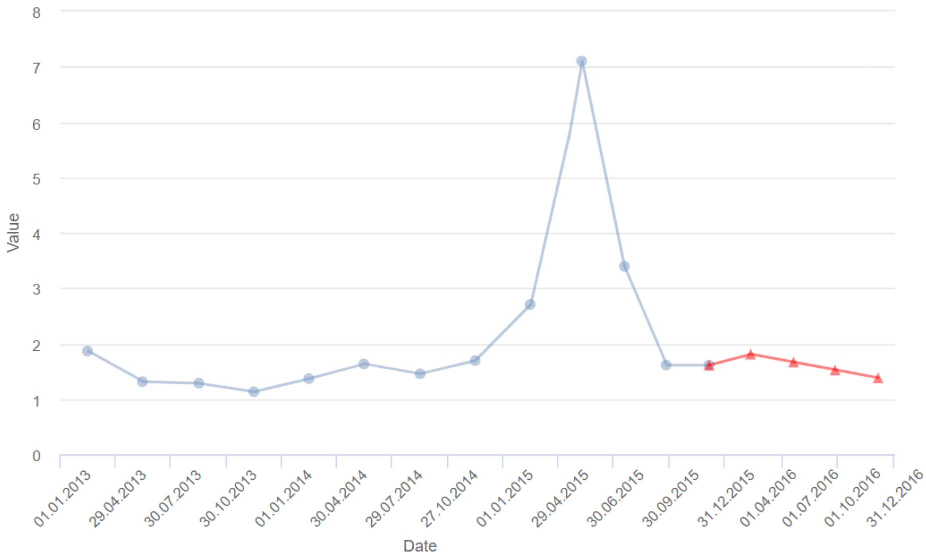

Figure 2. Current Ratio Forecast.

An analysis of the numerical forecast may show that the state of the indicator "current liquidity ratio" is stable. It is difficult to track the economic consequences of random outliers or non-systematic components, considering the history of changes in its dynamics. It is important to consider the expert evaluation and adjust the conclusions on the indicator forecast from the point of view of a company management.

Graphically, this is shown in the Figure 3.

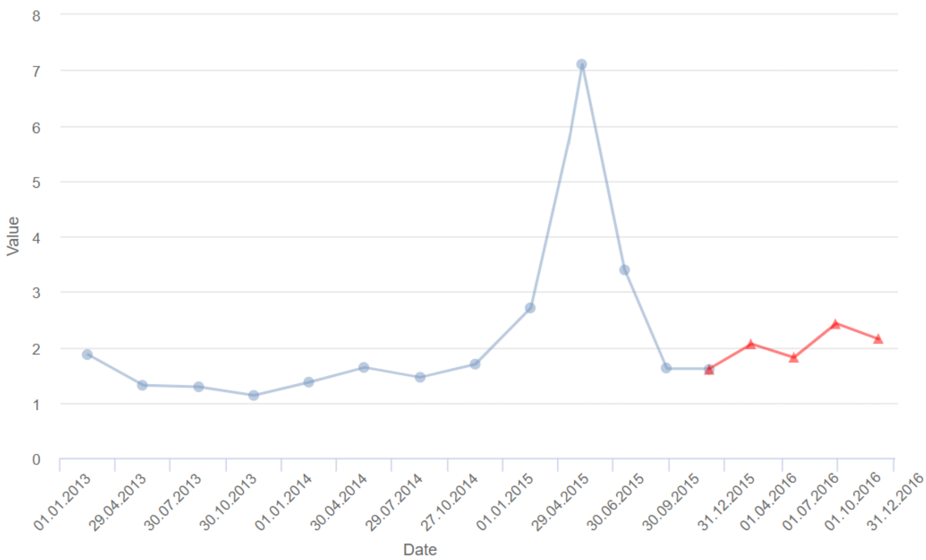

Figure 3. Rule-Based Current Ratio Forecast.

There may be significant discrepancies in indicator evaluation at the model testing stage by SMAPE criterion. The knowledge base allows to build a forecast that more accurately reflects the needs of a company.

The following expression can be used for a balanced approach:

$$forecast = \alpha * ts\_forecast + \beta * kb\_forecast, \tag{3}$$

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where α, β are the weight coefficients of the model components; $forecast$ is a common tendency of a forecast value; $ts\_forecast$ is a tendency of a forecast value based on time series analysys; $kb\_forecast$ is a tendency of a forecast value based on rule base inference.

6. Conclusions

The proposed approach allows to gain in the quality of forecasting time series where the volume of initial information is insufficient. Quantitative indicators characterizing the financial state of a company represent an array of data interesting from the point of research view. Its feature is that the presented indicators represent a system and have obvious dependencies. The main aim of the study is the problem of predictive analytics. This task was solved considering the limitations of small and medium companies: the presence of a short history of changes in financial indicators. The developed two-component forecasting model allows to get higher quality forecasts with comparison to known methods. The limitations of this approach are the need to form or extract the initial rule base. If requirements are established and patterns for expressing management rules are known, then the approach can be easily applied.

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