

Article

Contextual Analysis of Financial Time Series

Nadezhda Yarushkina , Aleksey Filippov *  and Anton Romanov 

Department of Information Systems, Ulyanovsk State Technical University, 32 Severny Venetz Street, 432027 Ulyanovsk, Russia; jng@ulstu.ru (N.Y.); a.romanov@ulstu.ru (A.R.)

* Correspondence: al.filippov@ulstu.ru; Tel.: +7-908-485-8390

Abstract: The evaluation of the financial state of small and medium-sized companies is a pressing issue today. This article introduces a novel method to evaluate a company's financial state, implemented as a module within a decision support system. This component uses fuzzy logic and knowledge engineering methods. The article describes an ontological model that provides the framework for data analysis and financial time-series modeling. The ontological framework simplifies the representation of the trends in the financial indicators under analysis. Integrating an ontology and a set of fuzzy rules makes it possible to develop control systems based on fuzzy inference. This approach provides the analysis and interpretation of results. The experimental results validate the accuracy and effectiveness of the proposed method.

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

MSC: 37M10; 68T30



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1. Introduction

This article describes an approach to the analysis of financial time series as a component of a decision support system to evaluate a company's financial state [1]. The primary users of this development are small and medium-sized companies. Precise analysis and prediction of trends in financial indicators are crucial for these companies for various reasons:

- The need to minimize errors in management decisions.
- The efficiency of resource allocation must be improved, as small companies typically have limited resources.
- Access to expensive consulting services for rapid analysis is often not applicable for small and medium-sized companies.
- Modern statistical software for operational analysis and forecasting of financial time series can be costly. In addition, these tools require managers to have expertise in mathematical statistics and significant intellectual and time investments. The existing models and methods for time-series analysis are complex and varied.

Consequently, small and medium-sized companies need affordable and user-friendly software solutions to evaluate their financial state, particularly in an unstable economic environment.

The application of machine learning methods in this context is challenging, as it complicates the understanding of the analysis and forecasting processes. Moreover, small companies typically lack the data needed to effectively use these methods [2].

2. Related Works

The analysis of financial indicators is crucial to the management of different systems [3,4]. This analysis can be conducted by examining risks and various factors that affect a company's sustainable growth and development.

Different approaches can be used for this analysis. Time-series analysis (both statistical and intelligent) is one of the most prevalent methods [5]. It is necessary to consider the historical context of these indicators [4,5]. Management decisions can then be applied to the company's financial system and broader management challenges.

The financial sector faces a variety of tasks, including identifying security issues [6,7], performing financial audits [8], and managing human resources [9].

Payment data from various systems currently show significant inconsistencies. These include payment processing data, transaction settlement data, and data from various e-commerce platforms that use different payment methods [10,11].

Various financial planning applications exist [12] that allow users to create financial plans based on personal data [13]. This trend originated from the needs of insurance companies [14–16], which developed an integrated knowledge-based model for AI-based advisors [17–20] to evaluate stock portfolios and analyze positive and negative responses to portfolio risk management. In addition, some applications are used to evaluate mutual fund services [21].

The following methods are commonly used for financial data analysis:

- Neural networks. The study in [8] discusses using an autoencoder to identify unusual entries in financial transaction logs. This method is helpful when dealing with datasets that have various features, making it challenging to establish simple statistical rules.
- Fuzzy logic methods. These methods demonstrate performance that is comparable to, or slightly less than, neural network models in terms of accuracy. However, they are excellent in explainability. The authors of [22] recommend fuzzy logic as a suitable approach for financial service applications.
- Ensemble learning methods. Modern approaches frequently use decision trees with gradient boosting. Researchers highlight the importance of feature selection for machine learning models, as it increases accuracy and improves the interpretability of results [23].

It is important to analyze not only the company's indicators in financial data analysis, but also to consider the impact of external factors on internal company processes. For example, several studies have investigated the effects of COVID-19 on company performance [24–26].

The primary focus of our research is to develop an approach that offers a meaningful interpretation of results with time-series analysis, fuzzy time-series modeling, and knowledge engineering methods. This proposed approach should be adaptable for small and medium-sized companies that may lack datasets applicable to machine learning methods. The innovation of this approach lies in the hybridization of time-series modeling and knowledge engineering for forecasting financial indicators and evaluating a company's financial state.

3. Financial Time-Series Analysis

Various behavioral patterns of objects over specific time intervals can be used as indicators to evaluate the state of a system. In addition, the preservation of long-term trends at a particular value of a significant indicator may signal a dangerous situation.

Time-series analysis involves the construction of a model that describes this series. The resulting model can identify dependencies and be used for forecasting. A critical aspect of the analysis is capturing the semantic component of the time series.

In financial time-series analysis, the semantic interpretation of forecast trends is a key point. Significant attributes of the trend include its duration, intensity, and direction. Experts can express knowledge about technical and financial time series with statements like: “If there is a long-term intensive increase in the value of a certain indicator, then ...”, “If there is a short, slight decline in the value of a certain indicator, then ...”, and “If a certain indicator shows long-term stability, then ...”, etc. This raises the challenge of describing the time series in these specified terms.

The formal representation of the time series can be expressed as

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

where $ts_i = [t_i, v_{t_i}]$ indicates an element of the time series at time t_i , with v_{t_i} being the corresponding value.

The proposed approach includes the following steps:

1. Determine the piecewise linear trend of the time series through smoothing [27]:

$$Tend_{TS} = Tend(TS), Tend_{TS} = tend_j, j < i.$$

The smoothed time series can be determined as

$$ts'_t = k * ts_t + (1 - k) * (ts'_{t-1} - T_{t-1}),$$

where ts'_t represents the smoothed value at the current time t ; k is the time-series-smoothing coefficient; ts_t is the current value of the series; ts'_{t-1} denotes the smoothed value from the previous period; $T_{t-1} = b * (ts'_t - ts'_{t-1}) + (1 - b) * T_{t-1}$ indicates the trend value from the previous period; and b is the trend-smoothing coefficient.

The coefficients k and b were selected through a grid search aimed at maximizing forecast accuracy on the test interval of the time series.

2. Label the levels of trends in the time series with semantically meaningful descriptions. The expert creates the set of labels according to the task requirements. A fuzzy representation of the trend series can be expressed as

$$Tend'_{TS} = Fuzzy(Tend_{TS}).$$

3. Predict the following value of the trend series:

$$tend'_{j+1} = Forecast(Tend_{TS}),$$

where $j + 1$ denotes the time point for the trend forecast.

4. Provide a semantic interpretation of the identified trend. Create the forecast for the time series for the upcoming period based on the inference using a knowledge base. Section 4 contains a complete description of this process.

4. Contextual Analysis of Financial Time Series

Our research focuses on describing and predicting a company's financial state through the analysis of time-series data. This task includes the following subtasks:

- Identify the indicators that define a company's financial state. Table 1 presents these indicators. It is also necessary to determine the methodology for the calculation

of indicator values and trends and the criteria to evaluate a company's financial state. The calculation formulas are derived from the values of the regulated financial statements in the Russian Federation: the balance sheet (form 1) and the profit and loss statement (form 2).

- Construct time series for each selected indicator and identify the general trends for each series. This process typically involves extracting and accumulating data from the company's information system databases. Therefore, it is necessary to analyze the company's statements over multiple periods and recalculate the indicators using the established formulas.
- Evaluate the financial state of the company using a set of expert rules adapted to the chosen indicators. Each indicator has unique characteristics regarding its dynamics and standard value ranges. For example, an increase in the current liquidity ratio positively influences the company's financial state, while a decrease adversely affects it. The current liquidity ratio being between 1 and 2 is normal; a value below 1 shows that a company lacks sufficient working capital to meet its short-term debt obligations, whereas a ratio above 2 can also negatively impact the company's financial state, suggesting inefficient use of funds. The company's financial state may be evaluated according to these guidelines.
- Analyze the trend and forecast future trends for each indicator, providing an economic interpretation of these projections. Understanding the expected dynamics of the indicators is crucial for correct management decisions.

The input data include the time series of the selected financial indicators, while the output data include the predicted trends of these indicators, along with their contextual interpretations.

Table 1. Indicators of a company's financial state [28–32].

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 working capital

Proposed Rule Base for Financial State Evaluation

The financial state model Φ enables the evaluation of a company's financial state based on its indicators [28–32]. This model simplifies both predictive and descriptive analytics. A collection of financial indicators characterizes any company, and these indicators can be extracted from the company's information systems. Some indicators can be calculated from the values of other indicators. The system of indicators used to evaluate a company's financial state can be conceptualized as a tree structure. This relationship uses $\Phi(I)$ to denote an indicator I within the proposed model.

The dependencies between the model indicators can be represented as $\mathbb{D}$. The function $\uparrow$ allows for the collection of a set of indicators necessary for calculating the current indicator, provided that such dependencies exist. The expression $I^{\mathbb{D}} = \uparrow^I I$ shows that I is a derived indicator, and $I^{\mathbb{D}}$ includes the values required for its calculation. If two indicators I and J belong to $\mathbb{D}$, it can be said that I depends on J , and represented as $I \Rightarrow J$, with $I^{\mathbb{D}} = \uparrow^I I$. In addition, transitive dependencies may exist for some indicators, such as $I \Rightarrow \dots \Rightarrow J \Rightarrow \dots \Rightarrow K$, where $I^{\mathbb{D}} = \uparrow^I I$, and $l \geq 2$.

The rules regulating the calculation of the indicators are defined by the set $\mathbb{R}$. Each rule specifies a method for computing an indicator I by considering the dependencies $I^{\mathbb{D}} = \uparrow^1 I$, using arithmetic operations from the set $\mathbb{F} = \langle +, -, \times, \div \rangle$.

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

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

where $I \in \Phi$ is an indicator for calculating the company's financial state; $\mathbb{A} = \{a_1, a_2, \dots, a_n\}$ represents the set of rules s ; and $I^{\mathbb{D}}$ describes the set of indicators required 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 $I_i^{\mathbb{D}}, I_k^{\mathbb{D}} \in I^{\mathbb{D}}, I^{\mathbb{D}} = \uparrow^1 I, I \Rightarrow I_i^{\mathbb{D}}, I \Rightarrow I_k^{\mathbb{D}}$ represents the indicators for calculating the value of the indicator I ; and $\mathbb{F}_j \in \mathbb{F}$ is an arithmetic operation.

The dependency tree built from $\mathbb{D}$ defines the order in which the rules are executed. It also considers transitive dependencies among indicators. The calculation of the financial state cannot proceed if any rule lacks the dependencies.

A set of rules $\mathbb{S}$ is used to evaluate a company's financial state. Each rule within $\mathbb{S}$ specifies the condition of a particular indicator I . Additionally, dependencies can be established between indicators to further evaluate the company's financial state. The structure of a rule $s \in \mathbb{S}$ resembles that of a rule $r \in \mathbb{R}$ (as shown in expression (1)). The distinction between the rules s and r lies in the composition of the atoms in the s rule:

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

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

$$s_1 \text{ or } s_2 \text{ or } \dots \text{ or } s_n.$$

Let us explore an example of the proposed methodology. Semantic Web technologies have been selected to represent expert knowledge. The OWL 2 language [33] is used to represent the knowledge model, while the SWRL language [34] is used for rule definition. Inference based on the content of the knowledge base is produced using the Pellet reasoner [35], and the SWRLF reasoner [36] is applied for fuzzy logic inference.

Semantic Web technologies significantly reduce the costs associated with creating a knowledge base to evaluate a company's financial state. The combination of OWL 2, SWRL, and the Pellet reasoner simplifies the verification of ontology consistency and the generation of new knowledge through inference. Fuzzy inference allows experts to define the rules to evaluate the financial state in verbal terms, minimizing the costs related to rule formation.

The *SHOIQF(D)* (DL) [37] dialect of description logic is used to represent the knowledge model of the proposed knowledge base. Table 2 presents the DL operators and axioms used to represent the components of the proposed knowledge base model.

The *TBox* terminology of the proposed knowledge base includes a definition of the following classes:

- The Finance class describes a set of indicators to evaluate of the company's financial state;
- The Object class describes a company.

The Finance and Object classes are declared disjoint:

$$\text{Finance} \sqcap \text{Object} \sqsubseteq \perp.$$

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

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

- The StateIndicators class describes a set of indicators extracted from numerical data found in the company's balance sheet.
- The State class describes potential states of the company. The state is inferred by the StateIndicators indicator.

Table 2. DL operators and axioms [38].

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 StateIndicators and State classes are declared as disjoint:

$$\text{StateIndicators} \sqcap \text{State} \sqsubseteq \perp.$$

The StateIndicators class has the following subclasses:

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

The classes mentioned earlier relate to a set of indicators reflecting a company's financial state, as shown in Table 1. All classes used to characterize these financial indicators are defined as disjoint:

$$\begin{aligned} &\text{CapitalizationRatio} \sqcap \text{CashRatio} \sqcap \text{CurrentRatio} \sqcap \\ &\quad \sqcap \text{IndebtRatio} \sqcap \text{QuickRatio} \sqcap \text{ReserveRatio} \sqsubseteq \perp. \end{aligned}$$

Calculations must be conducted to determine the company's financial state indicators. The starting data for these calculations are the numerical data from the company's balance sheet. The following attributes of the Object class are used to evaluate the values of these numerical indicators:

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

Each property of the Object class is functional and corresponds to a company balance sheet indicator. Object class properties are used to calculate the indicators of a company's financial state (Table 1).

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

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

An SWRL rule consists of two parts: a condition (antecedent) and a conclusion (consequent). The antecedent and consequent of each SWRL rule contain a set of atoms. Each atom is related to an ontology axiom of *TBox* or *ABox*, as well as to a set of variables. The atoms within the rule are joined by the logical operator AND ($\wedge$). The antecedent of Rule (2) is

$$\text{currentAssets}(\text{?o}, \text{?ca}) \wedge \text{currentLiabilities}(\text{?o}, \text{?cl}) \wedge \text{swrlb : subtract}(\text{?owc}, \text{?ca}, \text{?cl})$$

The antecedent of Rule (2) contains the following atoms:

- $\text{currentAssets}(\text{?o}, \text{?ca})$. This atom can be interpreted as: For any individual in the ontology that has the currentAssets property, retrieve the value of that property and assign it to the ?ca variable, while also saving a reference to the individual in the ?o variable.
- $\text{currentLiabilities}(\text{?o}, \text{?cl})$. Comparable to the previous atom, but focused on the currentLiabilities property.
- $\text{swrlb : subtract}(\text{?owc}, \text{?ca}, \text{?cl})$. The swrlb namespace comprises the implementation of arithmetic operations ($\mathbb{R}$). This rule atom computes the result of subtracting the variable ?cl from the variable ?ca, and the resulting value is assigned to the variable ?owc.

A list of values is generated as a result of executing the antecedent of Rule (2). Each item in this list can be expressed as

$$antecedent_i = \langle ?o, ?cl, ?ca, ?owc \rangle,$$

where each individual ?o is assigned the values ?ca and ?cl for the properties currentAssets and currentLiabilities, respectively, along with the result of the subtraction ?owc.

The consequent of Rule (2) contains only one atom:

- ownWorkingCapital(?o, ?owc). This atom should be interpreted as: Create a property called ownWorkingCapital for the individual ?o and assign the value of the variable ?owc to this property.

Therefore, Rule (2) describes the expression

$$\text{ownWorkingCapital} = \text{currentAssets} - \text{currentLiabilities}.$$

Additionally, a set of functional properties has been defined for the Object class to represent the values of financial state indicators (Table 1):

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

Each of the functional properties mentioned above defines the set $\mathbb{D}$.

The values of a company's financial state indicators are calculated through an inference. The calculation is based on the following SWRL rules from the set $\mathbb{R}$ (Table 1):

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

The following properties of the Object class are used to evaluate a company's financial state by analyzing the values of the calculated indicators:

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

The values of the properties mentioned above are calculated through fuzzy inference by the SWRLF module. The functions of the SWRLF module are based on OWL annotations, with each type of annotation setting the parameters and configurations of the fuzzy inference algorithm [36].

Fuzzy inference consists of the following steps [39,40]:

1. **Fuzzification.** This process involves translating numerical indicators of object properties into linguistic terms. Each value of the input variables is associated with a specific linguistic term, along with a corresponding membership value. The input variables for fuzzification are the numerical values of the financial indicators.
2. **Aggregation.** The truth degree for the antecedents of each rule from the $\mathbb{S}$ set is determined during the aggregation phase. This truth degree is calculated using the membership value associated with the linguistic term. The truth degree of an antecedent is equal to the truth degree of an atom if an antecedent of a fuzzy rule comprises a single atom. When an antecedent includes multiple atoms, the truth degree is calculated by applying fuzzy logic operations on the truth degrees of the antecedent atoms, typically using the fuzzy logical AND (min) operator.
3. **Activation.** The truth degree for each consequent atom of a fuzzy rule is determined at the activation stage. This degree is calculated as the algebraic product of the weight of the current rule and the truth degree of its antecedent. In addition to the algebraic product, minimum and average functions can also determine the truth degree. If the weight for a rule is not defined, it defaults to one.
4. **Accumulation.** The accumulation stage involves forming a membership function for each linguistic variable derived from the consequents of activated fuzzy rules. A rule is activated if the truth degree of its consequent is greater than zero. The accumulation process is based on the union of fuzzy sets belonging to all consequent atoms related to a particular linguistic variable.
5. **Defuzzification.** The result of defuzzification yields crisp values for each output linguistic variable, based on the accumulation results of all output linguistic terms from the fuzzy rule consequent. The set of output linguistic variables is determined based on the atoms of the consequent of the activated rules.

The stages of fuzzy inference can be executed through multiple methods. Various fuzzy logic algorithms, various techniques for accumulating sets, and differing strategies for activation and defuzzification can all be used.

The properties of the Object class listed below were labeled as input variables for the fuzzy inference algorithm using the fuzzyInputVariable annotation:

- capitalizationRatio;
- cashRatio;
- currentRatio;

- indebtRatio;
- quickRatio;
- reserveRatio.

Specific *ABox* axioms were used to describe linguistic terms for each indicator. For example, regarding the indicator *CapitalizationRatio* this is as follows:

CapitalizationRatioLow: CapitalizationRatio
 CapitalizationRatioMiddle: CapitalizationRatio
 CapitalizationRatioHigh: CapitalizationRatio
 $\text{CapitalizationRatio} \sqsubseteq \{$
 CapitalizationRatioLow, CapitalizationRatioMiddle, CapitalizationRatioHigh
 $\}$.

The fuzzyTerm annotation was used to define the relationship between the input variable and its associated linguistic terms and membership functions. The settings for all linguistic terms are presented in Table 3.

Table 3. Fuzzy inference settings [28–32].

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

Here are some examples of fuzzy rules created by an expert to evaluate the current liquidity ratio (Figure 1):

1. Long-term growth indicates a positive situation for the company.
2. A long- or medium-term decrease indicates a negative situation for the company.
3. A short and intense decrease signifies that the company should focus more on its reserves and assets.

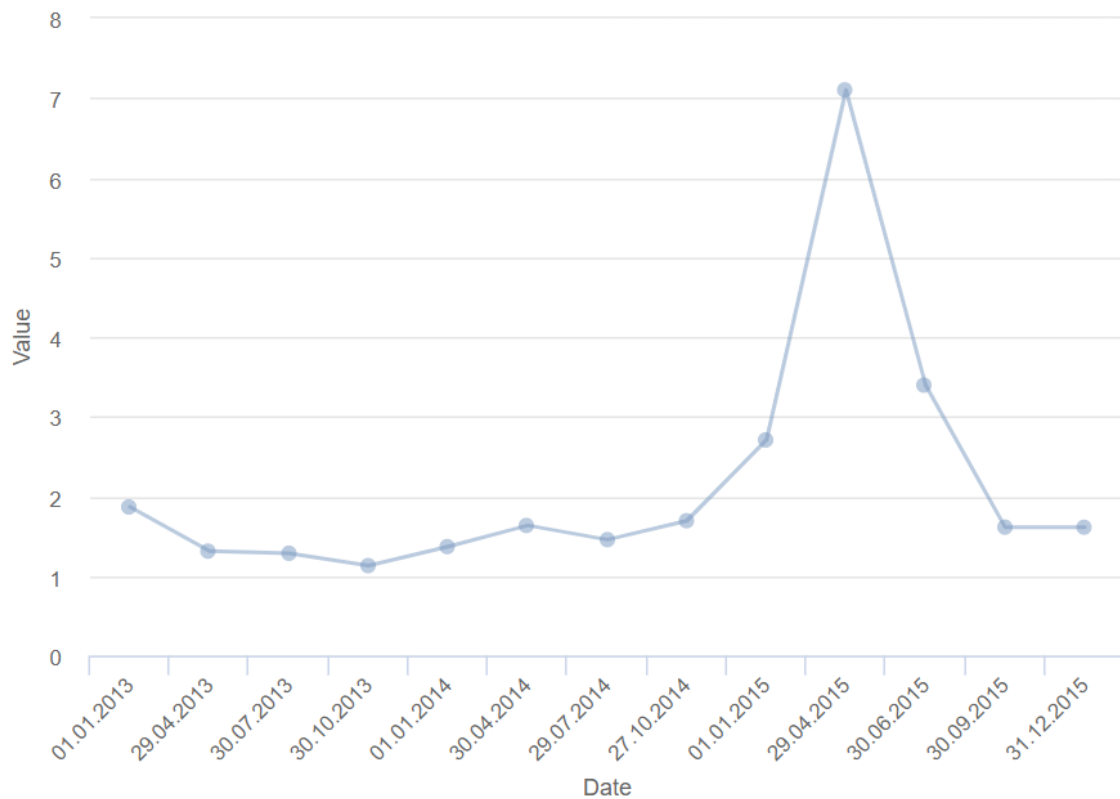


Figure 1. Current liquidity ratio.

The expert rules from the $\mathbb{S}$ set were formalized as the following SWRL rules [28–32]:

```

hasCurrentRatio(?o, CurrentRatioLow) ∧ hasQuickRatio(?o, QuickRatioLow) →
    → hasState(?o, StateLow)
hasCurrentRatio(?o, CurrentRatioMiddle) ∧ hasQuickRatio(?o, QuickRatioLow) →
    → hasState(?o, StateLow)
hasCurrentRatio(?o, CurrentRatioLow) ∧ hasQuickRatio(?o, QuickRatioMiddle) →
    → hasState(?o, StateLow)
hasCurrentRatio(?o, CurrentRatioMiddle) ∧ hasQuickRatio(?o, QuickRatioMiddle) →
    → hasState(?o, StateMiddle)
hasCurrentRatio(?o, CurrentRatioMiddle) ∧ hasQuickRatio(?o, QuickRatioHigh) →
    → hasState(?o, StateMiddle)
hasCurrentRatio(?o, CurrentRatioHigh) ∧ hasQuickRatio(?o, QuickRatioMiddle) →
    → hasState(?o, StateMiddle)
hasCurrentRatio(?o, CurrentRatioLow) ∧ hasQuickRatio(?o, QuickRatioHigh) →
    → hasState(?o, StateLow)
hasCurrentRatio(?o, CurrentRatioHigh) ∧ hasQuickRatio(?o, QuickRatioLow) →
    → hasState(?o, StateMiddle)

```

$$\begin{aligned}
& \text{hasCurrentRatio}(?o, \text{CurrentRatioHigh}) \wedge \text{hasQuickRatio}(?o, \text{QuickRatioHigh}) \rightarrow \\
& \quad \rightarrow \text{hasState}(?o, \text{StateHigh}) \\
& \text{hasCurrentRatio}(?o, \text{CurrentRatioHigh}) \wedge \text{hasQuickRatio}(?o, \text{QuickRatioMiddle}) \wedge \\
& \quad \wedge \text{hasCapitalizationRatio}(?o, \text{CapitalizationRatioHigh}) \rightarrow \text{hasState}(?o, \text{StateHigh}) \\
& \text{hasCurrentRatio}(?o, \text{CurrentRatioMiddle}) \wedge \text{hasQuickRatio}(?o, \text{QuickRatioHigh}) \wedge \\
& \quad \wedge \text{hasCapitalizationRatio}(?o, \text{CapitalizationRatioHigh}) \rightarrow \text{hasState}(?o, \text{StateHigh}) \\
& \text{hasCurrentRatio}(?o, \text{CurrentRatioHigh}) \wedge \text{hasQuickRatio}(?o, \text{QuickRatioMiddle}) \wedge \\
& \quad \wedge \text{hasCashRatio}(?o, \text{CashRatioHigh}) \rightarrow \text{hasState}(?o, \text{StateHigh}) \\
& \text{hasCurrentRatio}(?o, \text{CurrentRatioMiddle}) \wedge \text{hasQuickRatio}(?o, \text{QuickRatioHigh}) \wedge \\
& \quad \wedge \text{hasCashRatio}(?o, \text{CashRatioHigh}) \rightarrow \text{hasState}(?o, \text{StateHigh}).
\end{aligned}$$

Let us take an example of evaluating a company's financial state. Define a specific company as an individual object of the Object class and set the values for its numerical indicators:

```

object: Object
(object, 6154721): currentAssets
(object, 3818380): currentLiabilities
(object, 7018805): assets
(object, 7018800): liabilities
(object, 3818380): attractCapital
(object, 3622864): reserve
(object, 3200440): equity.

```

The values of the properties related to the individual object were determined after applying the rules from the $\mathbb{R}$ set:

```

(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.

```

The SWRL library has already implemented the $\uparrow$ function to control dependencies among rules and determine their execution order [41].

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

Table 4. Fuzzification results.

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

Next, the steps of aggregation and activation were executed. Consequently, the truth degree of the consequent of the logical rules was calculated. The following rules have a truth degree value of the consequent greater than 0:

Truth degree: 0.65

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

Truth degree: 0.00078

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

Consequently, two conclusions can be inferred based on the company's state:

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

The proposed approach for contextual evaluation of a company's financial state can compute various financial indicators. To achieve this, a set of rules must be defined to calculate these indicators. Each rule can describe the calculation method for a specific indicator based on the currently available data. A set of fuzzy rules must be created to evaluate a company's financial state. The crisp values of indicators that are not known at the moment can be calculated with fuzzy inference.

Figure 2 illustrates the time series forecast using the Holt exponential method with an additive trend, which does not include a seasonal component, compared to the forecast based on the knowledge base fuzzy inference (Figure 3).

An analysis of the numerical forecast might reveal that the "current liquidity ratio" indicator is stable. However, it is challenging to identify the economic impacts of random outliers or non-systematic factors given the historical fluctuations in its dynamics. Therefore, it is crucial to deal with expert evaluations and clarify the conclusions regarding the indicator forecast from the perspective of company management.

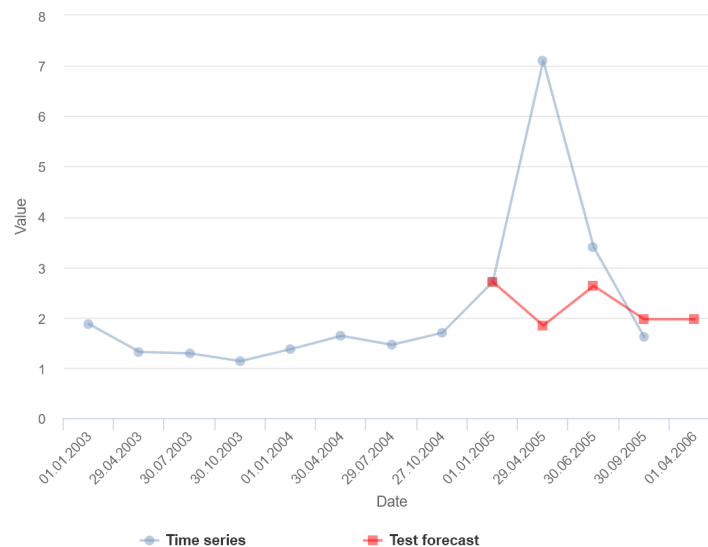


Figure 2. Current liquidity ratio forecast based on Holt method.

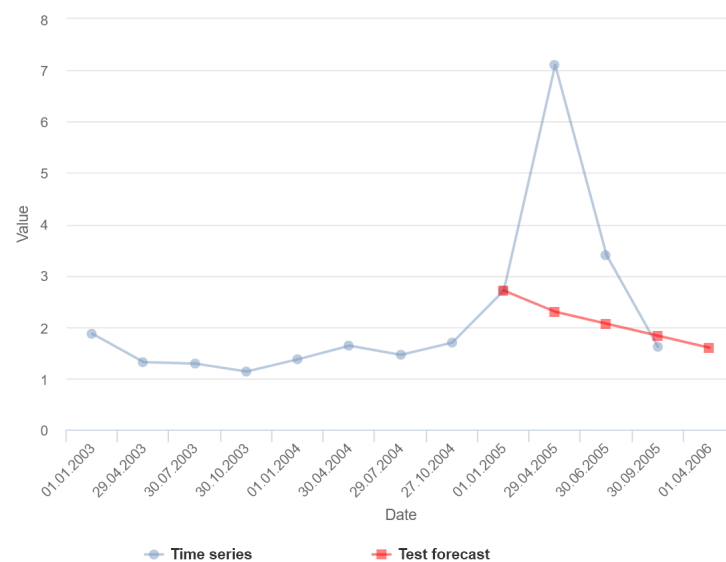


Figure 3. Current liquidity ratio rule-based forecast.

As shown in Figures 2 and 3, there can be notable differences in indicator evaluation during the model testing phase with the SMAPE criterion. The knowledge base creates forecasts that more accurately reflect the indicator behavior. Thus, the SMAPE estimation for the forecast shown in Figure 2 is 36%, and for Figure 3 it is 33%.

The following expression represents a balanced approach to forecasting:

$$forecast = \alpha * ts_forecast + \beta * kb_forecast, \quad (3)$$

where α and β are the weighting coefficients for the model components. In this context, *forecast* indicates the overall trend in the forecast value, *ts_forecast* reflects the trend derived from time-series analysis, and *kb_forecast* represents the trend based on rule-based inference.

6. Conclusions

The proposed approach improves the quality of forecasting time series, particularly when there is a lack of enough data for analysis. Quantitative indicators that define a company's financial state represent data that are interesting for research. These indicators

describe a system and have obvious dependencies. The main aim of the study is the problem of predictive analytics, especially for small and medium-sized companies, which often have limited historical data on financial indicators. The two-component forecasting model developed in this research provides forecasts with higher quality compared to traditional methods. However, the limitations of this approach are the necessity of forming the rule base.

The results of ten experiments show that the proposed method achieves an average forecast quality of 12.8% according to the SMAPE criterion, compared to 16.2% for forecasts using exponential smoothing techniques. The forecasting task faced limitations for short time series, with an inability to extract periodic components, making it challenging to apply more advanced statistical and neural network models.

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