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Enhancing Decision Support for Resource Allocation Through Markov Chain-Based Receivables Forecasting: A Robustness Analysis Using Monte Carlo Simulation*

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Abstract

Efficient resource allocation by individuals, firms, and society represents one of the central issues in economic theory and practice. The achievement of economic objectives depends on the ability to allocate scarce resources under uncertainty. Receivables collection forecasting contributes to more efficient and lower-risk resource allocation by supporting decisions regarding the future allocation of corporate assets. This study develops and applies a forecasting framework based on an absorbing Markov chain model, complemented by a Monte Carlo robustness analysis, to estimate collection probabilities, expected collection times, and projected cash inflows from receivables over both short- and long-term horizons. The proposed approach enables the quantification of collection dynamics and provides additional information for financial planning and investment decisions. The findings indicate that reliable receivables forecasting can improve asset allocation efficiency and reduce decision-making risk, thereby supporting improvements in corporate profitability.

Keywords: *accounts receivables forecasting, decision-making, energy industry, Markov chains, Monte Carlo simulation*

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1. Introduction

The early decades of the twenty-first century were characterized by increased market volatility and uncertainty, which heightened the risks associated with corporate resources allocation (Best, 2010; Bilan et al., 2019; Reinhart & Rogoff, 2009). The forecasting of financial indicators serves as a critical mechanism for ensuring market sustainability and enhancing the quality of managerial decision-making processes (Stanojević et al., 2017; Shmueli et al., 2019). In accordance with fundamental economic principles, economics examines how individuals, companies, and societies allocate their limited resources, which must be used efficiently because of their scarcity (Mankiw, 2021).

The allocation of a firm's limited resources is closely related to both short-term and long-term receivables, which are generated through the sale of goods and services (Hill et al., 2010; García-Teruel & Martínez-Solano, 2010). The allocation of limited capital is enhanced by forecasting the total amount of receivables expected to be collected or written off in the future (Keyser et al., 2025). Consequently, forecasting the dynamics of collectible and uncollectible receivables supports more effective investment decision-making processes and contributes to improved business performance (Aktas et al., 2015; Keyser et al., 2025).

The distinction between deterministic and stochastic processes is essential to predictive modelling and decision-making under current market conditions (Janssen at al., 2013; Ross, 2014; Grimmett & Stirzakar, 2020). Deterministic models cannot adequately represent stochastic processes because they do not account for inherent randomness (Rüschendorf, 2023). The evolution of variables according to predictable pattern belongs to the domain of deterministic processes (Ross, 2014; Jansssen et al., 2013). In contrast, stochastic processes involve inherent uncertainty, and their evolution cannot be predicted with certainty (Laurence, 2017).

Predictive modelling may be based on discrete or continuous time. Stochastic processes include both discrete and continuous variables (Bas, 2019). Markov processes have been applied to predict variable behaviour over discrete or continuous intervals (Gagniuc, 2017). Forecasting variable trends supports more informed and lower-risk decision-making (Stojić et al., 2019). Accounts receivable from customers play a crucial role in firms' liquidity and working capital management (Hill et al., 2010; Yao & Deng, 2018). The company's liquidity is largely determined by the collectability of these receivables (Michalski, 2008). Thus, the analysis of receivables as a balance sheet item becomes both a subject of theoretical economics and a critical component of the decision-making process (García-Teruel & Martínez-Solano, 2010).

Receivables collection is influenced not only by internal managerial decisions but also by external market factors encountered by individuals and firms (Bougheas et al., 2009; Ferenčak et al., 2018). The process of allocating limited company resources is enhanced through accurate forecasting and effective management of receivables (Tangsucheeva & Prabhu, 2014). Efficient resource management directly contributes to the optimization of a firm's profitability (Maritan & Lee, 2017). Accordingly, this study develops an absorbing Markov-chain model to estimate future collection probabilities, expected collection times, and receivables collectability, thereby supporting more efficient resource allocation and corporate decision-making.

2. Theoretical background

The theoretical background of this research is grounded in the concept of Markov chains, relevant scientific theories, and applied forecasting models. This section outlines the proposed conceptual framework and research hypotheses. It also provides a theoretical overview of the application of Markov models to forecast the collectability of corporate receivables. The fundamental assumptions underlying Markov processes are discussed, as these must be satisfied to ensure robust forecasting of balance sheet positions and to support more accurate and insightful financial analysis.

Markov chains represent an idealized structure that effectively captures the relationship between different variables (Bäuerle & Rieder, 2011). These models are stochastic in nature because future transitions are governed by probability distributions rather than deterministic rules (Pardoux, 2008; Meyn & Tweedie, 2012). The proposed models are based on current probabilities to predict the realization of future movements in the values of the observed variables (Levin & Peres, 2017). The core principle of Markov processes is that future changes in variable values depend solely on their current values, without reference to past values (Tolver, 2016). The analysis and prediction of future variable movements are carried out based on the current values of those variables, without consideration of their historical trajectories (Davis, 2018). By applying Markov models and interpreting the resulting data, corporate decision-makers are able to support strategic choices that significantly influence the short-term operational success of the company (Nguyen, 2018; Tian & Shen, 2019). Variations in balance sheet positions and the overall effectiveness of business policies depend heavily on managerial proactivity and the ability to accurately forecast the collectability of receivables over the short- and long-term horizons (Aktas et al., 2015; Keyser et al., 2025). To support future investment decisions and enhance the quality of financial planning, this study develops a predictive model to estimate the future collectability of firm receivables.

The receivables position in the balance sheet includes the categories of *internal account collections* and *delivery of value*. Internal collections include advance payments to suppliers, salary advances, short-term investments, and advance payments of liabilities owed by the company (Kang et al., 2019; Kieso et al., 2025). The receivables position is observed in the balance sheet and is defined as an accounting term for money owed to a company for goods and services previously delivered, but not yet paid for (Kieso et al., 2025). The measure of a company's business success is reflected in the value of individual positions in the balance sheet and the income statement (Rutkowska-Ziarko & Pyke, 2017). Return on assets (ROA), return on investment (ROI), and return on equity (ROE) are widely used profitability measures for evaluating financial performance and firm value (Tantra et al., 2019). Enhancing the decision-making process and improving the allocation of resources are supported through forecasting the total collectability of receivables or the potential need for their write-off (Omerašević & Selimović, 2020; Zdeněk et al., 2024). Markov process modelling represents an effective method for forecasting the collectability of corporate receivables (Keyser et al., 2025). Corporate receivables management policies should be adapted to changes in firms' operating and financial environments, including customer credit risk and financing conditions (Michalski, 2008; Bougheas et al., 2009; Hill et al., 2010). Namely, receivables management requires monitoring of credit terms, accounts receivable levels, and financing conditions to support liquidity and efficient working capital management (Bougheas et al., 2009; García-Teruel & Martínez-Solano, 2010).

Decision-making based on intuition is reduced through more precise forecasting of the future movements of financial variables (Tenyakov, 2014). To predict future states of the system, current probabilities of receivables collection are calculated. Given the dynamic nature of the system, a transition probability matrix is formed, with element values calculated to represent transitions between time intervals (Sericola, 2013). The rows and columns of the transition probability matrix correspond to possible system states and reflect how the system evolves over time. A fundamental assumption of the Markov chain is that the various states of the observed system are mutually exclusive. Accordingly, the system can occupy only one state at any given moment and cannot exist in multiple states simultaneously (Grimshaw & Alexander, 2011).

Here is an overview of the basic assumptions underlying Markov models for reliable forecasting and financial analysis (Norris, 1998; Ross, 2014; Kulkarni, 2016):

1) The state of the system at a given time depends solely on its state at the immediately preceding time point.

2) There is a finite and identifiable set of possible system states, which serves as the basis for constructing the forecasting model.

3) The states of the observed system are mutually exclusive, implying that the system can occupy only one state at any given time.

4) The transition probability matrix, which is specific to each Markov chain, is assumed to be stationary, meaning that it remains constant throughout the observed period.

Since the early 20th century, a significant number of studies have examined the application of Markov processes in finance and theoretical economics (Douc et al., 2018). Financial forecasting is conducted over both discrete and continuous time intervals, based on the analysis of current financial indicators (Davis, 2018). Depending on the nature of the time dimension, different types of Markov processes are distinguished. Markov chains are classified into two groups: discrete time and continuous-time Markov chains (Levin & Peres, 2017; Rüschendorf, 2023).

According to Sericola (2013), discrete-time Markov processes include models such as Random Walks on the Number Axis and the Gambler's Ruin problem. In contrast, continuous-time Markov processes include models such as Brownian Motion and the Poisson Point Process (Morozov & Skripkin, 2011). These models have found broad application across a range of scientific disciplines, including ecology, biology, chemistry and physics (Walter, 2021).

Based on the previously discussed theoretical concepts, and in alignment with the subject matter of this scientific research, the following research hypotheses are proposed:

> H1: *Forecasting the future movement of corporate receivables using an absorbing Markov-chain model, completed by Monte Carlo simulation, improves managerial decision-making and enhances the efficiency of resource allocation processes.*
>
> H2: *The application of predictive models for estimating the collectability of corporate receivables contributes to reducing risk in decisions regarding the future allocation of investment capital.*

In this study, two hypotheses are proposed and will be tested primarily using the absorbing Markov-chain model, while Monte Carlo simulation is employed as a complementary robustness analysis. The focus of this research is based on the premise that the application of economic-mathematical models to predict the collectability of corporate receivables reduces managerial decision-making risk and mitigates subjectivity in investment decisions. The research aims to test the thesis that the application of economic-mathematical models for forecasting corporate receivables enhances the decision-making process and optimizes resource allocation in future business cycles.

3. Mathematical definition of Markov models

This section provides an economic-mathematical definition of Markov processes, outlining the essential elements required for the construction of the proposed model. The development of the Markov model involves calculating the Markov transition probability matrix, which serves as the fundamental component of the Markov chain. Therefore, the prediction of the future states of corporate receivables is conducted based on the current state of the system and the values contained in the transition probability matrix.

The theoretical framework assumes that, for the purposes of determining the initial and future states of a Markov process, the system is represented by state vectors defined in a precisely specified form (Davis, 2018). The symbol S(t) is used for the state vector of the system at period t, while the symbol $S_n(t)$ refers to the state of the system in a future period. The state of the system in the initial period for predicting future system states is determined through the system state vector in period t, as well as the probabilities of transitioning to one of the n possible states (Bäuerle & Rieder, 2011).

$$\mathrm{S(t)} = (\mathrm{S_1(t)}, \mathrm{S_2(t)}, \mathrm{S_3(t)}, \mathrm{S_4(t)}, \dots, \mathrm{S_n(t)}) \tag{1}$$

To describe transitions from the current to the future state of the system over two consecutive periods, a Markov transition probability matrix is constructed (Gagniuc, 2017). The probability of transitioning from one state of the system to another determines the values of the matrix elements (Levin & Peres, 2017). The matrix is denoted by the symbol (T). Matrix (T) represents the conditional probability of transitioning from the current state to the future state during the period (t, t + 1). The Markov transition probability matrix (T) constitutes the fundamental element of the Markov chain (Grimshaw & Alexander, 2011):

$$\mathrm{T} = \begin{bmatrix} T_{11} & T_{12} & T_{13} & T_{14} & \dots & T_{1n} \\ T_{21} & T_{22} & T_{23} & T_{24} & \dots & T_{2n} \\ T_{31} & T_{32} & T_{33} & T_{43} & \dots & T_{3n} \\ T_{41} & T_{42} & T_{43} & T_{44} & \dots & T_{4n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ T_{n1} & T_{n2} & T_{n3} & T_{n4} & \dots & T_{nn} \end{bmatrix} \tag{2}$$

The Markov transition probability matrix (T) contains all the probabilities of the system transitioning between different states in the initial and future periods (Bäuerle & Rieder, 2011). The probabilities on the main diagonal (T_{11}, T_{22}, T_{33}, T_{44}, ..., T_{nn}) indicate the probability that the system remains in the same state after the end of the period (t, t + 1).

The probabilities within the rows of the matrix (T_{n1}, T_{n2}, T_{n3}, T_{n4}, ..., T_{nn}) and the probabilities within the columns of the matrix (T_{1n}, T_{2n}, T_{3n}, T_{4n}, ..., T_{nn}) refer to the probabilities of transitions between system states during the period (t, t + 1).

The main diagonal of the Markov transition probability matrix contains the probabilities that the system remains in the same state, while the sum of the probabilities in each row is equal to one. Thus, the transition probability matrix satisfies the normalization condition (Grimshaw & Alexander, 2011).

$$\sum_{f=1}^{n}(T_{cf} = 1) \qquad \text{for each } c = 1,2,3,4, ..., n$$
$$0 \le T_{cf} \le 1 \tag{3}$$

The current state of the system and the values of the Markov transition probability matrix are used to predict future system states (Hirsa & Neftci, 2013):

$$\begin{aligned} S_{(t+1)} &= S_{(t)}T \\ S_{(t+2)} &= S_{(t+1)}T = S_{(t)}T^2 \\ S_{(t+3)} &= S_{(t+2)}T = S_{(t)}T^3 \\ &\dots \\ S_{(t+L)} &= S_{(t+(L-1))}T = S_{(t)}T^L \end{aligned} \tag{4}$$

The process of predicting future states of a system does not require information about the past values of the variables. Instead, predictions are made based on the current state of the system (Tolver, 2016). Therefore, the equilibrium state of the system is determined by multiplying the system state vector and the Markov transition probability matrix (T):

$$S(E) = S(E)T \tag{5}$$

In the empirical part of the research, the equilibrium state of the system is determined using a system of equations and the Markov transition probability matrix (T) (Ross, 2014; Kulkarni, 2016; Stojić et al., 2019):

$$(E) = \big(S_1(E), S_2(E), S_3(E), S_4(E), \dots, S_n(E)\big)T$$
$$\big(S_1(E), S_2(E), S_3(E), S_4(E), \dots, S_n(E)\big)\begin{bmatrix} T_{11} & T_{12} & T_{13} & T_{14} & \cdots & T_{1n} \\ T_{21} & T_{22} & T_{23} & T_{24} & \cdots & T_{2n} \\ T_{31} & T_{32} & T_{33} & T_{34} & \cdots & T_{3n} \\ T_{41} & T_{42} & T_{43} & T_{44} & \cdots & T_{4n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ T_{n1} & T_{n2} & T_{n3} & T_{n4} & \cdots & T_{nn} \end{bmatrix} = \tag{6}$$
$$(S_1(E), S_2(E), S_3(E), S_4(E), \dots, S_n(E))$$

If the previously presented system of equations for “$S_j(E)$” is simplified, its solution yields the equilibrium state of the system:

$$S_j(E) = S_j$$

$$S_1 = S_1T_{11} + S_2T_{21} + S_3T_{31} + S_4T_{41} + \ldots + S_nT_{n1}$$

$$S_2 = S_1T_{12} + S_2T_{22} + S_3T_{32} + S_4T_{42} + \ldots + S_nT_{n2}$$

$$S_3 = S_1T_{13} + S_2T_{23} + S_3T_{33} + S_4T_{43} + \ldots + S_nT_{n3}$$

$$S_4 = S_1T_{14} + S_2T_{24} + S_3T_{34} + S_4T_{44} + \ldots + S_nT_{n4}$$

$$\ldots$$

$$S_n = S_1T_{1n} + S_2T_{2n} + S_3T_{3n} + S_4T_{4n} + \ldots + S_n T_{nn}$$

subject to the following condition:

$$\sum_{j=1}^{n} S_J = 1 \tag{7}$$

Based on the set of equations for S_j and a precisely defined transition probability matrix, the equilibrium state of the system is determined (Tolver, 2016). The final result is calculated using the Markov chain model. The current and future states of the system are identified, as well as the probabilities of transitioning from the current to the future state of the system (Tian & Shen, 2019).

In the next iteration, the current state of the system is transformed through the Markov transition probability matrix to determine the future system state. According to Siekelova et al. (2019), the results of Markov processes are represented by the probabilities of transitions between different system states, while their analysis leads to the determination of the equilibrium-state probabilities and predictions of future receivables collectability.

This section has presented the mathematical formulation of the absorbing Markov chain model has been presented to predict the direction and intensity of changes in the value of corporate receivables in future periods. The collectability and non-collectability of receivables are estimated using the Markov transition probability matrix, the fundamental Markov matrix, and the absorption probability matrix. Therefore, the Markov model provides an analytical framework for supporting managerial decision-making and improving resource allocation under uncertainty.

4. Methodology and data

This section presents the sampling methods and data collection process, along with the key methodological tools used in this study. The analytical framework section is based on an absorbing Markov-chain model, while Monte Carlo simulation is employed as a complementary robustness analysis. The development of the analytical Markov-chain model begins with the construction of the transition probability matrix, followed by the formation of the fundamental matrix and the calculation of the absorption probability matrix. Based on the elements of the resulting matrices, forecasts of the collectability of corporate receivables are generated for future periods.

4.1. Sampling methods and data collection process

The empirical part of this research is based on data collected from the balance sheets of a leading company in the field of electrification, automation, and digitalization. The selected company holds a dominant market position in the production of energy-efficient technologies designed to support the conservation of natural resources. A review of the financial statements indicates that the company has a significant market share in the production and transmission of electricity across different countries. The company is headquartered in Berlin, Germany, and operates in more than 190 countries, with approximately 377,000 employees (Siemens AG, 2017). The company pursues competitive advantage by adapting its marketing strategy to local market conditions while maintaining a globally consistent brand identity (Zou & Cavusgil, 2002). The company maintain its market position through investments in research and development, frequent product innovations, and a strong focus on product quality, improved decision-making, and efficient resource allocation (Barney, 1991; Teece, 2007).

For the empirical analysis, the analytical model is constructed using the financial results of one of the company's subsidiaries operating within the Serbian energy sector. Forecasting the amount of receivables to be collected and the subsequent allocation of company assets are carried out based on the balance sheet positions representing the current state of the system through the application of the absorbing Markov-chain model (Davis, 2018). The decision-making process and resource allocation based solely on current balance sheet positions and insights from financial statements are often insufficient for effective managerial decision-making (Collier, 2015). The probability of receivables collection and the Markov transition probability matrix represent the key elements required for the development of an economic-mathematical model (Hirsa & Neftci, 2013).

In the subsequent methodological stage of the research, the fundamental matrix and the absorption probability matrix are derived. Based on the estimated transition probabilities, the transition probability matrix is constructed (Grimshaw & Alexander, 2011). The estimated transition probabilities constitute analytical basis for the absorbing Markov-chain model. The complete set of transition probabilities is used to construct the analytical Markov-Chain model, whereas the transition probabilities directly associated with receivables collection are subsequently employed as input parameters in the Monte Carlo robustness analysis.

Table 1: Overview of the estimated transition probabilities used in the Markov chain model

Receivables from domestic customers		Symbol	Probability
Probabilities of receivables collection within one year from domestic customers			
1.	Probability of receivables collection within one year	T_{51}	23%
2.	Probability of non-collection of receivables within one year	T_{52}	18%
Probabilities of receivables collection over one year from domestic customers			
3.	Probability of receivables collection over one year	T_{61}	38%
4.	Probability of non-collection of receivables over one year	T_{62}	12%
Receivables from foreign customers		Symbol	Probability
Probabilities of receivables collection within one year from foreign customers			
1.	Probability of receivables collection within one year	T_{73}	28%
2.	Probability of non-collection of receivables within one year	T_{74}	15%
Probabilities of receivables collection over one year from foreign customers			
3.	Probability of receivables collection over one year	T_{83}	36%
4.	Probability of non-collection of receivables over one year	T_{84}	14%

Note: Foreign customers - customers located in foreign markets to whom the company exports and sells its products

Source: Authors' calculation based on the financial statements obtained from the Serbian Business Registers Agency (SBRA)

The probabilities of receivables collection from domestic and foreign customers over short- and long-term horizons, together with the probabilities of receivables retention and transitions between receivables due within one year and those due after more than one year, constitute the elements of the transition probability matrix (Table 2). Based on the probabilities presented in Tables 1 and 2, a transition probability matrix is constructed, and its elements are used to forecast the amount and temporal dynamics of receivables collection for the selected company.

Table 2: Retention and transition probabilities between receivables due within one year and receivables due after more than one year

Domestic customer receivables		Symbol	Probability
Retention and transition probabilities of domestic customer receivables			
1.	Retention of receivables up to one year	T_{55}	18%
2.	Transition from receivables up to one year to receivables over one year	T_{56}	41%
3.	Retention of uncollected receivables over one year	T_{66}	50%
Foreign customer receivables		Symbol	Probability
Retention and transition probabilities of foreign customer receivables			
1.	Retention of receivables up to one year	T_{77}	15%
2.	Transition from receivables up to one year to receivables over one year	T_{78}	43%
3.	Retention of uncollected receivables over one year	T_{88}	50%

Notes: *Data are derived from the annual financial statements obtained from the Serbian Business Registers Agency (SBRA) and are based on the balance sheet items reported as receivables from domestic customers due within one year, receivables from foreign customers due within one year, receivables from domestic customers due after one year, and receivables from foreign customers due after one year

**Foreign customers refer to customers located in foreign markets to whom the company exports and sells its products

Source: Authors' calculation of retention and transition probabilities based on the financial statements obtained from the Serbian Business Registers Agency (SBRA)

In the first part of the methodological framework, forecasting of receivables collection from domestic and foreign customers will be conducted through the construction of the Markov transition probability matrix (T_{ij}), the fundamental matrix (F) and the absorption probability matrix (K). Based on this approach, an absorbing discrete Markov-chain model with a finite state space is defined, and the Markov transition probability matrix (T_{ij}) is specified.

A discrete Markov chain is defined as a stochastic process (Norris, 1998; Gallager, 2013; Kulkarni, 2016):

$$\{X_t\}_{t\geq 0} \tag{8}$$

where the random variable X_t represents the state of the system at time t, with a finite state space (Norris, 1998; Gallager, 2013; Ross, 2014):

$$S = \{S_1, S_2, \cdots, S_8\} \tag{9}$$

Such a process is characterized by the following Markov-chain model property (Norris, 1998; Ross, 2014):

$$P(X_{t+1} = j \mid X_t = i, X_{t-1}, \ldots, X_0) = P(X_{t+1} = j \mid X_t = i) \quad (10)$$

which implies that the future state of the system depends solely on the current state of the system, while previous states have no influence on the distribution of future state transitions (Gallager, 2013; Ross, 2014). More precisely, the conditional probability of transition from the current state to a future state is influenced only by the current state of the system, while previous states are not taken into account (Kulkarni, 2016).

The transition probability matrix of the model is defined as follows:

$$T = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ T_{51} & T_{52} & T_{53} & T_{54} & T_{55} & T_{56} & T_{57} & T_{58} \\ T_{61} & T_{62} & T_{63} & T_{64} & T_{65} & T_{66} & T_{67} & T_{68} \\ T_{71} & T_{72} & T_{73} & T_{74} & T_{75} & T_{76} & T_{77} & T_{78} \\ T_{81} & T_{82} & T_{83} & T_{84} & T_{85} & T_{86} & T_{87} & T_{88} \end{bmatrix}$$

where each element of the transition matrix represents a conditional transition probability defined by the following expression (Norris, 1998; Ross, 2014):

$$T_{ij} = P(X_{t+1} = j \mid X_t = i) \quad (11)$$

where (T_{ij}) denotes the probability of transition from system state (i) to system state (j) during a single time period (Norris, 1998; Kulkarni, 2016).

In constructing the Markov transition probability matrix, the following condition applies to each individual row of the matrix:

$$\sum_{j=1}^{8} T_{ij} = 1 \quad (12)$$

which implies that the normalization condition requires the sum of all possible transitions from one system state to all posible future states to be equal to one. Furthermore, the Markov transition probability matrix is a matrix of conditional probabilities (Norris, 1998; Ross, 2014). Following the construction of the Markov transition probability matrix, each row of the matrix is analyzed to estimate the collectability of customer receivables, and identify the risk of receivables transitioning into categories with longer maturities, and assess the probability of uncollectible receivables (Norris, 1998; Kulkarni, 2016).

The fifth row of the Markov transition probability matrix (T_{ij}) specifies the transition probabilities of short-term domestic customer receivables with maturities of up to one year. Its elements represent the probabilities of collection, retention within the same category, or transition to receivables with longer maturities. The sixth row of the Markov transition probability matrix (T_{ij}) specifies the transition probabilities of short-term foreign customer receivables with maturities of up to one year. The elements of this row represent the probabilities of collection of short-term foreign customer receivables or their transition to receivables with longer maturities. The seventh row of the Markov transition probability matrix (T_{ij}) specifies the transition probabilities of domestic customer receivables with maturities exceeding one year. The elements of the seventh row represent the probabilities of retention within the same receivables category or transition to the category of uncollectible receivables. The eighth row of the Markov transition probability matrix (T_{ij}) specifies the transition probabilities of long-term foreign receivables, including retention within the same category or transition to uncollectible receivables.

Using the transition probability matrix (B), the fundamental matrix is defined as follows (Kemeny & Snell, 1976; Norris, 1998):

$$F = (I - B)^{-1} \tag{13}$$

Alternatively, the fundamental matrix can be expressed as an infinite series:

$$F = I + B + B^2 + B^3 + \cdots \tag{14}$$

The condition for the existence of the fundamental matrix is defined as:

$$\rho(B) < 1 \tag{15}$$

where ρ(B) denotes the spectral radius of matrix (B) (Kulkarni, 2016).

The elements of the fundamental matrix are defined as:

$$n_{ij} = \mathbb{E}[\text{number of visits to state } S_j \mid X_0 = S_i] \tag{16}$$

where (n_{ij}) denotes the expected number of visits to the transient state (S_j) prior to absorption, given that the process starts in state (S_i) (Norris, 1998; Kulkarni, 2016).

The vector of expected absorption times is defined by the following expression:

$$t = F1 \tag{17}$$

where:

$$1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \tag{18}$$

The individual elements of the expected absorption time vector are expressed as follows (Grinstead & Snell, 2012; Kulkarni, 2016):

$$t_i = \sum_j n_{ij} \tag{19}$$

where t_i denotes the expected number of steps until absorption, given that the process starts in state (S_i). Based on the fundamental matrix, the absorption probability matrix is determined (Kemeny & Snell, 1976; Grinstead & Snell, 2012):

$$K = F \cdot A \tag{20}$$

where the matrix is obtained as the product of (F) and (A), with (A) containing transition probabilities from transient to absorbing states (Kulkarni, 2016).

To examine the robustness of receivables collection forecasts for domestic and foreign customers with maturities up to and over one year, Monte Carlo simulation is employed as a complementary stochastic analysis (Selto, 2020; Li, 2023).

The analytical Markov-chain model and the Monte Carlo simulation serve different methodological purposes. While the analytical model estimates the expected receivables collection by incorporating the complete transition matrix together with the absorption probabilities, the Monte Carlo simulation is based on the key transition probabilities associated with receivables collection (Glasserman, 2004; Selto, 2020). The Monte Carlo simulation is not intended to reproduce the complete Markov-chain process. Instead, it evaluates the variability of receivables collection outcomes under stochastic realizations of the selected transition probabilities.

The Monte Carlo simulation is performed using a 95% confidence interval and 10,000 simulation iterations. As input data, transition probabilities (T_{51}) and (T_{61}), together with the estimated receivables collected over a two-year period, are used for domestic customers. The same approach is applied to foreign customers using transition probabilities (T_{73}) and (T_{83}), together with the estimated receivables collected over the same period. The resulting empirical collection intervals provide a complementary assessment of the robustness of the analytical findings under stochastic variation in the selected transition probabilities.

4.2. Measurement

This section presents the methodological framework used to estimate the collectability of corporate receivables through the application of an absorbing Markov-chain model. Based on the estimated transition probabilities (T_{ij}), the Markov transition probability matrix is constructed and subsequently used to derive the fundamental matrix and the absorption probability matrix:

$$T = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0.23 & 0.18 & 0.00 & 0.00 & 0.18 & 0.41 & 0 & 0 \\ 0.38 & 0.12 & 0.00 & 0.00 & 0 & 0.50 & 0 & 0 \\ 0.00 & 0.00 & 0.28 & 0.15 & 0 & 0 & 0.15 & 0.43 \\ 0.00 & 0.00 & 0.36 & 0.14 & 0 & 0 & 0 & 0.50 \end{bmatrix} \text{(Transition Probability Matrix)}$$

The transition probability matrix is partitioned into the identity matrix (I), the transient-state transition matrix (B), and matrix (A), which contains the transition probabilities from transient to absorbing states.

$$I = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad B = \begin{bmatrix} 0.18 & 0.41 & 0 & 0 \\ 0 & 0.50 & 0 & 0 \\ 0 & 0 & 0.15 & 0.43 \\ 0 & 0 & 0 & 0.50 \end{bmatrix} \quad A = \begin{bmatrix} 0.23 & 0.18 & 0 & 0 \\ 0.38 & 0.12 & 0 & 0 \\ 0 & 0 & 0.28 & 0.15 \\ 0 & 0 & 0.36 & 0.14 \end{bmatrix}$$

The matrix difference (I – B) is given by:

$$I - B = \begin{bmatrix} 0.82 & -0.41 & 0.00 & 0.00 \\ 0.00 & 0.50 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.85 & -0.43 \\ 0.00 & 0.00 & 0.00 & 0.50 \end{bmatrix} \tag{21}$$

The fundamental matrix (F) is calculated as the inverse of the matrix difference between matrices (I) and (B):

$$F = (I - B)^{-1} \tag{22}$$

The resulting fundamental Markov matrix is obtained by substituting matrices (I) and (B) into Equation (22):

$$F = \left(\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} - \begin{bmatrix} 0.18 & 0.41 & 0 & 0 \\ 0 & 0.50 & 0 & 0 \\ 0 & 0 & 0.15 & 0.43 \\ 0 & 0 & 0 & 0.50 \end{bmatrix} \right)^{-1} \tag{23}$$

The resulting fundamental Markov matrix is presented in Equation (24):

$$\text{Fundamental Markov matrix (F)} = \begin{bmatrix} 1.21 & 1 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 1.17 & 1 \\ 0 & 0 & 0 & 2 \end{bmatrix} \tag{24}$$

The absorption probability matrix (K) is obtained by multiplying the fundamental matrix (F) by matrix (A), where matrix (A) contains the transition probabilities from transient to absorbing states:

$$\mathrm{K} = \mathrm{F} * \mathrm{A} \tag{25}$$

The resulting absorption probability matrix is:

$$\text{Absorption probability matrix (K)} = \begin{bmatrix} 0.66 & 0.34 & 0 & 0 \\ 0.76 & 0.24 & 0 & 0 \\ 0 & 0 & 0.69 & 0.31 \\ 0 & 0 & 0.72 & 0.28 \end{bmatrix} \tag{26}$$

where each element K_{ij} satisfies $0 \leq K_{ij} \leq 1$, and represents the probability of eventual absorption into absorbing state (j), given that the process starts from transient state (i).

The first two rows of matrix (K) describe the absorption probabilities for receivables from domestic customers. Receivables due within one year are expected to be collected with a probability of 66%, whereas the probability of non-collection of receivables from domestic customers is 34%. For receivables with maturities exceeding one year, the estimated collection probability increases to 76%, whereas the probability of non-collection decreases to 24%.

The last two rows of matrix (K) present the absorption probabilities for receivables from foreign customers. Receivables due within one year are expected to be collected with a probability of 69%, while the probability of non-collection is 31%. For receivables from foreign customers with maturities exceeding one year, the probability of collection is estimated at 72%, whereas the probability of non-collection equals 28%.

5. Results and discussions

This section provides the results of the empirical analysis. The analytical findings obtained from the absorbing Markov-chain model are first presented, followed by a complementary Monte Carlo robustness analysis. The Markov-chain model provides the principal forecasts of receivables collectability, whereas the Monte Carlo simulation offers an additional assessment of the robustness of these forecasts under stochastic variation in the selected transition probabilities. The analysis continues by estimating the collectability of corporate receivables through the absorption probability matrix, which provides the probabilities of receivables collection within one year and beyond one year (Tian & Shen, 2019). Further analysis is conducted for receivables from domestic and foreign customers (Grimshaw & Alexander, 2011). Based on the financial statements of a company in the Serbian energy sector, the future probabilities of receivables collection and non-collection are estimated for domestic and foreign customers using the current balance sheet positions (Davis, 2018).

According to the company's annual financial report, obtained from the database of the Serbian Business Registers Agency (SBRA), the average receivables collection time was 89.25 days during 2021-2022. The company achieved strong business results, with an average receivables collection time of 73.12 days during 2020-2021. The elements of the fundamental matrix and the absorption probability matrix are used to predict the expected collection period for receivables from domestic customers and foreign customers. A comparative analysis is then performed to evaluate the difference between the observed average collection period and the expected collection period estimated by the Markov-chain model.

Table 3: Expected time required to collect receivables from both domestic and foreign customers

	Expected receivables collection	Period expressed in years and days	
Type of receivables	Time period for receivables collection	Number of years	Number of days
Receivables due within 1 year-domestic customers	1.219018717	1	79.94
Receivables over 1 year - domestic customers	2	2	
Receivables due within 1 year-foreign customers	1.176328116	1	64.35
Receivables over 1 year - foreign customers	2	2	

Source: Author's calculation, based on QM for Windows v5

The values presented in Table 3 indicate that receivables from domestic customers with a maturity of up to one year are expected to be collected within approximately one year and 80 days, with an estimated collection probability of 66%. Simultaneously, 34% of receivables are expected to remain uncollected and may subsequently be reclassified into the category of receivables with a maturity exceeding one year. Therefore, the obtained results suggest that a portion of short-term receivables may transition into the category of long-term receivables.

Receivables from domestic customers with a maturity exceeding one-year exhibit one year a collectability probability of 76% and an expected collection period of two fiscal years. Meanwhile, the estimated probability of non-collection is 24%, indicating that a proportion of receivables may remain outstanding for periods exceeding two years. The obtained findings provide useful information for managerial decision-making concerning future receivables management and resource allocation.

Regarding receivables from foreign customers, the results indicate that receivables with a maturity of up to one year are expected to be collected approximately one year and 64 days, with a collection probability of 69%. At the same time, 31% of receivables from foreign customers are expected to remain uncollected and may subsequently be transferred into the category of receivables with a maturity exceeding one year.

Receivables from foreign customers with a maturity exceeding one year demonstrate a collection probability of 72% and an expected collection period of two years, while the estimated probability of non-collection amounts to 28%. The obtained results indicate the existence of both collectible and non-collectible receivables within foreign markets, emphasizing the importance of forecasting receivables collection dynamics for reducing uncertainty in future business activities. The findings also provide additional support for managerial decision-making regarding the management and collection of outstanding receivables from foreign customers.

The empirical analysis further shows that receivables from domestic customers amounting to 2,440,687 thousand RSD are expected to be collected in the amount of 1,696,482 thousand RSD over short- and long-term periods, while the estimated uncollectible portion equals 744,205 thousand RSD. Additionally, receivables from foreign customers amounting to 258,900 thousand RSD are expected to be collected in the amount of 181,543 thousand RSD, whereas the uncollectible portion is estimated at 77,357 thousand RSD over both short- and long-term periods.

The empirical analysis requires a systematic classification of corporate receivables based on the customer type, collection status, and maturity structure. The categories used in the empirical analysis are presented in Table 4.

Table 4: Classification of corporate receivables by category and customer type

	Categories of company receivables	Obligation fulfilment
1	Collected receivables from domestic customers	yes
2	Uncollected receivables from domestic customers	no
3	Collected receivables from foreign customers	yes
4	Uncollected receivables from foreign customers	no
5	Receivables with a maturity of up to one year from domestic customers	less < 1
6	Receivables with a maturity over one year from domestic customers	more > 1
7	Receivables with a maturity of up to one year from foreign customers	less < 1
8	Receivables with a maturity over one year from foreign customers	more > 1

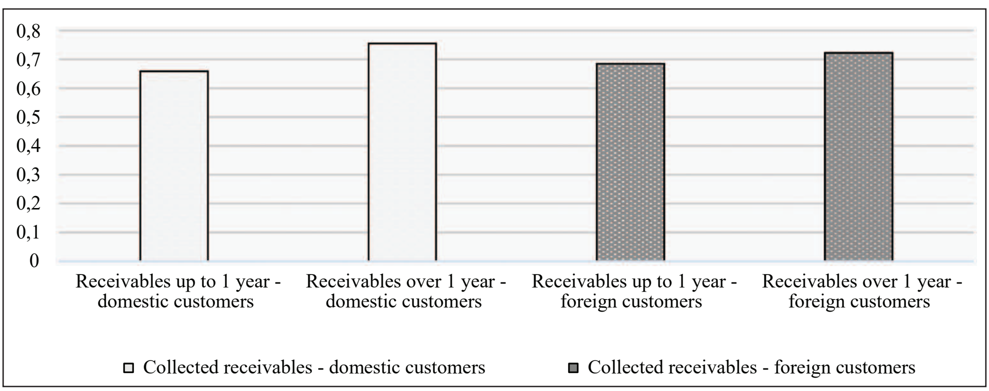
Source: Authors' classification of receivables by category based on financial statements, obtained from the Serbian Business Registers Agency (SBRA)

In the continuation of the research, the vector v represents receivables collected within one year and receivables collected after one year, while the matrix K represents the absorption probability matrix. If the final results of the research are denoted by R, then the following matrix expression is obtained:

$$\text{Absorption probability matrix (K)} = \begin{bmatrix} 0.66 & 0.34 & 0 & 0 \\ 0.76 & 0.24 & 0 & 0 \\ 0 & 0 & 0.69 & 0.31 \\ 0 & 0 & 0.72 & 0.28 \end{bmatrix}$$

$$\text{R} = \text{Vektor } (v) * \text{Absorption probability matrix (K)} \tag{27}$$

Figure 1: Receivables Collection Forecasts from Domestic and Foreign Customers



Note: The figure presents a comparison of receivables collection from domestic and foreign customers for receivables due within one year and receivables due after more than one year.

Source: Authors' elaboration

The analysis of the results obtained from the matrix (R), which reflects the degree of collectability of receivables in the future period, provides the following implications:

For domestic customers, the balance sheet item representing receivables due within one year amounts to 1,519,421 thousand RSD. The model predicts that receivables from domestic customers in the amount of 1,000,698 thousand RSD will be collected, while 518,723 thousand RSD is expected to remain uncollectible. Receivables from domestic customers with a maturity exceeding one year amount to 921,266 thousand RSD, of which 695,784 thousand RSD is expected to be collected beyond one year, while 225,482 thousand RSD is estimated to remain uncollectible.

For foreign customers, receivables with a maturity of up to one year amount to 147,161 thousand RSD. The obtained results indicate that 100,080 thousand RSD of receivables from foreign customers will be collected within this period, while 46,361 thousand RSD is expected to remain uncollectible. Furthermore, receivables from foreign customers with a maturity exceeding one year amount to 111,739 thousand RSD, of which 80,742 thousand RSD is forecast to be collected beyond one year, whereas 30,997 thousand RSD will remain uncollectible.

By modelling the receivables collection rate, managers may more accurately forecast the total resources available for future allocation. Consequently, forecasting cash flow dynamics through receivables collection contributes to more efficient allocation of limited company resources and supports managerial decision-making. As a complementary robustness analysis, Monte Carlo simulation was applied to evaluate the variability of receivables collection outcomes under stochastic realizations of the selected collection probabilities. The simulation was not intended to reproduce the complete analytical Markov-chain model but to assess the variability of receivables collection outcomes under stochastic realizations of the selected transition probabilities.

The forecasting of the receivables collection interval was conducted using Monte Carlo simulation, incorporating a 95% confidence level. The simulation was based on the transition probabilities of 23% for receivables due within one year and 38% for receivables due beyond one year. The resulting empirical distribution of simulated collection outcomes produced an estimated collection interval ranging from 1,640,722 thousand RSD to 1,644,764 thousand RSD.

The forecasting of the collection interval for receivables from foreign customers was also conducted using Monte Carlo simulation with a 95% confidence level. The simulation was based on the transition probabilities of 28% for receivables due within one year and 36% for receivables due beyond one year. The resulting empirical distribution of simulated collection outcomes produced an estimated collection interval ranging from 174,066 thousand RSD to 174,468 thousand RSD.

To examine the accuracy of forecasting balance sheet positions, the company's operational results were analysed using financial reports published during 2022 and 2023. The predictive validity of the developed model was tested by comparing the forecasted values against the company's balance sheet and income statement data for the two fiscal years following the forecast period.

According to the financial reports for 2022, the company collected receivables from domestic customers due within one year amounting to 1,084,438 thousand RSD. The financial reports for 2023 indicate that receivables collected from domestic customers due beyond one year amounted to 1,750,108 thousand RSD. Furthermore, the company's 2022 financial reports indicate that receivables collected from foreign customers due within one year amounted to 154,474 thousand RSD.

The company's financial statements for 2023 indicate that the observed company collected receivables from foreign customers in the amount of 186,494 thousand RSD due beyond one year. The predictive validity of the developed analytical model was evaluated by comparing the forecasted and actual receivables collection values.

For the forecast of receivables collection from domestic and foreign customers beyond one year, the accuracy of the model was validated within a deviation margin of +/– 3%. Similarly, the forecast accuracy for receivables due within one year from both domestic and foreign customers was confirmed within a deviation margin of +/– 5%. Therefore, these results support the conclusion that inputting current balance sheet data into the developed mathematical model enables reliable prediction of future balance sheet positions. This approach demonstrates its applicability across firms operating in the market.

The forecasting results regarding the collectability of customer receivables over short- and long-term horizons, obtained through the application of the absorbing Markov-chain model and the complementary Monte Carlo robustness analysis, can be compared with findings reported in the existing literature. The results provide a basis for discussing similarities and differences relative to previously developed forecasting models.

The mid-twentieth century witnessed the emergence of pioneering studies applying Markov chains to forecast the collectability of customer receivables. In their study, Cyert et al. (1962) developed an absorbing Markov chain for estimating expected losses arising from uncollectible receivables in a retail company. In contrast to managers' intuitive assessments, the authors proposed an approach based on transition probabilities between different receivables aging categories. The proposed model was based on the stability of the transition matrix and represented one of the earliest applications of Markov chains in receivables management. Corcoran (1978) developed receivables collection and cash inflow models through the application of Markov transition matrices. The study demonstrated that payment patterns serve as a basis for forecasting receivables collection. In addition, the empirical analysis was based on estimated transition probabilities between receivables states, with particular emphasis on forecasting cash inflows (Corcoran, 1978).

The application of Markov processes in finance expanded during the 1980s and 1990s through the modelling of receivables states and credit risk. These models employ homogeneous transition matrices to explain the probabilities of customers moving between different payment categories (short-term and long-term) or delinquency states. Such findings contributed to improving receivables collection forecasting, credit policy management, and corporate credit risk control. Kallberg and Saunders (1983) applied Markov chains to analyse the behaviour of revolving credit customers by modelling transitions between repayment and indebtedness states. The results indicate that repayment patterns and account characteristics predict future borrower behaviour. Building on these findings, subsequent studies incorporated borrower heterogeneity, improving the predictive performance of Markov models in credit risk assessment and receivables collection forecasting.

Over the last two decades, the methodological framework of this research area has expanded through the use of time-inhomogeneous transition matrices, the incorporation of macroeconomic factors, and simulation techniques. Some studies have employed Bayesian methods to estimate transition matrices and forecast transitions between repayment and delinquency states (Grimshaw & Alexander, 2011). Other studies have applied discrete Markov chains to quantify collection activities in consumer lending. The results indicate that collection activities influence transition probabilities between account states and shape borrower repayment behaviour (He et al., 2015). Among recent studies, Keyser et al. (2025) applied an absorbing discrete Markov chain with five transient and two absorbing states: collected and written-off receivables. Using balance sheet data on receivables, they constructed a transition probability matrix was constructed to estimate collection probabilities and the expected time to receivables resolution.

The findings of this research are consistent with earlier studies that recognize Markov processes as an effective approach to modelling receivables collection (Cyert et al., 1962; Kallberg & Saunders, 1983). It should be emphasized that earlier studies relied primarily on analytical estimates derived from transition matrices, whereas the present research complements the analytical Markov-chain model with a Monte Carlo robustness analysis to evaluate the variability of receivables collection outcomes under stochastic realizations of the selected transition probabilities. Therefore, this research builds upon studies that combine Markov-chain models for forecasting borrower behaviour patterns with simulation methods for assessing receivables collectability, as demonstrated by Baynes et al. (2023). However, unlike more complex credit risk assessment models, the proposed approach is adapted to the evaluation of corporate receivables collectability, with lower procedural complexity and fewer data requirements.

A multi-stage methodology integrating several analytical procedures is employed in this research. In the first stage, an absorbing Markov chain is used to estimate transition probabilities and receivables collectability. Subsequently, Monte Carlo simulation is applied as a complementary robustness analysis to construct confidence intervals for the simulated collection outcomes. One of the distinctive features of this research relates to the implementation of the empirical analysis, which is not based on a single corporate portfolio but on four distinct categories. The first dimension of segmentation classifies customers into domestic and foreign customers, while the second dimension classifies receivables into receivables due within one year and receivables due after more than one year. Such segmentation enables a more comprehensive analysis of the probability of receivables collection from domestic and foreign customers, as well as the time required for receivables to be collected, transition to another state, or ultimately to be classified as uncollectible receivables.

A limitation of this research relates to the insufficient transparency of corporate financial reporting. Specifically, corporate financial reports are publicly available only for a limited period, while balance sheets and income statements for certain fiscal years are not publicly available. Furthermore, some balance sheet items are omitted from the published financial statements, which significantly limits the accuracy and scope of the forecasting process. Future research should extend the application of the proposed model to a larger number of companies operating across different industries, as well as in countries with diverse business environments. Future studies may compare the business performance of firms that implement the proposed model with those that do not. Such an approach would provide valuable insights into the model's effectiveness in supporting efficient resource allocation and managerial decision-making.

6. Implications and conclusions

In this study, a model based on Markov chains was developed and applied to forecast the future value of corporate receivables. The proposed model represents an effective tool for managers by supporting business decision-making and reducing the risk associated with the future allocation of corporate resources. The findings of this research provide both theoretical contributions and practical implications.

The efficient allocation of a company's limited resources represents a fundamental function of economic systems and a core principle underlying the effective operation of individuals, firms, and societies. An inaccurate assessment of the future collectability of receivables may lead to high-risk investment decisions that are often based on managerial intuition rather than data-driven analysis. In this context, the theoretical and practical application of Markov processes is employed to forecast the collectability of receivables over both short- and long-term horizons. The analytical results are complemented by a Monte Carlo robustness analysis, which provides additional information on the variability of simulated collection outcomes. The modelling process confirms that Markov chains, as a class of stochastic processes, facilitate the prediction of variable values over both short and long-term horizons. The proposed approach does not require information on previous system states or historical company balance sheets. Instead, it relies on current financial statements to forecast future movements of the analysed variables with greater accuracy.

The findings indicate that receivables can be categorized into two distinct groups based on a qualitative assessment of financial statements. The first category comprises receivables from domestic customers, while the second includes receivables from foreign customers. By observing and monitoring the values of these balance sheet items, and through the development of forecasting models based on Markov processes complemented by Monte Carlo simulation, forecasts were generated for the collectability and non-collectability of receivables from both domestic and foreign customers over short-term and long-term horizons.

This research confirms the first hypothesis: that the application of the absorbing Markov-chain model, complemented by Monte Carlo robustness analysis, provides a reliable framework for predicting future business outcomes and supports more informed and effective managerial decision-making, notwithstanding the acknowledged limitations of the study. Decision-makers must take into account the volume of potentially uncollectible receivables when formulating short- and long-term strategies and making investment decisions.

The findings also confirm the second hypothesis, indicating that the application of the proposed modelling framework reduces risk in the decision-making process and enables a more efficient allocation of the company’s limited resources. Ultimately, the absorbing Markov-chain model, complemented by Monte Carlo robustness analysis, enables accurate forecasting of receivables collectability, which contributes to risk reduction and enhances managerial decision-making, thereby supporting a more efficient allocation of company resources in the observed markets. The findings of this research are consistent with a fundamental principle of economics: understanding how individuals, companies, and societies make decisions and allocate scarce resources to improve their outcomes, strengthen their market position, and, more broadly, enhance overall social welfare.

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Poboljšanje potpore odlučivanju u alokaciji resursa primjenom Markovljevih lanaca za prognoziranje naplate potraživanja: Analiza robusnosti primjenom Monte Carlo simulacije

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Sažetak

Učinkovita alokacija resursa od strane pojedinaca, poduzeća i društva predstavlja jedno od središnjih pitanja ekonomske teorije i prakse. Postizanje ekonomskih ciljeva ovisi o sposobnosti raspodjele oskudnih resursa u uvjetima neizvjesnog poslovnog okruženja. Prognoziranje naplate potraživanja doprinosi učinkovitijoj i manje rizičnoj alokaciji resursa jer podupire donošenje odluka o budućoj raspodjeli imovine poduzeća. Ovo istraživanje razvija i primjenjuje okvir za prognoziranje temeljen na apsorbirajućem Markovljevom lancu, dopunjen analizom robusnosti putem Monte Carlo simulacije, kako bi se procijenile vjerojatnosti naplate potraživanja, očekivana vremena naplate, te projicirani novčani priljevi iz potraživanja u kratkom i dugom roku. Predloženi pristup omogućuje procjenu dinamike naplate i pruža dodatne informacije za financijsko planiranje i investicijske odluke. Rezultati ovog istraživanja pokazuju da pouzdano prognoziranje potraživanja može poboljšati učinkovitost alokacije imovine i smanjiti rizik pri donošenju investicijskih odluka, čime se podupire unaprjeđenje profitabilnosti poduzeća.

Ključne riječi: *prognoziranje naplate potraživanja, donošenje odluka, energetska industrija, Markovljevi lanci, Monte Carlo simulacija*

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Appendix

Table A.1: Forecasting receivables collection intervals using Monte Carlo simulation

2021/2022	Collectability of receivables from domestic customers		
	Confidence interval	Receivables collection rate	Expected collection of receivables
Receivables from domestic customers up to one year	95%	66%	1,696,482
Receivables collection interval forecasts (domestic customers)			
Receivables from domestic customers over one year	95%	76%	1,640,722 - 1,644,764
2021/2022	Collectability of receivables from foreign customers		
	Confidence interval	Receivables collection rate	Expected collection of receivables
Receivables from foreign customers up to one year	95%	68%	181,543
Receivables collection interval forecasts (foreign customers)			
Receivables from foreign customers over one year	95%	72%	174,066 – 174,468

Note: The amounts reported in Table A.1 are expressed in thousand Serbian dinars (RSD)

Source: Authors' calculations

Table B.1: Forecast of receivables collectability and non-collectability using the Markov Chain model

	Collected receivables from domestic customers	Uncollected receivables from domestic customers	Collected receivables from foreign customers	Uncollected receivables from foreign customers
Receivables from domestic customers up to one year	350,223.50	272,991.50	0.00	0.00
Receivables from domestic customers over one year	347,888.00	112,740.00	0.00	0.00
Receivables from foreign customers up to one year	0.00	0.00	40,492.00	22,059.00
Receivables from foreign customers over one year	0.00	0.00	40,371.00	15,498.50
	Receivables from domestic customers up to one year	Receivables from domestic customers over one year	Receivables from foreign customers up to one year	Receivables from foreign customers over one year
Receivables from domestic customers up to one year	272,991.50	623,215.00	0.00	0.00
Receivables from domestic customers over one year	0.00	460,628.00	0.00	0.00
Receivables from foreign customers up to one year	0.00	0.00	22,059.00	62,551.00
Receivables from foreign customers over one year	0.00	0.00	0.00	55,869.00

Note: The amounts reported in Table B.1 are expressed in thousand Serbian dinars (RSD)

Source: Authors' calculations