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An integrated approach of system dynamics simulation and fuzzy inference system for retailers' credit scoring

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The assessment of retailers' credit risk is a complex task in which financial risks enable different behaviour mechanisms and this adds to the complexity of the problem. The modelling approach of this article incorporated behavioural styles of retailers in repayment of their liabilities into an integrated fuzzy system dynamics model of retailers' credit scoring. This study introduces an integrated system dynamics model to study credit risk of retailers. To this end, first the influencing factors on the retailers' credit risk should be determined. Then the relation between these variables should be specified in the system dynamics model. The fuzzy uncertainty also is dealt with using the integration of system dynamics model and fuzzy inference system (FIS). The contribution of this article is twofold. First, this is the first study that proposes a system dynamics model to analyse credit risk of the retailers. Second, the proposed model of this study integrates system dynamics model with FIS modelling concept to address the fuzzy uncertainty and non-linearity in the modelling environment.

Keywords: credit risk; retailer; credit scoring; system dynamics; fuzzy inference system (FIS)

JEL classification: C45

1. Introduction

Distribution companies face different business risks, among them credit risk is one of the most important risks. This is mainly due to the fact that some customers (mainly retailers) after receiving goods are not able to repay their liabilities or maybe they do not intend to repay their payable accounts. Although, in the past, retailer crediting may be done without any objective assessment of the retailer, the difficulties a distributor has encountered at the due date of repayment have encouraged the development of new tools for retailers' credit scoring in order to ensure repayments and circulation of the financial resources. The related literature show that the first research studies regarding credit risk have targeted bank customers and financial institutes.

In corporate finance domain, some studies have used macro-economic variables such as GDP and economy structure as well as financial ratios for credit scoring. But at the micro-level, especially for retailers, non-financial indicators should be used along with financial indicators to reflect well on credit risks (Altman & Sabato, 2007). But this approach in practice is likely to suffer from lack of reliable data since in some

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traditional business markets there are no track records of such financial transactions and this is a serious issue for retailers' credit scoring. To address this issue, this article proposes a fuzzy system dynamics model which is less dependent on the accessibility of large data sets.

Credit risk scoring is one of the tasks that whole sellers or distribution companies perform to assess their retailers. Usually the credit risk of retailers reflects the history of business transactions in repayment of their received financial credits. For this reason in the literature the historical transactions are the basis to develop the credit risk indicators. However besides financial variables, non-financial variables also have been used in the credit risk modelling.

In recent years, different intelligent and machine learning techniques have been used for credit scoring (Lessmann, Baesens, Seow, & Thomas, 2015; Wu, Hu, & Huang, 2014). These techniques include neural networks (Kiruthika & Dilsha, 2015; Zhao et al., 2015), Bayesian Network (Leong, 2015), Genetic Algorithms (Kozeny, 2015), regression model (Barriga, Cancho, & Louzada, 2015), fuzzy rule base (Sadatrasoul, Gholamian, & Shahanaghi, 2015), learning classifiers (Abellán & Mantas, 2014; Koutanaei, Sajedi, & Khanbabaie, 2015), support vector machines (Harris, 2015; Sun, Li, Chang, & Huang, 2015). However, to the best knowledge of the author, there is no study that integrates systems dynamic models with fuzzy inference systems (FIS) for credit scoring. This integration brings about some unique advantages for real world credit scoring applications.

This study considers the mechanisms enabled by retailers credit risk and analyse them in a cyclic and dynamic manner. Examples for these mechanisms are ending the transaction with retailer, claiming for compensations, returning delivered goods. The integrated system of influencing variables and the credit risk mechanisms is modelled into a system dynamics model in which the accumulated amount of overdue payments is considered as the indicator for retailers' credit risk. At the heart of every systems dynamics model, there are some linear or non-linear equations which specify the relation between variables and their derivatives. But in practice determining such equations is not an easy task and estimating their parameters demands a considerable amount of data. Here we propose an integrated model of system dynamics and adaptive FIS to address this issue. FISs benefit from a fuzzy rule base to model the non-linear and complex relations in ambiguous and fuzzy environments. Moreover, the fuzzy rule base can be developed by extracting knowledge from the expert domain and this can be efficient when not enough data is accessible. Finally adaptive FIS can learn and adapt to even small set of data which may exist in the modelling environment.

The contribution of this article is twofold. Firstly, this is the first study that proposes a system dynamics model to analyse credit risk of the retailers. Secondly, the proposed model of this study integrates system dynamics model with FIS modelling concept to address the fuzzy uncertainty and non-linearity in the modelling environment.

2. Literature review

The literature survey of this study is presented in two parts. First, the influencing variables of the retailers' credit risk are reviewed. Second, the application of system dynamics and FISs in the modelling of credit risk is reviewed.

The credits to retailers are of three types: non-interest bearing credits, leasing, and sales in cash. Credit risk is the costs from non-collectable receivables or over-due receivables. Between the tools for such risk management is pre-assessment of some

indicators to assure receiving back the credits. Some indicators used by financial institutes are 5c, LAPP, and 5p (Bellovary, Giacomino, & Akers, 2007).

The techniques for measuring credit risk fall into two general categories. (1) Parametric credit scoring models including linear probabilistic model, logit model, probit model (Ohlson, 1980); and (2) non-parametric credit scoring models including linear programming, decision trees, analytic hierarchy process, artificial neural network and genetic algorithms. Among the most important and widely used techniques are multiple regression models, mathematical programming, and expert systems (Sabato, 2010). Bellovary et al. (2007) reported that in the past 50 years, techniques for credit risk scoring has grown very fast (Allen, 2007; Baourakis, Conisescu, Van Dijk, Pardalos, & Zopounidis, 2009; Doumpos & Pasiouras, 2005; Jones & Hensher, 2008). Credit risk models are subject to the nature of financial transactions and can be specific to the business sector (Altman, 1968). Credit scoring models may be used for a new customer for whom there is not enough transactional history. They also may be behavioural when there is enough information regarding the behavioural style of the customer and may be data driven collective models when a lot of historical information regarding the transactions with the customer are collected (Beaver, 1967). Among different models some researchers reported on the successful application and superiority of the conditional logit model (Becchetti & Sierra, 2003; Sabato, 2010). Some models used multiple financial ratios with multi criteria scoring for example z-score (Altman, Haldeman, Narayanan, & Zeta-Analysis, 1977) for credit risk scoring.

Neural networks and neuro-fuzzy techniques are also used for credit scoring. Akkoç (2012) used the combined model of neural networks and neuro-fuzzy to assess the risk of loan credits. This author compared the performance of combined model with the conditional logit model and concluded that the combined model of neural networks and neuro-fuzzy outperforms logit model when used for credit scoring. Tsai and Wu (2008) used the multilayer perceptron (MLP) network trained by the back-propagation learning for classification of different customers according to their credit risks. West (2000) used five types of neural networks including MLP, mixture-of-experts, radial basis function, learning vector quantisation, and fuzzy adaptive resonance for credit scoring. He reported that radial basis function shows better performance in credit scoring than logit model and linear discriminate analysis. Lee and Chen (2005) used a two-phased combined approach of regression and neural networks for credit scoring. In the first phase, the regression analysis is used to determine the significant influencing variables. Then the neural network model is constructed with the determined variables as network inputs. This approach is important in that insignificant input variables have been eliminated from the model and the need for more data is alleviated. Blanco, Pino-Mejias, Lara, and Rayo (2013) stated that there is a need to develop non-parametric models for measuring credit risk in microfinance industry. They proposed a neural networks model with the use of a data-set of 5500 customer transaction data. They also concluded that the neural network model is superior to conventional models of linear discriminant analysis, quadratic discriminant analysis, and logistics model.

There are not many research studies which directly consider retailers' credit risk. However, one of the research studies which exactly pointed the credit risk of retailers is the work by Karan, Ulucan, and Kaya (2013). In this study the historical transaction of a distribution company with its 6000 retailers are analysed. These variables fall into two categories: financial and transactional variables, and non-financial variables. Financial and transactional variables include purchase, total debt, early repayments, over-due repayments, number of items purchased, number of invoices, and frequency of repayments.

Some variables are averaged or their standard deviations are used in the model. Non-financial variables include the geographical location of retailers and the type of retailer (supermarket, chain supermarket or hypermarket). The dependent variable or output variable is a dummy binary variable which its value of one indicates satisfied level of risk associated with the retailer whereas the value of zero indicates a risky retailer. Before this, Karan et al. (2005) introduced a number of explanatory variables for retailers' credit scoring. Among these variables are the logarithmic forms of standard deviation of the number of items purchased, the ratio of overdue invoices to total number of invoices and the ratio of debt to sales. Some researchers emphasised the use of retailers' transaction history for credit scoring (Back, 2005). Cheng and Pike (2003) believe that the early repayments are an important factor in assessing credit risk of retailers. Armendáriz de Aghion and Morduch (2005) have shown that regularity and timing of repayments is an important indicator. Regarding the dependent variable in credit risk modelling, different variables have been considered for example default probability is the probability that total equity is less than total debts (Rosch & Scheule, 2004).

The application of system dynamics in modelling credit risk does not have a long history. Braje (2003) modelled the financial processes of a bank in the paying and repayment of loans. In their model, the time to debate resolution, the percentage of assets in default and write off fractions are integrated and their causal relationships are drawn. Moscardini, Loutfi, and Al-Qirem (2005) used system dynamics for evaluation of the customers who applied to receive bank loans. They drew the casual relationships between sales, income, net profit, account receivable, and accounts payable. Recently, Liu et al. (2012) applied system dynamics approach for modelling risk of outsourcing logistics operations. Qiang, Hui, and Xiao-dong (2013) used system dynamics modelling for risk assessment in e-commerce transactions.

Regarding the application of FIS for forecasting the risk of credits, Malhotra and Malhotra (2002) used adaptive FISs for differentiating between risky and non-risky customers. This model only tells if a customer is likely to repay their debts or not. Jiao, Syau, and Lee (2007) used adaptive FISs to forecast credit risk in small- and medium-sized enterprises (SMEs). In this work, fuzzy clustering techniques have been used to develop fuzzy rule base and then expert knowledge is used to tune rule base parameters. Wang et al. (2009) used adaptive FISs for credit risk scoring of power customers of a distributing company. Actually their model estimates the probability of overdue invoice payments. Lahsasna, Aïnon, and Wah (2008) exhibit the integrated application of adaptive FISs and genetic algorithms in the forecasting of credit risk. They have used historical data to develop and adapt the fuzzy rules and inference system parameters.

3. The proposed integrated model

3.1. Mechanisms and variables

Sterman (2000) specified the following steps in system dynamics methodology: problem statement, dynamic hypothesis formation, developing a simulation model, model test, and design of improvement scenarios.

One of the credit risk mechanisms will be active when the due payments are late or overdue. In this case the distributor decides to reduce goods transaction and if the number of overdue payments increases over time, finally the distributor decides to cut the relation and stop providing the retailer with the requested goods. This mechanism can be modelled by introducing the variable, 'the time between consequent goods delivery'.

On one hand, a variety of goods on the shelves and their abundance causes sales rates to increase and this creates positive cash flows which enable retailers to repay their due debts. On the other hand, low sales rate cause the retailer to have difficulty in making the repayments. Another mechanism worth considering is the behavioural style of the retailer. It is possible for some retailers that despite having cash available for debt repayment, they decide to delay the repayment and use their money in another market. Such decisions may depend on the personality traits of the retailers and also some cognitive factors such as the forecast on future economic conditions, interest rates, stock market, exchange market, etc.

Here retailers' credit risk is defined as the average of their overdue debts during a given time period. In the face of the defined mechanisms, the problem is how to model dynamic of retailers' debts so that the positive and negative effects of financial ratios as well as the effects of non-financial variables on the profile of retailers' debts could be analysed. The main variables in the system dynamics model are as follows: purchase rate, total debts, mean number of items purchased, standard deviation of the number of items purchased, mean time between invoices, assets in cash, debts, retailers' location and retailers' type or size.

3.2. Model assumptions

- Increase in payable debts cause a conflict between distributor and the retailer and ends in increase in time between purchase (TBP) because the distributor does not intend to deliver more goods.
- Sales rate is a function of goods variety and customer variety.
- The operational cost of retailer is a function of its location and size.
- The behaviour of retailer is a function of its location and size. To elaborate more, big and best location retailers have this potential to sale goods in the short time. Consequently they will have good flow of cash and goods in their business and their business behaviour will be affected by their size and location.

3.3. Causal loops

It should be noted that in modelling the causal relations between model variables (sales rate, repayment rate), negative exponential function is used. This function can be used to model saturating process and researchers have used this function to model profitability, work demand, and operational costs with saturating process (Gary, 2005; Mollona, 2010). The mathematical form of this function is represented in Equation 1.

$$y = a - e^{-bx} \quad (1)$$

In this function, increase in x will increase y but this process is a saturating process which is asymptotic to a when x reaches infinity. The parameters a and b in the system dynamics model could be tuned so that the model behaviour approached reference modes.

Causal loops are indications of positive or negative relationship. The first causal loop is associated with the purchase and delivery of goods (Figure 1). Goods inventory increases with purchase rate and accounts payable is proportional with total goods purchased. It should be noted that with increase in accounts payable, the time between

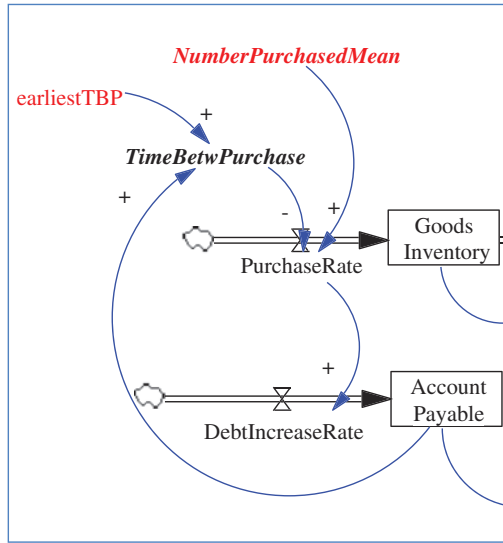


Figure 1. Causal loops for purchase and delivery of goods.
Source: Authors calculations.

purchases increases and this leads to lower rate of purchase. Purchase rate is mean monetary value of purchased goods divided by time between purchases. Finally the growth rate of accounts payable is proportional with purchase rate. The constant earliest TBP is the earliest time between purchases and it means that time between purchases never exceeds earliest TBP.

These causal relations are modelled in the system dynamics model using the following mathematical relationships. It should be noted that the values of the parameters have been estimated based on the data collected for a real food distribution company.

- (01) $\text{GoodsInventory} = \text{INTEG}(\text{PurchaseRate} - \text{SellRate}, 50)$
Units: Rials [0,?]
- (02) $\text{AccountPayable} = \text{INTEG}(\text{DebtIncreaseRate} - \text{DebtRepayRate}, 0)$
Units: Rials [0,?]
- (03) $\text{DebtIncreaseRate} = \text{PurchaseRate}$
Units: Rials per Day [0,?]
- (04) $\text{earliestTBP} = 4$
Units: Day
- (05) $\text{NumberPurchasedMean} = 20$
Units: Rials
- (06) $\text{PurchaseRate} = \text{NumberPurchasedMean} / \text{TimeBetwPurchase}$
Units: Rials per Day [0,?]
- (07) $\text{TimeBetwPurchase} = \max((11 - 10 * \text{EXP}(-\text{AccountPayable} / 300)), \text{earliestTBP})$
Units: Days

The second causal relationship is associated with retailer’s sales (Figure 2). Goods inventory decrease with sales rate. Sales rate depends on customer variety and goods

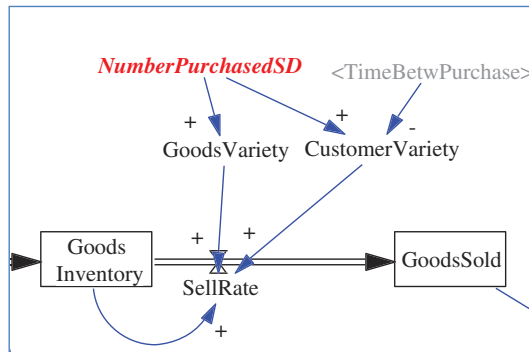


Figure 2. Causal loops for retailer's sales.
Source: Authors calculations.

variety. Goods variety can be measured by the standard deviation of the items purchased and customer variety is measured by a combination of standard deviation of the items purchased and time between purchases. Customer variety will be decreased if time between purchases increases because customers cannot find their favourite goods by the retailer and desperately start to buy goods from another retailer.

These causal relationships are quantified in the model through the following mathematical equations.

- (08) $GoodsSold = INTEG (SellRate, 0)$
Units: Rials [0,?]
- (09) SellRate calculated via a FIS with (GoodsInventory, GoodsVariety, CustomerVariety) as its inputs
Units: Rials per Day
- (10) $CustomerVariety = NumberPurchasedSD / TimeBetwPurchase$
Units: **undefined**
- (11) $GoodsVariety = NumberPurchasedSD$
Units: **undefined**
- (12) $NumberPurchasedSD = 10$
Units: **undefined**

The third casual loop is associated with repayment of debts or accounts payable (Figure 3). This loop also includes assets in cash which is used for repayments of debt of other payments such as operational costs, reinvestments. Accounts payable will decrease with debt repayment rate and total accounts paid increases with this rate. Debt repayment rate is dependent on three variables: assets in cash, retailer behaviour, and accounts payable. Accessibility to cash is the necessary condition for debt repayment. Retailer behaviour says that even if cash is available, whether or not the retailer intends to pay his due debts. Finally the more accounts payable is, the more will be psychological and external pressure for repayment of debts. By psychological pressure, we mean that debt in the business environment does not have a good image and no business wants to be under this pressure because it may hurt its brand. External pressure also comes from the risk of losing properties pledged as collaterals and claims for compensations.

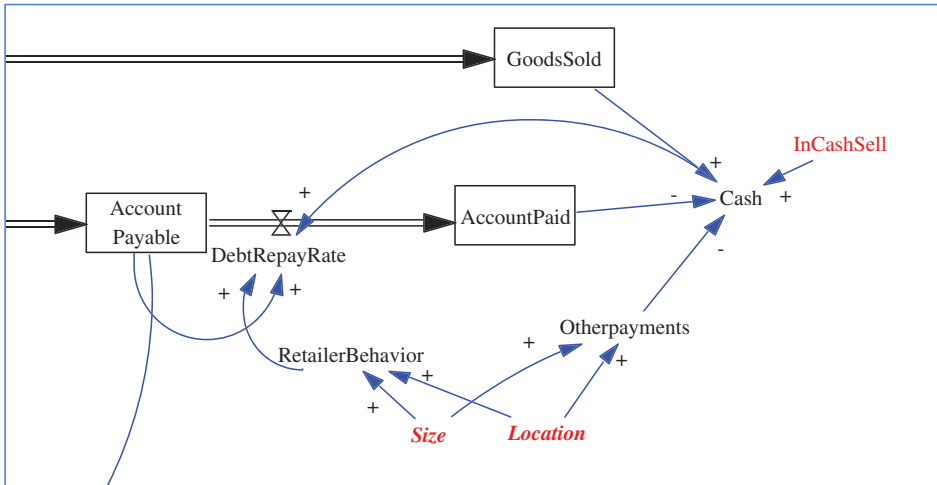


Figure 3. Causal loops for repayment of debts.
Source: Authors calculations.

These causal relationships are quantified in the model through the following mathematical equations.

- (13) $\text{AccountPaid} = \text{INTEG}(\text{DebtRepayRate}, 0)$
Units: Rials
- (14) $\text{Cash} = \text{GoodsSold} * \text{InCashSell} * (1 - \text{Otherpayments}) - \text{AccountPaid}$
Units: Rials [0,?]
- (15) DebtRepayRate is calculated via a FIS with (Cash, Retailer Behaviour, AccountPayable) as its inputs
Units: Rials per Day
- (16) $\text{InCashSell} = 0.9$ (estimated from actual data)
- (17) $\text{Location} = 0.5$
Units: **undefined**
- (18) $\text{Otherpayments} = 0.1 * (\text{Location} * \text{Size})$
Units: **undefined**
- (19) $\text{RetailerBehavior} = \text{Location} * \text{Size}$
Units: **undefined**
- (20) $\text{Size} = 0.5$
Units: **undefined**

Relation 15 shows that repayment rate is calculated by FIS and it is depends on three variables Cash, Retailer Behaviour, and Accounts Payable.

At the end of this section, the variables and parameters associated with simulation model and its time duration are set as follows:

- (21) INITIAL TIME = 0 (The initial time for the simulation)
Units: Day
- (22) FINAL TIME = 365 (The final time for the simulation)
- (23) TIME STEP = 1 (The time step for the simulation)
- (24) SAVEPER = TIME STEP (The frequency with which output is stored)

4. Fuzzy inference system modelling

In the next step, the uncertainty in the modelling environment is dealt with and addressed with the use of Takagi-Sugeno type FIS (Jang, Sun, & Mizutani, 1997; Takagi & Sugeno, 1985). Specifically three of model variables are fuzzy: (1) customer variety; (2) goods variety; and (3) retailers' behaviour. The rationale behind treating these variables as fuzzy variables is that quantification and estimation of these variables involve human judgment, ambiguity, and cognition and these are well known sources of fuzzy uncertainty. The fuzziness of these variables permeates into the causal loops and consequently some variable relations should be modelled in fuzzy environment. In the system dynamics model of Figure 3, the following two relations involve fuzzy variables (Figure 4):

$$\text{SellRate} = 0.02 * \text{GoodsInventory} * \text{GoodsVariety} * (1 - \text{EXP}(-\text{CustomerVariety}))$$

$$\text{DebtRepayRate} = \text{MIN}(\text{IF THEN ELSE}(\text{Cash} > 0, 0.01 * (1 - \text{EXP}(-\text{Cash})),$$

* $\text{RetailerBehavior} * \text{AccountPayable}, 0), \text{Cash})$

For each of these relations, an adaptive FIS will be developed and then the logic of these FIS will be integrated into system dynamics model. The working procedure to integrate FIS with a system dynamics model is presented in the next section.

5. Integration of FIS into system dynamics model

Consider the following Sugeno-type FIS with two fuzzy rules.

Rule 1: if a is A1 and b is B1 then $fA1B1 = 1 + a + b$

Rule 2: if a is A2 and b is B2 then $fA2B2 = 0.6 + a + b$

The membership functions in this fuzzy rule base are defined in Figure 5.

This FIS can be integrated in system dynamic model with the variables and relationships presented in Figure 6.

In Figure 3, parameters s and m are the standard deviation and mean value of the Gaussian membership functions, respectively. The calculation procedure in the FIS is modelled into the system dynamics model by defining the following mathematical relationships:

$$(19) f = \frac{fA1B1 * wruleA1B1 + fA2B2 * wruleA2B2}{(wruleA1B1 + wruleA2B2)}$$

$$(20) fA1B1 = 1 + a + b$$

$$(23) fA2B2 = 0.6 + a + b$$

$$(18) waA1 = 1 / \text{SQRT}(2 * 3.14 * sA1) * \exp(-0.5 * ((a - mA1) / sA1)^2)$$

$$(19) waA2 = 1 / \text{SQRT}(2 * 3.14 * sA2) * \exp(-0.5 * ((a - mA2) / sA2)^2)$$

$$(20) wbB1 = 1 / \text{SQRT}(2 * 3.14 * mB1) * \exp(-0.5 * ((b - mB1) / sB1)^2)$$

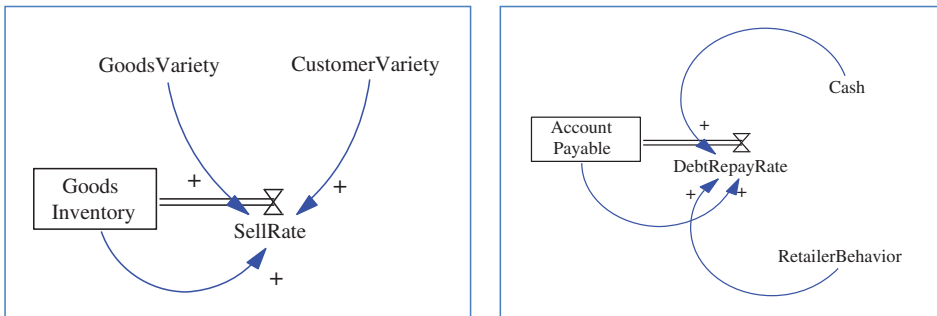


Figure 4. Causal loops involving fuzzy variables.
Source: Authors calculations.

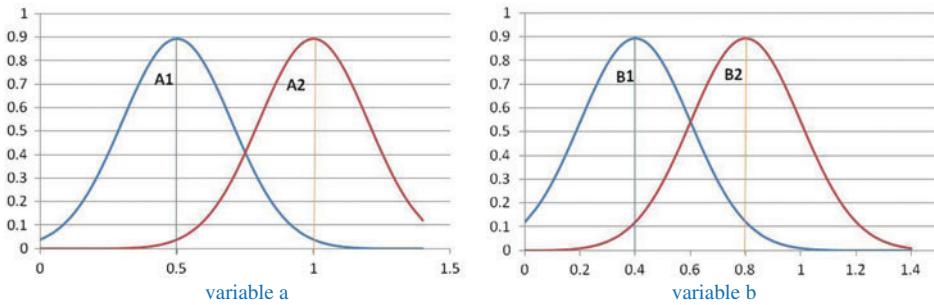


Figure 5. Fuzzy sets and their membership functions for variables a and b. Source: Authors calculations.

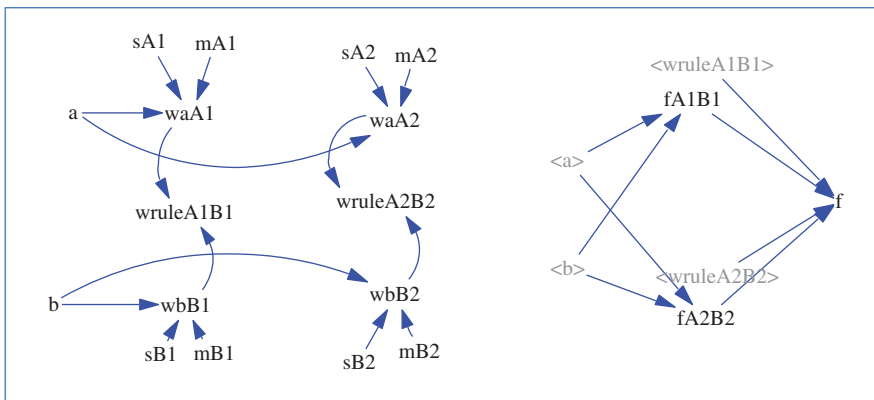


Figure 6. Integration of Sugeno-type FIS into system dynamics model. Source: Authors calculations.

$$(21) \text{wbB2} = 1/\text{SQRT}(2 * 3.14 * \text{sB2}) * \exp(-0.5 * ((\text{b} - \text{mB2})/\text{sB2})^2)$$

$$(22) \text{wruleA1B1} = \text{MAX}(\text{waA1}, \text{wbB1})$$

$$(23) \text{wruleA2B2} = \text{MAX}(\text{waA2}, \text{wbB2})$$

6. Fuzzy system dynamic modelling for debt repayment rate

The integrating procedure presented in the previous section is applied to integrate fuzzy rate of debt repayment into the developed system dynamics model. Figure 7 shows the parameters and the relationships.

The network in Figure 7 consists of two sub-networks on the left and on the right. The one on the left represents the rule base and the sub-network on the right represents the calculation logic to produce final output in FIS. The parameters in this network including membership functions’ parameters and the coefficients of first-order output functions are estimated based on the actual data collected from the food distributor company.

6.1. Fuzzy system dynamic modelling for sale rate

The integrating procedure presented in the previous section is applied to integrate the fuzzy rate of sale into the developed system dynamics model. Figure 8 shows the parameters and the relationships.

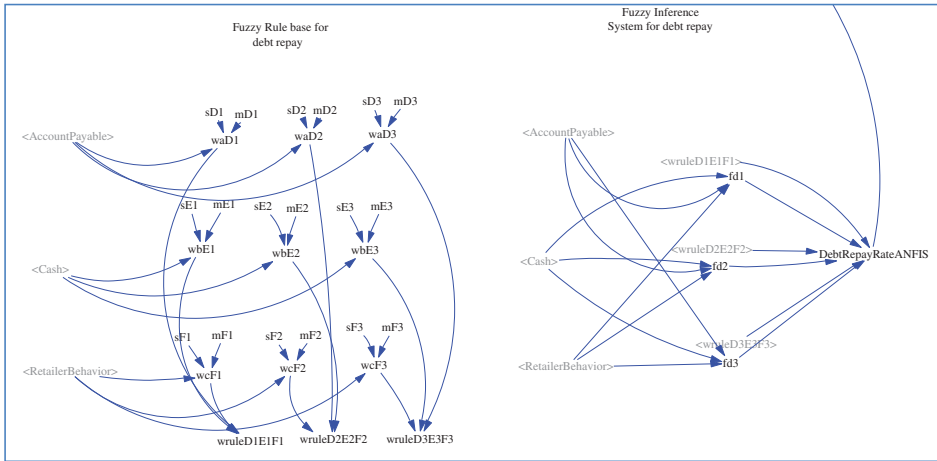


Figure 7. Fuzzy system dynamic modelling for debt repayment rate.
Source: Authors calculations.

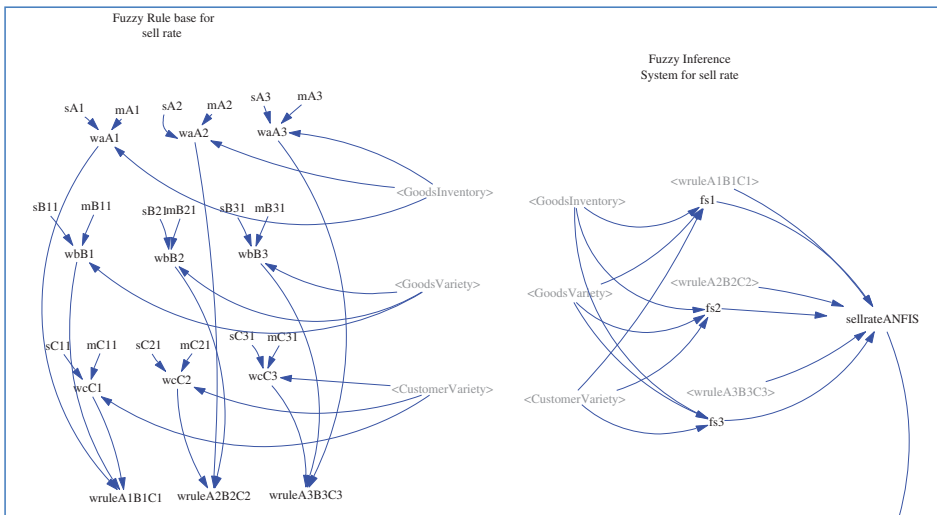


Figure 8. Fuzzy system dynamic modelling for sale rate.
Source: Authors calculations.

After the integration of these FIS into the system dynamics model of retailers' credit risk, the final fuzzy system dynamic model is drawn in Figure 9. The three causal relationships are also integrated into this fuzzy model. In this figure the variable credit risk score is calculated through Equation (4) where Credit risk score is the ratio of accounts payable divided by the sum of accounts paid and accounts payable.

$$Credit\ risk\ score = \frac{AccountPayable}{(AccountPaid + AccountPayable)} \quad (4)$$

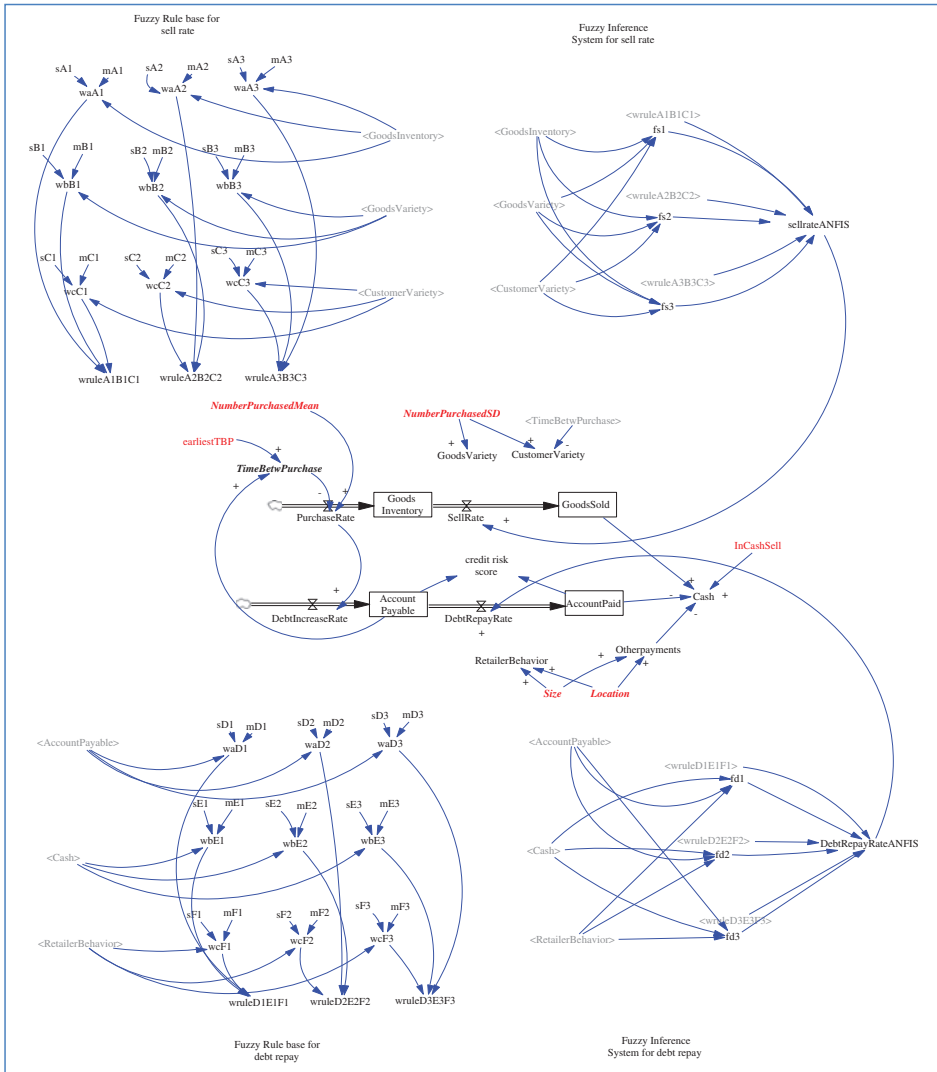


Figure 9. The integrated fuzzy system dynamics model of retailers' credit risk. Source: Authors calculations.

7. Results

7.1. Parameter estimation

The parameters in final system dynamics network (Figure 9) including membership functions' parameters and the coefficients of first-order output functions are estimated based on the actual data collected from the food distributor company. The results of estimation for sales rate are presented in Tables 1 and 2. Table 1 shows the estimated values for membership functions' parameters. Linear regression model with ordinary least squares technique is used to estimate these parameters. The actual data are confidential but the results of regression analysis using SPSS are available upon request from the corresponding author.

Table 1. Estimated values for membership functions' parameters in sales rate FIS.

	Set 1		Set 2		Set 3	
	STDEV (s)	Mean (m)	STDEV (s)	Mean (m)	STDEV (s)	Mean (m)
Goods inventory (A)	15.6	23.0	15.6	37.0	15.6	3.0
Goods variety (B)	6.4	8.2	6.3	14.9	6.2	13.2
Customer variety (C)	3.2	4.0	2.4	7.0	3.1	9.0

Source: Authors calculations.

Table 2 shows the estimated values for the coefficients of first-order output functions in sales rate FIS.

The results of estimation for debt repayment rate are presented in Tables 3 and 4. Table 3 shows the estimated values for membership functions' parameters.

Table 4 shows the estimated values for the coefficients of first-order output functions in debt repayment rate FIS.

7.2. Model validation

Different tests have been introduced by Sterman (2000) to test the validity of a system dynamics model. Among them are face validity, limit condition test, and behaviour reproduction test.

The model of this study has been tested against all these tests. For face validity, in every stage of model development the model has been checked and approved by the domain experts for its validity and rationality. The limit condition test is something to do with the robustness of the model. In this test the results of model is analysed for the model parameters being in their limits. A robust model never shows unexpected and irrational results.

For the current model, two limit conditions are drawn: lower bound limit and upper bound limit. In the lower bound limit, model parameters are set so that the maximum level of credit risk is expected. In the upper bound limit, model parameters are set so

Table 2. Estimated values for the coefficients of first-order output functions in sales rate FIS.

	Goods inventory	Goods variety	Customer variety	Constant
Rule 1	0.015	0.175	0.308	-0.759
Rule 2	0.201	0.856	-1.114	1.226
Rule 3	0.180	0.101	0.760	-8.131

Source: Authors calculations.

Table 3. Estimations for membership functions' parameters in debt repayment rate FIS.

	Set 1		Set 2		Set 3	
	STDEV (s)	Mean (m)	STDEV (s)	Mean (m)	STDEV (s)	Mean (m)
Accounts Payable (D)	184.6	261.0	184.6	441.0	184.6	501.0
Cash (E)	184.6	281.0	184.6	321.0	184.6	521.0
Retailer Behaviour (F)	0.1	0.5	0.2	0.7	0.3	0.0

Source: Authors calculations.

Table 4. Estimations for the coefficients of first-order output functions in debt repayment rate FIS.

	Account payable	Cash	Retailer behaviour	Constant
Rule 1	0.004	0.000	2.061	-0.765
Rule 2	0.008	0.001	3.217	-2.945
Rule 3	0.001	0.000	3.566	-0.217

Source: Authors calculations.

that the minimum level of credit risk is expected. Table 5 shows the values for model parameters in limit conditions as well as the results of the model in these limit conditions (also see Figure 10). As seen in the lower bound limit, the credit risk score is 0.91 showing a high level of credit risk. On the other hand, in the upper bound limit, the credit risk score is 0.26 showing a low level of credit risk. These results are compatible with the expectations and verify the robustness of the model results.

Reference modes are indications of expected behaviour of system dynamics variables. In our model, if the retailer is an un-risky retailer, its debts during time should not have steady increasing trend and their average should be almost constant over time. For a risky retailer, its debts over time have a steady increasing trend (Figure 11).

The behaviour reproduction test is about proper recognition of the main variables of the model. In this test usually the results of model is compared with reference modes. As it is mentioned before, the trend of accumulated accounts payable is different for risky and un-risky retailers. Figure 12 shows the trends of accounts payable for risky and un-risky retailers. As seen these trends are well compatible with the reference modes presented in Figure 11.

7.3. Simulation results

In this section the results of system dynamic simulation are presented in 6 classes. These classes are defined based on different values for the independent variables of the model (Table 6). These independent variables can be served as the unique characteristics of retailers. In fact each class represents a group of retailers who are different in four variables: size, location, average number of items purchased, and the standard deviation of the number of items purchased.

- Class 1s are those retailers who are big in size, in the best location, in each purchase they buy 100 items on average with standard deviation of 20 (high variety in goods purchased).

Table 5. Limit conditions test and behaviour reproduction test results.

	Lower bound limit	Upper bound limit	Risky retailer	Un-Risky retailer
Size	0.1	1	0.1	1
Location	0.1	1	0.1	1
AVERAGE items purchased	100	100	20	50
STDEV items purchased	5	20	5	20
Credit risk score at $t = 365$	0.91	0.26	0.94	0.27

Source: Authors calculations.

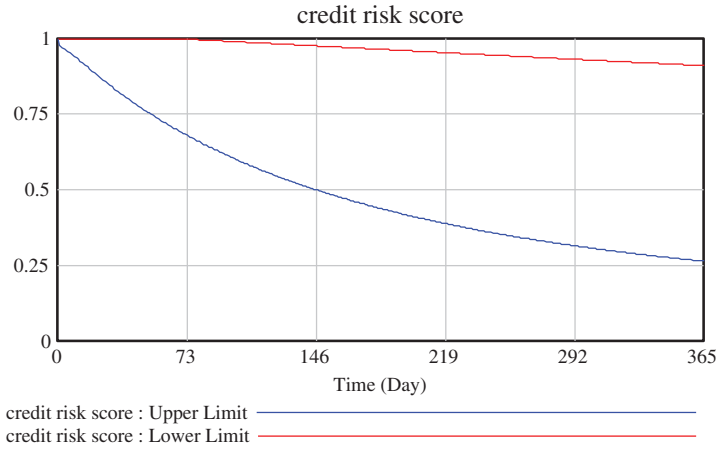


Figure 10. Credit risk score in lower and upper limits.
Source: Authors calculations.

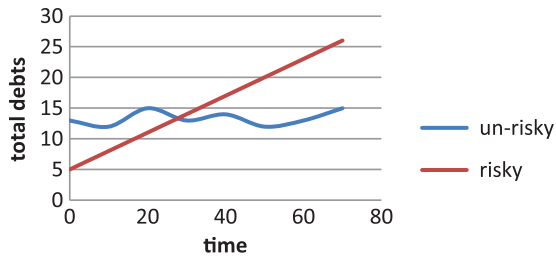


Figure 11. Reference modes for total debts.
Source: Authors calculations.

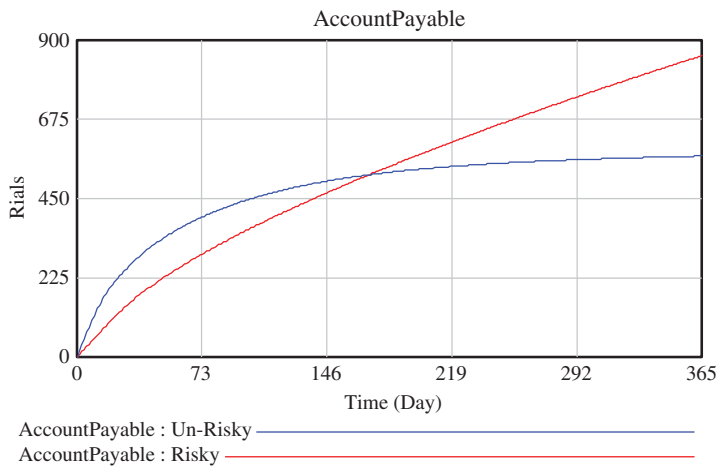


Figure 12. Accounts payable for risky and un-risky retailers (reproduction of reference modes).
Source: Authors calculations.

Table 6. Definition of retailers' classes.

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
Size	1	1	0.7	0.5	0.2	0.1
Location	1	1	0.7	0.5	0.2	0.1
AVERAGE items purchased	100	10	70	30	70	10
STDEV items purchased	20	5	15	10	10	5

Source: Authors calculations.

- Class 2s are those retailers who are big in size, in the best location, in each purchase they buy 10 items on average with standard deviation of five (low variety in goods purchased).
- Class 3s are those retailers who are relatively big in size, in a relatively good location but not in the best location, in each purchase they buy 70 items on average with standard deviation of 15 (relatively high variety in goods purchased).
- Class 4s are those retailers who are average in size, in a middle class location, in each purchase they buy 30 items on average with standard deviation of 10 (middle variety in goods purchased).
- Class 5s represents those retailers who are small in size, in a low class location, in each purchase they buy 70 items on average with standard deviation of 10 (relatively high variety in goods purchased).
- Class 6s represents those retailers who are small in size, in a very low class location, in each purchase they buy only 10 items on average with standard deviation of five (low variety in goods purchased).

Now, the system dynamics simulation is performed in different classes and the results are compared. The main outputs of the simulation model are the dynamics of accounts payable and the score calculated for credit risk. Such comparison reveals credit risk in different retailers' classes.

Customer variety is proportional with the standard deviation of items purchased and the time between purchases. Figure 13 shows the dynamic trend of customer variety in

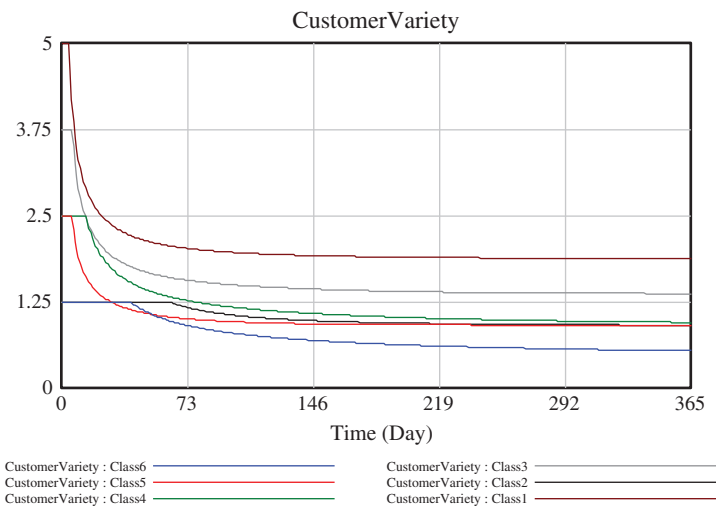


Figure 13. Dynamic trend of customer variety.
Source: Authors calculations.

different classes of retailers. As seen over time customer variety is decreasing in all the classes and then reaches equilibrium. However, retailers in class 1 maintain customer variety in a relatively higher level than other classes and class 6 are the lowest in customer variety. This may influence on the sales rate in different classes.

The average time between purchases (Figure 14) is tracking a saturating increasing trend and finally is in the highest level in class 5 and in lowest level in class 2. Retailers in class 2 are in a good location, big in size, with low average of items purchase. Therefore these retailers should order goods more frequently.

With respect to goods inventory, retailers in class 1 maintain the lowest level of inventory and class 5 maintains the highest inventory level (Figure 15). This is because retailers in class 1 are big and in the best location and they can sell goods in the short

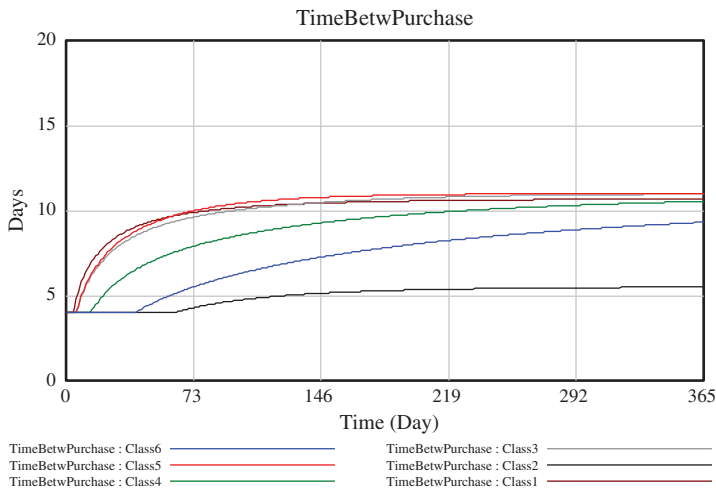


Figure 14. Dynamic trend of average time between purchases.
Source: Authors calculations.

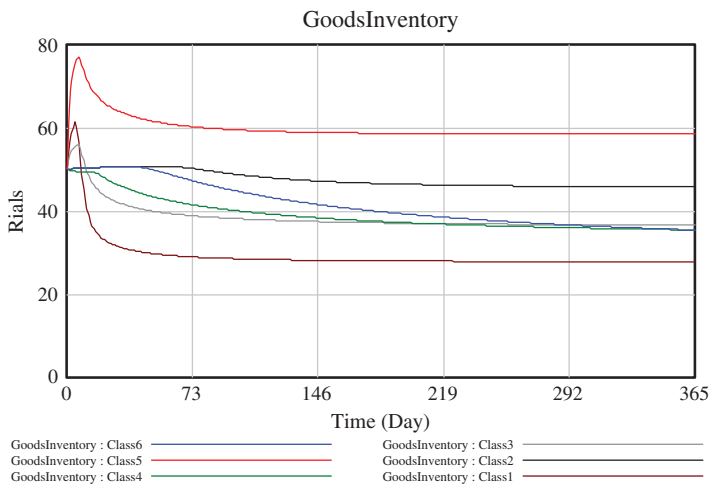


Figure 15. Dynamic trend of goods inventory.
Source: Authors calculations.

time and do not keep goods for a long time. Compliment to time between purchase analysis, is the trend analysis of sales rate.

Figure 16 depicts differences in sales rates in different classes. Retailers in class 1 with the highest sales rate easily could find customers and sell their goods however retailers in class 6 can hardly sell their goods and this may get them into trouble regarding the repayment of their debts. This can also be seen in Figure 14 where the total goods sold is the highest for class 1 and is the lowest for class 6 and 5.

The trend of accounts payable is ever growing in all the classes (Figure 18). However the slope of increase is different. The slope is the steepest for class 5. It should be noted that accounts payable is the total amount of money a retailer owes to distributor in a given time. However what is important for the credit risk is the proportion of accounts payable to the sum of account payable and accounts paid. This sum

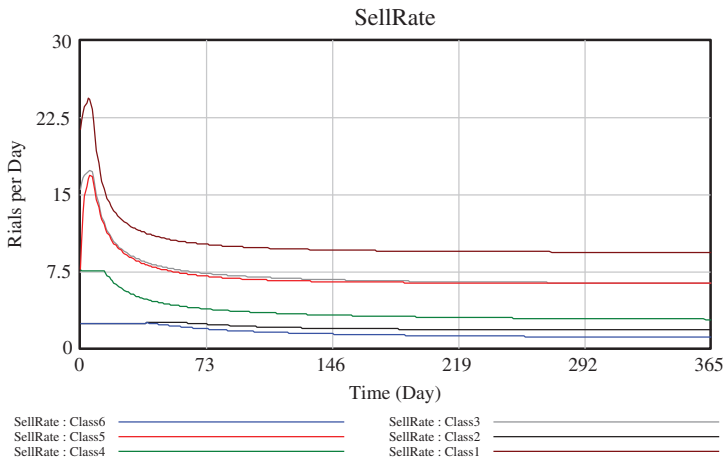


Figure 16. Dynamic trend of sell rate.
Source: Authors calculations.

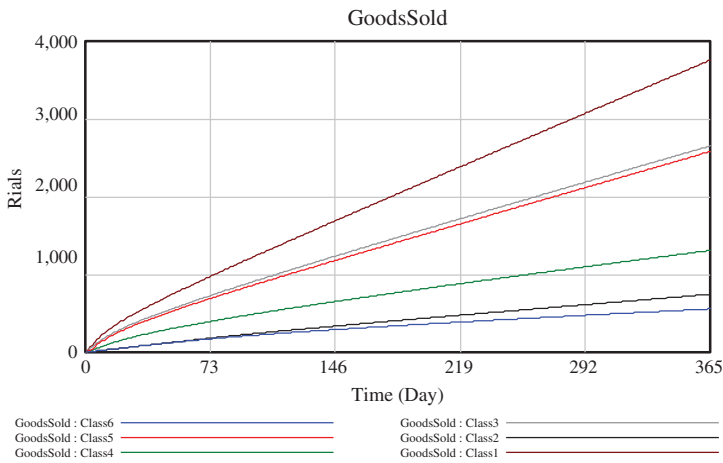


Figure 17. Dynamic trend of goods sold.
Source: Authors calculations.

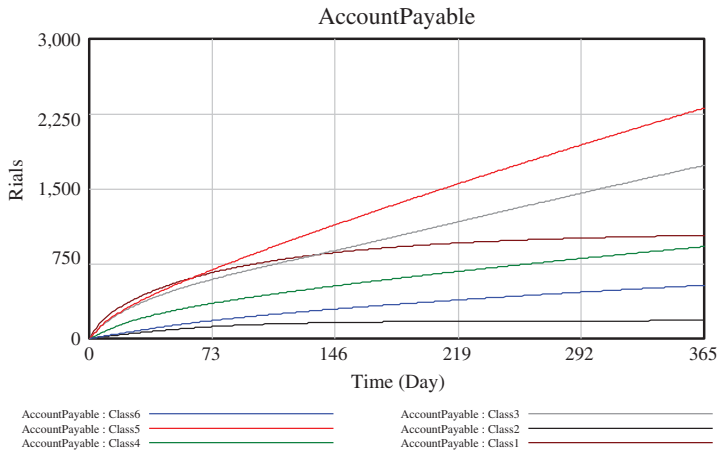


Figure 18. Dynamic trend of accounts payable.
Source: Authors calculations.

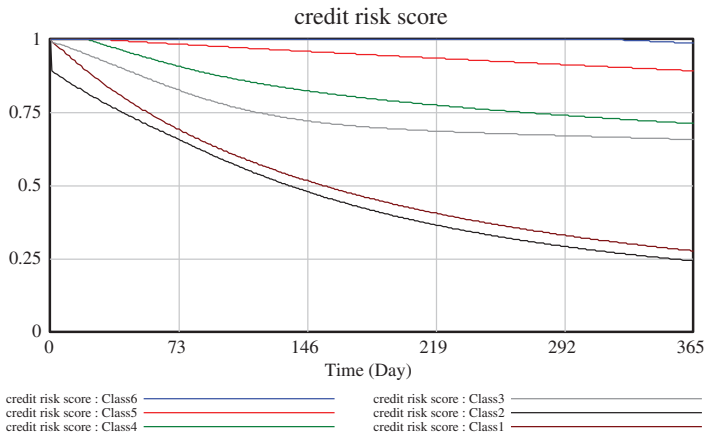


Figure 19. Dynamic trend of credit risk score.
Source: Authors calculations.

reflects the total business transactions between a retailer and the distributor and distributor wants to know what proportion of this total trade is not paid yet and this is regarded as the credit risk.

Figure 19 shows the dynamic of credit risk indicator in different retailer classes. The credit risk score is an indication for retailers' credit risk. This score puts on a value between zero and one where the value of zero indicates no risk in giving credit to the retailer while the value of one indicates the maximum level of risk in receiving back for the credits to a retailer. As seen in this figure, classes 5 and 6 are the riskiest classes. Credit risk for classes 3 and 4 is moderate and the least for classes 1 and 2. One can draw different clusters of retailers based on the figures of credit risk. The risky cluster includes those retailers in class 5 and 6 who their credit risk score is above 0.8. The un-risky cluster includes class 1 and 2 who their credit risk score is less than 0.3.

8. Conclusion

In corporate finance domain, some studies have used macro-economic variables such as GDP and economy structure as well as financial ratios for credit scoring. But in the micro-level, specifically for retailers, non-financial indicators should be used along with financial indicators to reflect well on credit risks. But this approach in practice is likely to suffer from lack of reliable data since in some traditional business markets there are no track records of such financial transactions and this is a serious issue for retailers' credit scoring. To address this issue, this article proposed a fuzzy system dynamics model which is less dependent on accessibility of large data sets. One important business risk that distribution companies face is credit risk. This is mainly due to the fact that some retailers after receiving goods are not able to repay their liabilities or they may have no intention of repaying their debts. The assessment of retailers' credit risk is a complex task in which financial risks enable different behaviour mechanisms and this adds to the complexity of the problem. The modelling approach of this article incorporated behavioural styles of retailers in repayment of their liabilities into an integrated fuzzy system dynamics model of retailers' credit scoring. At the heart of every systems dynamics model, there are some linear or non-linear equations which specify the relation between variables and their derivatives. But in practice determining such equations is not an easy task and estimating their parameters demands a considerable amount of data. Retailers' credit scoring in practice is more likely to suffer from a lack of reliable data since, in some traditional business markets, there are no track records of data that may be used to estimate the relations between variables. This article proposed an integrated model of system dynamics and adaptive FISs to address this issue. The proposed model of this study was proven to be a useful tool for retailers' credit scoring. This model calculates a credit risk score of a retailer based on the values provided by the user for four variables: retailers' location/size, average items purchased, and STDEV of items purchased. The validity of the proposed system dynamics model was tested for face validity, limit condition test, and behaviour reproduction test. Finally, sensitivity of the credit risk score to the model's parameters showed that retailers' location/size had an improving effect on credit risk. The average number of items purchased did not have a significant effect on credit risk score but its standard deviation had a significant effect on credit risk score.

The contribution of this article is twofold. Firstly, this is the first study that proposes a system dynamics model to analyse credit risk of the retailers. Secondly, the proposed model of this study integrates system dynamics model with the FIS modelling concept to address the fuzzy uncertainty and non-linearity in the modelling environment. To the best knowledge of the author, there is no study that integrates systems dynamic models with FISs for credit scoring. This integration brings about some unique advantages for real world credit scoring applications. Future research may consider the integration of other intelligent algorithms such as neural networks, ensemble classifiers, and support vector regressions into the systems dynamic model of retailers' credit risk.

Disclosure statement

No potential conflict of interest was reported by the authors.

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