INSOLVENCY FORECASTING THROUGH TREND ANALYSIS WITH FULL IGNORANCE OF PROBABILITIES[1]

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Abstract

The complex views of insolvency proceedings are unique, poorly known, interdisciplinary and multidimensional, even though there is a broad spectrum of different BM (Bankruptcy Models). Therefore, it is often prohibitively difficult to make forecasts using numerical quantifiers and traditional statistical methods. The least information-intensive trend values are used: positive, increasing, zero, constant, negative, decreasing. The solution of a trend model is a set of scenarios where X is the set of variables quantified by the trends. All possible transitions among the scenarios are generated. An oriented transitional graph has a set of scenarios as nodes and the transitions as arcs. An oriented path describes any possible future and past time behaviour of the bankruptcy system under study. The graph represents the complete list of forecasts based on trends. An eight-dimensional model serves as a case study. On the transitional graph of the case study model, decision tree heuristics are used for calculating the probabilities of the terminal scenarios and possible payoffs.

Keywords: forecast, insolvency, trend, qualitative, bankruptcy, transition
JEL Classification: G33, G34

Introduction

At this time, along with the increasing number of insolvency proceedings, efforts are being made to streamline processes and identify links between majority creditors (Mrázová and Zvirinský, 2015). These are concurrent with data mining investigations to find different ways of effectively solving insolvency proceedings in various regions of the Czech Republic (Mrázová and Zvirinský, 2014). More and more professional research is concerned with the question of why the number of insolvency proceedings for both legal and natural persons is increasing (Paseková and Crhová Kuderová, 2014). Some studies are focused on the descriptive state of the domestic market over a certain period after the introduction of the Insolvency Act (Smrčka, Schőnfeld and Ševčík, 2013) or what effect the amendments and amendments to the act itself have on the practice, which addressed some of the fundamental issues regarding powers in decision-making in insolvency proceedings (Richter, 2013). Few scientific studies deal with the recovery of claims from insolvency proceedings, for natural or legal persons, or for practical solutions to insolvency that affect various market determinants (Jakubík, 2007).

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1 This paper was supported by grants FP-S-18-5074 "Development trends of the economic management of the enterprise in the European economic environment".

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Insolvency proceedings as such are subject to the influence of many factors from the whole economic environment. Some factors (determinants) cannot be quantified and basic statistical models cannot be used (Sen, Singer, 1994). So, the use of trend research is appropriate (Vícha and Dohnal, 2008; Dohnal, 2016). This means that knowledge items of different levels of subjectivity must be taken into consideration to develop the best possible model of a unique task under study. Therefore, many bankruptcy observations are required. However, they are not available. This is the reason why information non-intensive formal tools are used more and more frequently, see e.g. fuzzy and/or rough sets (Pavláková Dočekalová and Kocmanová, 2016; Meluzín et al., 2016).

1. Alternative Decision-Making Methods in the Process

Decision-making analyses are often used to help decision-makers choose between alternatives based on the expected utility associated with the function of its consequences and potential impacts. Therefore, for example, in a study (Wang et al., 2018) a multicriteria decision model is developed. Although many successful studies have been conducted on the detection of bankruptcy, rarely have probabilistic approaches been made. In research (Antunes, Ribeiro and Pereira, 2017), a probabilistic aspect is assumed by applying Gaussian processes. Bankruptcy and reorganisation prediction models are often used in auditing large corporate transactions (mergers and acquisitions, strategic alliances, etc.), in making investment decisions and in the judiciary, where judges are final arbitrators in bankruptcy proceedings.

However, all existing insolvency models are inadequate mainly because the research methods were defective. The authors merely put rigid mathematical models into bankruptcy. Models do not follow an interdisciplinary approach, do not allow optimisation and simulation to derive the best conditions for minimising financial threats. The study (Nwogugu, 2006) presents various dynamic models for insolvency decision-making and develops the framework and basis for further research into the use of dynamic systems and artificial intelligence in modelling bankruptcy decisions and legal arguments.

This paper deals with bankruptcy forecasting under conditions of severe information shortages. Such bankruptcies are often described by non-numerical quantifiers, e.g. words – low, medium, high. However, the transfer of such verbal values into fuzzy sets is very subjective (Yi-Chung Hu and Tseng, 2007).

2. Trend Models

There are many different interpretations of trend concepts (Kamstr and Kennedy, 1998; Stekler and Symington, 2016). The trend concepts as it is used in this paper is based on four values (Vicha and Dohnal, 2008; Bredeweg, 2009):

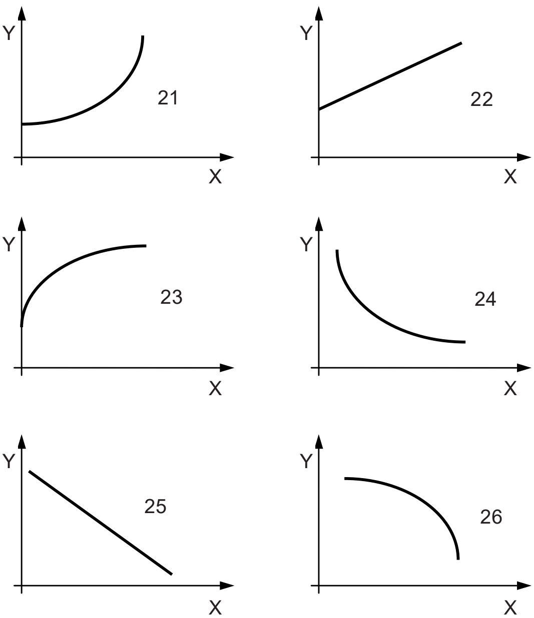
Positive	Zero	Negative	Any Value	
+	0	-	*	(1)

An equationless trend model M is a set of *w* pair-wise relations

$$M = P_s\,(X_i, X_j) \qquad s = 1, 2, \ldots\ldots w \tag{2}$$

Examples/shapes of the relations P (2) are given in Figure 1:

Figure 1 | Trends relationships



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An algorithm, which can be used to solve the model (2), is based on the pruning of a specially generated tree of combinations. It is not the goal of this paper to describe such an algorithm, as it is a purely mathematical combinatorial task (Vicha and Dohnal, 2008).

The model (2) is solved and the set of *n* dimensional scenarios is obtained **S**(n, m). There are *m* scenarios:

$$\mathbf{S}(\mathrm{n},\mathrm{m}) = (X_1, \mathrm{D}X_1, \mathrm{DD}X_1), (X_2, \mathrm{D}X_2, \mathrm{DD}X_2),\ldots, (X_n, \mathrm{D}X_n, \mathrm{DD}X_n)_j, \quad j = 1, 2,\ldots, m, \tag{3}$$

where D*X* is the first and DD*X* is the second time trend derivatives. For example, the following three-dimensional scenario, n = 3 (3).

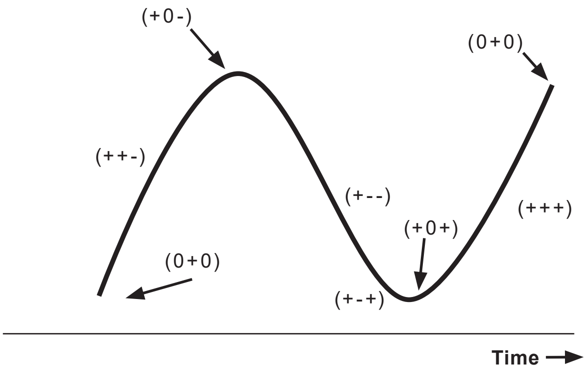
$$\begin{array}{lll} X_1 & X_2 & X_3 \\ (+\,+\,+) & (+\,-\,0) & (+\,-\,-). \end{array} \tag{4}$$

The model (2) is solved and the set of *n* dimensional scenarios is obtained **S**(n, m). There are *m* scenarios:

2.1 Transitional Graphs

The set of scenarios **S** (3) is not the only result of a trend modelling. It is possible to generate transitions among the set of scenarios.

Figure 2 | A trend description of a quantitative oscillation



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The triplets given in Figure 2 describe a broad spectrum of different oscillations, e.g. dumped oscillation or irregular oscillations with randomly or deterministically changing frequencies and/or amplitudes.

3. Case Study

Based on the heuristics of using trend methods, variables that have a major impact on the debt relief process have been carefully selected after discussions with insolvency experts. In the next chapter, the variables will be described with an explanation of how their existence individually affects the insolvency process. Subsequently, these variables were used to build a trend model based on time-dependent insolvency management scenarios.

There are no published trend models of bankruptcies. A team of two experts was contacted and the list of case study variables was generated:

SEL	Selling of Assets	
ENJ	Ensured Justice	
GRD	Level of Greed	
TAX	Tax Burden	
SAT	Satisfaction of Creditors	(5)
SOL	Solution of Debtors Assets	
POL	Political Influence	
BUL	Bullying of Creditors	
INF	Inflation	

Selling of assets

In principle, it is right that a secured creditor would decide on how the property of the creditor is secured. However, the practice is more complex and reflects a number of partial interests of the subjects who immediately decide on the method of monetisation and, in this sense, they instruct the insolvency administrator. Although the insolvency trustee may refuse the orders of the hedged creditor if they consider that the object of the hedge can be monetised more advantageously.

Ensured justice

It is a variable that represents the moral and fair behaviour of the insolvency court, which should perform a catalytic and independent role in the insolvency process. The insolvency court is the regional court where the debtor`s insolvency proceedings are conducted. If it is a legal entity, it is a regional court in the region where the debtor is based. In the case of a natural person, it is the court where the debtor resides.

Level of greed

The level of greed is a variable understood in trend modelling as the irrational behaviour of the debtor, which pushes against other variables for amortisation of the debt and the satisfaction of the creditor`s requirements. It has been selected as an important factor in the entire insolvency process and is also a suitable variable for trend modelling in terms of its vagueness and difficulty in quantifying.

Tax burden

For trend modelling purposes, the tax load variable is applied as a contradictory constant (depending on the type of debtor/creditor and the case to which the insolvency proceedings are dedicated). Unlike other process variables, it is of a sharp nature.

Satisfaction of creditors

Satisfaction of creditors is the first of the variables that are perceived in the model as target variables to represent the best possible state for the question under investigation. It is a fair payment of debts to creditors from debtors where, based on the court`s decision, the creditor(s) and creditor committees are split into secured and unsecured.

Solution of debtor assets

In the trend decision model, this variable is seen as one of the goals that should be as cost-effective as possible for the subject, so that the creditor`s claim and the economic and social status of the debtor are maintained.

Political influence

It is not possible to analyse the country`s economy by only taking into account market factors (Radu, 2015). Every economic system must be integrated and harmonized with the country`s continuing development, a trend that reflects technological change and innovation as well as political conflicts that lead to the representation and changing of different interests and institutions. Therefore, it is important to include political factors to analyse the economic process (Boyer, 2011)

Bullying of creditors

Being bullied by a creditor is against the law. Although creditors have many options to claim their right to repayment of the debt, which is considered legal, there are also many practices that are widely used that are not lawful (Kirwan, 2018). The initiation of insolvency proceedings not only has negative legal consequences (e.g. limiting the alleged debtor in relation to the handling of his property) but also has non-legal consequences (damage to the alleged debtor`s reputation, doubt of his credibility and economic situation).

Inflation

Simple inflation refers to an increase in the price level. In everyday life, an increase in inflation may mean that consumers pay more at a grocery store or, for example, at a petrol station (Vicki, 2017). Increased inflation also affects services and their providers. These traders need to adjust their service prices adequately to inflationary developments because their rising costs are dependent on increasing suppliers` prices and can have a direct effect on the entire debtor/creditor system.

2.1 Model of Insolvency Proceedings

Build variables (5), which play an important role in the decision-making process, and form a complete set of scenarios, were selected after discussions with experts on insolvency. The very nature of the variables used suggests that it is very difficult to quantify, see, for example, GRD. Therefore, the use of trend models is justified.

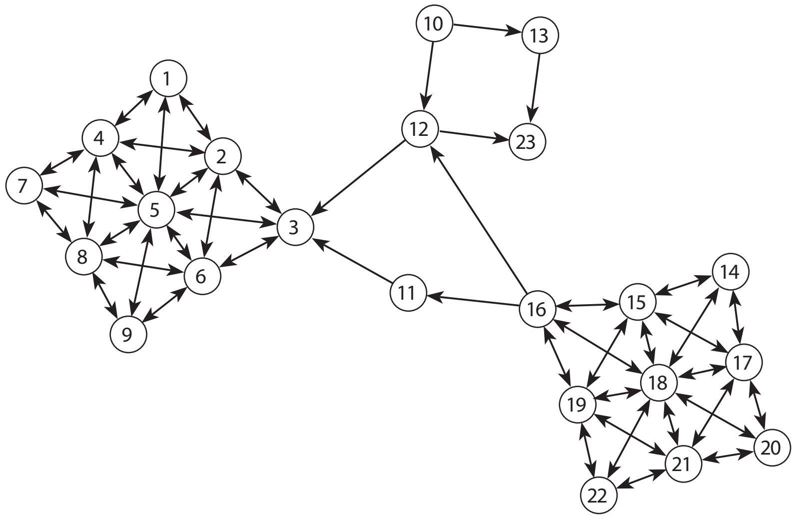
See e.g. Figure 1 Trends relationship 1, (1) X Y

1	+	SEL	ENJ	
2	25	SEL	GRD	
3	21	SEL	SAT	
4	24	SEL	SOL	
5	23	ENJ	TAX	(6)
6	-	ENJ	BUL	
7	+	TAX	POL	
8	-	SAT	BUL	
9	+	POL	INF	

There are 23 scenarios, m = 23(6).

#	SEL V	ENJ V	GRD V	TAX V	SAT G	SOL G	POL O	BUL O	INF O	
1	+++	+++	+--	+++	+++	+-+	+++	+--	+++	
2	+++	+++	+--	+++	+++	+-0	+++	+--	+++	
3	+++	+++	+--	+++	+++	+--	+++	+--	+++	
4	+++	+++	+--	++0	+++	+-+	++0	+--	++0	
5	+++	+++	+--	++0	+++	+-0	++0	+--	++0	
6	+++	+++	+--	++0	+++	+--	++0	+--	++0	
7	+++	+++	+--	++-	+++	+-+	++-	+--	++-	
8	+++	+++	+--	++-	+++	+-0	++-	+--	++-	
9	+++	+++	+--	++-	+++	+--	++-	+--	++-	
10	++-	++-	+-+	++-	++-	+-+	++-	+-+	++-	
11	+0+	+0+	+0-	+0+	+0+	+0-	+0+	+0-	+0+	
12	+00	+00	+00	+00	+00	+00	+00	+00	+00	(7)
13	+0-	+0-	+0+	+0-	+0-	+0+	+0-	+0+	+0-	
14	+-+	+-+	++-	+-+	+-+	+++	+-+	++-	+-+	
15	+-+	+-+	++-	+-+	+-+	++0	+-+	++-	+-+	
16	+-+	+-+	++-	+-+	+-+	++-	+-+	++-	+-+	
17	+-+	+-+	++-	+-0	+-+	+++	+-0	++-	+-0	
18	+-+	+-+	++-	+-0	+-+	++0	+-0	++-	+-0	
19	+-+	+-+	++-	+-0	+-+	++-	+-0	++-	+-0	
20	+-+	+-+	++-	+--	+-+	+++	+--	++-	+--	
21	+-+	+-+	++-	+--	+-+	++0	+--	++-	+--	
22	+-+	+-+	++-	+--	+-+	++-	+--	++-	+--	
23	+--	+--	+++	+--	+--	+++	+--	+++	+--	

Figure 3 | Transition graph based on a set of 23 scenarios (7)



Source: Authors` own processing

Any forecasting is heavily predetermined by interpretations of variables (5). The choice of the sets V, O, G, is of crucial importance and is based on the current point of view.

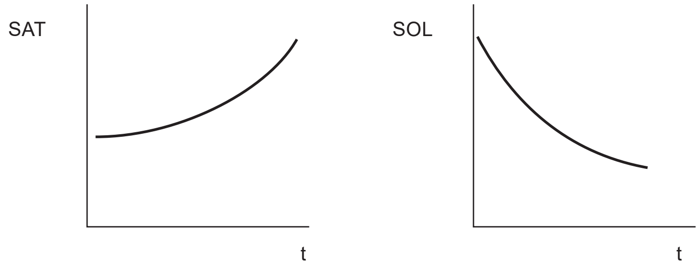
Any forecasting/decision-making will be based on an *n*-dimensional model M(**X**). A set **X** of *n* variables is a union of Decision variables **V**, Goals variables **G** and Off-control variables **O** (8).

SEL	V	Selling of Assets	
ENJ	V	Ensured Justice	
GRD	V	Level of Greed	
TAX	O	Tax	
SAT	G	Satisfaction of the Creditors	(8)
SOL	G	Solution of Debtor`s Assets	
POL	O	Political Influence	
BUL	V	Bullying of Creditors	
INF	O	Inflation	

O = [POL, INF, TAX]
G = [SAT, SOL] (9)
V = [SEL, ENJ, GRD, BUL]

A simple common-sense analysis indicates that there is one view and forecast from the creditor`s point of view:

Figure 4 | Creditor`s view – where t represents a variable time



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The best trend description of the creditor`s view:

SAT	Increase more and more rapidly	DSAT = +	DDSAT = +	(10)
SOL	Decreasing more and more slowly	DSOL = -	DDSOL = +	

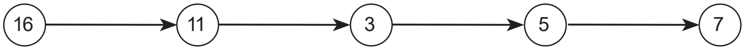
The worst trend description of the creditor`s view:

SAT	Decreasing more and more slowly	DSAT = -	DDSAT = +	(11)
SOL	Increase more and more rapidly	DSOL = +	DDSOL = +	

The best scenario is S_7 (7). The shortest path is the path leading from the worst scenario S_{16} to the target scenario S_7 (see Figure 3):

$$S_{16} \rightarrow S_{11} \rightarrow S_3 \rightarrow S_5 \rightarrow S_7 \tag{12}$$

Figure 5 | A simplified transition graph based on a set of 23 scenarios (7)



Source: Authors` own processing

The sequence of scenarios is, see (23):

No.	SEL V	ENJ V	GRD V	TAX V	SAT G	SOL G	POL O	BUL O	INF O
16	+-+	+-+	++-	+-+	+-+	++-	+-+	++-	+-+
11	+0+	+0+	+0-	+0+	+0+	+0-	+0+	+0-	+0+
3	+++	+++	+--	+++	+++	+--	+++	+--	+++
5	+++	+++	+--	++0	+++	+-0	++0	+--	++0
7	+++	+++	+--	++-	+++	+-+	++-	+--	++-

(13)

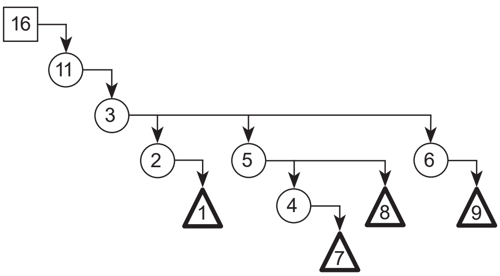
A decision-maker has no free choice to change the variables (5). Some variables are not under his/her control (8). Therefore, there are variables selected by O as out of control. This means that any forecast is partially based on available descriptions of O variables (13) e.g. probability distributions.

3.2 Probability Distributions

Based on the transitional graph from the case study in Figure 5, the path from the worst kind of scenario to the best kind of scenario according to the creditor´s point of view was used.

The transition graph in Figure 3 has been transformed into a decision tree where some of the decision-making heuristics can be used for obtaining the probabilities and to determinate the forecast. The resulting terminal scenarios, which also reflect the positive status for creditors, were designated as termination points. Where S_{16} was designated as the root node and S_7 was the termination node (with the others S_1, S_8 and S_9). Where the termination scenarios have slightly different outputs.

Figure 6 | The transition graph has been transformed into a decision tree (7)



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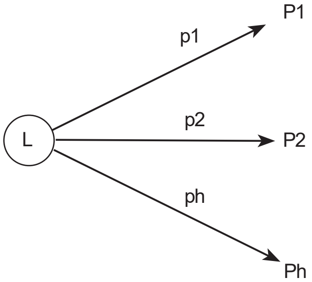
Decision-Making trees

IB decision trees are based on nodes, branches, endpoints, strategy, payoff distribution, certain equivalent, and the rollback method (Rose, 1976). An example of a decision tree is given in Figure 6. Nodes are divided into single decision root nodes, decision nodes and lotteries/chance nodes (Magee, 1964). The root node is the top of any decision tree, see node no. 16, Figure 6. Oriented arcs that connect nodes are called branches.

Figure 7 | Lottery nodes



Source: Authors` own processing

Lottery nodes are plotted as small circles, see nodes 3 and 2 etc. Figure 6. Each lottery branch has its probability p, and its profit P. There are many different algorithms on how to evaluate LNV (lottery node value) (Rose, 1976). For example, risk aversions are sources of different modifications LNV modifications (Rose, 1976). The following simple formula will be used in this paper:

$$LNV = (p_1P_1 + p_2P_2 + \ .\ .\ .\ . + p_nP_n)$$
$$p_1 + p_2 + .\ .\ .p_n = 1. \qquad (14)$$

Water probability

If we imagine a situation where decision-makers have no information, e.g. no probabilities of the situations outgoing from node no. 2 (splitting ratios), see Figure 8, about IB decision-making problem/task; the decision-making problem is solved under total ignorance (only the topology of the decision tree is known) (Doubravský and Dohnal, 2015). The following table shows the profits of the individual edges of the decision and the relevant probabilities/splitting ratios of edges by the heuristics H1:

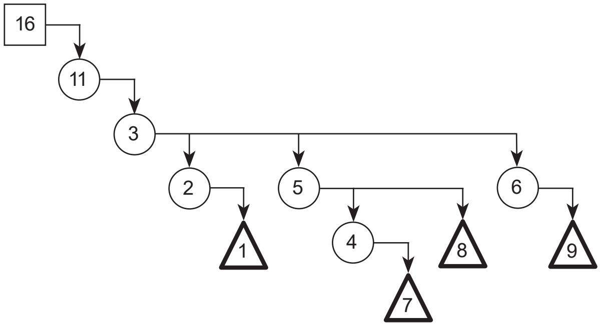
H1: A longer decision tree sub-path is less probable (15)

The heuristics H1 is based on a strong analogy between a water flow through a one root tree system of pipes and the decision tree of the same topology. Let us suppose that one litre of water is pumped into the root node of the decision tree each second and there is no accumulation of water inside the tree (Poláček, 2017).

Topological resistance

A decision tree has one root node 16; see e.g. Figure 8, where the circles/nodes represent the lotteries in Figure 7.

Figure 8 | The transition graph has been transformed into a decision tree (7)



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S_{ij} Number of edges of the sub-tree where i is the root of the sub-tree and j is the node next to the sub-root. S_i Number of all edges of the sub-tree where i is the sub-root (water-resistance of the ith node) (Doubravský and Dohnal, 2015):

$$S_i = \sum_j s_{ij} \text{ see e.g. } S_3 = s_{36} + s_{32} + s_{35} = 2 + 2 + 4 = 8, \tag{16}$$

where j represents the nearest downstream node of the sub-tree next to the ith node.

$$s_{ij}^* = S_i - s_{ij}, \text{ for all i, j} \in N - T,\ s_{36}^* = S_i - s_{36} = 8 - 2 = 6. \tag{17}$$

$\mathbf{S_i^*}$ Number of edges of the ith sub-tree:

$$S_i = \sum_j s_{ij}^* \text{ see e.g. } S_i^* = s_{36}^* + s_{35}^* + s_{32}^* = 6 + 6 + 4 = 16, \tag{18}$$

where j represents the nearest downstream node of the sub-tree next to the ith node.
This paper is based on the following definition of the splitting fraction. Splitting ratio from the ith node to the jth node:

$$\alpha_{ij} = s_{ij}^* / S_i^*, \text{ for all i, j} \in N - T,\ \alpha_{36} = s_{36}^* / S_3^* = 6/16 = 0.375. \tag{19}$$

Table 1 | Splitting ratio

Branch	Probability
16 – 11	1
11 – 3	1
3 – 6	0.375
6 – 9	1
3 – 2	0.375
3 – 5	0.25
4 – 7	1
5 – 4	0.333
5 – 8	0.666
2 – 1	1

Source: Authors` own processing

The following table shows the profits of the individual edges of the decision and the relevant probabilities/splitting ratios of edges by the heuristics H1 (15).

Table 2 | Specified probabilities

Branch	Probability	Terminal probability
16 – 11	1	
11 – 3	1	
3 – 6	0.375	
6 – 9	1	0.375
3 – 2	0.375	
3 – 5	0.25	0.4
4 – 7	1	0.0833
5 – 4	0.333	
5 – 8	0.666	0.167
2 – 1	1	0.375

Source: Authors` own processing

In Table 3 can be seen the calculated terminal probability of scenarios for selected routes from a decision tree.

Conclusion

A broad spectrum of research activities in artificial intelligence has generated many different methods, algorithms and methodologies, which can potentially be used for forecasting and related areas.

There are three main advantages of the trend-based forecasting:

- No numerical values of constants and parameters are needed
- It is possible to develop multidimensional models based on verbal knowledge items, e.g. heuristics
- The set of trend scenarios is a superset of all meaningful scenarios, i.e. forecasts.

Based on previous research in the area of insolvency proceedings under the Czech Insolvency Act, a qualitative model based on trend analysis was prepared, which includes a mixture of vague and sharp variables from macroeconomics and insolvency proceedings (Poláček, 2018). The result of this model was a list of scenarios where we can see the sensitivity of individual variables to changes in the process as well as the efficient use of the transition graph to define the ideal path from the "worst" scenario to the "best" possible, taking into account the variables that are under the control of the decision-makers and those that are not influenced by the process. After selecting such an ideal path, it was possible to simply formulate a graph in the form of a decision tree by simply modifying the transition graph, where some of the heuristic decisions could be applied to the decision tree. The water probability method (Doubravský and Dohnal, 2015) was chosen for the purpose of the study because of the lack of knowledge of probability on lottery nodes. As a result, the probability of the resulting termination nodes, i.e. final scenarios, see e.g. Table 3:

Table 3 | Final scenario probability

Node/scenario	Probability
1/S_1	0.375
7/S_7	0.083
8/S_8	0.167
9/S_9	0.375

Source: Authors` own processing

Developments of the trend models do not require knowledge of complicated theories of artificial intelligence. These methods are used as black boxes. An important advantage of the trend forecasts is that anybody can develop a model based on elementary knowledge of mathematics. The authors are ready to make the relevant calculations of a model that is delivered.

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